Optimization Techniques Based Sentiment Analysis

A Thesis Submitted
in Partial Fulfillment of the Requirements
for the Degree of

DOCTOR OF PHILOSOPHY

by

Neha Punetha

(2K20/PHD/AM/02)

Under the supervision of

Dr. Goonjan Jain

Department of Applied Mathematics,

Delhi Technological University, Delhi

to the

Department of Applied Mathematics

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi -110042, India

January, 2024

Declaration

I declare that the research work in this thesis entitled “Optimization Techniques Based Sentiment Analysis” for the award of the degree of Doctor of Philosophy in Mathematics has been carried out by me under the supervision of Dr. Goonjan Jain, Department of Applied Mathematics, Delhi Technological University, Delhi, India, and has not been submitted by me earlier in part or full to any other university or institute for the award of any degree or diploma.

I declare that this thesis represents my ideas in my own words and where others’ ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission.

Neha.

Neha Punetha

(2K20/PHD/AM/02)

Date: **January 2024**

Certificate

This is to certify that the research work embodied in the thesis entitled "**Optimization Techniques Based Sentiment Analysis**" submitted by **Ms. Neha Punetha** (2K20/PHD/AM/02) is the result of her original research carried out in the Department of Applied Mathematics, Delhi Technological University, Delhi, for the award of **Doctor of Philosophy** under my supervision. It is further certified that this work is original and has not been submitted in part or fully to any other university or institute for the award of any degree or diploma. This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

Date: January 2024
Place: Delhi, India

Dr. Goonjan Jain
(Supervisor)

11/1/24

Prof. Ramesh Srivastava
(Head of Department)

Acknowledgments

While presenting my Ph.D. thesis, I must first express my sincere gratitude to the almighty for his countless blessings and presence in my life, which I experience every day through my family, teachers, and friends.

I would like to thank my supervisor, Dr. Goonjan Jain, for her patient guidance and unwavering faith in me throughout my Ph.D. I consider myself incredibly fortunate to have a guide who genuinely cares about her students and pushes them professionally to achieve their goals in life. Her determination, positive outlook, and confidence has always been a source of inspiration for me.

I would also like to extend my gratitude to the Head of the Department, Prof. Ramesh Srivastava, and other faculty members of the department for providing all the facilities necessary for conducting my research. Their constant guidance and kind words of encouragement and concern offer a healthy working space to carry out research. I am also grateful to the department staff for their kind assistance throughout my Ph.D.

The eternal source of my mental and emotional strength is my parents and brothers. Their unconditional love and perpetual support are the sole reason my thesis sees the light of day. I am also highly indebted to my good friend, Vaibhav Sharma who has been my partner in research and whose unconditional support motivated me during challenging times.

Completing this work would have been all the more difficult without the support and friendship of my colleagues Dyvavani, Supriya, Vinita, Himani, Annie, and Reetika. I would like to thank them individually for not only assisting me but also for their extraordinary friendship, which made this journey so memorable. I would like to thanks Deepak and Ishaan for being my friends which made this journey so memorable.

Finally, I extend my heartfelt thanks to all whose names are not mentioned here but have helped me in any way and at any time throughout my Ph.D.

Neha.

Neha Punetha

Place: DTU, Delhi, India

Dedicated
To
My Family

Table of Contents

Abstract

Sentiment Analysis is a task under the domain of Natural Language Processing that plays a crucial role in understanding and quantifying emotions, opinions, and attitudes. The abundance of online data drives businesses to leverage sentiment analysis as a means to monitor and gauge consumer sentiments and emotions, enabling them to make informed decisions and tailor their services to meet customer needs. Many existing approaches heavily rely on machine learning, necessitating large datasets for pre-training and incurring significant computational complexity. To tackle this issue, we propose unsupervised sentiment classification models for sentiment analysis.

This thesis introduces frameworks based on mathematical optimization techniques namely game theory and Multi Criteria Decision Making. The integration of these mathematical techniques generates robust algorithms for sentiment tagging. We use textual feedback and star ratings of reviews and apply mathematical optimization techniques to deduce the correct sentiment for the reviews.

In the thesis, we have performed binary and tertiary classification of review comments on datasets of varied domains. We have also introduced two explicit models for sentiment analysis of Hindi review comments. This assures that the mathematical optimization techniques with minor modifications can adapt to any language. We have also addressed the negation handling challenge of the sentiment analysis. To ascertain the relevance of the sentiment analysis task, we used it to generate two recommendation models, which produce promising results.

In summary, our novel unsupervised sentiment classification models present effective solutions to the challenges posed by the vast amounts of online data and the resource-intensive nature of conventional machine learning approaches. By utilizing mathematical optimization models, we offer efficient, scalable, and accurate sentiments of written reviews. Furthermore, the models guarantee logical and consistent outcomes, instilling confidence in the accuracy of sentiment classifications.

List of Publications

Papers Published / Accepted in International Journals

- Punetha, N. and Jain, G., (2023). "Bayesian game model based unsupervised sentiment analysis of product reviews." *Expert Systems with Applications*, *214*, pp.119-128. **(Impact Factor – 8.55)(SCIE).**

- Punetha, N. and Jain, G., (2023). "Optimizing Sentiment Analysis: A Cognitive Approach with Negation Handling via Mathematical Modelling." *Cognitive Computation*, pp.1-17. **(Impact Factor – 5.4)(SCIE).**

- Punetha, N. and Jain, G., (2023). "Game theory and MCDM-based unsupervised sentiment analysis of restaurant reviews." *Applied Intelligence*, pp.1-22. **(Impact Factor – 5.32)(SCIE).**

- Punetha, N. and Jain, G., (2023). "Aspect and orientation-based sentiment analysis of customer feedback using mathematical optimization models." *Knowledge and Information Systems*, *65*(6), pp.2731-2760. **(Impact Factor – 2.71)(SCIE)**.

- Punetha, N. and Jain, G., (2023). "Unsupervised sentiment analysis of Hindi reviews using MCDM and game model optimization techniques." *Sādhanā*, *48*(4), pp.195-203. **(Impact Factor – 1.6)(SCIE)**.

- Punetha, N. and Jain, G., (2023). "Integrated Shannon entropy and COPRAS optimal model-based recommendation framework." *Evolutionary Intelligence*, pp.1-13. **(Impact Factor – 2.6)(ESCI)**.

- Punetha, N. and Jain, G, *Mathematical Optimization Techniques-Based Sentiment Evaluation.* **(Under revision).**

- Punetha, N. and Jain, G, *Recommendation framework for Products using Optimization algorithms.* **(Under revision).**

- Punetha, N. and Jain, G*, Analyzing Sentiment Dynamics with the Hawk-Dove Model for Hindi Language Text via A Mathematical Optimization Approach*. **(Communicated).**

- Punetha, N. and Jain, G, *Advancing Sentiment Classification through Unsupervised Techniques: A Population Game Model Approach.* **(Communicated).**

- Punetha, N. and Jain, G, *Enhancing Text Sentiment Categorization Using MCDM And Game Theory Algorithms.* **(Communicated).**

Book Chapter

- Punetha, N. and Jain, G, Optimizing Sentiment Analysis Model for Sustainable Stock Forecasting Management. *"Management for Sustaintable Development intregating social, economic and environmental goals" Taylor & Francis*. **(Accepted)**

Papers Presented/Published in International Conferences

- Punetha, N. and Jain, G, Sentiment Analysis of Stock Prices and News Headlines Using the MCDM Framework, *4th International Conference on Artificial Intelligence and Speech Technology (AIST) (2022) pp. 1-4,* https://doi.org/10.1109/AIST55798.2022.10065221.

- Punetha, N. and Jain, G, Hawk Dove model-based stock sentiment analysis of news headlines.*5th International Conference on Recent Advances In Mathematical Sciences With Application In Engineering And Technology (2022).*

List of Figures

List of Tables

List of Notations

Notations	Description
P	The positive sum of positive rating and positive context.
N	The negative sum of negative rating and negative context.
RP	Positive Rating.
RN	Negative Rating.
CP	Positive Context.
CN	Negative Context.
S	Satisfactory Service Feedback
U	Unsatisfactory Service Feedback
H	Happy emotion
A	Angry emotion
S	Sad emotion
F	Fear emotion
S_p	Surprised emotion
PS	Polarity is positive, and service feedback is satisfactory.
PU	Polarity is positive, and service feedback is unsatisfactory.
NS	Polarity is negative, and service feedback is satisfactory.
NU	Polarity is negative, and service feedback is unsatisfactory.
$(PCS^{\otimes})$	Normalized Positive Context score
$(NCS^{\otimes})$	Normalized Negative Context score
$(OCS^{\otimes})$	Normalized Neutral Context score
$(PES^{\otimes})$	Normalized Positive Emotion score
$(NES^{\otimes})$	Normalized Negative Emotion score
$(OES^{\otimes})$	Normalized Neutral Emotion score
$(A_j)_p$	Action performed by R_j is positive.
$(A_j)_N$	Action performed by R_j is negative
$(A_i)_{Cp}$	Context type of review R_i while performing positive action.

$(A_i)_{Cn}$	Context type of review R_i while performing negative action.
$(A_i)_{Rp}$	Rating type of review R_i while performing positive action.
$(A_i)_{Rn}$	Rating type of review R_i while performing negative action.
C_P	Context is positive
C_N	Context is negative
R_P	Rating is positive
R_N	Rating is negative
$(R_i)_{CP}$	Review *i* having a positive strategy of context type matrix
$(R_i)_{CN}$	Review *i* having a negative strategy of context type matrix
$(R_j)_{CP}$	Review *j* having the positive strategy of context type matrix
$(R_j)_{CN}$	Review *j* having the negative strategy of context type matrix
$C^1{}_P$	Positive context of Player 1
$C^1{}_N$	Negative context of Player 1
$C^2{}_P$	Positive context of Player 2
$C^2{}_N$	Negative context of Player 2
$E^1{}_P$	The positive emotion of Player 1
$E^1{}_N$	Negative emotion of Player 1
$E^2{}_P$	The positive emotion of Player 2
$E^2{}_N$	Negative emotion of Player 2
V	The fitness value of the fight
C	Fitness cost of injury
DPR	Degree of positive rating
DRN	Degree of negative rating
DRO	Degree of neutral rating

Chapter 1

Introduction

In this chapter, we embark on a comprehensive journey into the realm of sentiment analysis. *Section 1.1* serves as the starting point, where we introduce the foundational concepts of sentiment analysis. As we progress, *Section 1.2* unfolds the applications of sentiment analysis, showcasing its practical relevance across various domains. In *Sections 1.3* and *1.4,* we explore its diverse types and the various methods employed for sentiment analysis. Our exploration continues with *Section 1.5*, where we delve into the utilization of lexicon databases, shedding light on their pivotal role in sentiment analysis. In *Section 1.6*. we address various challenges faced by sentiment analysis. In *Section 1.7*, we pivot towards mathematical optimization techniques, dedicating specific attention to game theory as elucidated in *Section 1.7.1*, and the different concepts of MCDM (Multi-Criteria Decision Making) outlined in *Section 1.7.2*. The relationship between MCDM and game models is unveiled in *Section 1.7.3*. *Section 1.8* provides an insightful discussion of the diverse evaluation metrics for assessing the efficiency of the proposed model. *Section 1.9* formally introduces the core problem statement, anchoring our research objectives. The objectives of this thesis are discussed in *Section 1.10*. *Section 1.11* explores the motivations behind performing sentiment analysis research. Finally, we culminate this chapter by providing a comprehensive overview of the thesis's organizational structure, offering a clear roadmap for what lies ahead in the subsequent chapters.

1.1 Sentiment Analysis

Sentiment Analysis is a Natural Language Processing (NLP) task to identify, extract, and quantify sentiments. Computerized methods are used to decipher text sentiments or views [1]. In sentiment analysis, we study a text's subjective information and examine people's feelings, opinions, emotions, or attitudes toward a product. Sentiments are classified as positive, negative, or neutral. For example,

"I like the new design of your dress" → **Positive Sentiment**
"I do not like the new design" → **Negative Sentiment**
"The new design is okay!" → **Neutral Sentiment**

Sentiment analysis of text, also known as opinion mining, is a sophisticated and dynamic natural language processing technique that plays a vital role in today's information-driven world. With the explosive growth of digital content across various platforms, including social media, online reviews, news articles, and blogs, sentiment analysis has become an indispensable tool for understanding the emotions and attitudes expressed by individuals and groups. At its core, sentiment analysis involves the automatic extraction of subjective information from textual sources, aiming to determine the emotional valence associated with particular words, phrases, or entire documents. The process typically begins with text pre-processing, where the data is cleaned and transformed into a format suitable for analysis. This step involves tasks like tokenization (breaking text into words or sentences), stemming (reducing words to their base form), and removing stop words (common words like “the” and “and” that don't carry much meaning)[2].

Analyzing sentiment in social media posts or news articles related to political events or figures, researchers can gauge public sentiments and political inclinations, providing useful insights for policymakers and political strategists. However, sentiment analysis is not without its challenges. The complexity of human language, sarcasm, irony, and context-dependent sentiment can sometimes lead to misinterpretations or incorrect classifications[3]. Additionally, sentiments may vary across cultures and demographics, making it essential for sentiment analysis models to be continuously updated and adapted to reflect evolving language trends and societal changes[4].

In summary, sentiment analysis is a multifaceted and ever-evolving task that has revolutionized our ability to understand and interpret the vast volumes of textual data in the digital age. By deciphering the emotions and attitudes expressed through data, sentiment analysis empowers businesses, researchers, and decision-makers to harness the power of language to gain valuable insights, shape strategies, and enhance the overall understanding of human behavior and opinions[5]. As the world generates an ever-increasing volume of content, sentiment analysis will undoubtedly remain a critical tool for unlocking the hidden sentiments buried within the written word. In this thesis, we have performed a sentiment analysis of the written text [6].

1.2 Need of Sentiment Analysis

In this section, we discuss some applications of sentiment analysis.

i) Dealing with an Overwhelming Amount of Textual Data: As the volume and variety of textual information generated by various channels, such as social media, reviews, news articles, and online discussions, continues to grow, the difficulty of manually comprehending and analyzing underlying sentiments becomes an increasingly complex challenge for human analysts [7].

ii) Sentiment Analysis in the Market Dynamics: In the domain of market research, sentiment analysis emerges as an illuminating tool, facilitating the dissection of public sentiments and attitudes towards products, competitors, and marketing campaigns. Its implications are evident in the formulation of finely calibrated marketing strategies, the elucidation of consumer behavior, and the predictive discernment of market trends [8].

iii) Unveiling the Emotional Pulse of Social Media: Social media is a constantly changing place where people post content in real-time. In this case, sentiment analysis becomes a way for companies and organizations to understand how people feel about their products and services, which helps them see how well their brand is known in the online community [9].

iv) Enhancing Customer Support with Sentiment Analysis: The efficacy of sentiment analysis extends to the improvement of customer support frameworks by identifying latent emotions contained in customer inquiries. This analytical prowess guides the prudent prioritization and dispatching of requests, ensuring prompt and germane responses to urgent or deleterious concerns, resulting in a customized and satisfying customer experience.

v) Enhancing Customer Support with Sentiment Analysis: Beyond the corporate sphere, sentiment analysis finds applicability within healthcare. Through the analysis of patient feedback and sentiments, healthcare professionals can discern emotional distress and mental health indicators, leading to improved patient support and care strategies [10].

1.3 Types of Sentiment Analysis

Sentiment analysis can be performed at various levels of granularity to extract and understand the sentiments expressed in a piece of text. The different levels of sentiment analysis are given in *Fig. 1.1*.

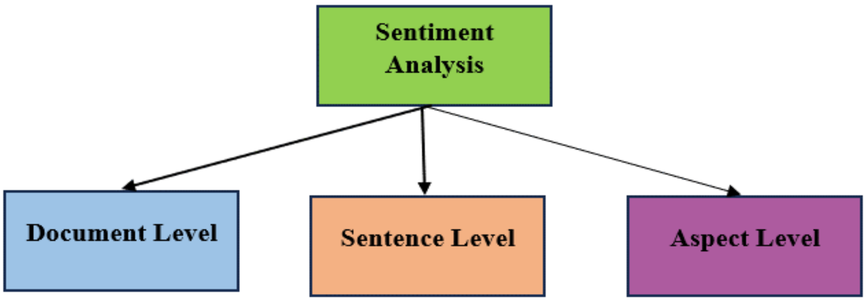

Fig. 1.1: Different Levels of Sentiment Analysis

i) Document-level Sentiment Analysis: At this level, we analyze the entire piece of text, like an article, to figure out the overall sentiment expressed in it. The goal is to classify the sentiment as positive, negative, or neutral for the entire document. For example, we can determine if a movie review is positive or negative based on the overall content of the review[11].

ii) Sentence-level Sentiment Analysis: In this level of analysis, we look at individual sentences within the text to understand the sentiment expressed in each sentence. This approach allows us to get a more detailed understanding of the sentiments conveyed throughout the text. Some sentences may contain positive feelings, while others may express negative or neutral sentiments[12].

iii) Aspect-level Sentiment Analysis: Aspect-level analysis is directed towards specific aspects or entities mentioned in a text. We focus on determining the sentiment towards particular features or attributes of a product, service, or entity. For example, in a product review, we identify the sentiment towards aspects like performance, design, price, and so on[13].

1.4 Methods of Sentiment Analysis

There are different proposed methods of sentiment analysis in the literature.

i) Lexicon-based methods rely on sentiment lexicons or dictionaries that contain words with pre-assigned sentiment scores. The sentiment score of a document is calculated using the sentiment polarity of words in the text. Although straightforward to implement, these methods struggle to capture contextual nuances and may not effectively handle language expressions like sarcasm or negations[14].

ii) Machine learning algorithms harness the power of supervised learning to analyze textual data. These algorithms are trained on labeled datas1ets, where each document is associated with its corresponding sentiment category. By learning patterns and features from the training data, machine learning models become adept at distinguishing different sentiment categories, allowing for more context-aware sentiment analysis[15].

iii) Deep learning models have revolutionized sentiment analysis with their ability to capture long-term dependencies and semantic relationships in textual data. By employing layers of artificial neural networks, these models can grasp complex language structures and disentangle intricate sentiments, leading to state-of-the-art performance in sentiment analysis tasks[16].

iv) Rule-based approaches utilize predefined rules or patterns to identify sentiments in text. These rules can be based on linguistic rules, syntactic patterns, or regular expressions. Rule-based methods offer the advantage of being adaptable to specific domains or languages, but they may require substantial manual effort to create and maintain the rules, limiting their scalability[17].

v) Hybrid approaches represent a fusion of multiple sentiment analysis methods to capitalize on their strengths and overcome individual weaknesses. For instance, a hybrid system might use lexicon-based methods for initial sentiment classification and then refine the results using machine learning or deep learning models to improve accuracy and robustness[18].

The choice of method depends on several factors, including the size and complexity of the dataset, the available computational resources, the desired level of granularity, and the specific application domain. In this thesis, we employed a mathematical optimization model for generating unsupervised techniques for sentiment analysis.

1.5 Lexicons Databases

In this thesis, we use two lexicon databases. For extracting polarity scores of English text we used SentiWordNet (SWN)[19] and for Hindi text, we used Hindi SentiWordNet (HSWN)[20].

i) SWN: It contains a list of words with respective positive and negative polarities values. *Fig. 1.2* shows an excerpt of SWN.

POS	ID	PosScore	NegScore	SynsetTerms	Gloss
a	00005107	0.5	0	uncut#7	complete; "the full-length play"
a	00005718	0.125	0	infinite#4	total and all-embracing;
a	00006245	0	0	relational#1	having a relation or being related
a	00016532	0	0.375	torrential#3	pouring in abundance; "torrential rains"
a	00016647	0.125	0.5	verdant#1	characterized by abundance of verdure
a	00017688	0.375	0.25	unabused#1	not physically abused; treated properly
a	00016247	0.125	0.5	superabundant#1	most excessively abundant
a	00018069	0.25	0	bankable#2	acceptable to or at a bank;
a	00020103	0.125	0	remote#4 outback#1	inaccessible and sparsely populated;
a	00013887	0	0.25	abundant#1	present in great quantity;

Fig. 1.2: Excerpt of SWN lexicon.

ii) HSWN: The HSWN database stores a collection of words that have either positive or negative polarity values. The positive and negative degrees of HSWN are shown in *Fig. 1.3*.

POS_TAG	ID	POS	NEG	LIST_OF_WORDS
a	10363	0.0	0.0	अनौपचारिक
a	2627	0.0	0.75	मृत
a	11476	0.125	0.0	परवर्ती
a	28106	0.25	0.375	अच्छा,बढ़िया
a	1156	0.875	0.0	सौभाग्यशाली,खुशकिस्मत,खुशनसीब,तक़दीर_वाला,नसीब_वाला,भाग्यवान,भाग्यशाली,ख़ुशक़िस्मत,ख़ुशनसीब
a	2279	0	1.0	दुर्भाग्यशाली,अभागा,बदनसीब,भाग्यहीन,मनहूस,बदकिस्मत,मंदभाग्य,बदक़िस्मत,दईमारा,कमबख्त,कमबख़्त,अधन्य,अभागी
a	2384	0.0	0.875	आवासहीन,आश्रयहीन,गृहहीन,गृहविहीन,बेघर,बेघरबार,अगतिक,अगेह,अनिकेत
a	4714	0.25	0.125	सुगंधित,सुगन्धित,ख़ुशबूदार,सुगंधपूर्ण,सुरभित,अधिवासित,खुशबूदार
a	1488	0.0	0.75	बदबूदार,दुर्गंधपूर्ण,दुर्गंधयुक्त,दुर्गंधित
a	29150	0.0	0.0	लगा,लगा_हुआ

Fig. 1.3: Excerpt of HSWN lexicon.

1.6 Challenges in the Field of Sentiment Analysis

The challenges in sentiment analysis are multifaceted and integral to the complexity of deciphering human emotions from textual data. These challenges are significant drivers of research and innovation in the field.

i) Contextual Complexity: One of the most substantial hurdles is the inherent complexity of language and context. Sentiments often rely on the broader context in which words are used. Identifying sarcasm, irony, and nuanced emotional tones requires an understanding of the surrounding text, making accurate sentiment analysis a daunting task[21].

ii) Subjectivity and Tone: Different individuals might interpret the same text differently based on their personal experiences and cultural backgrounds. Accurate sentiment analysis requires accounting for varying levels of subjectivity and tone, which can be especially challenging when dealing with diverse audiences[22].

iii) Slang and Abbreviations: Informal language, slang, and abbreviations are prevalent in digital communication platforms. These expressions can be challenging for sentiment analysis models to decipher accurately, leading to misinterpretations or inaccuracies in sentiment classification[23].

iv) Domain Specificity: Sentiments can vary significantly across different domains, industries, and subject matters. Developing a sentiment analysis model that performs well across diverse domains requires substantial training data and continuous adaptation to different linguistic styles and jargon[24].

v) Negation handling challenges: The presence of negation words like "not" or "never" can dramatically alter the sentiment conveyed by subsequent words, necessitating algorithms to adeptly identify and address these instances. Managing the scope of negations, deciphering the nuances of multiple negations, and accurately interpreting the contextual intent of negations pose significant difficulties. Additionally, variations in word order, nested negations, and the context-dependent nature of domain-specific sentiments further complicate the task. Overcoming these challenges requires advanced linguistic parsing, contextual understanding, and adaptive models to ensure accurate sentiment analysis, even in the presence of negations[25].

Addressing these challenges necessitates advanced NLP techniques, robust training data, and research to enhance the performance of sentiment analysis algorithms. As the field evolves and communication methods change, these challenges remain at the forefront of sentiment analysis research and development. In this thesis, we address a few of these challenges.

1.7 Mathematical Optimization Modelling Techniques

This thesis utilizes mathematical algorithms and techniques to generate a sentiment tagger for the text. In this thesis, we used game theory and multi-criteria decision-making (MCDM)[22] techniques for sentiment categorization of text. In *subsection 1.7.1* we give a brief overview of the game and MCDM's brief overview is introduced in *subsection 1.7.2* and their relationship is discussed in *subsection 1.7.3.*

1.7.1 Game Theory

Game theory is a mathematical framework that analyses strategic interactions between rational decision-makers. It provides a powerful tool for understanding and predicting behavior in situations where the outcomes depend on the choices of multiple participants[26]. Game theory studies a wide range of scenarios, from simple two-player games to complex interactions involving multiple players. It examines how certain strategies emerge, persist, or become extinct based on their relative success in a given environment. Game theory is the mathematical framework that consists of players, strategies, and payoff [27]. Each player has certain strategies and reaches the best response using the concept of Nash equilibrium.

- The game consists of a finite number of players $i = 1,.., n$, a set of pure strategies $S_i = s_1,.., s_m$, and a utility function $u_i : s_1, s_2 \dots s_n \rightarrow \mathbb{R}$ that maps utility values to strategy sets. The utility function of a game is determined not only by the strategy a single player chooses to employ but also by the strategies all other participants in the game employ simultaneously.
- The players select their strategies on an individual basis while considering what the other players can do and trying to determine the best strategy profile to use in a game using some strategies. A strategy k^* is said to be dominant iff *Equation (1.1)* is satisfied.

$$u(k_i^*, k_j) > u_i(k_i, k_j) \quad \forall \ k_i, k_j \in K \tag{1.1}$$

  where k represents all strategy sets other than players.
- Payoffs represent the outcomes or utilities associated with different strategies in terms of reproductive success. They reflect the advantages or disadvantages of each strategy in the context of the game is modeled.
- Nash equilibrium assumes complete information and rational decision-making based on this information. In Nash equilibrium, players have complete information about the game, including the strategies chosen by other players and the payoffs associated with these strategies. Players select their strategies based solely on this complete information and the assumption that all players have the same knowledge. Nash equilibrium is a situation where each player's strategy is the best response to the strategies chosen by others, and no player can unilaterally change their strategy to achieve a better outcome.

Some of the different types of game models are given below.

i) Cooperative Game: The cooperative game model examines strategic collaborations where players form coalitions to achieve shared goals. Through characteristic functions, it quantifies coalition values and fosters equitable payoff distributions. The core concept identifies stable allocations that can't be surpassed by subgroups. Solution methods like the Shapley value and Nash bargaining shed light on fair distribution. Applied to partnerships, resource allocation, and negotiations, the cooperative game model enriches our understanding of cooperative dynamics and optimal outcomes[28].

ii) Non-Cooperative Game: A non-cooperative model refers to a mathematical and scientific framework that analyses strategic interactions among rational individuals or agents who do not explicitly cooperate. It assumes that the agents pursue their interests and make decisions independently, without any agreements or communication. Scientifically, non-cooperative models are used to analyze and understand a wide range of strategic interactions, including economic markets, negotiations, conflict resolution, voting systems, and more. Non-cooperative models have applications in various fields, including economics, political science, sociology, computer science, and biology, enabling researchers to analyze and predict behavior in complex social systems[29].

iii) Evolutionary Game Model: The evolutionary game model is a mathematical and scientific framework used to study strategic interactions in populations of individuals over time. It draws inspiration from the theories of evolution and natural selection to analyze how different strategies or behaviors can emerge, persist, or disappear in a population based on their relative success or fitness[30]. In an evolutionary game model, the following components are typically considered.

- **Population:** The model involves a population of individuals, where each individual can adopt one of several possible strategies or behaviors[31].
- **Fitness:** Fitness represents the reproductive success or relative advantage of an individual's strategy in a given environment. Higher fitness implies a higher chance of survival and reproduction.
- **Reproduction and Selection:** The model assumes that individuals reproduce and pass their strategies to their offspring, similar to genetic inheritance. The selection process determines which individuals have a higher probability of passing on their strategies to the next generation.
- **Mutation:** Mutations can introduce new strategies or modify existing ones, allowing for the exploration of different behaviors.

1.7.2 MCDM

Multiple Criteria Decision Making (MCDM)[32] is a decision-making paradigm that evaluates different alternatives based on a mix of qualitative and quantitative criteria. There are two types of criteria in an MCDM problem: benefit criteria that should be maximized and cost criteria that should be minimized. In MCDM, a decision matrix M is used, where each entry m_{ij} represents how well the i^{th} alternative performs concerning the

j^{th} criterion denoted by *Equation (1.2)*. To make informed decisions, we also consider a weight vector W, where w_j indicates the importance of the j^{th} criterion.

$$M = [m_{ij}]_{m\times n} \quad , \qquad W = [w_j]_n \tag{1.2}$$

The typical formulation of an MCDM problem involves m alternatives (A_1, A_2, ..., A_m) and n criteria (C_1, C_2, ..., C_n) given by *Equation (1.3)*. where m_{ij} is the performance of the i^{th} alternative under the j^{th} criterion for i = 1, 2, ..., m and j = 1,2, ..., n.

$$M = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} m_{11} & m_{12} & \dots & m_{1q} \\ m_{21} & m_{22} & \dots & m_{2q} \\ \dots & \dots & \dots & \dots \\ m_{p1} & m_{p2} & \dots & m_{pq} \end{bmatrix} \end{array} \tag{1.3}$$

MCDM allows consideration of multiple factors, such as semantic content, contextual information, and linguistic features, to enhance the accuracy of sentiment classification. By applying MCDM methods, sentiment analysis models can weigh and integrate these factors to make more accurate predictions about sentiment polarity. Overall, MCDM empowers sentiment analysis by incorporating multiple criteria and facilitating informed decision-making for improved results. Various MCDM techniques used in this thesis as given below:

i) Combinative distance-based assessment (CODAS)[33].
ii) Complex Proportional Assessment (COPRAS)[34].
iii) Evaluation Based on Distance From Average Solution (EDAS)[22].
iv) Grey Relational Analysis (GRA)[35].
v) Multi-Objective Optimization based on a Ratio Analysis (MOORA)[36].
vi) Preference Selection Index (PSI)[37].
vii) Preference Ranking Organization Method For Enrichment Evaluation (PROMETHEE-I)[38].
viii) Simple Additive Weighting (SAW)[35].
ix) Technique For Order Performance By Similarity To Ideal Solution (TOPSIS)[38]
x) VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)[39].

1.7.3 MCDM and Game Theory Relationship

Madani et al. [40] established the one-on-one relationship between different parameters of MCDM and game theory. In the MCDM model, there are three main components: criteria, alternatives, and how each alternative performs based on those criteria. These aspects can be directly related to the fundamental elements of strategic games: the players or participants, the strategies they choose, and the rewards or payoffs they receive from the expected outcomes. *Fig. 1.4* depicts the relationship between the MCDM model and the game model.

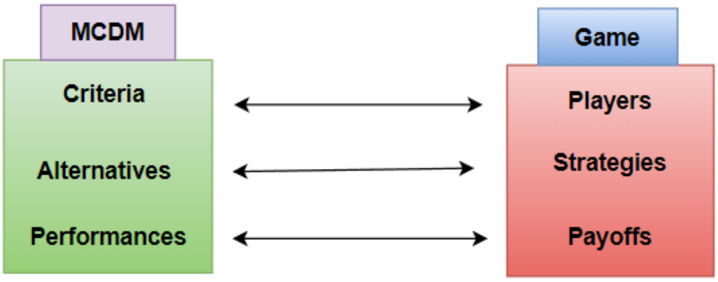

Fig. 1.4: MCDM-Game Relationship.

1.8 Evaluation Measures

After developing the model, it's crucial to evaluate its performance using various metrics. These metrics help us understand how well the model is performing and if it's making accurate predictions. All the evaluation measures used in this thesis are given below.

i) Accuracy: Accuracy measures how many predictions the model got right out of all the instances it predicted and is evaluated using *Equation (1.4)* However, it might not be the best choice when dealing with imbalanced datasets, where one class is much larger than the other[41].

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{1.4}$$

ii) Precision: Precision tells us how many of the positive predictions made by the model are correct. It shows the proportion of true positive predictions compared to all the positive predictions. Higher precision means fewer false positives and is calculated using *Equation (1.5)*[42].

$$Precision = \frac{TP}{TP + FP} \tag{1.5}$$

iii) Recall: Recall, also known as sensitivity or true positive rate, evaluates the model's ability to identify positive instances correctly and is evaluated using *Equation (1.6)*[43].

$$Recall = \frac{TP}{TP + FN} \tag{1.6}$$

iv) Matthews Correlation Coefficient (MCC): MCC is a correlation metric that takes into account true positives, true negatives, false positives, and false negatives. It is particularly useful in scenarios with imbalanced datasets, offering a comprehensive assessment of the model's classification performance given by *Equation (1.7)* [44].

$$MCC = \frac{(TP * TN - FP * FN)}{\sqrt{(TP + FP) * (TN + FN) * (FP + TN) * (TP + FN))}} \tag{1.7}$$

v) Micro Average Precision: The proportion of correctly identified positive predictions among all positive predictions made by the model given by *Equation (1.8)* [44].

$$Micro - averaged\ precision = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} (TP_i + FP_i)} \tag{1.8}$$

vi) Macro Average Precision: The average of precision values for different classes, providing an overall measure of positive prediction accuracy measured by *Equation (1.9)*[45].

$$Macro-averaged\ Precision = \frac{\sum_{i=1}^{n} Precision_i}{n} \tag{1.9}$$

vii) Micro Average Recall: The proportion of true positive predictions for all classes relative to the total number of actual positive instances calculated by *Equation (1.10)* [45].

$$Micro-averaged\ recall = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} (TP_i + FN_i)} \tag{1.10}$$

viii) Macro Average Recall: The average of recall scores for different classes, indicating the overall ability to correctly identify positive instances evaluated using *Equation (1.11)* [45].

$$Macro-averaged\ Recall = \frac{\sum_{i=1}^{n} Recall_i}{n} \tag{1.11}$$

ix) Macro-F1 Score: The average of F1 scores for individual classes, considering both precision and recall in a balanced manner calculated using *Equation (1.12)*[45].

$$Macro-\mathrm{F1}-score = 2.\frac{Macro-Precision_i \times Macro-Recall}{Macro-Precision_i + Macro-Recall} \tag{1.12}$$

x) Micro F1-Score: The harmonic mean of precision and recall, offering an overall measure of positive instance identification measured using *Equation (1.13)*[45].

$$Micro-\ \mathrm{F1}-score = 2.\frac{Micro-Precision_i \times Micro-Recall}{Micro-Precision_i + Micro-Recall} \tag{1.13}$$

1.9 Problem Statement

To develop unsupervised techniques to analyze sentiments of written text using game theory and other optimization techniques.

1.10 Objectives

We laid down the following objectives to tackle the problem statement.

i) To perform binary classification (positive and negative) of English text using a mathematical model.

ii) To classify text based on their emotions like anger, love, happiness, etc. using a non-cooperative optimization technique.

iii) To explore game theory-based models and check their applicability for sentiment analysis.

iv) To perform mathematical optimization technique-based sentiment classification of text with negation handling.

v) To design an algorithm for multi-class classification of sentences like weak positive, strongly positive, etc. using mathematical modeling.

1.11 Motivation

In the field of sentiment analysis, previous research has explored various methods to understand and classify sentiments in text. These methods can be categorized into supervised, semi-supervised, and unsupervised approaches, each offering its strengths and facing its challenges. Supervised machine learning techniques like SVM[46] and ANN[47] provide high accuracy in sentiment classification, but they can be time-consuming and require manual data labeling. Deep learning algorithms[48], such as DNN[49], CNN[41], and RNN[50], show promise but suffer from longer training times, high computational costs, and overfitting. Semi-supervised methods like generative and co-training approaches have their uses, but generative approaches may not work well for sentiment tasks, and co-training methods can be sensitive to noise. Unsupervised approaches like hierarchical and partition methods also present their challenges, with hierarchical algorithms being computationally expensive and partition methods prone to poor accuracy with noisy data. Lexicon-based approaches[51], though not needing data labeling, rely heavily on linguistic resources and may lack precision. Fuzzy-based approaches using fuzzy logic are valuable in handling uncertainty, but they face issues with complex rules, high computational complexity, and scalability in high-dimensional data. Despite their drawbacks, ongoing research seeks to enhance their effectiveness in various applications. Interestingly, there is an untapped opportunity to explore the application of mathematical optimization models in sentiment analysis, which could offer novel and efficient approaches to address current limitations. The major motivation is to generate unsupervised approaches for sentiment analysis tasks so that the system will become training-independent with enhanced accuracy.

1.12 Organization of the Thesis

In *Chapter 1* we introduce various concepts of Sentiment Analysis and preliminaries of mathematical techniques. In *Chapter 2*, we conduct a review of existing research within the realms of sentiment analysis, game theory applications, and MCDM techniques. *Chapter 3* is dedicated to introducing the application of game theory-based techniques to enhance the efficiency of sentiment classification. In *Chapter 4* we address one of the prominent challenges in sentiment analysis - handling negations. *Chapter 5* discusses the integration of MCDM-based techniques with non-cooperative game theory. This fusion results in the development of robust sentiment analysis methodologies. *Chapter 6* introduces unsupervised methods designed for the analysis of sentiment in Hindi text. These approaches leverage an integrated MCDM and non-cooperative game model to provide a novel solution for the Hindi text. *Chapter 7* Application of Sentiment Analysis for Designing Recommendation Systems. *Chapter 8* concludes the thesis, and summarizes the main findings and contributions. It also outlines potential future directions for further innovation and research in the field of sentiment analysis.

Chapter 2

Literature Review

In this chapter, we have organized the literature review into three subsections. In *Section 2.1,* we present the related work of sentiment analysis using various approaches. Moving forward, in *Section 2.2*, we cover the literature that explores the MCDM techniques application in various tasks. Finally, in *Section 2.3,* we focus on the related work concerning various techniques of game theory and its different types.

2.1 Sentiment Analysis Techniques

In this section, we cover the related work of sentiment analysis techniques.

Attention-based Point Network (AttPNet) is a novel model introduced by Yang et al. [52]. that employs attention mechanisms for global feature masking and channel weighting. It consists of two branches: one generates attention masks for each point, while the other utilizes convolution layers with a channel attention block to extract global features. Evaluation of the ModelNet40 dataset shows that AttPNet outperforms the best existing model in classification tasks by 0.7% without voting.

ABCDM (Attention-based Bidirectional CNN-RNN Deep Model) is proposed by Basiri et al. [49], leveraging bidirectional LSTM and GRU layers to capture both past and future contexts. The model incorporates an attention mechanism to adjust word emphasis and utilizes convolution and pooling to extract position-invariant local features. The author[53] utilized regression analysis and sentiment analysis (TF-IDF) to investigate the relationship between text data features and user characteristics on Twitter. Unlike previous studies focused on American politics, the British political landscape and multiple parties necessitated the use of typological analysis by human classifiers to identify tweets. The study aimed to uncover insights into the connection between text data and user characteristics in the context of British politics Another author[54] proposes KPRO (knowledge processing and representation based on ontology), a method to incorporate knowledge from opinion datasets into deep learning algorithms for sentiment classification. KPRO differs from other methods by directly adding raw data representation based on expert knowledge from the ontology. This approach enhances sentiment classification by including significant dataset features in the word embedding layer.

Pablos et al. [55] proposed W2VLDA, a nearly unsupervised system for aspect-based sentiment analysis that employs topic modeling and other unsupervised techniques. W2VLDA performs aspect category classification, aspect-term separation, and sentiment polarity classification in any domain or language. Evaluation of the multilingual SemEval 2016 task 5 (ABSA) dataset demonstrates its efficacy in aspect and sentiment classification.

Vashishtha [56] proposed a fuzzy system that integrates NLP techniques and Word Sense Disambiguation for sentiment classification. Their unsupervised nine fuzzy rule-based approach was compared with multiple Twitter datasets, sentiment lexicons, unsupervised methods, and a supervised machine learning method. The system effectively categorized posts into positive, negative, or neutral sentiment classes.

Song et al. [57] introduce a method for sentiment lexicon embedding that improves the representation of sentiment words without manual annotation. The proposed framework combines morpheme and POS tag encoding, training important lexical morphemes in the embedding space. Experimental results confirm its effectiveness compared to the two baseline models.

The author [58] introduces a knowledge-enabled language representation model, BERT, for aspect-based sentiment analysis. The proposed approach enhances BERT by incorporating sentiment domain knowledge from a sentiment knowledge graph.

The author [59] introduces interpretable HMM-based methods for sentiment recognition in text, showcasing their performance across various architectures, training methods, orders, and ensembles. These methods demonstrate competitive performance, outperforming traditional HMMs, and provide insights into the sentiment evolution within sentences.

The author[60] explored leveraging unsupervised ML for topic detection in tweets to enhance a selected transformer model's predictive performance. For consistency with SemEval, their metrics were adopted, and models were deployed on SemEval-2017 data.

The author[61] proposes Sentic GCN, a graph convolutional network based on SenticNet, to enhance sentence dependency graphs by leveraging affective dependencies for specific aspects.

Swathi et al.[62] introduced a new model combining TLBO and LSTM for sentiment analysis in stock price prediction using Twitter data. By examining the correlation between tweets and stock market prices, this approach offers insights into their relationship and dynamics. The model aims to provide valuable insights into the impact of sentiment on stock market behavior.

Chiha et al.[63] proposed a model that operates at both the aspect and sentence levels. The model begins with ABSA, which consists of two interconnected tasks: aspect extraction and aspect sentiment classification. The latter involves a unified-trained model utilizing deep learning techniques to extract aspects and determine their sentiment polarities.

Wu et al. [64] developed a framework for hotel selection using sentiment analysis from online reviews and consensus group decision-making. Their approach employed the Word2Vec algorithm and OVO-SVM for multi-granularity sentiment analysis, enabling the extraction of valuable information from text reviews.

Lin et al.[65] introduced multi-channel word embedding and proposed a modified model architecture based on the Bert model by Google. They optimized the Softmax function to reduce search time and increase training speed. Additionally, they developed a method to effectively control the structure of the generated sentences after training the model.

Wang et al.[66] propose TETFN, a novel method for unified multimodal representations. TETFN utilizes text-based multi-head attention for sentiment-related non-linguistic representations. It combines cross-modal mappings and unimodal label prediction to enhance representation learning.

Perikos et al. [68] have come up with new Hidden Markov Models (HMMs)-based methods that are easy to understand for figuring out how people feel in text. They looked at how well these methods worked by using different designs, training methods, model orders, and groups. The novel models can figure out how a phrase makes you feel and highlight those parts. They can also show how the feeling changes throughout the sentence. The experts did a full trial study that showed that the suggested HMM-based methods and training approaches are very competitive with machine learning methods and even do better than traditional HMMs.

Zhang et al.[69] presented a model that integrates syntactic and semantic sentence analysis. In addition, they proposed a simple yet effective fusion mechanism to facilitate a better integration of aspect and context information. The researchers conducted exhaustive experiments on the SemEval 2014 benchmark datasets and obtained exceptional results, outperforming the current state-of-the-art.

Liang et al. [70] present a comprehensive decision-support model designed to aid consumers in locating desirable online products. The model is composed of three major modules: information acquisition, information transformation, and information integration. This linguistic intuitionistic imprecise information is then transformed by the information transformation module into linguistic intuitionistic normal clouds (LINCs).

Peng et al.[71] offer an innovative co-gate, an interactive gating system. It can better merge the information of context and aspect terms and capture emotional semantic characteristics than the standard interactive feature extraction process, as well as eliminate the interference of noisy words. The pretraining file of BERT Post Training (BERT-PT) is utilized in this study to fine-tune the CGBN model, which improves BERT's capacity to be tweaked using domain data.

Zhang et al.[72] presented the Integrated Consistency and Difference Networks (ICDN), a unique method for modeling the interplay between modalities. When tested on the CMU-MOSI and CMU-MOSEI benchmark datasets, the ICDN methodology demonstrated better results in sentiment classification compared to other popular approaches for multimodal sentiment analysis.

Gu et al.[73] introduce an innovative method for sentiment analysis at the sentence level based on aspect words termed the Oriented Inter-Aspect Modelling Hierarchical Network (IA-HiNET). IA-HiNET aims to discover and improve links between various aspect terms. The indicative relevance of various aspect words is also taken advantage of to provide aspect-based sentence-level emotional analysis.

Li et al. [74] conducted an extensive investigation of MOOC programs at universities around the world for their study. The study identified two major categories of courses based on the intended outcomes of learners: knowledge-seeking and skill-seeking MOOCs.

Wang et al.[75] came up with a method called SASC (Sentiment Analysis based on Sentiment Clustering) to fix the fact that review sentiment clustering techniques were not very accurate and were not stable. The suggested method uses a two-stage approach to sentiment clustering to find buried mood information in review texts. This makes the clustering results more accurate and stable. In the first step, the topic model LDA (Latent Dirichlet Allocation) is used to show how to build a review representation vector.

2.1.1 Sentiment Analysis of Hindi Text

The 5W task, developed by Das et al. [76] and colleagues, tries to extract the semantic information of nouns in a phrase by distilling it into the responses to five key questions: Who, What, When, Where, and Why. According to tag labels, the following accuracy values have been recorded for the system: 79.56% for Who, 65.45% for What, 73.35% for When, 77.66% for Where, and 63.50% for Why.

In this article, Das et al.[77] suggest a variety of computational ways for creating SentiWordNet(s) for Indian languages, including WordNet-based, dictionary-based, corpus-based, or generative approaches. SentiWordNet(s) are now being created for Bengali, Hindi, and Telugu, three Indian languages.

To assess the scope and reliability of the created SentiWordNet(s), a variety of automated, semi-automatic, and human validation and assessment approaches have been used.

Balamurali et al. [78] propose an alternative method for Cross-Language Sentiment Analysis (CLSA) by using WordNet senses as features for supervised sentiment classification. The sense-based approach obtains an accuracy of 72% for the classification of Hindi sentiments and 84% for the classification of Marathi sentiments in CLSA tasks.

Arora et al.[79] offer a graph-based approach to mining WordNet for a subjective lexicon of the Hindi language. Their method entails adding synonym and antonym connections to a seed list to grow it into a full lexicon. The built vocabulary is shown accurate by two methods of assessment used by the authors.

To develop a subjective lexicon for the Hindi language using WordNet, Arora et al.[80] suggest a graph-based approach. Their strategy entails adding synonym and antonym connections to a pre-annotated seed list to transform it into a full lexicon. Their work's key contributions include building an annotated corpus of Hindi reviews and establishing a subjective lexicon of adjectives using Hindi WordNet.

As their primary goal, Patra et al.[81] sought to categorize tweets into positive, negative, and neutral polarity. To do this, they used a variety of tweets for testing and training. Six different teams each reported their findings, and the systems were graded according to their accuracy. Bengali, Hindi, and Tamil each had accuracy levels that were at their highest of 43.2%, 55.67%, and 39.28%.

The “Rule-based system” is presented by Modi et al.[82]. There are 29 common part-of-speech tags used, including two unique tags for date and time in various forms. Regex-based special tags like punctuation, time, and date are used. The system produces average precision and accuracy of 91.84% and 85.45%, respectively.

Akhtar et al. [83] presented sentence- and aspect-level sentiment analysis on four Hindi datasets from different topics. We test our technique on two benchmark English datasets to demonstrate its generality. The suggested technique consistently outperforms state-of-the-art systems across datasets.

Akhtar et al.[84] provide a baseline setting to evaluate the difficulties associated with SA in Hindi. For classification purposes, we use Conditional Random Field (CRF) for aspect phrase extraction and Support Vector Machine (SVM) for sentiment analysis. The average F-measure for aspect phrase extraction was 41.07%, while the average accuracy for sentiment classification was 54.05%, according to the evaluation findings.

Pandey et al.[85] present AugmentGAN, a simple, effective generative adversarial network-based text augmentation model that assures syntactic coherency in freshly produced samples. AugmentGAN outperforms other text augmentation methods on all datasets. AugmentGAN works for English, Hindi, and Bengali.

These investigations were conducted on datasets from Twitter (SAIL 2015), IIT-Patna product and service reviews, and IIT-Patna movie reviews. A subjective lexicon-based approach for sentiment analysis of Hindi tweets associated with the keywords “JAIHIND” and “World Cup 2015” was presented by Yakshi Sharma et al.[86].

Jha et al.[87] suggested a reputation system capable of assessing trust among all legitimate eBay merchants and effectively ranking them.

Jha et al.[88] investigated sentence-level subjectivity and attained an accuracy of nearly 80 % on the Hindi dataset. Garg et al.[89] performed sentiment analysis on tweets related to Prime Minister Mr. Narendra Modi's radio broadcast " Mann Ki Baat " using a lexicon-based technique.

Kunchukuttan et al.[90] published the IndicNLP word embedding for the IITP-Movie and IIIT-Product evaluation datasets in 2020.

To address WSD and its morphological version, Hussaini et al. take into account book evaluations and employ score-based sentiment analysis [91].

Several supervised and unsupervised methodologies have been proposed in the literature. However, due to the lack of standard trained Hindi datasets, supervised approaches are less reliable and neither domain nor language-independent. Their training is a daunting task. On the contrary, unsupervised algorithms need datasets only for evaluating the algorithm. However, the results generated by unsupervised algorithms are inferior to supervised algorithms.

2.2 MCDM Related Work of all the Techniques

Wang et al.[35] developed a hybrid multi-criteria decision-making (MCDM) strategy that combines simple additive weighting (SAW), TOPSIS, and GRA. A strong hybrid decision-making model is created by combining MCDM assessment methodologies.

Anvari et al.[92] used the best-worst method (BWM) and simple additive weighting (SAW) to rank lost or obscured target locations in a novel MCDM technique. SAW ranks locations by decision factors, whereas BWM weights criteria. This method prioritizes probable target sites.

Li et al.[93] created a hybrid MCDM machine tool selection model. FDEMATEL subjective weights are combined with EW objective weights. LDVIKOR ranks possibilities for a complete decision-making framework.

Krishaqn Kumar et al.[94] employed MCDM to enhance employee selection. Fuzzy-based approaches, such as intuitionistic fuzzy sets (IFS), were utilized to handle ambiguity and imprecision effectively. IFS provided degrees of membership and non-membership for preference elicitation in the MCDM context.

Qi et al.[95] introduce a customer-involved design concept evaluation (DCE) approach. The proposed method, integrated rough VIKOR (IR-VIKOR), incorporates customers' preferences and designers' perceptions to evaluate design concepts effectively. Empirical comparisons and sensitivity analysis experiments validate the reliability and feasibility of the IR-VIKOR model in DCE.

Guleria et al. [96] improve VIKOR and TOPSIS MCDM techniques using (R, S)-Norm Pythagorean fuzzy entropy and discriminant measure. They propose modified algorithms in two stages for hydrogen power plant site selection, considering a wider range of Pythagorean fuzzy information measures. The study emphasizes the alignment of essential criteria to enhance decision-making in the site selection process.

Youssef et al.[97] present a novel MCDM approach using TOPSIS and BWM to rank CSPs based on evaluation criteria, enhancing feasibility, efficiency, and consistency. This method offers an effective decision-making framework for selecting Cloud Service Providers.

The author[98] introduces the application of the TOPSIS method in Group Support Systems (GSS), utilizing the multi-criteria decision-making (MCDM) approach known for its effectiveness in evaluating and selecting both classical and environmental criteria. This highlights the effectiveness of MCDM in various aspects of decision-making.

Raju et al.[99] employed integrated MCDM approaches, namely AHP-TOPSIS and AHP-MOORA, to rank aluminum-coconut shell ash (CSA) composites. AHP was used to calculate criterion weights, which were then utilized in TOPSIS and MOORA for material ranking. This integrated approach enhances the decision-making process for evaluating and ranking the CSA composites effectively.

Sowmya et al.[100] proposed a hybrid MCDM model that utilized FAHP weights for ranking. TOPSIS and EDAS methods were employed to evaluate the feasibility of using locally available biomass. The proposed methods showed excellent agreement with each other and aligned closely with experimental results.

The author[101] introduced a new MCDM method for selecting commercial aircraft alternatives based on multi-dimensional evaluation. Unlike previous studies, this approach incorporates hybrid IT2FAHP and IT2FTOPSIS methods using interval type-2 fuzzy logic. The proposed method enhances decision-making accuracy and offers a comprehensive analysis of aircraft selection.

Dhumras et al.[102] proposed a modified EDAS methodology with a new score/accuracy function and Dombi aggregation operators. The methodology was applied to a case study in digital farming, showcasing its efficacy in selecting the optimal alternative for sustainable agrifarming. The study highlights the practical application of the proposed methodology in agricultural decision-making processes.

Liu et al.[22] developed an integrated fuzzy MCDM approach using Pythagorean fuzzy sets for evaluating additive manufacturing alternatives in the automotive industry. The CRITIC technique determined the significance levels of the criteria, and the EDAS method prioritized the alternatives. This approach offers a comprehensive framework for decision-making in additive manufacturing assessment for automotive applications.

Akram et al.[103] introduce a novel approach using a pairwise deviation formula and the score function to create preference functions. The PROMETHEE I method assesses positive and negative outranking flows, establishing a partial order among alternatives. The PROMETHEE II approach calculates the net outranking flow, determining the overall ranking of alternatives.

Ye et al. [104] ranked cotton textiles in PFS (Possibility-Fuzzy-Soft) using PROMETHEE. PF-PROMETHEE defuzzed alternatives utilizing PFS linguistic scales and a scoring function. The PF-PROMETHEE ranking results showed a high association with other score functions, proving its practicality and efficacy. This study advances PFS fabric ranking and decision-making.

Cunha et al.[105] developed a MATLAB-based mathematical model using PROMÉTHÉE II and PROMÉTHÉE GDSS methods for preference ranking and group decision support. Specialists assessed alternatives through questionnaires based on predefined criteria.

George et al.[106] found HDFC to be the best-performing private sector bank, setting a performance standard. However, applying MCDM techniques, such as PROMETHEE, ranked ICICI first and HDFC second. Different methodologies resulted in varied rankings for other banks, suggesting the need for future studies to compare different bank types and extend the analysis timeframe beyond PROMETHEE rankings.

Burak et al.[107] proposed a hybrid MCDM method for evaluating and selecting irrigation methods, using the HF-AHP-PROMETHEE II approach. HF-AHP determines criterion weights, while HF-PROMETHEE II assesses and ranks alternative irrigation methods. The HF-AHP-TOPSIS method is also employed for comparative analysis.

The author[108] provides information on natural fiber insulating materials for energy-efficient construction insulation and recommends the most effective option. A novel integrated MCDM model incorporating PSI, MEREC, LOPCOW, and MCRAT methods is utilized to handle the complexity of criteria and alternatives. This research offers a comprehensive framework for decision-making in selecting natural fiber insulation materials.

This empirical study from China utilizes a combination of FDM, EWM, and GRA methods to assess performance in higher vocational colleges. The research presents a comprehensive approach for measuring and evaluating performance in this educational context. The findings contribute to a better understanding of performance measurement in higher vocational colleges[109].

Maidan et al.[110] suggest employing grey relational analysis (GRA), an MCDM method, to address the material selection challenge. Material selection is crucial in product design, particularly for composites that demand special considerations. Substituting conventional materials with natural fibers as a more environmentally friendly option is a common practice to reduce the environmental impact caused by high material consumption in the mass production of plastic components.

Garg et al.[111] applied TOPSIS and GRA, aided by q-RO-m-PFS information, for the selection of ventilator manufacturers during the COVID-19 epidemic. Linguistic terms were translated into numeric values to express the q-RO-m-PFS information. The proposed approaches proved highly effective in selecting suitable ventilator manufacturers for COVID-19 patients.

An ELICIT information-based ORESTE method incorporating GRA-DEMATEL is proposed for Failure Mode and Effect Analysis (FMEA), considering risk correlation. The approach enhances FMEA by utilizing ELICIT information and effectively assessing risk correlations. The integration of GRA-DEMATEL provides a comprehensive framework for analyzing failure modes and their effects[112].

A hybrid MCDM model based on the Bayesian Best-Worst Method and DQ-GRA technique is proposed to evaluate the comprehensive performance of 5G base stations. The model enables a comprehensive assessment of multiple criteria and provides a robust decision-making framework. The study contributes to evaluating the performance of 5G base stations using an integrated MCDM approach[113].

One of the studies [114] introduces a straightforward MCDM methodology based on the TOPSIS method for selecting an industrial robot for arc welding. The Entropy weight method is used to determine the significance weights based on objective preferences. The TOPSIS-Entropy technique provides a ranking order, and the results demonstrate the effectiveness of MCDM approaches in robot selection for welding operations.

One of the studies [115] employs a TOPSIS-based MCDM model in a fuzzy environment for the safety assessment of an excavation system. The model provides a comprehensive approach to evaluating the system's safety by considering multiple criteria. By incorporating fuzzy logic, the model accounts for uncertainty and ambiguity in the assessment process, enhancing the accuracy of safety evaluations.

2.3 Game Theory Application in NLP

In recent years, there has been a notable increase in the application of Game Theory in the field of Natural Language Processing (NLP). Researchers have recognized the potential of Game Theory to provide valuable insights into the dynamics of language and communication. By incorporating strategic decision-making principles from Game Theory, NLP applications have been enhanced, leading to more sophisticated and effective language models.

In recent years, the application of Game Theory in the field of Natural Language Processing (NLP) has witnessed significant growth. Notably, Bu et al.[116] introduced a remarkable Game Theory-based emotional evolution prediction system. This system leverages strategic decision-making principles from Game Theory to effectively predict the evolution of emotions in the context of NLP applications.

Tripodi et al.[117] contributed to the field of NLP by introducing a novel approach to word sense disambiguation using Game Theory. Word sense disambiguation is a challenging task in NLP, and the utilization of Game Theory in this context offers new perspectives for tackling this problem. The modeling presented in their work showcases how strategic interactions between word senses can be harnessed to improve disambiguation accuracy.

Ahmad et al.[44] made significant strides in the domain of multi-document summarization by incorporating Game Theory principles into their framework. By leveraging the strategic interactions between documents and incorporating insights from Game Theory, their approach enables more informative and concise summarization of multiple texts. This contributes to more efficient information retrieval and comprehension.

Liu et al.[118] introduced the innovative Explosion-Trust (ET) Game Model to detect rumor spreading, a critical issue in today's social media landscape. By applying Game Theory to model rumor propagation, their research sheds light on the strategic behavior of individuals and helps in devising effective strategies for rumor control and mitigation.

Ruseti et al.[119] proposed a game theory-based sentiment analysis model tailored for a specific domain. Sentiment analysis is a fundamental task in NLP that involves understanding emotions and opinions from text. Their model takes into account the strategic interactions between sentiment-bearing elements in a domain-specific context, enhancing sentiment classification accuracy.

Jain et al.[120] explored the application of the Shapley Value from cooperative game theory for rumor detection in social networks. This novel approach considers the cooperative influence of users in spreading rumors, enabling the identification of influential individuals who play a significant role in rumor dissemination.

Jain et al.[121] devised the GOLD algorithm, which utilizes cooperative game theory principles to identify opinion leaders in online social networks. By assessing the strategic cooperation among users in disseminating opinions, this approach identifies key influencers who hold substantial sway over public sentiment.

Huang et al.[122] utilized the concept of Nash equilibrium from game theory for rumor detection. Nash equilibrium represents a state where no player has an incentive to unilaterally change their strategy. By applying this concept to rumor detection, their research offers insights into the stable and strategic nature of rumor propagation dynamics.

Saxena et al.[123] applied Game Theory to tackle the critical phrase extraction task in NLP. Their approach leverages the strategic importance of phrases in a text, identifying key phrases that carry essential meaning and contribute significantly to the overall content.

Jain et al., (2021) Jain et al.[124] demonstrated how evolutionary Game Theory can be employed to enhance accuracy and efficiency for query expansion. By considering the strategic evolution of query expansion strategies, this research contributes to more effective information retrieval and retrieval system optimization.

The study conducted by Jain et al.[120] proposed an evolutionary game theory framework for sentiment analysis, enabling a deeper understanding of the strategic interactions between sentiment-bearing elements. This innovative framework extends traditional sentiment analysis methods by considering the evolving nature of sentiment in language.

Jain & Lobiyal [125] put forward a cooperative game theory approach to address the word sense disambiguation task. By capturing the cooperative behavior of word senses, this research aims to achieve more robust and contextually accurate disambiguation results.

Xia et al.[126] applied an evolutionary game model to detect rumor and anti-rumor propagation mechanisms. This research investigates the strategic interactions between the spread of rumors and counteracting anti-rumor measures, providing valuable insights for managing and controlling rumors in online environments.

Bayesian game models have shown promise in various fields, and Sharma's[127] proposal of a Bayesian game-based (Dec-POMDPs) model for decision-making in a stochastic environment is no exception. This approach combines the decision-theoretic framework of Partially Observable Markov Decision Processes (POMDPs) with Game Theory principles, offering a powerful tool for decision-making in uncertain and dynamic situations.

Dahiya and Gupta [128] contributed to the field of pricing mechanisms by introducing a Bayesian game mechanism-based pricing scheme with penalty imposition. Their approach enables the[129] design of fair and efficient pricing strategies by considering strategic interactions between participants in a market.

Xiao et al.[130] harnessed Bayesian models to facilitate Vehicle-to-Vehicle Electricity Trading, a domain that requires strategic negotiation and decision-making. By applying Bayesian game models, they enable participants to make informed decisions in electricity trading, optimizing resource allocation and enhancing the overall efficiency of the trading process.

Abapour et al.[129] explored the application of Bayesian game strategies in the electricity market and cybersecurity in industries. By considering the strategic behaviors of market participants and adversaries, their research contributes to more secure and efficient decision-making processes in these critical domains.

2.3.1 Non-Cooperative Game Model

Abedian et al.[131] utilize game theory to optimize marketing-mix tactics in dynamic competitive marketplaces. Two leading Iranian automobile parts businesses' marketing tactics were optimized using the suggested approach.

Wang et al.[28] propose a new method that merges game theory and machine learning to overcome restrictions imposed by outsourcing automation. Using an adversarial reinforcement learning framework, they offer a meta-modeling game where autonomous AI agents produce experimental data, calibrate a constitutive model, and enhance its robustness by searching for the Nash equilibrium without any human involvement.

Smirnov et al.[132] provides a decision-making model for switching lanes at heavily trafficked urban crossroads based on game theory. Co-AutoSim was used to verify the model, which included driving-related characteristics of approaching cars, leading to a 100% success rate in lane change predictions and an overall 83.3% success rate.

Zhang et al.[133] provide a Rate-Splitting Multiple Access (RSMA) based satellite-vehicular communication system to guarantee secure data transfer. The chance of system failure is analyzed using the Shadowed-Rician model in this research.

The Division Non-Cooperative Game LEACH (DivNCGL) routing technique was developed by Asvial et al.[134] as a variation of the Low Energy Adaptive Clustering Hierarchy (LEACH) strategy. In comparison to the LEACH technique, simulation findings show a considerable improvement in WSN lifetime of up to 30% with steady energy dissipation.

Boyd et al.[135] investigate how game theory might be used in resource-allocation circumstances when the "first come, first serve" heuristic leads to inequitable outcomes. To address this imbalance, they offer a Generalised Nash Equilibrium Model in which the participants are ordered sequentially over a directed line graph.

An efficient approach for transmitting channel transactions is proposed by Zhang et al.[136] By doing a balancing analysis and using an iterative sub-gradient approach to locate a Nash equilibrium point, the program can optimize the routing of transactions. Analyses comparing it to SilentWhispers and SpeedyMurmurs show that it is better.

Zhao et al.[137] propose a non-cooperative game-based P2P trading method for interconnected FDNs spanning multiple regions. The method establishes a two-tiered framework for trading to reduce costs and enhance voltage profiles. In addition, it includes a trading adjustment mechanism to improve operational profits and system performance.

Liu et al.[138] present two behavioral decision-making approaches for cooperative vehicle platoon systems based on non-cooperative game theory. These approaches take complete and fragmentary information scenarios into account. The competitive game incorporates platooning performance factors such as fuel economy, convenience, safety, and the development of self-driving technology.

Zhao et al.[139] offer a resilient Shapley function for biform games in hesitant fuzzy linguistic environments. Their method accurately analyses profit generation and distribution by considering individual hesitancy and information fuzziness. They develop an entropy metric that incorporates fuzziness and hesitation, improving on previous measurements.

2.3.1.1 Bayesian Game Model (Framework)

Dahiya et al.[128] suggest a strategy for service providers to maximize societal welfare by using insights from Bayesian game theory. They equip law-abiding customers to combat cybercriminals by using price regulations and incentives. To reach Bayesian Nash Equilibrium, we design a price and auction mechanism based on Bayesian theory. This method uses probabilistic data in a way that helps both service providers and genuine consumers.

Liu et al.[140] create a unified methodology for the automated modeling and analysis of cyber-physical attacks against ICSs. They present colored weighted Petri nets and cyber-physical attack models. Using a Bayesian attack-defense game, they determine model weights and demonstrate their stability in the face of parameter changes.

Lalropuia et al.[141] study bandwidth faking threats in 5G wireless communications networks. They suggest a Bayesian game model to record the interactions between attackers and network defenders during these strikes. This will make it possible to find good defense methods.

Tian et al.[142] come up with a dynamic Bayesian game-theory approach for dealing with FDI threats when we don't know everything. Using past profiles and links, they use a bi-level optimization model to figure out payoffs and change the player's ideas about the type of attacker. In this situation, the study shows that type belief and Bayesian Nash equilibrium are the same thing.

Chen et al.[143] examine the problem of discovering the unknown probability distribution of types in a two-player repeated Bayesian game, a crucial model in network security. However, since it depends on the attacker's prediction function inside the game model, the straight computation of the type distribution is difficult.

Bi et al.[144] propose a privacy-preserving personalized service framework (Persian) based on a static Bayesian game to provide privacy protection based on users' specific security needs in social IoT.

Maccarone et al.[145] analyzed the residual heat removal system of a boiling water reactor utilizing a Bayesian game-theoretic approach. In their investigation, threat agents were depicted as categories in the game using a threat agent library that outlined the characteristics of each threat.

Sawadsitang et al.[146] examine a scenario in which multiple shippers can collaborate to reduce the cost of drone delivery. They proposed the BCoSDD framework for Bayesian Shipper Cooperation in Uncertain Drone Delivery. The framework consists of three functions: package allocation, merchant cooperation formulation, and cost management.

Zhang et al.[147] experimented with their proposed method and compared it to existing approaches. Turing tests were used to evaluate the algorithm's human likeness. The results demonstrate that their Bayesian game-theoretic framework generates human-like decision-making scenarios in autonomous vehicle interactions, demonstrating its viability and effectiveness.

Govindaraj et al.[148] proposed a system that depicts the interaction between the system and subject as a two-player Bayesian signaling zero-sum game. The game's Nash equilibrium provides optimal strategies for both the assailant and the system, prohibiting payoff increases on one side only. The system includes a prevention subsystem that consists of a game engine, database, and search engine, enabling the computation and storage of the Nash equilibrium.

Shi et al.[149] provide an auction model that combines blockchain technology and Bayesian game theory. Two Bayesian Nash Equilibriums (BNEs) are included in the model to allow the selection of affordable providers for creating federated cloud services and to guarantee accurate monitoring of federated SLAs. They also suggest a timed message submission (TMS) technique to protect auction privacy while messages are being sent.

Tu et al.[150] recommend V2V energy swapping as an alternate charging option for electric cars (EVs). This technique intends to reduce residential microgrid (MG) congestion caused by uncoordinated charging during peak hours. Considering EVs' stochasticity, they use a Bayesian game model to represent diverse players.

Christensen[151] advocates conserving essential natural resources while increasing biomass production. This transformation requires rural and coastal resource policies for environmental sustainability. Three game-theoretic assumptions about rural biomass resource management are developed.

Abapour et al.[152] used game theory to optimize demand response (DR) aggregator bidding techniques in deregulated energy markets. Their concept incorporates customer benefit functions and pricing elasticity to construct DR economic responsive load models. Market dynamics and consumer preferences are considered to improve DR deployment efficiency.

2.3.2 Evolutionary Game Model

Antoci et al.[153] examine how a novel approach to environmental preservation adopted by the government of a popular tourist area has affected the area's economy. The plan's objective is to boost tourism while reducing negative impacts on the natural world. Furthermore, it provides a payment option for companies that want to use non-polluting technology, covering any further expenditures incurred until environmental quality exceeds a certain target.

Chica et al. [154] present an evolutionary trust game that takes punishment and protection into account to study the development of trust in the so-called sharing economy.

In this trust model for the sharing economy, there are four different sorts of participants: reliable providers, dishonest providers, reliable consumers, and reliable disreputable consumers.

Zhang et al.[155] employed a Variable-Population Evolutionary Game Model to Cooperative Cognitive Relay Network resource allocation. The objective of this study was to optimize resource distribution in these networks using an evolutionary strategy. Their findings illuminate effective cooperative resource allocation strategies in cognitive relay systems.

Wolfi et al.[156] summarise research that has used evolutionary game theory to understand cancer and improve therapy. These game-theoretic models help us understand the eco-evolutionary dynamics of cancer and how we may use evolutionary therapy to steer those dynamics in a more patient-beneficial direction. They investigate the practical implications of current game-theoretic cancer models and point up areas for further research.

Alam et al.[157] assess the efficacy of isolation and quarantine programs using mathematical epidemiology and evolutionary game theory. Their research aims to determine whether the method—isolation or quarantine—is more effective in stopping the spread of contagious illnesses. The study clarifies the ideal sickness containment plan by fusing various techniques.

Victoria et al.[158] utilized an evolutionary game-theoretic method to examine Iran's industrial sector's switch to renewable power supply, providing light on the technical change and its causes. Their research offers insightful knowledge that will help industry leaders comprehend and direct the implementation of sustainable energy.

Zhu et al.[159] integrate green awareness into the green supply chain system and use the evolutionary game model for green businesses and customers to change over time. Their study shows how it might be possible to reach an ideal state that is stable in terms of evolution if all businesses and customers used green production methods and bought green products.

Tian et al.[160] say that judging reputation management plans should include dynamic and different ways to target. They use evolutionary game theory to model how the ways that evil users attack change over time and talk about how the simulation works. The researchers also use their review method on a plan for managing reputations that have more than one useful function and then look at the results.

Pi et al.[161] introduce a safety performance (SP) framework for Chinese construction projects and propose a safety information system to improve safety supervision among industry participants. Using ideation sessions, they determine that multiple evolutionarily stable strategies (ESSs) exist, with different situations leading to various ESSs.

Khan et al.[162] present a novel evolutionary game theoretic (EGT) framework for automated node clustering and cluster leader nominations in VANETs to improve cluster stability. They conduct an empirical examination of the performance of the proposed evolutionary game using various cost functions in both static and mobile scenarios.

Zhau et al.[163] present a study examining the effect of policy incentives on the development of electric vehicles (EVs) using an evolutionary game theoretical analysis based on system dynamics. Their study investigates the dynamic relationship between policy incentives and the evolution of the EV market. The results shed light on the efficacy of policy measures in promoting EV adoption and development.

Mahmoudi et al.[31] use a two-population evolutionary game theory to analyze potential situations whereby government goals and producers' goals are at odds with one another. The research considers a range of possible outcomes, including maximizing profits while minimizing negative effects on the environment, minimizing negative effects while maintaining a minimal profit threshold, and striking a balance between the two.

Yang et al.[164] suggest MAIAD, a multistage asymmetric information attack and defense paradigm for IoT systems. To resolve information asymmetry, MAIAD expands the single-stage game model by combining dynamic and evolutionary game theory. Using simulation results to identify the best defense techniques for different IoT systems, the model quantifies the advantages of attack and defense.

2.3.2.1 Hawk Dove Game Model (Example)

Hall et al.[165] propose an iterative model of the Hawk-Dove game to investigate the stability of sharing and dominance relationships based on resource-holding potentials (RHPs). When combat costs are low and contestants have comparable RHPs, numerical simulations demonstrate that stable sharing relationships exist, whereas dominance relationships prevail in other circumstances.

Lie et al.[166] created a hawk-dove game model that included "foreign-local auto enterprises" to investigate the strategies and conditions necessary for system stability and attaining a balanced state. The findings reveal that the income and input costs of competitors play significant roles in determining the competition and cooperation behaviors of automobile enterprises.

Sakiyama[167] used the hawk-dove game (HD) model to explore how links evolve in network systems. According to the study, participants made time-dependent modifications to the network structure by dynamically connecting or disconnecting with their neighbors depending on their experiences. Using this model as a foundation, the inquiry investigates population dynamics and how they relate to an important phenomenon.

Maruotti et al.[168] present a model to examine the potential use of the Hawk technique in asset management. The research shows that beginning possession, property, and personality attributes have a major influence on motivating hawkish behaviors. The results highlight the significance of the possession and the means by which it was obtained in predicting the propensity to use the Hawk tactic.

Galanthay et al.[169] present a novel consumer-resource model that addresses existing issues and permits an examination of its dynamic behavior. Through an analysis of consumer-resource models incorporating Hawk-Dove game interactions, this study provides novel insights into how aggression levels may vary with environmental abundance, animal mortality, and combat duration.

Zhao et al.[170] proposed a Hawk-dove study on the selection of green railway alignments. The Effects of a Fast Hawk-Dove-Bully Game on the Dynamics of a Stage-structured Population were indicated by Moussaoui et al.[171].

A new spatial hawk-dove model, with an emphasis on link evolution, has been suggested by Sakiyama et al.[172] Changes to the originally regular lattice network structure result from players forming and breaking links with their neighbors in this model. This gives players the freedom to join or disengage with whatever partners they desire.

Chapter 3

Game Theory-Based Sentiment Classification of Written Text

Game Theory plays a vital role in numerous NLP applications, particularly in the realm of dialogue systems[173]. By leveraging game theory principles, NLP systems can analyze the user's intentions, anticipate their future actions, and generate appropriate responses. Concepts like Nash equilibrium and optimal strategies enable systems to make strategic decisions based on the user's behavior and objectives. Additionally, game theory aids in conflict resolution and negotiation within dialogue systems, empowering the system to navigate trade-offs and find mutually beneficial solutions. Through the integration of game theory, NLP applications can significantly improve their ability to understand user input, generate coherent and contextually relevant responses, and ultimately optimize the overall conversational experience. In this chapter, we discuss the application of various game models for the sentiment classification of text.

In *section 3.1*, we discuss the Bayesian game model-based sentiment classification. In *section 3.2*, population game model-based sentiment analysis is discussed. *Section 3.3* discusses the Hawk dove game-based sentiment classification. In *section 3.4,* we conclude the chapter.

This chapter introduces three mathematical frameworks for sentiment analysis based on game theory to enhance the task of sentiment classification. It presents a range of game theory models, with a particular focus on their applications in the engineering domain. Within the scope of sentiment classification, the chapter explores two distinct types of game models: non-cooperative game models and evolutionary game models.

The chapter delves into the application of three specific game models: the Bayesian game model, the Population game model, and the Hawk-Dove game model. These models are strategically employed for binary sentiment classification tasks aimed at evaluating reviews. Notably, these game-based models exhibit a high degree of adaptability, making them well-suited for the task of sentiment classification. These models serve as valuable tools for the analysis and optimization of various systems, processes, and decision-making scenarios.

3.1 Bayesian Game Model-based Unsupervised Sentiment Analysis of Product Reviews

In this section, we discuss an algorithm for sentiment analysis of reviews each review contains textual feedback and rating. We analyze the implicit information in the textual feedback of reviews by calculating the context scores. Using these context scores and review ratings, games are played among the reviews. The sentiment tag for each review is determined using a principle called Bayesian Nash Equilibrium (BNE). We test the model on three English datasets. We achieved state-of-the-art results, showcasing the effectiveness of the model. Our study demonstrates the novel application of mathematical optimization for sentiment tagging of reviews, which opens up exciting possibilities for improving sentiment analysis techniques.

This section is further organized as follows: We introduce the Bayesian game in *subsection 3.1.1*. The proposed algorithm for sentiment analysis is given in *subsection 3.1.2*. In *subsection 3.1.3*, we discuss illustrative examples to showcase the application of the proposed algorithm.

3.1.1 Bayesian Game

In a Bayesian game, a player may not know the exact payoff functions of the other players. Bayesian Game includes type spaces, action spaces, payoff functions, and prior beliefs. A player's strategy is a comprehensive plan of action that addresses every possibility that may emerge for a player [174]. It is unknown which player will select which type of strategy; hence, a prior probability distribution is used to predict other player's strategy. To achieve optimal points in Bayesian games, the principle of Bayesian Nash Equilibrium (BNE) is used [174]. BNE is an extended variation of Nash equilibrium designed to achieve equilibrium under uncertainty. Each player must create an optimum gaming strategy to maximize their utility against other players' randomized mixed strategies.

We adapted the Bayesian Game Model to perform sentiment analysis of review comments. The Bayesian Game Model is mathematically represented by a tuple $G = <N, (T_i), (A_i), (p_i), (u_i)>$.

- N denotes the number of players *(1,2,3, ..., n)*. In the proposed work, each review is treated as a player.
- T_i tells the sets of types of a player. Types capture the private information a player can have. A type profile $t = (t_1, \ldots, t_N)$ is a list of types, one for each player. In the proposed approach, we perform sentiment analysis of a review. Each review has two components – textual feedback and star rating. We take each review as a player where each player has two types – context type and rating type. The context type is derived from the textual feedback and rating type is derived from the star rating of the review. Thus, type set of each player consists of two components given below:
  $$T_i \in \{C, R\} \text{ for } i = 1,2,3, \ldots, n,$$
  where 'C' denotes the context and 'R' denotes the rating.
- A_i is a collection of actions performed to achieve a specific goal. Actions can be either positive or negative, i.e., $A_i \in \{P_i, N_i\}$.
- p_i is the probability of occurrence of the type of review T_i and is given by *Equation (3.1)* and *Equation (3.2).* The probability of occurrence of rating type is
  $$P(R) = p \tag{3.1}$$

and context type is

$$P(C) = 1 - P(R) = 1 - p \tag{3.2}$$

The context and rating are two independent events, and thus the sum of the probabilities of occurrence is 1. If $p = 1$, then $1 - p = 0$. Thus, if 1-p turns out to be 0, then the contribution of context in the evaluation of sentiment gets eliminated. To balance the impact of both context and rating of a review, we perform probability smoothing such that $p = 0.9$ and thus $1 - p = 0.1$. This minor adjustment does not make any major amendments in the sentiments emanated by the rating and context component of a review. However, it ensures that the sentiments of contextual feedback are not nullified by mere multiplication with 0.

- The utility function u_i: $T_i \times A \rightarrow R$ indicates the payoff of each review for any action profile or type. $A = A_1 \times A_2$. Our algorithm has the same set of actions for both the context and rating of a review. However, the review's probability of taking various actions might vary depending on the context and rating.

We consider that the context of a review is of two types: positive context (C_P) and negative context (C_N), and the rating of a review is also of two types: positive rating (R_P) and negative rating (R_N). The final sentiment tag of a review is deduced by establishing *BNE*.

Definition 3.1: Bayesian Nash Equilibrium

In a Bayesian game, players have incomplete or imperfect information about the game, other players, or payoffs. They have beliefs or subjective probabilities about unknown aspects of the game. Players not only choose their strategies based on their private information but also take into account their beliefs about the unknown characteristics, types, or strategies of other players. BNE occurs when players' strategies are optimal not only based on their private information but also their beliefs about the uncertain aspects of the game. No player can unilaterally change their strategy to achieve a better outcome, given their beliefs.

BNE is described as a strategy profile that optimizes each player's expected payoff given their beliefs and the strategies used by the other players. For games of incomplete information, BNE is an extension of Nash equilibrium. A strategy of the i^{th} player is a function s_i: $T_i \rightarrow A_i$. s^* is a BNE of the Bayesian game $G = <N, (T_i), (A_i), (p_i), (u_i)>$ if and only if for each $i \in N$ and each $t_i \in T_i$.

$$U(s^*;t_i) \geq U(a_i, s^*_{-i};t_i) \text{ for all } a_i \in A_i \tag{3.3}$$

where
$$U_{t_i}(s_{t_i}, s_{-t_i}) = \phi_{t_{-i}}[U_i(s_i(t_i), s_{-i}(t_{-i}); t_i, t_{-i})] \tag{3.4}$$

$$U_{t_i}(s_{t_i}, s_{-t_i}) = \sum_{t_{-i} \in T_{-i}} p_{robablity(i)}(t_{-i|} \mid t_i).u_i(s_1(t_1), (s_2(t_2)................, s_n(t_n); t_i, t_{-i}) \tag{3.5}$$

where U_{t_i} refers to the utility/expected payoff of player i conditioned on the type t_i given by *Equation (3.5)*.

In summary, while BNE extends this concept to situations where players have incomplete information and make decisions considering their own beliefs about uncertain aspects of the game or opponents' characteristics. Bayesian Nash equilibrium incorporates beliefs and uncertainty into the analysis of strategic interactions, allowing for a more nuanced understanding of games with incomplete information.

3.1.2 Proposed Algorithm for Sentiment Analysis

We use the review's textual comments and star ratings for sentiment analysis. The flowchart of the proposed model is shown in *Fig. 3.1*. The proposed algorithm is divided into the following four steps:

Step 1: Determine context scores and rating scores of a review comment.
Step 2: Normalize the context and rating scores.

Step 3: Play Bayesian games among the reviews.
Step 4: Deduce the sentiment tag of a review.

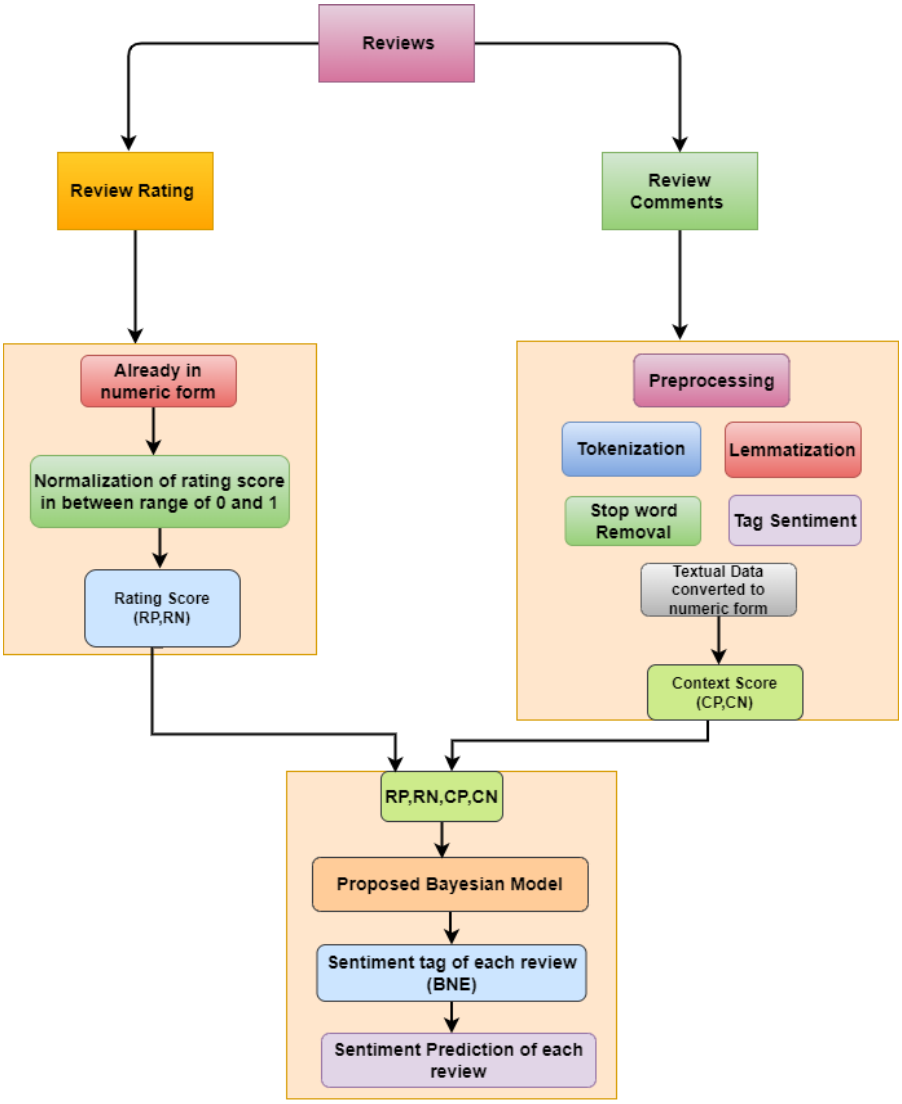

Fig. 3.1: Flowchart of the proposed model for sentiment analysis of reviews

Step 1: Determine context scores and rating scores of a review comment: In this step, we calculate context scores and rating scores for each review. Each review has two context scores – positive context score and negative context score and two rating scores – positive rating score and negative rating score.

We determine the context scores of textual comments using SentiWordNet (SWN). SentiWordNet is a lexical resource that assigns sentiment scores to words. We take POS-tagged content words of a review comment. For each word, we extract the positive and negative scores. These scores reflect the magnitude of positivity and negativity associated with the word's meaning. Further, we compute the mean of the polarities to get the context scores of a review.

Algorithm 3.1 shows the steps to compute the context scores of a review comment. It begins by initializing C_P (Positive Context Score) and C_N (Negative Context Score) to zero for every review. The $P_{Sentiscore}$ and $N_{Sentiscore}$ are then updated by accumulating the positive and negative scores across all words in the review. To normalize the scores and make them comparable across different reviews, the algorithm computes the normalized positive context score $(C_P)/(PCS^{\otimes})$ and the normalized negative context score $(C_N)/(NCS^{\otimes})$ This normalization process involves dividing the cumulative positive and negative scores by the total number of words in the review.

Algorithm 3.1: Calculate context scores of reviews

Input: *W - a set of open class and parts of speech tagged words extracted from the given sentence, SWL - SentiWordNet list of words with positive and negative sentiment value of each word.*

Output: *Context Scores of i^{th} review $\{C_P, C_N\}$, where C_P = positive context score and C_N = negative context score.*

1. *Initialize, $C_P = 0$ and $C_N = 0$; such that $C_i = \{0, 0\}$.*
2. *Take $W = (w_1, w_2, ..., w_i, ..., w_n)$ where w_i represents the i^{th} $(1 \leq i \leq K)$ word in the input review.*
3. *If $(w_i \in SWL)$ then*

$$P_{Sentiscore} = p + positive\ sentiment\ score\ of\ w_i$$
$$N_{Sentiscore} = n + negative\ sentiment\ score\ of\ w_i$$

4. *Normalize the $P_{Sentiscore}$ and $N_{Sentiscore}$ between [0, 1].*
5. *Normalized value of $P_{Sentiscore}$ and $N_{Sentiscore}$ are $C_P/(PCS^{\otimes})$ and $C_N/(NCS^{\otimes})$.*

$C_P/PCS^{\otimes} = \frac{P_{sentiscore}}{K}$ and $C_N/NCS^{\otimes} = \frac{N_{sentiscore}}{K}$ *// K is the number of words in set W*

To calculate the rating scores, we use the star rating given to the review. Equations (3.6) and (3.7) show the formulae to calculate the rating scores.

$$R_P = \text{Given rating to the review (p)} \qquad (3.6)$$
$$R_N = (5 - R_P) \qquad (3.7)$$

Step 2: Normalize the context and rating scores: The context scores range between 0 and 1 while the rating scores are between 1 and 5. To neutralize the dominance of one parameter over the other, we normalize the scores by dividing each value of rating and context by the maximum numeric value of rating and context in the dataset. We normalize C_P, C_N, R_P, and R_N scores such that their values range between 0 and 1.

Step 3: Play Bayesian games among the reviews: Bayesian game is played between two reviews, R_i and R_j. We consider R_i to have either "context type" or "rating type". On the contrary, R_j has only one type (either context or rating). The R_i knows its type as well as the type of R_j. However, R_j has incomplete information and does not know the type of R_i but knows the probabilities of the type and action of R_i.

In *Table 3.1,* α and ψ represent the numeric values for the positive context of R_i and R_j, respectively. The respective numeric values for the negative context of R_i and R_j are denoted by γ and ω. Similarly, β and Ω depict the numeric values of the positive ratings of R_i and R_j. δ and ϵ denote the numeric value of the negative ratings of R_i and R_j, respectively.

Table 3.1: Different values of context and rating types

Reviews	Parameters	Values
R_1	Positive Context	α
	Negative Context	γ
	Positive Rating	β
	Negative Rating	δ
R_2	Positive Context	ψ
	Negative Context	ω
	Positive Rating	Ω
	Negative Rating	ϵ

Fig. 3.2 shows the implementation of the proposed model. In the figure, there are four matrices, and two payoffs are given in each cell of the matrices. The first value of each cell indicates the payoff of the first player (R_j), and the second value is the payoff of the second player (R_i).

First matrix (i) is the context matrix and the probability of occurrence of context matrix, $P(T_{ic}) = 1\text{-}p$. In this matrix, we denote the context type of R_i by T_{ic} that can have two actions, either positive $(A_i)_{CP}$ or negative $(A_i)_{CN}$**.** Similarly, review R_j can have actions positive $(A_j)_P$ or negative $(A_j)_N$.

The second matrix (ii) is the rating matrix and the probability of occurrence of the rating matrix, i.e., $P(T_{jR}) = p$. In this matrix, we denote the rating type of R_i by T_{iR} that can have two actions, either positive $(A_i)_{RP}$ or negative $(A_i)_{RN}$**.** Similarly, review R_j can have actions positive $(A_j)_P$ or negative $(A_j)_N$. As context and rating are mutually exclusive the combined probability of the Context matrix and Rating matrix is $P(T_{jR}) + P(T_{jc}) = 1$.

The third (iii) and fourth (iv) matrices are obtained by multiplying the context and rating matrices with their respective probabilities. The context matrix and rating matrix are described below:

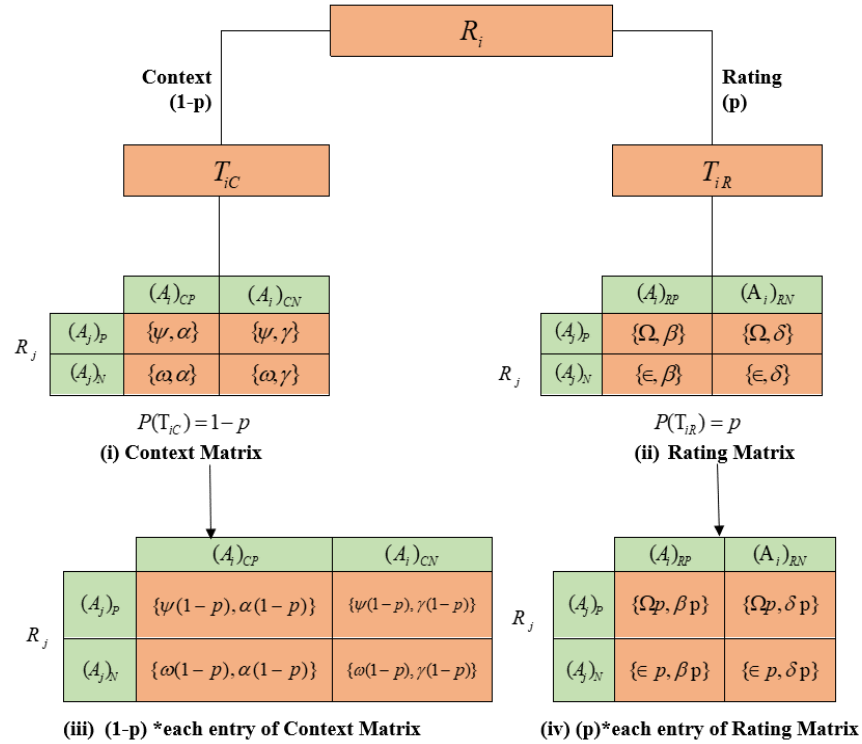

Fig. 3.2: Implementation of Proposed Bayesian Model.

After evaluating matrices *(iii)* and *(iv)* of *Fig. 3.2*, we combine these two matrices. The combined matrix is shown in *Fig. 3.3*. There are two equations in each cell, the first Equation evaluates the payoff of the first review, and the second Equation evaluates the payoff of the second review. The matrix results in the best response of players of each type and computes the average payoff of the first player based on the probabilities of the type of the second player. We follow *Algorithm 3.2* to deduce the sentiment tag of a review. Next, we evaluate the players' dominant strategy and reach the Nash equilibrium.

R_i

R_j		$(A_i)_{CP}.(A_i)_{RP}$	$(A_i)_{CP}.(A_i)_{RN}$	$(A_i)_{CN}.(A_i)_{RP}$	$(A_i)_{CN}.(A_i)_{RN}$
	$(A_j)_P$	$\{(\psi(1-p)+\Omega p),$ $(\alpha(1-p)+\beta p)\}$	$\{(\psi(1-p)+\Omega p),$ $(\alpha(1-p)+\delta p)\}$	$\{(\psi(1-p)+\Omega p),$ $(\gamma(1-p)+\beta p)\}$	$\{(\psi(1-p)+\Omega p),$ $(\gamma(1-p)+\delta p)\}$
	$(A_j)_N$	$\{(\omega(1-p)+\in p),$ $(\alpha(1-p)+\beta p)\}$	$\{(\omega(1-p)+\in p),$ $(\alpha(1-p)+\delta p)\}$	$\{(\omega(1-p)+\in p),$ $(\gamma(1-p)+\beta p)\}$	$\{(\omega(1-p)+\in p),$ $(\gamma(1-p)+\delta p)\}$

Fig. 3.3: Combined Matrix of context and rating type multiplied with respective probabilities.

Algorithm 3.2: Deducing sentiment tag using Game Model

Input: *Reviews data file R with context score $\{C_P, C_N\}$ and the rating score $\{R_P, R_N\}$.*

Output: *Tagged Sentiment, i.e. $\{R_P, R_N\} \in \{P, N\}$, where a set of strategies $\{s_{-i}, s_i\} \in \{P, N\}$.*

1: *Make two matrices of context $\{C_P, C_N\}$ and rating $\{R_P, R_N\}$ with strategy positive & negative.*

2: *Calculate payoffs of R_i and R_j,*

$$U_i(R_i, R_j) = (1-p).u_i(R_i, R_{jc}) + (p).u_i(R_i, R_{jR})$$ *, where p is probability.*

3: *Calculate the combined matrix of context and rating by multiplying with respective probabilities.*

4: *Apply Game Theory strategies and evaluate the best response. If*

$$U_{t_i}(s_i^*(t_i), s_{-i}(t_{-i})) > U_{t_i}(s_i, s_{-i}(t_{-i})) \; || \; U_{t_i}(s_i^*(t_i), s_{-i}(t_{-i})) \geq U_{t_i}(s_i, s_{-i}(t_{-i}))$$

Then

$$U_{t_i}(s_{t_i}, s_{-t_i}) = \sum_{v_{-i} \in T_{-i}} p_{robability(i)}(v_{-i} \mid t_i) U_i(t_i, v_{-i}, s_{t_i}, s_{v_{-i}})$$

5: *The best response strategy is the sentiment tag of individual review. If* $s_i(t_i) \rightarrow BNE$ *, then*

$$s_i(t_i) \in \arg\max_{s_i^{'} \in S_i} \sum_{t_{-i}} p_{robabilty(i)}(t_{-i} \mid t_i) U_i(s_i^{'}, s(t_{-i}), t_i, t_{-i})$$

6: *Repeat steps 1 to 5 for all combinations of reviews in the dataset.*

{R_i, R_j} → {P, N}.

3.1.3 Illustrative Example on Bayesian Game Model

Let us consider two reviews R_1 and R_2 taken from the dataset.

> ***R_1* (4 star):** "*I have buy several of the Vitality can dog food product and have find them all to be of good quality. The product looks more like a stew than a processed meat and it smell better. My Labrador be finicky and she appreciate this product good than most*."
> ***R_2* (1 star):** "*Product arrived labeled as Jumbo Salted Peanuts…the peanuts were actually small sized unsalted. Not sure if this was an error or if the vendor intended to represent the product as Jumbo".*

First, we convert the written textual feedback of reviews to numeric values following *Algorithm 3.1. Table 3.2* shows the normalized positive and negative values of context and rating of reviews R_1 and R_2. The reviews R_1 and R_2 can interact in two possible ways.

Table 3.2: Positive and Negative values of Context and Rating of R_1 and R_2.

Reviews	Parameters	Values
R1	Positive Context	0.1079
	Negative Context	0.0114
	Positive Rating	4.0000
	Negative Rating	1.0000
R2	Positive Context	0.0515
	Negative Context	0.1397
	Positive Rating	1.0000
	Negative Rating	4.0000

Interaction 1: In the first interaction, we consider R_1 does not know the actions and type of R_2, but R_1 knows the action and type of R_2, or we can say R_1 has incomplete information about R_2. R_2 only knows the probability of occurrence of the context type matrix, i.e., $p = 0.8$, and the probability of occurrence of rating type matrix $p = 0.2$. The interaction between the players R_1 and R_2 is given in *Fig. 3.4*.

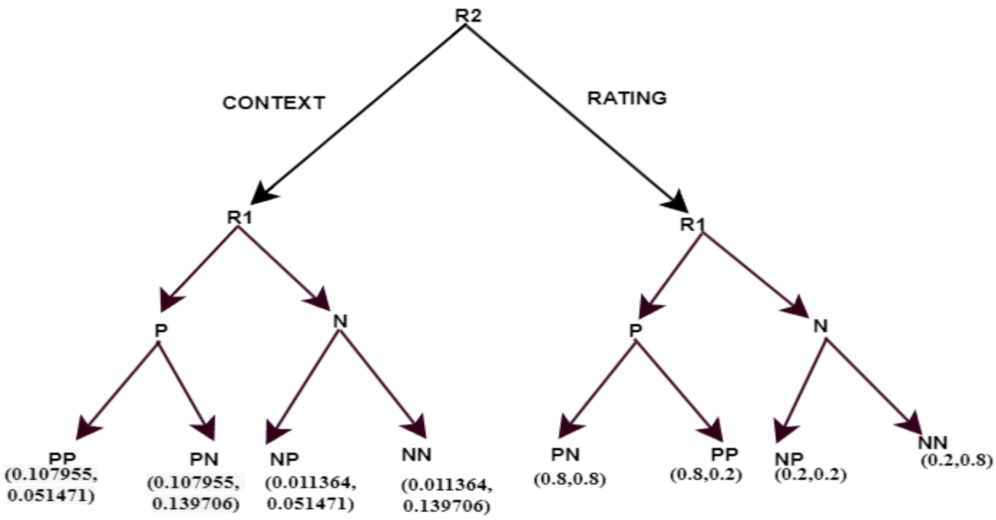

Fig. 3.4: Extensive form of R_2 and R_1 interaction.

Table 3.3 and *Table 3.4* show the normalized context matrix and rating matrix, respectively. The first value in each cell is the payoff of R_1 for choosing a particular action and the second value is the payoff of R_2 for choosing a specific action.

Table 3.3: Context Type Matrix.

		R_2	
		P	***N***
R_1	***P***	(0.1079,0.0515)	(0.1079, 0.1397)
	N	(0.0114,0.0515)	(0.0114,0.1397)

Table 3.4: Rating Type Matrix.

		R_2	
		P	***N***
R_1	***P***	(0.8000,0.2000)	(0.8000,0.8000)
	N	(0.2000,0.2000)	(0.2000,0.8000)

Table 3.5 is the combined matrix of *Table 3.3* and *Table 3.4.* Payoff values are calculated by multiplying the payoffs in context and rating matrices with respective probabilities of different types (*section 3.2* from *step 3*). Next, we apply *Equation (3.3)* to evaluate the dominant actions of R_1 and R_2.

Table 3.5: Combined matrix of Context and Rating of both players (R_1, R_2).

		R_2			
		PP	***PN***	***NP***	***NN***
R_1	***P***	(0.2463,0.0814)	(0.2463,0.2014)	(1.0231,0.1518)	**(1.0231,0.2718)**
	N	(0.0491,0.0814)	(0.0491,0.2014)	(0.0491,0.1518)	(0.0491,0.2718)

The dominant payoff is **(1.023,0.2718),** where **1.023 and 0.2718** are the payoff values of R_1 and R_2, respectively. The BNE is (*P*, *NN*) where *P* is the best response of R_1 and *NN* is the best response of R_2. The first *N* in *NN* implies that the context type chooses negative action while the second *N* suggests that the rating type also chooses negative action. *Table 3.6* and *Fig. 3.5* show the BNE of interaction 1 among the players.

Table 3.6: Bayesian Nash Equilibrium: Best response of the individual players

		R₂
		NN
R_1	***P***	**(1.0231,0.2718)**

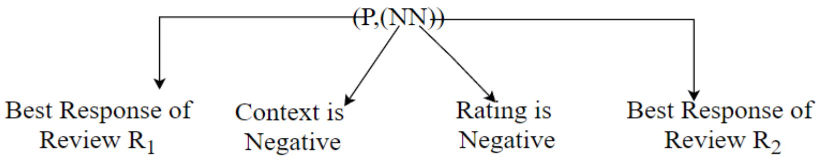

Fig. 3.5: BNE of interaction 1.

Interaction 2: In the second interaction, we reverse the sequence of interactions as illustrated in *Fig. 3.6* and then apply the Proposed Bayesian Model to obtain the BNE. *Table 3.7* and *Table 3.8* show the numeric values of context and rating matrices.

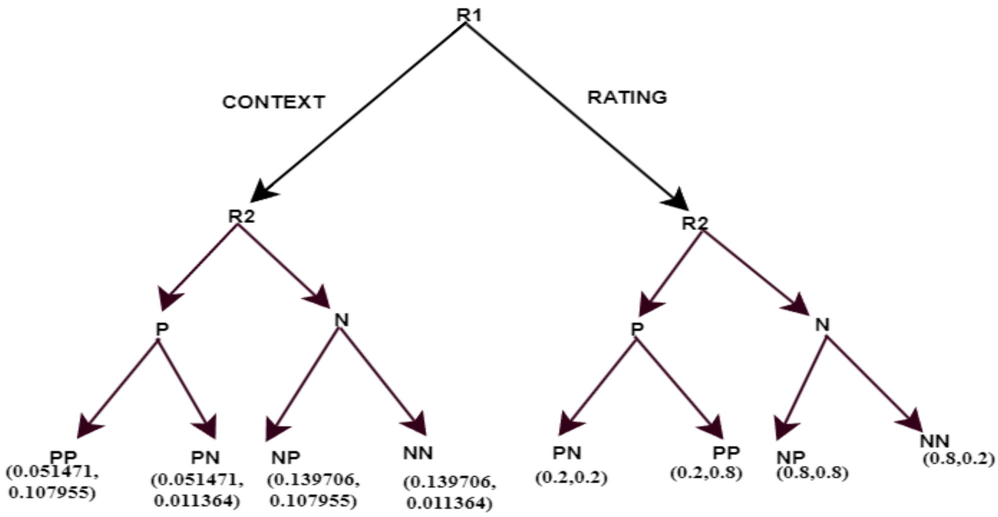

Fig. 3.6: Extensive form of R_1 and R_2 interaction.

Table 3.7: Context Matrix of R_1 and R_2.

		R_2	
		P	***N***
R_1	***P***	(0.0515,0.1079)	(0.0515, 0.0114)
	N	(0.1397, 0.1080)	(0.1397,0.0114)

Table 3.8: Rating Matrix of R_1 and R_2.

		R_2	
		P	***N***
R_1	***P***	(0.2000,0.8000)	(0.2000,0.2000)
	N	(0.8000,0.8000)	(0.8000,0.2000)

Table 3.9 is the combined context and rating matrix. *Fig. 3.7* and *Table 3.10* give the strongly dominant action of interaction 2, i.e., (*N*, *PP*) where *N* is the best response of

R_2 and *PP* is the best response of R_1. The first *P* in *PP* implies context is positive, and the second *P* gives the rating is positive.

Table 3.9: Combined matrix of both Context and Rating type matrix.

		R_1			
		PP	***PN***	***NP***	***NN***
R_2	***P***	(0.0103,0.0216)	(0.1703,0.1816)	(0.1703,0.6470)	(0.1703,0.1623)
	N	**(0.6679,0.6676)**	(0.6679,0.1816)	(0.6680,0.6470)	(0.6674,0.1623)

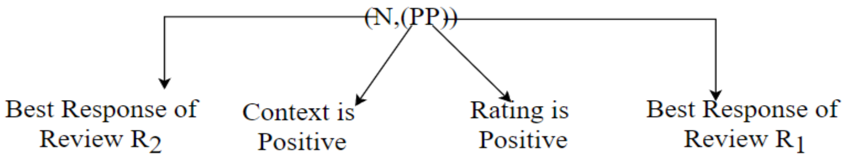

Fig. 3.7: BNE of interaction 2.

Table 3.10: Bayesian Nash Equilibrium: Best response of the individual player.

		R_1
		PP
R_2	***N***	**(0.6679,0.6676)**

After performing two Bayesian interactions, we deduce a sentiment tag for the review. *Table 3.11* combines the two BNEs to deduce a tag. *Table 3.11* shows that the deduced sentiment tag for review R_1 is positive while for R_2 is negative.

Table 3.11: Best responses of Interaction 1 and Interaction 2.

	R_1 (4 Star)	**R_2 (1 star)**
BNE of Interaction 1	(P)	(NN)
BNE of Interaction 2	(PP)	(N)
Total Sentiment tag	$P(1+P)$	$N(1+N)$
Deduced sentiment tag for each review	Positive	Negative

Similarly, we perform pairwise interactions among all reviews in a dataset and tag reviews with their corresponding sentiments. The Bayesian game model outperforms other existing approaches in terms of generalization as shown in the result and experimentation *section 3.4*.

3.2 Population Game Model-based Unsupervised Sentiment Analysis of Product Reviews

In this section, we discuss an unsupervised method of sentiment analysis using a population game model. This section is further organized as follows: The population game theory is discussed in *subsection 3.2.1*. In *subsection 3.2.2*, we discuss the proposed algorithm for sentiment analysis is given. The illustrative examples are given in *subsection 3.2.3*.

3.2.1 Population Game Theory

The population game model is a mathematical framework that integrates concepts from game theory and evolutionary biology to analyze the dynamics of strategic interactions within a population. It explores the evolution of different strategies as individuals engage in random contests and accumulate payoffs based on their chosen strategies. The model takes into account factors such as frequency-dependent selection, where the fitness of a strategy depends on its prevalence in the population.

- Population game in evolutionary game theory involves a population of individuals playing a game repeatedly, where the strategies of individuals evolve based on their performance in the game.
- The population consists of N individuals, and each individual has a strategy chosen from a set of strategies S.
- The payoff matrix represents the payoffs received by individuals when they interact with others in the population. It is denoted as $A = [a_{ij}]$, where a_{ij} represents the payoff for an individual playing strategy i against an individual playing strategy j.
- The frequencies of different strategies in the population are denoted by p_j, representing the proportion of individuals using strategy j in the population.
- The fitness of an individual ($E(i, \pi)$). It used as the payoff they receive from playing the game with their chosen strategy against other individuals in the population given by *Equation (3.8)*. It helps us understand which strategies are more effective in maximizing payoffs and providing individuals with a competitive advantage.

$$E(i,\pi) = (a_{ij} * p_j) \tag{3.8}$$

- The expected fitness of the population, denoted as $E(\pi, \pi)$, is the average expected payoff of individuals in the population, considering the frequencies of different strategies. It is calculated by taking the weighted average of expected payoffs for each individual, where the weights are given by the frequencies of strategies in the population evaluated using *Equation (3.9).*

$$E(\pi,\pi) = (p_j * E(i,\pi)) \tag{3.9}$$

- The frequencies of strategies in the population can change over time according to the replicator dynamics, which describe how the frequencies evolve based on the fitness of different strategies.
- Replicator dynamics can be represented as a set of differential Equations where the rate of change of the frequency of strategy j is determined by the difference between the fitness of strategy i and the average fitness of all strategies in the population. The rate of change of frequencies in time t is denoted by $\frac{dp_i}{dt}$ known as replicator dynamics as illustrated by *Equation (3.10).*

$$\frac{dp_i}{dt} = p_i * [E(\mathrm{i},\pi) - E(\pi,\pi)] \tag{3.10}$$

- The dynamics of the population game can be analyzed by studying the long-term behavior of the replicator dynamics, such as by identifying steady-state solutions where the frequencies of strategies no longer change over time and this is known as the Nash equilibrium of the game.

$$\text{As} \lim_{t\to\infty} p_i \; and \; \frac{dp_i}{dt}=0 \; \text{then} \; p_i^*[E(\mathrm{i},\pi)-E(\pi,\pi)]=0 \; as \; p_1+p_2=1 \tag{3.11}$$

and then evaluate the values of p_1 and p_2 solving *Equation (3.11)*.

- A population game aims to identify an Evolutionarily Stable Strategy (ESS), which refers to a set of strategies that, once prevalent in the population, resists being replaced by any alternative strategy. In essence, ESS represents the stable state of strategies within the population where the prevailing strategy or strategies cannot be easily overtaken by other competing strategies.

3.2.2 Proposed Methodology of Population Game Model

In this method, we calculate two scores viz. context scores and emotions scores from the written review comments. The proposed approach is subdivided into the following steps:
Step 1: Evaluation of context scores of a review.
Step 2: Evaluation of emotion scores of a review.
Step 3: Play a population game between the reviews.

Fig. 3.8 shows the flowchart of the framework of the proposed population algorithm.

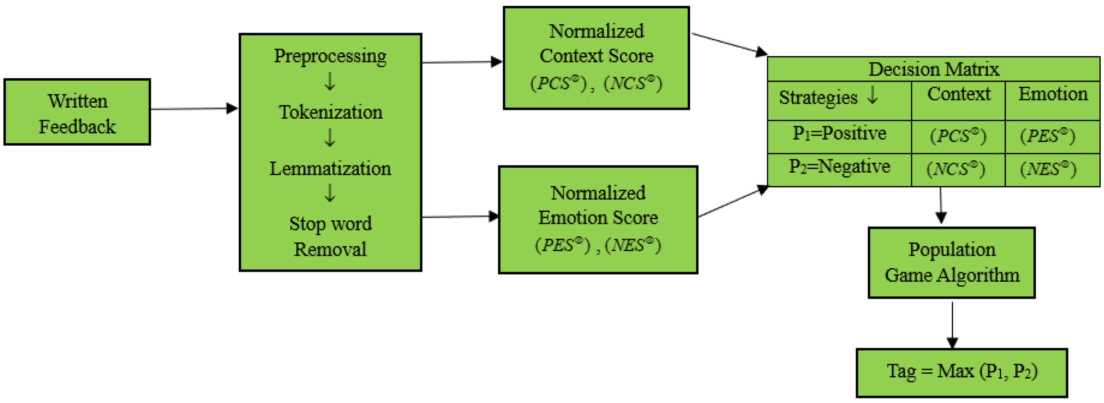

Fig. 3.8: Flowchart of the framework of the proposed population algorithm

Step 1: Evaluate Context Scores of Reviews ($PCS^{\otimes}, NCS^{\otimes}$): Context scores are objective numerical measures evaluated to effectively quantify the magnitude of positive or negative sentiment conveyed by textual review feedback. These scores are calculated using *SWN*. The resulting context scores exhibit values that reside within the closed interval *[0, 1]*. We used *Algorithm 3.1* to calculate the context scores.

Step 2: Evaluate the Emotion scores of reviews ($PES^{\otimes}, NES^{\otimes}$). The emotions are categorized into distinct categories, i.e. happy (*H*), angry (*A*), sad (*S*), surprised (*Sp*), and fear(*F*). We have not taken fear emotion into account. To quantify the emotions present in the text, we used Python's text2emotion library[1]. It is a python library, which encapsulates various functions, that extract the emotions from the text. This library provides numerical representations of the intensity of the identified emotions in the text.

[1] pip install text2emotion (https://pypi.org/project/text2emotion/)

The emotions have been further categorized the emotions into two groups: normalized positive emotions ($PES^{\otimes}$) and normalized negative emotions ($NES^{\otimes}$) score. The resulting values of ($PES^{\otimes}$) and ($NES^{\otimes}$) fall within the range of 0 to 1. The categorization of emotions is performed using *Algorithm 3.3*.

Algorithm 3.3: Evaluate the Emotion scores of a review.

Input: *A sequence of words (W) in a review R.*

Output: *Normalised Positive Emotion Score* $(PES^{\otimes})$ *and Negative Emotion Score* $(NES^{\otimes})$.

1. Initialise emotion score variables H =0, A=0, S=0 and S_p *=0.*

2. *For all W in R,* $if\ \ W \in EmotionWords$

$$EmotionScores \leftarrow GetEmotionScores(W)$$

// GetEmotionScores is the function in library text2emotion. This gives five emotions score for Happy, Angry, Sad, Surprised and Fear.

$$\begin{aligned} &For\ each\ emotionScore\ \ variables \\ &H \leftarrow H + emotion\_score(H) \\ &A \leftarrow A + emotion\_score(A) \\ &S \leftarrow S + emotion\_score(S) \\ &S_P \leftarrow S_P + emotion\_score(S_P) \end{aligned}$$

4. *Total emotion score E of R*

$$E \leftarrow H + A + S + S_P$$

6: *Positive emotion score (EP) and negative emotion score (EN).*

$$EP \leftarrow H + S_P \ \ || \ \ EN \leftarrow A + S + S_P$$

7: *Normalised Positive Emotion Score* $(PES^{\otimes})/(E_p)$ *and Negative Emotion Score* $(NES^{\otimes})/(E_N)$.

$$(NES^{\otimes})/(E_N) = \frac{EN}{E} \ \ || \ \ (PES^{\otimes})/(E_p) = \frac{EP}{E}$$

Step 3: Play Population Game: To apply the proposed Population game to the sentiment tagging task, we consider a review *R* as a game with two players: context and emotion. *Table 3.12* contains different values of positive and negative scores of context and emotion of any review *R*. Each player has two strategies, Normalised Positive Context Score $(PCS^{\otimes})$ and Negative Context Score $(NCS^{\otimes})$ and Normalised Positive Emotion Score $(PES^{\otimes})$ and Negative Emotion Score $(NES^{\otimes})$. These strategies have values between (0,1], ensuring that their sum is always 1 (p_1 + p_2 = 1). Then *Algorithm 3.4* is implemented and a detailed explanation of each step of *Algorithm 3.4* is given in *Fig. 3.9*. The first step involves constructing a 2x2 matrix that represents the scores associated with these strategies. This matrix serves as a basis for further analysis. In the second step, the fitness of strategies for both players is evaluated. The fitness of a strategy for player 1 (context) is denoted as $E\left[1,\pi\right]$, and for player 2 (emotion), it is denoted as $E\left[2,\pi\right]$. These fitness measures capture the effectiveness of each strategy in the game. Next, in the third step, the expected fitness $E\left[\pi,\pi\right]$ is calculated. The fourth step involves determining the replicator dynamics, which describe the rate of change of strategies over time. For player 1, this is represented by $\frac{dp_1}{dt}$

, and for player 2, it is represented by $\frac{dp_2}{dt}$. As time approaches infinity (t → ∞), the strategies of both players reach a Nash equilibrium, where they no longer change their strategies. At this point, the rate of change of Player 1's strategy becomes zero ($\frac{dp_1}{dt}=0$), and for Player 2, it also becomes zero ($\frac{dp_2}{dt}=0$). In the penultimate step, three Equations (as illustrated in *step 6* of *Fig. 3.9*) need to be solved. *Equation (a)* and *(b)* can be combined into a single variable using *Equation (c)*as illustrated in *Fig. 3.9*. Finally, by solving the equation, the values of p_1 and p_2 are determined. The maximum value between p_1 and p_2 indicates the dominant strategy, which determines the sentiment tag assigned to review *R*.

Table 3.12: Context and Emotion scores of review R

Review R			
Strategies		**Players**	
		Context	**Emotion**
	***P₁* = Positive Score**	$PCS^{\otimes}=\alpha$	$PES^{\otimes}=\beta$
	***P₂*= Negative Score**	$NCS^{\otimes}=\gamma$	$NES^{\otimes}=\delta$

Algorithm 3.4: Sentiment tagging of Reviews using Population Game

Input: *Normalised* $(PCS^{\otimes})$, $(NCS^{\otimes})$, $(PES^{\otimes})$ *and* $(NES^{\otimes})$.

Output: *Sentiment tag to the reviews.*

Step 1: *Construct a decision matrix of 2×2 order.*

Step 2: *Evaluate the Fitness of the player playing strategy i.*

$$E(i,\Pi)=\sum a_{i,k}.p_k=A_{i\Pi} \qquad \forall\ i\in\{1,2\}$$

Step 3: *Calculate the expected fitness of both player*

$$E(\pi,\pi)=\sum_{i=1}^{n}p_i[\sum_{k=1}^{n}a_{i,k}\,p_k]=\pi A\pi^T$$

Step 4: *Calculate replicator dynamics.*

$$\frac{dp_i}{dt}=p_i[E(\mathrm{i},\pi)-E(\pi,\pi)]$$

Step 5: *At the steady state* $\lim_{t\to\infty}p_i$ *and* $\frac{dp_i}{dt}=0$

$$p_i^*[E(\mathrm{i},\pi)-E(\pi,\pi)]=0$$

Step 6: *Put* $p_2=1-p_1$ *and solve the equation.*

Step 7: *Calculate* p_1 *and* p_2 *values* $\forall\ p_1,p_2\in[0,1]$.

Step 8: *Sentiment Tag = max* (p_1, p_2).

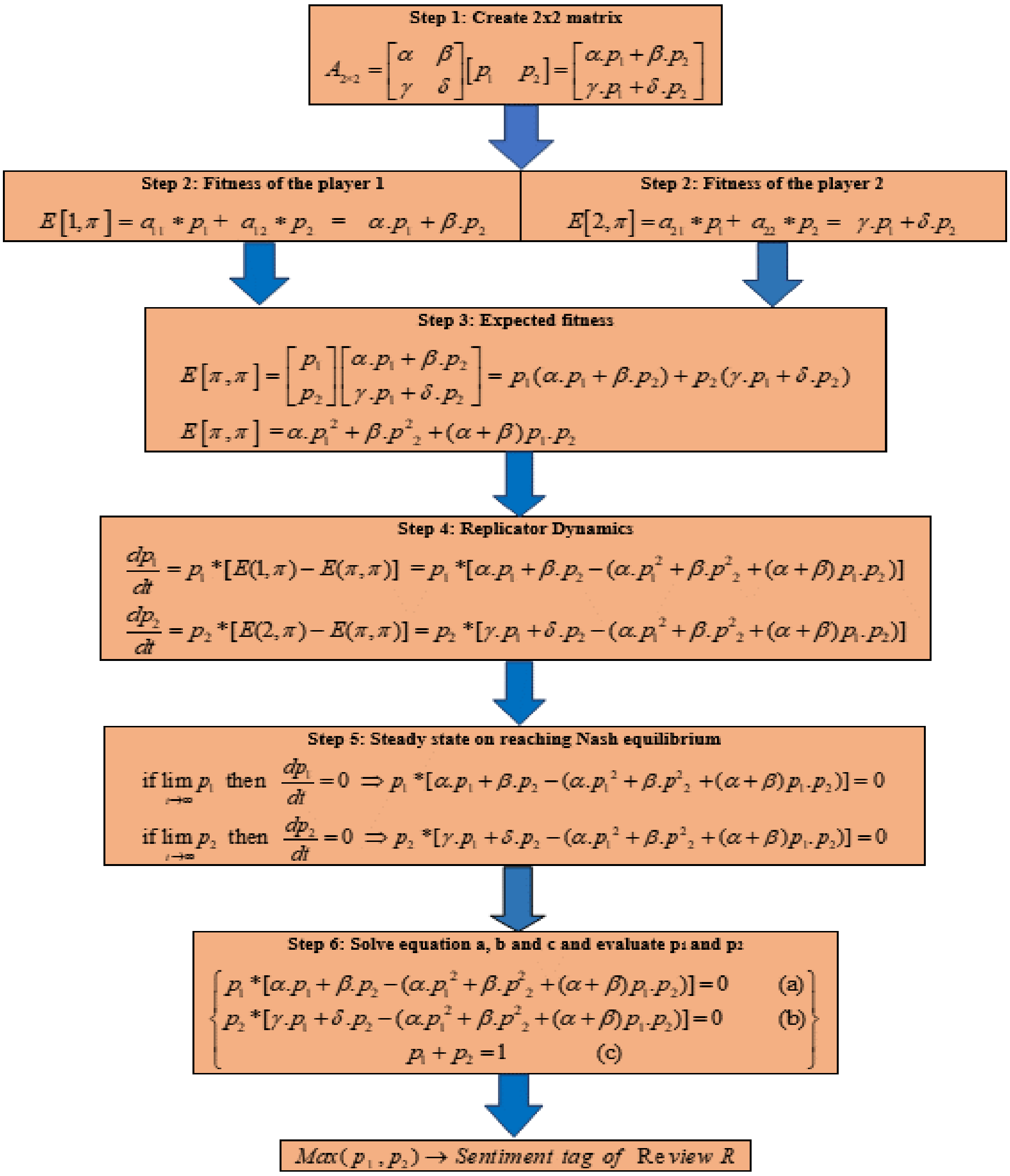

Fig. 3.9: Demonstration of the population game model with equation involved in each step

The maximum of both strategies (p1, p2) is the sentiment tag in the text. The strategy, which is the sentiment tag for the text, is the evolutionarily stable strategy of the game. This implies that with the rate of change of strategy concerning time, this sentiment-tagged strategy will not change. That's why it's known as the ESS of this game.

3.2.3 Numerical Illustration of Population Game Model

Let us examine a 4-star rating review.

Review (4 stars): *"Deal was awesome! Arrived before Halloween as indicated and was enough to satisfy trick-or-treaters. I love the quality of this product and it was much less expensive than the local store's candy."*

Table 3.13 contains the context and emotions scores of the review that form a decision matrix. Then we follow *Algorithms 3.1* and *3.3* to generate a decision matrix *Table 3.13* and evaluate p_1 and p_2 following *Algorithm 3.4*.

Table 3.13: Context and Rating Scores of Review

Review R_i			
Strategies		**Players**	
		Context	**Emotion**
	***P_1* = Positive Score**	0.75	0.8
	***P_2*= Negative Score**	0	0.2

We play the population game between two players i.e. positive (P_1) and negative (P_2) of review *R*. The fitness of a player using positive $E[1,\Pi]$ and negative $E[2,\Pi]$ strategies can be expressed mathematically using Equation (3.12).

$$E[1,\Pi] = 0.75\bullet p_1 + 0\bullet p_2 \quad \text{and} \quad E[2,\Pi] = 0.8\bullet p_1 + 0.2\bullet p_2 \tag{3.12}$$

and the average fitness in the population is given by Equation (3.13) and (3.14)

$$E[\Pi,\Pi] = [p_1, p_2]\bullet\begin{bmatrix}0.75\bullet p_1 + 0\bullet p_2 \\ 0.8\bullet p_1 + 0.2\bullet p_2\end{bmatrix} = (0.75\bullet p_1 + 0\bullet p_2)p_1 + (0.8\bullet p_1 + 0.2\bullet p_2)\bullet p_2 \tag{3.13}$$

$$E[\Pi,\Pi] = 0.75\bullet p_1^2 + 0.2\bullet p_2^2 + 0.8\bullet p_1\bullet p_2 \tag{3.14}$$

We evaluate replicator dynamics using *Equation (3.15)* for player 1 and *Equation (3.16).*

$$\frac{dp_1}{dt} = p_1\bullet[0.75\bullet p_1 + 0\bullet p_2 - (0.75\bullet p_1^2 + 0.8\bullet p_1\bullet p_2 + 0.2\bullet p_2^2)] \tag{3.15}$$

$$\frac{dp_2}{dt} = p_2\bullet[0.8\bullet p_1 + 0.2\bullet p_2 - (0.75\bullet p_1^2 + 0.8\bullet p_1\bullet p_2 + 0.2\bullet p_2^2)] \tag{3.16}$$

As $p_1 + p_2 = 1 \Rightarrow p_2 = (1 - p_1)$.

For a further long time $\lim_{t\to\infty} p_i(t)$ and at a steady state, the rate of change of strategies becomes zero with time given by *Equation (3.17).*

$$\frac{dpi(t)}{dt} = 0 \tag{3.17}$$

$$p_1\bullet[0.75\bullet p_1 + 0\bullet p_2 - (0.75\bullet p_1^2 + 0.8\bullet p_1\bullet p_2 + 0.2\bullet p_2^2)] = 0 \tag{3.18}$$

$$p_2\bullet[0.8\bullet p_1 + 0.2\bullet p_2 - (0.75\bullet p_1^2 + 0.8\bullet p_1\bullet p_2 + 0.2\bullet p_2^2)] = 0 \tag{3.19}$$

$$p_1 + p_2 = 0 \tag{3.20}$$

Solving *Equation (3.18)* and *Equation (3.19)* with the help of *Equation (3.20)* we get the values of p_1 and p_2 in the below calculations.

$$p_1 = [0.75\bullet p_1 - (0.75\bullet p_1^2 + 0.8\bullet p_1\bullet(1 - p_1) + 0.2\bullet(1 - p_1)^2] = 0$$

$$p_1 = [0.75\bullet p_1 - (0.75\bullet p_1^2 + 0.8\bullet p_1 - 0.8\bullet p_1^2 + 0.2\bullet(1 - 2.p_1 + p_1^2)] = 0$$

$$p_1 = [0.75\bullet p_1 - (0.15\bullet p_1^2 + 0.4\bullet p_1 + 0.2)]$$

$$p_1 = 0.15\bullet p_1^2 - 0.35\bullet p_1 + 0.2 \Rightarrow p_1 = (1.333\ ,\ 1)$$

Hence on solving, we get two values for p_1. $p_1 \neq 1.333$ as $p_1 + p_2 = 1$ so p_1 can never be greater than 1. So, the value of $p_1 = 1$ and $p_2 = 0$, and $p_1 > p_2$ so the tag for this review is positive. The deduced tag to the review is max (p_1, p_2) i.e., max ($p_1 = 1, p_2 = 0$) which is $p_1 = 1$ so strategy p_1 is the ultimate tag to the review i.e., $R \to p_1 \to positive\ tag$.

Here the positive strategy is the sentiment tag for the text, which is the evolutionary stable strategy of the game. This implies that with the rate of change of strategy concerning time, this sentiment-tagged strategy will not change. That's why positive strategy is the ESS of this game.

3.3 Sentiment Analysis using Hawk Dove Game

In this section, we discuss an algorithm to perform sentiment analysis using Hawk Dove Game. We present the theoretical Hawk dove game in *subsection 3.3.1*. and the proposed Hawk-Dove Sentiment Tagging (HDST) Model for sentiment analysis in *subsection 3.3.2.* The detailed illustrative example is in *subsection 3.3.3.*

3.3.1 Hawk Dove Game

The hawk-dove game explores the evolution of aggressive and peaceful strategies in a population of individuals. It is used to understand the dynamics of conflict resolution and resource allocation in evolutionary settings. The game is based on the strategies of "hawk" and "dove" and their associated payoffs. Researchers use mathematical models, simulations, and analytical techniques to study the evolutionary dynamics of the Hawk-Dove model and gain insights into the evolution of conflict and cooperation in biological and social systems. The frequency used terms are explained below:

i) **Population:** The game considers a population of individuals, each of which can adopt either a hawk or a dove strategy.

ii) **Hawk Strategy:** When an individual chooses the hawk strategy, it behaves aggressively and confrontationally. Hawks are willing to escalate conflicts and fight until they win or the opponent retreats. They seek to claim resources through forceful means.

iii) **Dove Strategy:** Individuals adopting the dove strategy behave peacefully and non-confrontationally. Doves avoid conflicts and choose to retreat or back down instead of fighting. They seek to avoid the costs and risks associated with aggressive behavior.

iv) **Payoff Matrix**: The outcomes of conflicts between individuals depend on the strategies chosen by both players. A payoff matrix represents the benefits or costs associated with each combination of strategies. The payoffs are typically assigned in terms of relative fitness or reproductive success such that V = Fitness value of fight and C = Fitness cost of injury.

   a) **Hawk vs. Hawk**: When both players choose the Hawk strategy, they engage in a fight. Hawk wins 50% of fights and is injured in 50% of fights resulting in a moderate payoff ($(V\text{-}C)/2$) for each player. This reflects that both hawks bear the costs of fighting and injured but neither emerges as the clear winner.

b) **Hawk vs. Dove**: When a Hawk encounters a Dove, the Hawk claims the resource and receives a higher payoff (*V*) since it asserts dominance. However, the Dove, being peaceful and non-confrontational, gets injured (*C*).

c) **Dove vs. Hawk**: When a Dove encounters a Hawk, the Dove chooses to avoid the fight. The Hawk, being aggressive, receives the full benefit (*V*) of claiming the resource and the dove may get injured (*C*).

d) **Dove vs. Dove**: When both players choose the Dove strategy, they peacefully share the resource, resulting in a moderate payoff (*V/2*) for each player. This signifies that both doves benefit equally from the resource without engaging in conflict.

Table 3.14: Hawk Dove Game Model

	R_2		
	Payoff	**Hawk**	**Dove**
R_1	**Hawk**	$\frac{V-C}{2}, \frac{V-C}{2}$	V,C
	Dove	C,V	$\frac{V}{2}, \frac{V}{2}$

Table 3.14 represents the normal form representation of the hawk dove game model where R_1 and R_2 are two players. Each player has two strategies to play the game that is either hawk or dove strategy. The rows of the matrix represent the strategy chosen by the "first player", while the columns represent the strategy chosen by the "second player". The intersection of a first and second represents the resulting payoffs for each player.

3.3.2 Proposed Methodology of Hawk Dove Model

The HDST model aims to classify sentiments of reviews according to the emotional content of their context. We fetch two parameters from a customer's textual feedback: context and emotion. Fig. 3.10 depicts the HDST model's pipeline.

- Step 1: Evaluate the Context Score of a review
- Step 2: Evaluate the Emotion score of a review
- Step 3: Play Hawk Dove Game between reviews

Step 1: Evaluate Context Scores of Reviews (C_P, C_N): Context scores are numerical values allocated to quantify the magnitude of positive or negative sentiment conveyed from the context of a review. These scores are calculated using *SWN*. The resulting context scores reside within the closed interval [0, 1]. *Algorithm 3.1* is used to evaluate the normalized Positive Context Score (C_P) and Negative Context Score (C_N).

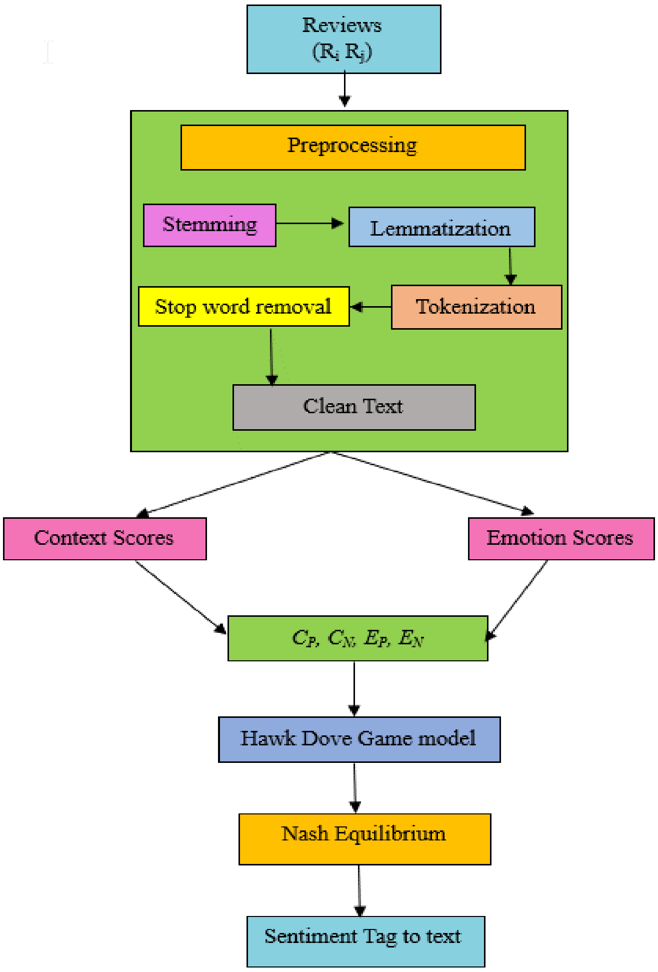

Fig 3.10: The framework of the Hawk Dove Game Model

Step 2: Evaluate the Emotion scores of reviews (E_P, E_N): In this study, we categorize the emotions into distinct categories, viz. happy (H), angry (A), sad (S), surprised (Sp), and fear (F). However, the emotion of fear is not taken into account. To quantify the emotions present in the text, the library in Python[2] is utilized. This library enables the computation of emotion scores, which provide numerical representations of the intensity or prevalence of the identified emotions in the text. After obtaining the emotion scores, the emotions E are further categorized into two groups: positive emotions E_P and negative emotions E_N score. The categorization of emotions into these two categories is performed using *Algorithm 3.3.* The resulting values of E_P and E_N scores, representing the degree of positive and negative emotions, respectively, fall within the range of 0 to 1. This range serves as a standardized scale for interpreting and comparing the emotional content of the analyzed text.

Step 3: Play Hawk Dove Game between reviews: After steps 1 and step 2, we evaluate C_P, C_N, E_P, and E_N scores for each review. To apply the Hawk-Dove model for sentiment tagging, we are conducting a two-person game in this study. We consider two reviews as two players, R_i and R_j. The Hawk strategy represents a positive sentiment, while the Dove strategy represents a negative sentiment in our game. The payoff matrix for the interaction between the positive and negative strategies is taken from the Hawk-Dove model, as

[2] pip install text2emotion

illustrated in *Table 3.15.* Based on the Hawk-Dove methodology, we create two matrices: the Context Matrix and the Emotion Matrix. These matrices capture the context and emotion scores of the reviewers. In *Table 3,* C_P^1, C_P^2, C_N^1, and C_N^2 represent the numeric scores of the positive and negative strategies for the context parameter of the review R_i and R_j, respectively. Similarly, E_P^1, E_P^2, E_N^1, and E_N^2 represent the numeric scores of the positive and negative strategies for the emotion parameter of the reviews. Now, let's reframe the three matrix scores (context score, emotion score, and interrogated score) between the two players, R_i and R_j.

Table 3.15: Different values of context and emotion type and individual strategies performed by reviews.

Reviews	Parameters	Values
R_i	Positive Context	$C^1{}_P$
	Negative Context	$C^1{}_N$
	Positive Emotion	$E^1{}_P$
	Negative Emotion	$E^1{}_N$
R_j	Positive Context	$C^2{}_P$
	Negative Context	$C^2{}_N$
	Positive Emotion	$E^2{}_P$
	Negative Emotion	$E^2{}_N$

a) Context Matrix: *Fig. 3.11* presents the block diagram of the Proposed Model, showcasing the interaction between two players, R_i and R_j. Both players have positive and negative strategies, and they operate within two domains: context and emotion. *Table 3.13* represents the context matrix, which captures the context scores for R_i and R_j. For R_i, there are two strategies: Context positive $(R_i)_{CP}$ or Context negative $(R_i)_{CN}$ for R_i. Similarly, R_j can adopt the strategies context positive $(R_j)_{CP}$ and context negative $(R_j)_{CN}$ strategy. To evaluate the payoffs, the hawk-dove game model is employed, as discussed in the previous section. In the context matrix, the *"V"* values from *Table 3.13* are considered as C_P in *Table 3.13*, while the *"C"* values are considered as C_N. Each cell in the matrix contains two payoffs, with the first value indicating the payoff of the first player (R_i), and the second value representing the payoff of the second player (R_j) with context scores. The payoffs in the matrix can be categorized as follows:

- Payoffs (α, β) : Interaction between $(R_i)_{CP}$ and $(R_j)_{CP}$ strategy of R_i and R_j player.
- Payoffs (ω, η) : Interaction between $(R_i)_{CP}$ and $(R_j)_{CN}$ strategy of R_i and R_j player.
- Payoffs (ψ, ν) : Interaction between $(R_i)_{CN}$ and $(R_j)_{CP}$ strategy of R_i and R_j player.
- Payoffs (ϕ, Ω) : Interaction between $(R_i)_{CN}$ and $(R_j)_{CN}$ strategy of R_i and R_j player.

Table 3.16 illustrates the normal form representation of the hawk-dove game played between the two players, capturing the payoffs for different strategy combinations.

Table 3.16: Context score matrix of R_i and R_j

		R_j	
R_i	**Payoff**	$(R_j)_{CP}$	$(R_j)_{CN}$
	$(R_i)_{CP}$	$\frac{C^1{}_P - C^1{}_N}{2} = \alpha, \frac{C^2{}_P - C^2{}_N}{2} = \beta$	$C^1{}_P = \omega, C^2{}_N = \eta$
	$(R_i)_{CN}$	$C^1{}_N = \psi, C^2{}_P = \nu$	$\frac{C^1{}_P}{2} = \varphi, \frac{C^2{}_P}{2} = \Omega$

(b) Emotion Matrix: *Table 3.17* represents the Emotion matrix, which captures the emotion strategies for R_i and R_j. Both players have two strategies: R_i's positive emotion strategy ($(R_i)_{EP}$) and R_i's negative emotion strategy $(R_i)_{EN}$. Similarly, R_j can adopt the positive emotion strategy $(R_j)_{EP}$ or the negative emotion strategy $(R_j)_{EN}$. Each cell in the matrix contains two payoffs, where the first value represents the payoff of the first player (R_i), and the second value represents the payoff of the second player (R_j). Similar to the context matrix, the payoffs in the emotion matrix are evaluated using the hawk-dove game model, as discussed in the previous section. The "V" values from *Table 3.16* correspond to E_P in *Table 3.17,* while the *"C"* values correspond to E_N. Each cell in the matrix contains two payoffs, with the first value indicating the payoff of the first player (R_i), and the second value representing the payoff of the second player (R_j) with emotion scores. *Table 3.17* illustrates the normal form representation of the hawk-dove game played between the two players, capturing the payoffs for each strategy combination. The payoffs in the matrix can be categorized as follows:

- Payoffs (κ, ℓ) : Interaction between $(R_i)_{EP}$ and $(R_j)_{EP}$ strategy of R_i and R_j player.
- Payoffs (θ, ϖ) : Interaction between $(R_i)_{EP}$ and $(R_j)_{EN}$ strategy of R_i and R_j player.
- Payoffs (σ, γ) : Interaction between $(R_i)_{EN}$ and $(R_j)_{EP}$ strategy of R_i and R_j player.
- Payoffs $(\in, \Theta)$: Interaction between $(R_i)_{EN}$ and $(R_j)_{EN}$ strategy of R_i and R_j player.

These payoffs reflect the outcomes of the game when players adopt specific emotional strategies. In summary, *Table 3.17* represents the emotion matrix, capturing the emotion strategies of R_i and R_j. The payoffs in each cell are evaluated based on the hawk-dove game model, considering the interaction between the players' emotional strategies. The resulting payoffs reflect the outcomes of the game.

Table 3.17: Emotion score matrix of R_i and R_j

		R_j	
R_i	**Payoff**	$(R_j)_{EP}$	$(R_j)_{EN}$
	$(R_i)_{EP}$	$\frac{E^1{}_P - E^1{}_N}{2} = \kappa, \frac{E^2{}_P - E^2{}_N}{2} = \ell$	$E^1{}_P = \theta, E^2{}_N = \varpi$
	$(R_i)_{EN}$	$E^1{}_N = \sigma, E^2{}_P = \gamma$	$\frac{E^1{}_P}{2} = \in, \frac{E^2{}_P}{2} = \Theta$

(c) Integrated Matrix: *Fig. 3.11* demonstrates the implementation of the hawk-dove model in the sentiment tagging task. *Fig. 2*. depicts two players, R_i and R_j., each having a context-type matrix and an emotion-type matrix. Both players can adopt either a positive or negative strategy. *Fig. 3.11* shows the context matrix, the emotion matrix, and the integrated matrix created by multiplying the strategies from the context and emotion type matrices. By combining the context and emotion information, we construct the integrated matrix. To determine the dominant strategy, we apply game theory principles. The dominant strategy represents the best response of the player in the game. The Nash equilibrium is an important concept in game theory, which states that players can achieve the desired outcome by not deviating from their initial strategy. In this sentiment tagging task, the Nash equilibrium corresponds to the point where the dominant strategies of both players align and are the best response of both players.

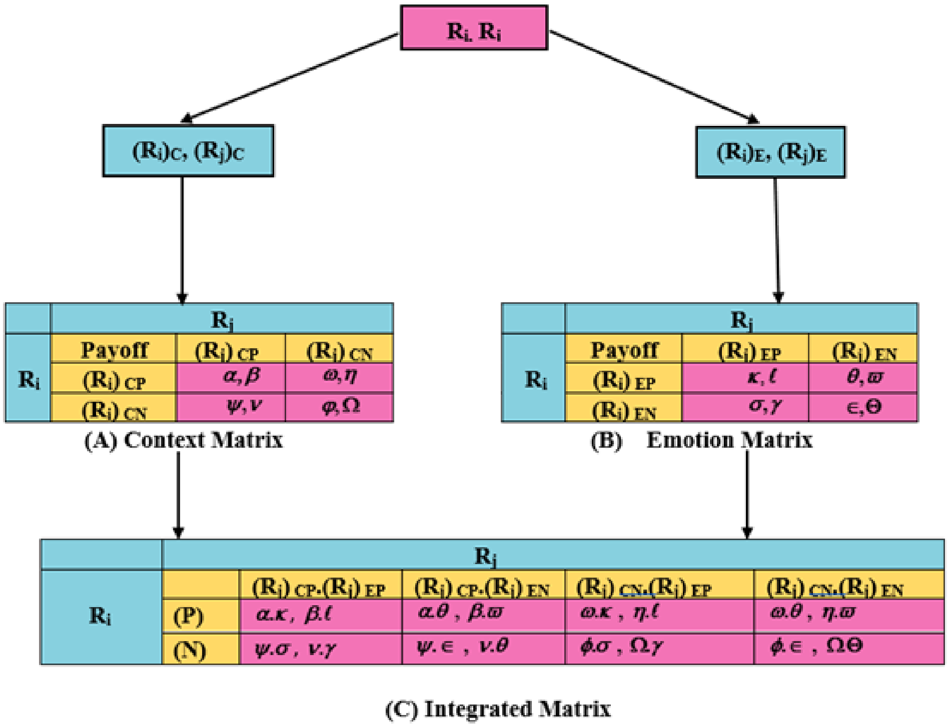

Fig 3.11: Demonstration of Hawk Dove model in sentiment tagging task

3.3.3 Numerical Illustration of Hawk Dove Model

We will examine two reviews, labeled R_i and R_j, which are presented in the following box:

***R**$_i$* **(4 stars):** *"Good flavor! these came securely packed... they were fresh and delicious! i love these Twizzlers!"*
***R**$_j$* **(2 Stars):** *"I was disappointed in the flavor and texture of this mix. I usually like most of the Low Carb things I have tried, but was disappointed in this specific one."*

First, we calculate the context and emotion score of the written text using *Algorithm 3.1* and *Algorithm 3.3,* and *Table 3.18* shows the numeric scores of positive and negative values of context and emotion score of reviews R_i and R_j.

Table 3.18: Numeric Score of the context and emotion score.

Reviews	Parameters	Values
R_i	Positive Context	0.813
	Negative Context	0.025
	Positive Emotion	0.63
	Negative Emotion	0.5
R_j	Positive Context	0.428
	Negative Context	0.531
	Positive Emotion	0.0128
	Negative Emotion	0.387

Subsequently, we utilize the numeric score of context (*Table 3.19*) and emotion (*Table 3.20*) scores. To present to assess the payoffs of both players, R_i and R_j. In the matrix, the first value in each cell denotes the payoff of the first player (R_i), while the second value represents the payoff of the second player (R_j). *Table 3.19* and *Table 3.20* comprise two distinct matrices: the context matrix and the emotion matrix.

Table 3.19: Context matrix of the review

	Context Matrix		
	R_j		
R_i		$(R_j)_{CP}$	$(R_j)_{CN}$
	$(R_i)_{CP}$	0.394, 0.0515	0.813, 0.531
	$(R_i)_{CN}$	0.025, 0.428	0.0128, 0.265

Table 3.20: Emotion matrix of the review

	Emotion Matrix		
	R_j		
R_i		$(R_j)_{EP}$	$(R_j)_{EN}$
	$(R_i)_{EP}$	0.065,0.129	0.63,0.387
	$(R_i)_{EN}$	0.5,0.128	0.25,0.194

Table 3.21 contains the integrated matrix of emotion and context matrix in which the payoff of each strategy of emotion matrix is multiplied by each strategy of context matrix. After applying the dominant strategy of game theory, we get the Nash equilibrium as shown in *Table 3.22* which is highlighted in bold fonts in *Table 3.21*.

Table 3.21: Integrated matrix of the context and emotion matrix.

		R_j			
R_i		$(R_j)_{CP}.(R_j)_{EP}$	$(R_j)_{CP}.(R_j)_{EN}$	$(R_j)_{CN}.(R_j)_{EP}$	$(R_j)_{CN}.(R_j)_{EN}$
	Positive	0.0251, 0.00666	0.24822, 0.0199	0.0528, 0.0687	**0.5122,0.2054**
	Negative	0.0125, 0.0547	0.00625, 0.05137	0.0064, 0.03398	0.0032, 0.05137

Table 3.22: Nash equilibrium of the integrated matrix.

		R_j
R_i		$(R_j)_{CN}.(R_j)_{EN}$
	Positive	0.5122,0.2054

Table 3.22 is the Nash equilibrium of the game. So, it is clear from *Table 3.22* that R_i has the positive sentiment tag whereas R_j gets the negative tag from both the emotion and context parameters of the review. So, in this way, we give sentiment tags to both the reviews R_1 and R_2.

3.4 Experimentation & Evaluation

In this section, we first collect the reviews of four domains in the English language. We implemented three-game models proposed in the above sections. Now the comparison is made with existing approaches. Later we discuss its various aspects and at the end, we conclude the chapter.

3.4.1 Datasets Collection

The proposed algorithm was executed on four distinct datasets comprising English review comments and corresponding ratings. The initial dataset comprised the TripAdvisor reviews dataset. Next, we extracted mobile device evaluations and scores from various online platforms from online sources. The third dataset corresponds to a specific statistical information of the utilized datasets is presented in *Table 3.23*.

Table 3.23: Data Statistics of Different Datasets

Data Set	Language	Positive	Negative
TripAdvisor reviews[3]	English	1256	1387
Mobile reviews[4]	English	1337	1266
Electronic reviews[5]	English	1287	1249
IMDb movies reviews[6]	English	1245	1233

3.4.2 Evaluation of the TripAdvisor Dataset

In our comparison study, we evaluated the performance of our proposed model against five different unsupervised models. We evaluated the evaluation measures using *Equation (1.4)* to *Equation (1.13)* in chapter1. One of the unsupervised approaches, called POST-VIA360 [175], utilized sentiment analysis and contextual information to suggest eateries and places of interest. Our proposed model outperformed POST-VIA360 significantly in terms of evaluation metrics. The DOC-ABSADeepL SA-MpMcDM methodology model, which included expert evaluations based on natural language reviews

3 https://www.kaggle.com/code/residentmario/exploring-tripadvisor-uk-restaurant-reviews/notebook

4 https://www.kaggle.com/code/prakharprasad/mobile-reviews-topic-modeling

5 https://www.kaggle.com/datasets/datafiniti/amazon-and-best-buy-electronics

6 http://www.imdb.com

and numerical ratings, was another cutting-edge decision aid that Zuheros et al. (2021) introduced. Our proposed model demonstrated superior precision, recall, and f-measure when compared to DOC-ABSADeepL. Additionally, our model exhibited better performance in terms of precision, recall, and f-measure compared to Buon Appetito [176], another unsupervised model we evaluated. This comparison is illustrated in *Fig 3.12* where our proposed model consistently outperformed all the unsupervised models, achieving an accuracy of 0.90. In chapter 3 we introduce a Bayesian game model-based mathematical framework proposed for sentiment classification of reviews, achieving an accuracy of approximately 0.87 and an F1 score of approximately 0.88 on the Tripadvisor dataset. However, our proposed model surpassed this performance with an accuracy of 0.93 and an F1 score of 0.94, indicating its superiority. Based on these results, it is evident that our proposed model offers better accuracy and performance compared to the existing unsupervised approaches evaluated in our study.

Meanwhile, the HDST model surpassed this performance with an accuracy of 0.93 and an F1 score of 0.94, indicating its superiority. Based on these results, it is evident that the HDST model offers better accuracy and performance compared to the existing unsupervised approaches evaluated in our study shown in *Fig. 3.12.*

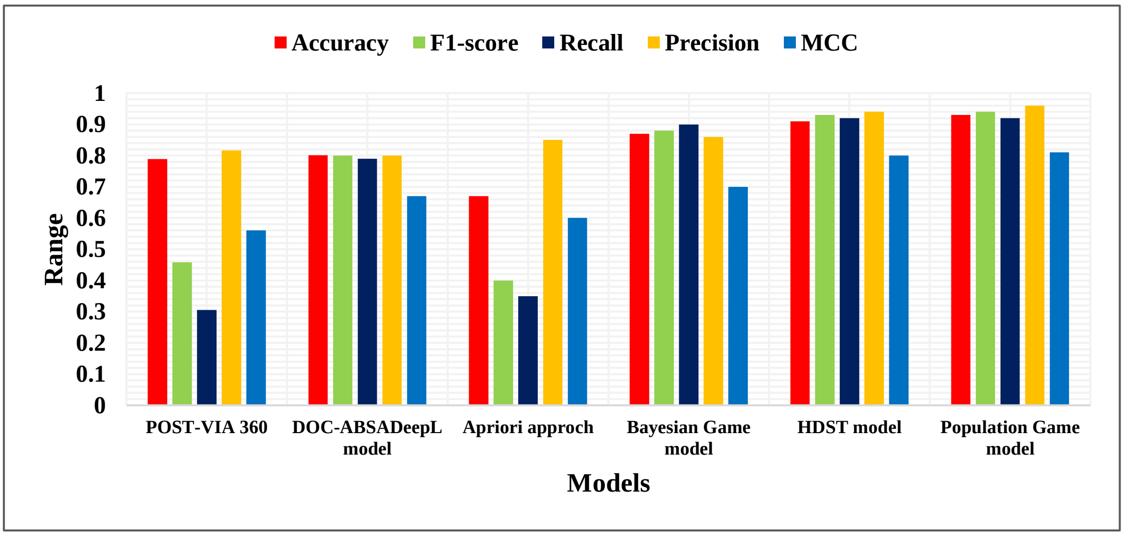

Fig. 3.12: Comparative analysis of the HDST model and unsupervised method

3.4.3 Evaluation of the Mobile Review Dataset

We conducted a performance evaluation to compare the HDST model with unsupervised techniques using *Equation (1.4) to Equation (1.13)* in chapter1.

Yiran and Srivastava (2019) employed methodologies based on topic modeling. They categorized topic-specific terms using their corresponding probability values to perform sentiment analysis. This unique summarization approach focuses on specific product characteristics rather than the sentiment expressed in the comments. In chapter 3 we proposed a Bayesian game model for sentiment analysis of reviews, achieving an accuracy of 0.94. Fig. 4 presents a comparative analysis of performance on the mobile dataset. The LDA model achieved an accuracy of 0.542, and F1-score of 0.55, a recall of 0.567, a precision of 0.59, and an MCC score of 0.48. On the other hand, the Bayesian game model achieved an accuracy of 0.94, an F1 score of 0.93, a recall of 0.93, a precision of 0.93, and a MCC score of 0.7. In terms of evaluation metrics, the HDST model achieved an accuracy of 0.96, an F1 score of 0.95, a recall of 0.95, a precision of 0.976, and an MCC score of 0.8. The population game model exhibited superior performance compared to the unsupervised techniques evaluated on the mobile dataset. HDST model exhibited superior performance compared to the unsupervised techniques evaluated on the mobile dataset. The Bayesian game model showed the highest accuracy, while the HDST model outperformed both the LDA model and the Bayesian game model across various evaluation metrics shown in *Fig. 3.13*.

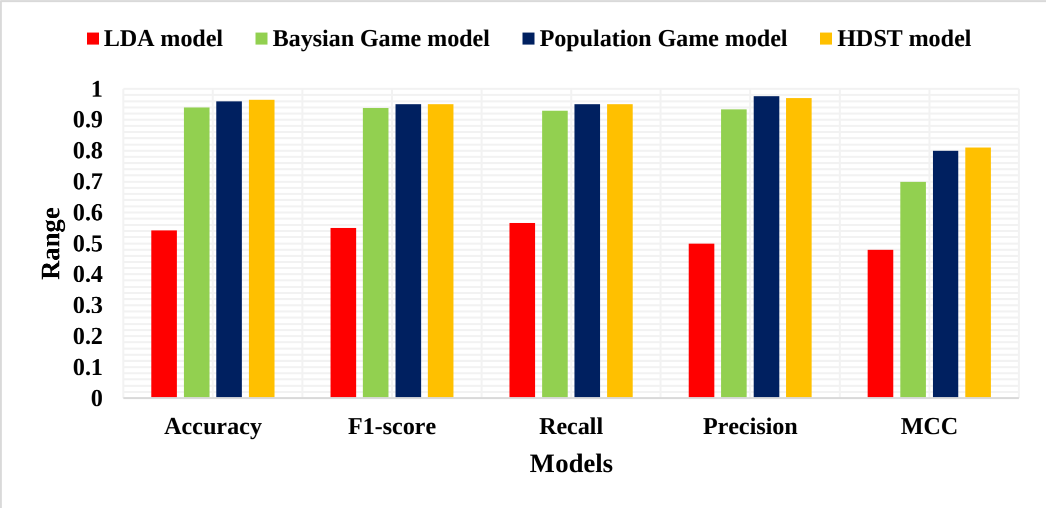

Fig. 3.13: Assessing the Game model techniques performance against other unsupervised Methods

3.4.4 Evaluation of Amazon Electronic Reviews

To evaluate the performance of the proposed model, use *Equation (1.4)* to *Equation (1.13)* in chapter1. We compared it to various methods as shown in *Fig. 3.14.* Daniel and Meena (2021) introduced the LSVM classifier approach, which archived accuracy and MCC scores of around 0.77 and 0.633. Next, we compared the proposed model with W2VLDA by García-Pablos et al. (2017) to see how well the proposed model can classify customer reviews with the appropriate sentiment label.

The archived accuracy over the electronic dataset is 0.834, and the MCC score is 0.658. Similarly, the next comparison is made with a mathematical optimization model in chapter 3, a Bayesian game model-based sentiment analysis of reviews whose accuracy and MCC score were recorded at 0.94 and 0.781, respectively. The author Dai et al. (2021) present a novel approach called selective domain adaptation (SDA), which focuses on selectively transferring private knowledge from the source domain that is closest to the target domain at the feature level. The accuracy of electronic reviews is 85.6%, and the MCC score is 0.699. The study introduces the BERT-MultiLayer Convolutional Neural Network (B-MLCNN) as a computationally viable integrated deep learning paradigm. The B-MLCNN considers the overall textual review as a single document and classifies the available sentiments. The accuracy obtained is around 0.95 for IMDB movie reviews. The obtained accuracy is about 0.95 by Atandoh et al. (2023) and the MCC score is 0.781. Hence, the proposed model shows outstanding accuracy, which is around 0.96, and an MCC score of 0.781, which is higher than the existing approaches as illustrated in *Fig. 3.14.*

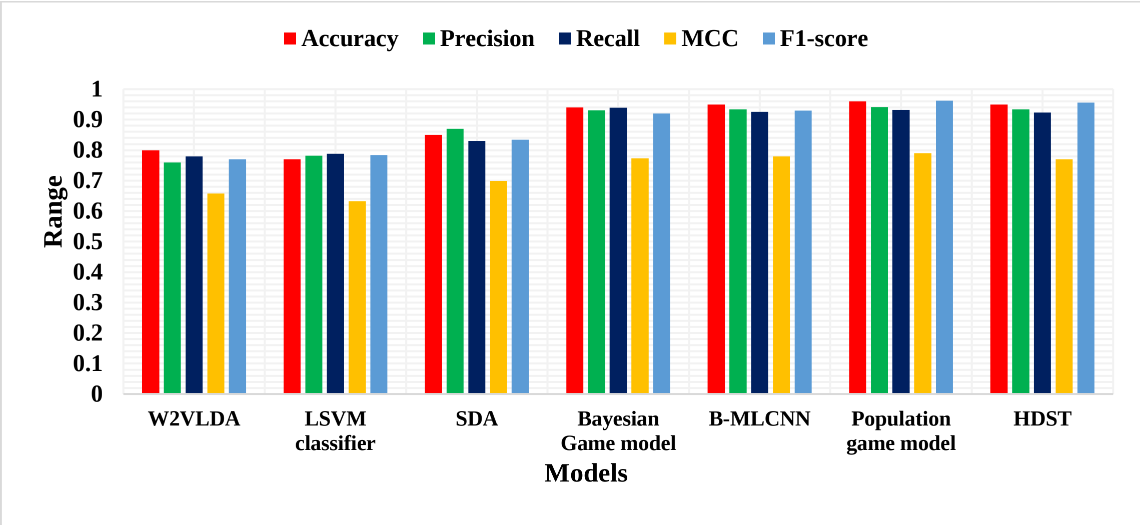

Fig. 3.14: Efficiency of the Game model techniques in comparison to Unsupervised Methods

3.4.5 Comparison on IMDb Movie Reviews

Vashishtha and Susan (2021) have proposed an unsupervised sentiment classification system that comprehensively formulates phrases, and computes their senti-scores (sentiment scores) and polarity using the SentiWordNet lexicon and fuzzy linguistic hedges. The unigram-bigram-trigram combination with the same scale has achieved the highest accuracy of 69.3% and the highest f-score of 0.691. A novel approach called SASC (Sentiment Analysis Based on Sentiment Clustering) is introduced. The accuracy of SASC is 75.42% [75]. Another study introduces a computationally efficient integrated deep learning paradigm called BERT-MultiLayered Convolutional Neural Network (B-MLCNN). B-MLCNN treats the entire textual review as a single document and performs sentiment classification. The achieved accuracy for IMDB movie reviews is approximately 0.95 by Atandoh et al. (2023). The accuracy archived by the Bayesian game model is 0.92 similarly F1score is 0.94, recall is 0.91, and precision is 0.93[181]. The HDST model outperforms all the existing approaches in all the parameters as shown in *Fig. 3.15*.

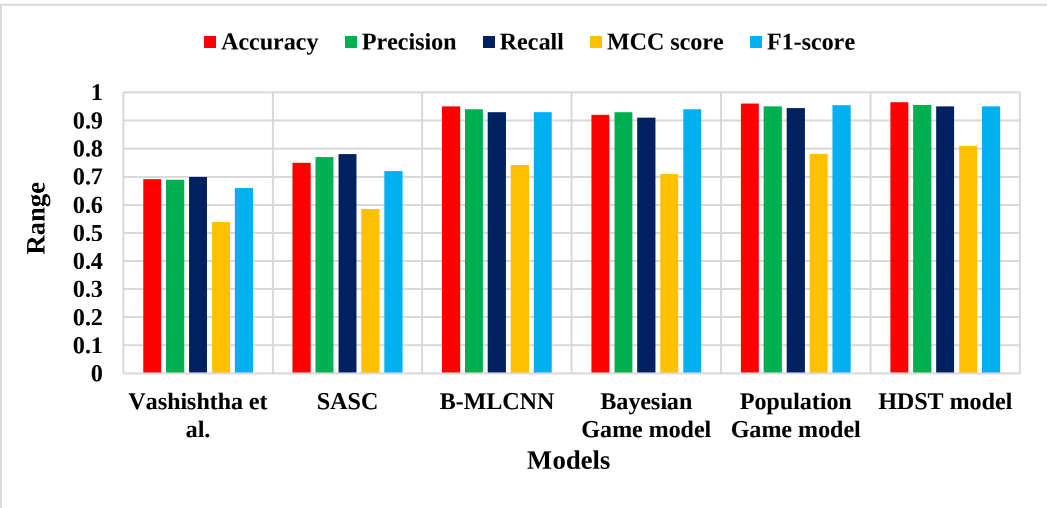

Fig. 3.15: Comparison of the HDST Model with other Unsupervised Algorithms

3.5 Discussion

Here we discuss various aspects of the proposed game models such as macro and micro evaluation. We address its various challenges and its computational complexity. We validated it statistically.

(i) Macro and Micro Evaluation: In our evaluation, we used macro and micro averages to assess the overall performance across different datasets (reviews). We calculated the macro and micro-averaged accuracy, F1-score, and recall values for the 4 datasets, ranging from *Equation (1.13)* to *(1.18) and* the results were remarkably consistent. Across the four datasets, we obtained micro and macro precision values of three evaluation metrics.

Fig. 3.16 shows the measures of various evaluation metrics over three datasets, further validating their effectiveness and robustness in sentiment analysis tasks. Out of the three game models' the population game model has the highest macro micro evaluation measures followed by the Hawk Dove model and then by the Bayesian game model.

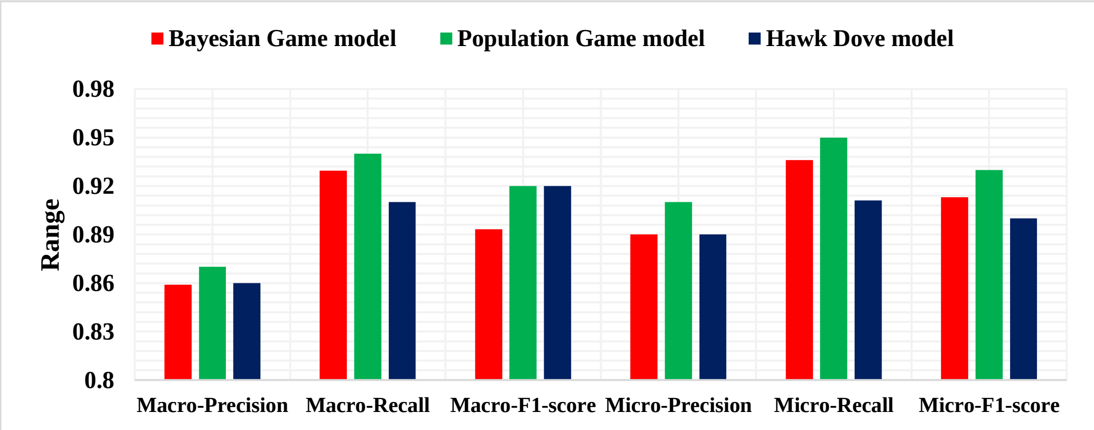

Fig. 3.16: Macro and micro evaluation of the three-game-based model

(ii) Statistical validation of the Game Model algorithms: A Z-test was conducted on two proportion tests, one utilizing information from the dataset of hotel reviews and the other from the dataset of movie reviews. Two distinct samples were extracted from datasets containing different domains as illustrated in *Table 3.24*. A Z-test was conducted to analyze the proportions of two populations (p_1 and p_2) while examining the alternative null hypotheses H_o and H_a. The results of the implementation provided have been condensed and presented in a tabular format as *Table 3.24.*

Table 3.24: Two Proportion Z-Test statistics across datasets

	Population Game Model		Bayesian Dove Model		Hawk Dove Game Model	
Parameters	**Sample 1**	**Sample 2**	**Sample 1**	**Sample 2**	**Sample 1**	**Sample 2**
Sample Size (n_1)	600	566	497	252	1000	500
Sample Proportion (p_1)	0.938	0.962	0.928	0.921	0.91	0.896
Favorable cases (X_1)	563	545	461	232	910	448
P	0.9494		0.925		0.9053	
Z	-1.869		0.344		0.873	
Hypothesis status	Ho is not rejected		Ho is not rejected		Ho is not rejected	

H_o: $p_1 = p_2$ i.e. the accuracy of sample 1 is equal to the accuracy of sample 2
H_a: $p_1 \neq p_2$ i.e. accuracy of sample 1 is not equal to the accuracy of sample 2

$$P = \frac{X_1 + X_2}{N_1 + N_2} \tag{3.21}$$

Two population proportions were analyzed using a two-tailed test and a z-test illustrated by *Equation (3.21)*. The z-statistic was computed utilizing *Equation (3.22).*

$$z = \frac{p_1 - p_2}{\sqrt{P(1-P)(1/n_1 + 1/n_2)}} \tag{3.22}$$

Fig. (3.17), (3.18), and *(3.19)* show a graphical representation of the accepted and critical region of the above hypothesis. We failed to reject the null hypothesis H_o. As a result, there is insufficient evidence to assert that the population proportion p_1 differs from p_2 at the α =0.05 significance level. This implies that the accuracy of our model is consistent throughout different sample sizes of the same datasets. Thus, the results of the Proposed Bayesian Model for accurate sentiment tagging can be trusted.

Fig. 3.17: Graphical representation of the critical region of the Hypothesis on the Bayesian Game model

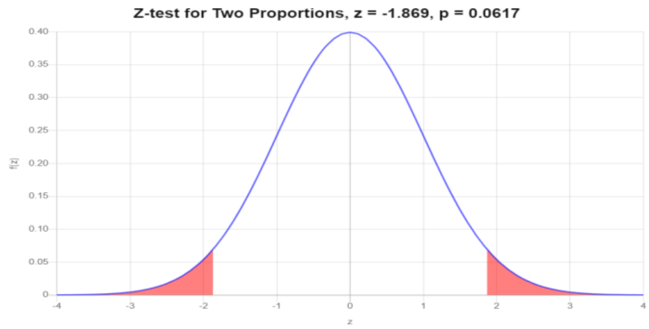

Fig. 3.18: Graphical representation of the critical region of the Hypothesis on Population game model

Fig. 3.19: Graphical representation of the critical region of the Hypothesis on the Hawk Dove model

(iii) Challenges of the game model: We used SWN and HSWN as a lexicon to fetch a word's sentiment in the proposed model. Sentiment analysis of Hindi and English literature relies on the SWN and HSWN vocabulary to provide sentiment scores for opinion terms. *Table 3.25* presents a few incorrectly tagged examples by the proposed model. The use of emoticons and slang phrases by consumers in the age of web applications has become increasingly commonplace. However, the proposed model cannot classify these kinds of structures (emoticons and slang terms).

Table 3.25: Example where the proposed model fails

S. No.	Text	Actual	Sentiment tag from game model
1	The smart phone is very fast and it does not lag anywhere between the high-end games.	Positive	Negative
2	After using this oil my hair became like Dwayne Johnson 😝 😟	Negative	Positive
3	I have never seen such a behetareen movie in my entire life.	Positive	Negative
4	#i_love_my_country	Positive	NULL
5	“I do not dislike noodles.”	Positive	Negative
6	“The movie is not good for first time watch. “	Positive	Negative

(iv) Computational Complexity: While computing the complexity of an algorithm, we measure its time and space complexity. The time complexity (T) measures the number of computational steps needed to accomplish a given task on a specific input dataset. Similarly, the space complexity (S) represents the memory usage of the algorithm during execution as a function of the input size (n). We evaluate the time complexity ($T(m,n)$) and space complexity ($S(m,n)$) of the algorithm under different scenarios, where m denotes the number of alternatives and n represents the number of criteria. The values of $T(m,n)$ and $S(m,n)$ indicate the performance of the algorithm in *Table 3.26*.

Table 3.26: Computational Complexity of Game models

S. No.	Techniques	T(m,n)	S(m,n)
1	Bayesian Game Model	$O(n^2)$	$O(n^2)$
2	Population Game model	$O(m+n)$	$O(m+n)$
3	HDST model	$O(m+n)$	$O(m+n)$

3.6 Summary

A mathematical framework rooted in Game Theory has been devised to do sentiment analysis on reviews. This chapter presents three approaches for sentiment analysis based on game theory: the Bayesian game model, the Population game model, and the HDST model. The Bayesian game model demonstrates exceptional performance as an unsupervised methodology for sentiment tagging. The accuracy of the Bayesian model was shown to be 92% across three distinct review datasets, including food, mobile, and electronic reviews. The use of the population game model, which is rooted in evolutionary game theory, offers a very promising framework for doing sentiment analysis. The HDST model, which is derived from the Hawk-Dove game, presents an innovative unsupervised methodology for doing sentiment analysis at the phrase level. The HDST model demonstrated a high level of accuracy, reaching 96%, when applied to various sources of movie reviews such as TripAdvisor, mobile platforms, electronic sources, and IMDb. The notable advantage of these models lies in their versatility for sentiment categorization in languages with limited resources. All of these models take into account the binary classification aspect of sentiment analysis. Researchers may make educated decisions when using game theory in sentiment analysis assignments by comprehending the advantages and disadvantages of various strategies. Moreover, it is worth noting that these models possess the capability to be expanded for multi-class sentiment classification, hence presenting a promising direction for future scholarly investigations.

Chapter 4

Sentiment Analysis of Written Text with Negation

In this chapter, we present an innovative approach to sentiment analysis, one adept at addressing the intricate challenge of negation in textual content. Our model is named "NEGVOT" (Negation Handling of Text using the VIKOR Optimization Technique). The chapter's structure unfolds as follows.

In *Section 4.1*, we introduce the VIKOR technique, laying the groundwork for our exploration. Next, in *Section 4.2*, we present the NEGVOT model and illustrate its functionality with a concrete example. *Section 4.3* is dedicated to showcasing the outcomes of our conducted experiments, providing insight into the model's performance. Moving forward to *Section 4.4*, we embark on a comprehensive discussion, dissecting various facets of the NEGVOT model, and offering a thorough examination of its components and capabilities. Finally, in *Section 4.5*, we draw this chapter to a close, summarizing the key findings and insights derived from our exploration of NEGVOT and its role in addressing negation within sentiment analysis.

4.1 VIKOR Method

The VIKOR technique is a method of multi-criteria decision analysis. The word VIKOR first emerged in 1990 [4] and is derived from the Serbian phrase “Multi-criteria Optimization and Compromise Solution,” which is pronounced, “VIKOR”[182]. It was first devised by Serafim Opricovic to address choice issues with competing and non-commensurable (different units) criteria.VIKOR assesses alternatives and selects the solution known as a compromise that comes closest to being ideal.

We first collect the alternatives and criteria. Then we evaluate different parameters used in the VIKOR technique as illustrated in *Fig.4.1.*

4.2 Proposed Methodology of the NEGVOT Model

The first step is to clean the data involving the following processes such as preprocessing, tokenization, lemmatization, and stopword removal. Next, we take the cleaned dataset and calculate the context and emotion scores of sentences in the dataset. Next, we apply the VIKOR technique to rank the alternatives. The output received by the VIKOR is directly applied to the text containing negation. For the sentences that do not contain negation, we complement the output of the VIKOR and rank the alternatives accordingly. We identify if a sentence contains negation or not using the Negex Python library[7]. The pipeline of the proposed model is given in *Fig. 4.1*. Then we calculate various notations as illustrated in *Fig. 4.1* x_i^* and x_i^-, S_j, R_j, S^*, S^-, R^*, R^-, and Q_i.

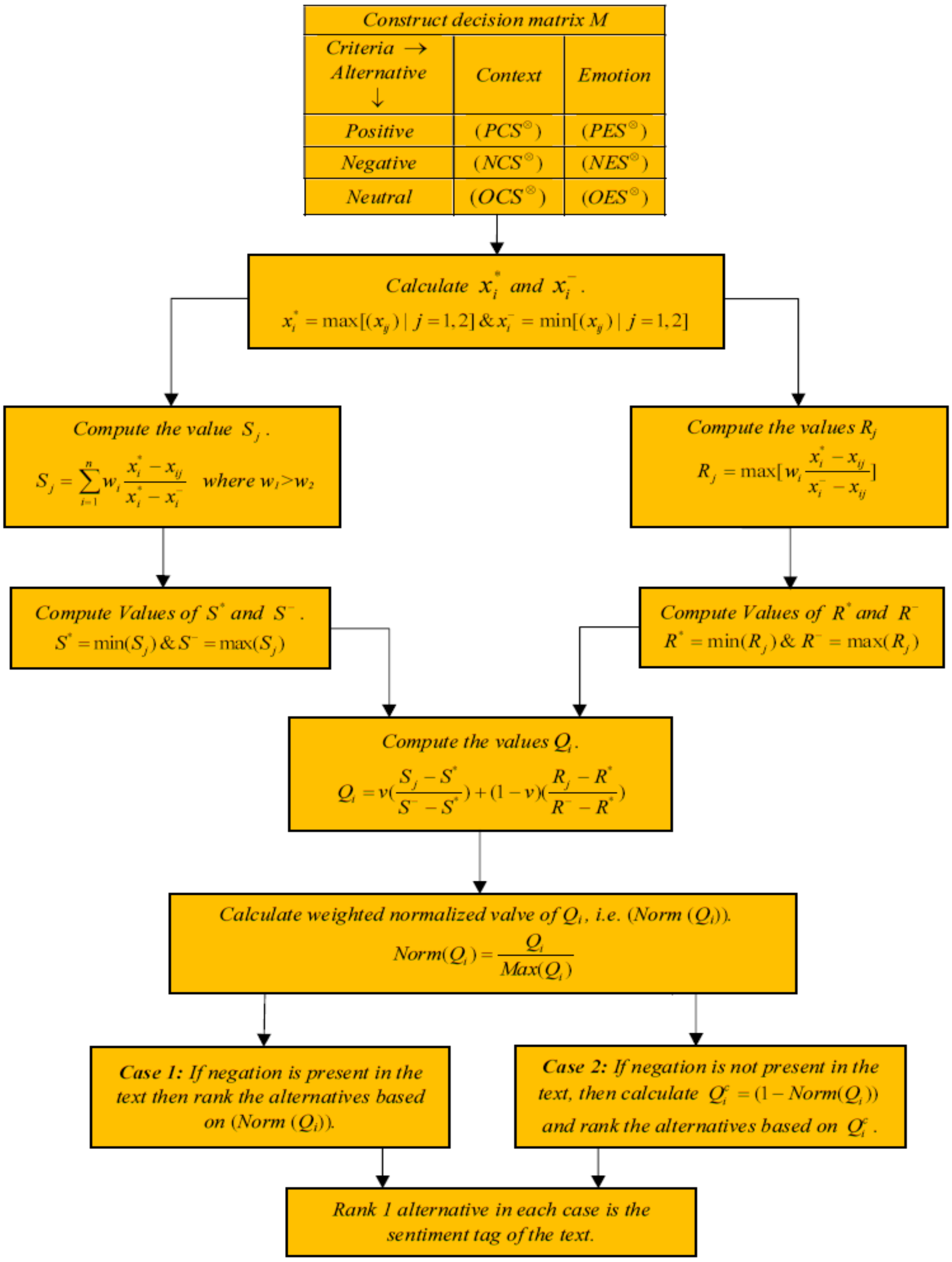

Fig. 4.1: Pipeline of the NEGVOT model for negation handling challenges in the text.

Step 1: Evaluation of Context Scores: This step involves utilizing SWN to calculate the context score of textual comments. The context score values are between 0 and 1. We evaluate the Normalised Positive Context Score $(PCS^{\otimes})$, Negative Context Score $(NCS^{\otimes})$, and Neutral Context Score $(OCS^{\otimes})$ following by using *Algorithm 4.1*.

[7] pip install negspacy

Algorithm 4.1: Evaluation of context scores.

Input: *A sequence of words (W) in a review R.*

Output: *Normalised Positive Context Score* $(PCS^{\otimes})$, *Negative Context Score* $(NCS^{\otimes})$, *and Neutral Context Score* $(OCS^{\otimes})$.

1: *Initialise PCS = 0, NCS = 0 and OCS=0 for each review.*

2: *Retrieve synsets for the word. Synsets=SentiWordNet.lookup(word).*

3: *Retrieve positive score negative score and neutral score for the synset.*

PS = synset. positiveScore
NS = synset. NegativeScore
OS= synset. NeutralScore

4: *Update positive context score (PCS) and negative context score (NCS).*

$$PCS \leftarrow PCS + PS \text{ , } NCS \leftarrow NCS + NS \text{ and } OCS \leftarrow OCS + OS$$

5: *Normalized positive context score* $(PCS^{\otimes})/(CP)$ *and negative context score* $(NCS^{\otimes})/(CN)$ *and neutral context Score* $(OCS^{\otimes})/(CO)$.

$$(PCS^{\otimes})/(CP) = \frac{PCS}{|W|} \;||\; (NCS^{\otimes})/(CN) = \frac{NCS}{|W|} \;||\; (OCS^{\otimes})/(CO) = \frac{OCS}{|W|}$$

Step 2: Evaluation of Emotion Scores: We evaluate the emotion scores using the text2emotion[8] python library. The emotion library can be categorized as Happy, Angry, Surprised, Sad, or Fear. We ignore the fear emotion in the current study. Expressions of happiness (*H*), anger (*A*), sadness (*S*), and surprise (*Sp*) are the four components. Using these four feelings, we estimated the Normalised Positive Emotion Score $(PES^{\otimes})$ Negative Emotion Score $(NES^{\otimes})$, and Neutral Emotion Score $(OES^{\otimes})$ following *Algorithm 4.2*.

Algorithm 4.2: Evaluate the Emotion score of reviews.

Input: *A sequence of words (W) in a review R.*

Output: *Normalised Positive Emotion Score* $(PES^{\otimes})$, *Negative Emotion Score* $(NES^{\otimes})$, *and Neutral Emotion Score* $(OES^{\otimes})$.

1: *Load a set of emotion words and associated scores.*

$$EmotionWords \leftarrow LoadEmotionWords()$$

2: *Initialise emotion score variables H =0, A=0 ,S=0 and* S_p *=0.*

3: *Tokenize each review into words.*

4: *For all W in R, if* $W \in EmotionWords$

$$EmotionScores \leftarrow GetEmotionScores(W)$$

5: *Update emotion score variables.*

$$\begin{aligned}
&For\ each\ emotionScore\ variables \\
&H \leftarrow H + emotion_score(H) \\
&A \leftarrow A + emotion_score(A) \\
&S \leftarrow S + emotion_score(S) \\
&S_P \leftarrow S_P + emotion_score(S_P)
\end{aligned}$$

6: *Total emotion score E of W.*

$$E \leftarrow H + A + S + S_P$$

7: *Positive emotion score (EP) and negative emotion score (EN).*

[8] https://pypi.org/project/text2emotion/

$$EP \leftarrow H + S_P \; || \; EN \leftarrow A + S + S_P \; || \; EO \leftarrow \frac{H + A + S + S_P}{2}$$

8: Normalised Positive Emotion Score $(PES^{\otimes})$, *Negative Emotion Score* $(NES^{\otimes})$, *Neutral Emotion Score.*

$$(PES^{\otimes}) = \frac{EP}{E} \; || \; (NES^{\otimes}) = \frac{EN}{E} \; || \; (OES^{\otimes}) = \frac{EO}{E} \; ||$$

Step 3: Assign sentiment tag: In this step, we first construct a decision matrix, as illustrated in *Table 4.1*. It consists of alternatives and criteria. Positive, negative, and neutral are the alternatives, and context and emotion are the criteria.

Table 4.1: The decision matrix consists of alternatives and criteria.

Criteria → **Alternative ↓**	**Context**	**Emotion**
Positive	$(PCS^{\otimes})$	$(PES^{\otimes})$
Negative	$(NCS^{\otimes})$	$(NES^{\otimes})$
Neutral	$(OCS^{\otimes})$	$(OES^{\otimes})$

The algorithm for NEGVOT is described in detail in *Algorithm 4.3*. The VIKOR algorithm is applied to each review from *step 1* to *step 8* in the algorithm. This gives us a weighted normalized value (Q_i). Further, in *step 9*, we calculate the complement-weighted normalized value (Q_i^c). If the text contains negation, we rank the alternatives based on the value of (Q_i). We use the Negspace[9] Python library to detect the negation in the text. The top-ranked alternative serves as the review's sentiment tag. In case, a review does not contain negation, the alternatives are ranked according to the value of (Q_i^c). The alternative with the highest score is the final tag for that text.

Algorithm 4.3: Sentiment tagging using NEGVOT Algorithm

Input: *Positive, negative, score of context score of text ((*$PCS^{\otimes}$*), (*$NCS^{\otimes}$*), (*$OCS^{\otimes}$*)), emotion ((*$PES^{\otimes}$*), (*$NES^{\otimes}$*), (*$OES^{\otimes}$*)).*

Output: *The sentiment tag to each text will be the highest rank alternative.*

1: *Construct decision matrix* $M = [M_{ij}]_{2\times 2}$ *using the input scores.*

2: Calculate x_i^* *and* x_i^-.

$$x_i^* = \max[(x_{ij}) \mid j = 1,2] \; \& \; x_i^- = \min[(x_{ij}) \mid j = 1,2]$$

3: *Compute the value* S_j.

$$S_j = \sum_{i=1}^{n} w_i \frac{x_i^* - x_{ij}}{x_i^* - x_i^-} \quad \textit{where} \;\; w1 > w2 \;\; (\text{i.e} \;\; w1 = 0.6 \;, w2 = 0.4)$$

4: *Compute the values* R_j

$$R_j = \max[w_i \frac{x_i^* - x_{ij}}{x_i^- - x_{ij}}]$$

5: *Compute Values of* S^* *and* S^-.

[9] https://pypi.org/project/negspacy/

$$S^* = \min(S_j) \,\&\, S^- = \max(S_j)$$

***6:** Compute Values of R^* and R^-.*

$$R^* = \min(R_j) \,\&\, R^- = \max(R_j)$$

***7:** Compute the values Q_i.*

$$Q_i = v(\frac{S_j - S^*}{S^- - S^*}) + (1-v)(\frac{R_j - R^*}{R^- - R^*})$$

***8:** Calculated weighted normalized valve of Q_i, i.e. Norm (Q_i).*

$$Norm(Q_i) = \frac{Q_i}{Max(Q_i)}$$

***9:** Calculate Q_i^c if negation is not present in the text.*

$$Q_i^c = (1 - Norm(Q_i))$$

***10:** If the Text contains negation, rank the alternatives according to step 8.*

***11:** If the text content does not contain the negation, proceed to step 9.*

***12.** The alternative with the highest rank is the tag to each text with sentiments.*

4.2.1 Illustrative Example 1 of text containing no Negations

Let us consider another review as illustrated below.

> **Illustrative Example 1: "***I am very satisfied with my Twizzler purchase. I shared these with others and we have all enjoyed them. I will be ordering more."*

We fetch the context and emotion scores using *steps 1* and *step 3* of the proposed method. The corresponding values for the review are given in *Table 4.2*. *Table 4.3* displays the normalized decision matrix. The values of the various parameters of the VIKOR method are displayed in *Table 4.4.* Since the review does not contain negation, we rank the alternatives based on the (Q_i^c) value. Thus, we deduce that the sentiment tag for the given review is positive.

Table 4.2: Context and emotion score of the reviews

Alternative	Context	Emotion
Positive	0.5714	0.0055
Negative	0.1429	0
Neutral	0.001	0.02

Table 4.3: Normalized Decision Matrix

Alternative	Context	Emotion
Positive	0.970143	1
Negative	0.242536	0
Neutral	0.0087	0

Table 4.4: Evaluating (Q_i^c) value and rank the alternatives

Alternative	S_i	R_i	Q_i	*Norm* (Q_i)	Q_i^c	Rank
Positive	0.412	0.398	0.011	0.01088	0.98912	1
Negative	0.651	0.589	1.011	1	0	2
Neutral	0.043	0.0123	0.0087	0.0013	0.012	3

4.2.2 Illustrative Example 2 of text containing Negations

We consider another illustrative example 2 as shown below that contains negation.

Illustrative Example 2: *"I would never recommend having lunch in that hotel."*

The context and emotion scores are provided in *Table 4.5. Table 4.6* contains the normalized decision matrix. *Table 4.7* displays the values of various parameters of the VIKOR method. Then ranking of alternatives is based on the (Norm (Q_i)) value. The alternative with the highest ranking is the final tag for the review, as indicated in *Table 4.7.*

Table 4.5: Context and emotion score of the reviews

Alternative	Context	Emotion
Positive	0.10	0.30
Negative	0.00	0.20
Neutral	0.02	0.02

Table 4.6: Normalized Decision Matrix

Alternative	Context	Emotion
Positive	1.00	0.83
Negative	0.00	0.55
Neutral	0.02	0.44

Table 4.7: Evaluating (*Norm* (Q_i)) value and ranking of the alternatives

Alternative	S_i	R_i	*Norm*(Q_i)	Rank
Positive	0.40	0.40	0.50	2
Negative	0.58	0.60	1.00	1
Neutral	0.02	0.03	0.20	3

Fig. 4.2 shows the deduced tags of reviews R_1 and R_2 following the proposed NEGVOT model.

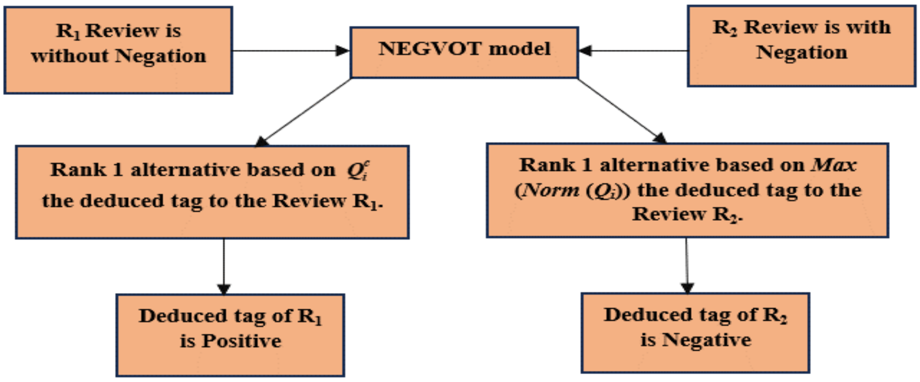

Fig. 4.2: Deduced Tag of reviews using the NEGVOT model**.**

4.3 Experimentation and Evaluation

In sub-section 4.3.1, we present the different collected datasets and then analyze the collected dataset and compare it with existing approaches as illustrated in *subsection 4.3.2.*

We implemented the NEGVOT model on three datasets. The results were then compared to conventional approaches. Several metrics were analyzed, and their efficacies were inspected. To demonstrate the model's language independence, we applied it to an English and Hindi language dataset and analyzed the encouraging results.

4.3.1 Data Collections

We used the three annotated datasets for implementation of the NEGVOT model and data statistics are given in *Table 4.8*. After implementing the NEGVOT model over these three datasets we compare it with state-of-art algorithms.

Table 4.8: Statistical information about diverse datasets

Data Set	Language	Positive	Negative	Neutral
Amazon Product reviews[10]	English	1576	1292	1345
SemEval2013 Twitter tweets[11].	English	1657	1132	1370
Stanford Sentiment Treebank movie domain dataset[12]	English	1512	1350	1189

4.3.2 Evaluation of the NEGVOT Model over three datasets

In the current study, we employed the NEGVOT model and compared it with existing models. Detailed analysis is explained in the below paragraphs. These three models are Sentineg, Gupta, et al., and MiMuSA models. We implemented the NEGVOT model on three datasets as illustrated in *Fig. 4.3, 4.4,* and *4.5.*

[10] *https://jmcauley.ucsd.edu/data/amazon/*

[11] *https://developer.twitter.com/en/docs/twitter-api/v1/tweets/filter-realtime/overview*

[12] https://nlp.stanford.edu/sentiment/code.html

In their study, Gupta et al. [1] employed a feature-based approach for sentiment analysis (TSA) on Twitter, incorporating an improved method to account for negation. The primary focus of their research was to examine the impact of negation, a crucial linguistic phenomenon capable of altering the polarity or intensity of opinionated words. To address this issue, the researchers devised an algorithm capable of handling tweets containing negation, recognizing that the presence of a negative word does not always indicate negation. The highest accuracy was achieved on Amazon product reviews, reaching approximately 0.65. This dataset also exhibited a high F1 score of 0.66, a recall of 0.67, a relatively lower Matthews Correlation Coefficient (MCC) score of 0.56, and a high precision of 0.64 on the Amazon reviews. On the SemEval 2013 Twitter dataset, the recorded accuracy is 0.56.

The SentiNeg[183] was proposed as a solution for handling negations at the sentence level. Its primary objective is to enhance processing efficiency by eliminating neutral sentences from the dataset. When evaluating SentiNeg, the SemEval2013 Twitter corpus demonstrated the highest accuracy, reaching 0.81, while the Amazon review dataset exhibited the lowest accuracy at 0.56. The SemEval2013 Twitter corpus also displayed the highest precision, approximately 0.8, whereas the Amazon review dataset had the lowest precision. Regarding the F1-score, the SemEval2013 Twitter corpus achieved the highest value of 0.78, while the Amazon Product reviews attained the lowest F1-score of 0.58. The MCC and Precision scores for the SemEval2013 Twitter corpus were 0.68 and 0.80, respectively. Conversely, the Stanford Treebank movie domain dataset yielded the lowest accuracy of about 0.67 among the datasets analyzed.

MiMuSA [28] introduces a novel approach to fine-grained multiclass sentiment analysis, aiming to bridge the gap between existing sentiment analysis methods. The key idea behind MiMuSA is to emulate human language comprehension processes through a modular structure with multiple levels. When evaluated, the MiMuSA model achieved an accuracy of approximately 0.769% across all three datasets. The SemEval2013 Twitter corpus demonstrated the highest F1-score of 0.78. Both the Amazon review dataset and the SemEval2013 Twitter corpus exhibited a recall of 0.76. The MCC score was 0.7 for all three datasets, indicating a consistently good performance. Precision was approximately 0.75 for all three datasets as well. For SemEval2013 Twitter tweets dataset the archived F1-score of 0.78. For Stanford Sentiment Treebank movie dataset has an accuracy of 0.769

Among the various models evaluated, the NEGVOT model demonstrated outstanding performance across different datasets. On the Amazon Product reviews, it achieved an accuracy of 0.83, an F1 score of 0.80, a recall of 0.81, an MCC score of 0.8, and a precision of 0.84. This indicates the NEGVOT model's ability to accurately classify sentiments in the context of Amazon reviews. Similarly, on the SemEval2013 Twitter corpus, the NEGVOT model achieved remarkable results with an accuracy of 0.85, an F1 score of 0.83, a recall of 0.84, an MCC score of 0.80, and a precision of 0.82. These metrics highlight the NEGVOT model's effectiveness in sentiment classification for Twitter tweets.

In the Stanford Sentiment Treebank movie domain dataset, the NEGVOT model continued to demonstrate promising performance, achieving an accuracy of 0.82, an F1 score of 0.80, a recall of 0.81, an MCC score of 0.83, and a precision of 0.85. The NEGVOT model consistently delivers the best results across all three datasets. Its high accuracy, F1 score, recall, MCC score, and precision signify its efficacy and reliability in sentiment classification tasks.

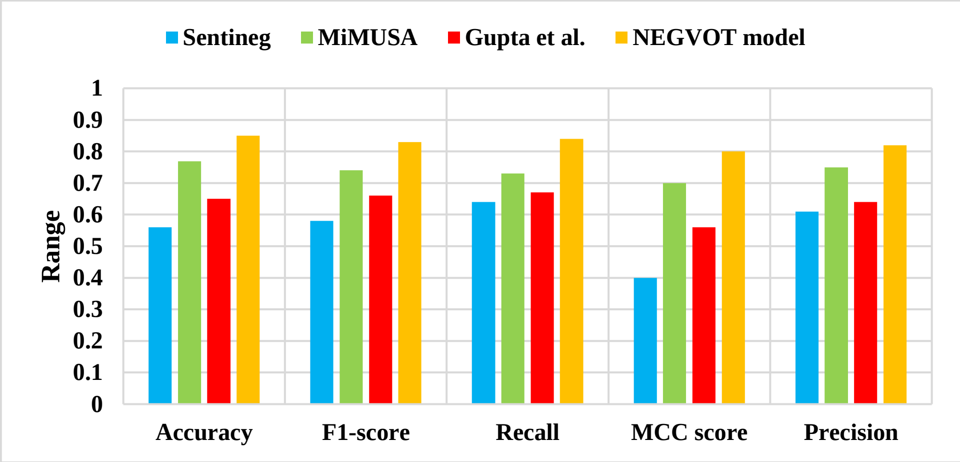

Fig. 4.3: Comparing the efficacy of the NEGVOT model with other algorithms for Amazon Product reviews

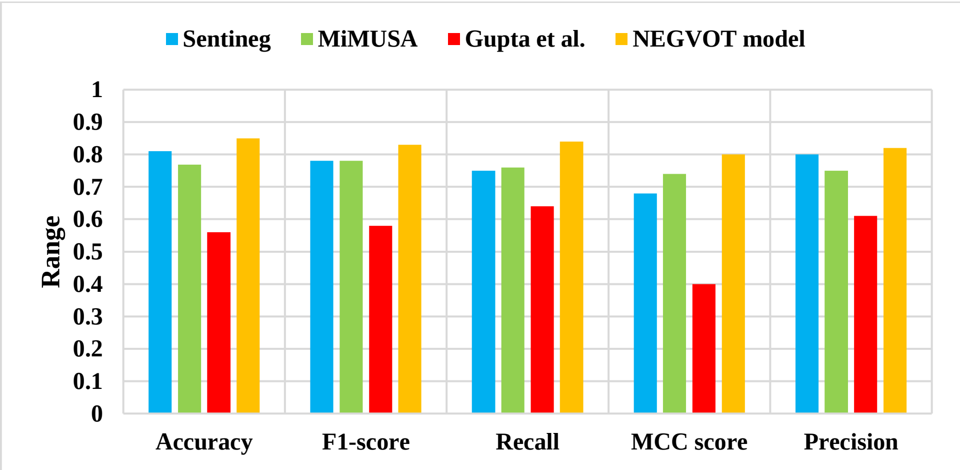

Fig. 4.4: Comparing the efficacy of the NEGVOT model with other algorithms for SemEval2013 Twitter corpus

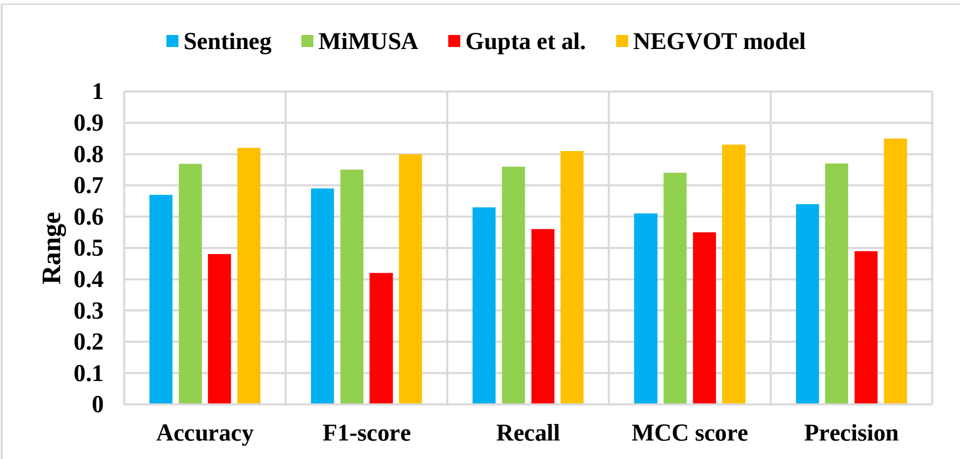

Fig. 4.5: Comparing the efficacy of the NEGVOT model with other algorithms for the Stanford Sentiment Treebank movie domain

4.4 Discussion

i) The proposed NEGVOT gives influencing results. However, it is not immune to certain limitations.

The primary limitation of this study is that MCDM methodologies for ranking alternatives are not always consistent. In the real world, there is little convergence in the solutions offered by different MCDMs. It is possible that a new and improved ranking of alternatives could be achieved by examining new criteria, even though this would make the problem more complex and experimental computing more difficult.

ii) The NEGVOT model uses of VIKOR MCDM techniques. VIKOR being an MCDM technique, consists of criteria and alternatives. Here NEGVOT model consists of two criteria: context and emotion. The weight for context criteria is $w_1 = 0.6$, and for emotion, $w_2 = 0.4$. The essential condition for the accurate working of the NEGVOT model is that $w_1 > w_2$. The proposed NEGVOT model fails when $w_1 = w_2 = 0.5$ and $w_1 > w_2$. The article proposes a methodology for classifying the sentiments of English-language texts, both with and without negations. The model was evaluated using three different data sets. To use words, the NEGVOT model makes use of the SWN. Emotions and constructive customer comments are used to glean the most helpful information. The sentiment scores of textual feedback are calculated using SWN, and the emotion scores are extracted using the Python Negex tools. The VIKOR MCDM approach was employed in the NEGVOT model. The NEGVOT model creates a sentiment label for each review by employing the MCDM approach. An observed 91% accuracy suggests that the method is reliable.

4.5 Summary

In this chapter, we address the challenge of negation handling in sentiment analysis by implementing the VIKOR optimization technique. By leveraging VIKOR, we aim to effectively manage the complexities introduced by negations and their impact on sentiment analysis results. The VIKOR MCDM approach was employed in the NEGVOT model. The NEGVOT model creates a sentiment label for each review by employing the MCDM approach. An observed 85% accuracy suggests that the method is reliable. The application of MCDM techniques in sentiment analysis tasks has demonstrated its efficiency and effectiveness. These techniques play a crucial role in sentiment categorization and provide valuable support in recommendation frameworks. By utilizing MCDM, sentiment analysis becomes more robust and accurate, allowing for a better understanding and classification of sentiments. Additionally, these techniques aid in the recommendation process, assisting users in making informed decisions based on their preferences and needs. Overall, the integration of MCDM techniques enhances the performance and reliability of sentiment analysis systems, making them valuable tools in sentiment categorization and recommendation tasks

Chapter 5

Integrated MCDM and Game Theory-based Sentiment Classification of Text

MCDM and Game theory are powerful mathematical optimization tools for solving complex problems. In this chapter, we integrate MCDM and game theory for the sentiment classification task. The integration of MCDM and game theory techniques allows for the consideration of multiple criteria or factors that influence sentiment, enabling a more comprehensive analysis of complex decision-making scenarios. Together these two paradigms offer a powerful tool for uncovering valuable insights from data and improving decision-making in fields such as marketing, finance, and social sciences[184].

The chapter is structured as follows. In *Section 5.1*, we introduce the Sentiment Orientation Tagger Model (SOTM) and Aspect Based Ranking Model (ABRM). Moving forward to *Section 5.2,* we present the TOPSIS-based Game theory sentiment tagger (TOGT-ST). *Section 5.3* introduces the Language-independent EDAS-based sentiment tagging using Game theory (LESTG). In *Section 5.4,* we discuss the CODAS and Game Theory based sentiment tagger (CODGT-ST). *Section 5.5* introduces the Grey Relational Analysis & Game theory-based Sentiment Tagger (GRAGT-ST). In *Section 5.6,* we provide an in-depth discussion of various aspects of the proposed methodologies. We conclude the chapter in *Section 5.7.*

5.1 Sentiment Orientation Tagger Model and Aspect-Based Ranking Model (SOTM - ABRM)

In this section, we tackle two primary tasks. Firstly, we assign sentiment tags to food reviews, and secondly, we rank various aspects of these reviews, including service, delivery, and food quality. To accomplish these objectives. The section is structured as follows: In *subsection 5.1.1*, we provide a brief introduction to the SAW method and the PSI method, which are crucial for understanding the underlying model. Subsequently, in *subsection 5.1.2,* we delve into the SOTM (Sentiment Tagging and Aspect Ranking Model). In *subsection 5.1.3,* we expound on the Aspect-Based Ranking Model (ABRM). To illustrate the concepts, we present examples in *subsection 5.1.4*. Lastly, in *subsection 5.2.4*, we discuss the experiments and results pertaining to the SOTM model.

5.1.1 Preliminaries

In the following sections, we will delve into the SAW and PSI MCDM techniques. Specifically, we will discuss these methods in detail in *subsections 5.1.1.1* and *5.1.1.2,* as elaborated in the subsequent sections below.

5.1.1.1 Simple Additive Weighting (SAW)

Simple Additive Weighting (SAW) [57] is a widely used multi-criteria decision-making (MCDM) technique that helps decision-makers choose the best alternative among a set of options. It is relatively easy to implement and understand, making it a popular choice in various fields, including business, engineering, and public policy. SAW is also referred to as the weight-adding technique.

5.1.1.2 Preferential Similarity Index (PSI)

The PSI MCDM technique is a powerful method used for evaluating and selecting alternatives in decision-making processes that involve multiple criteria. The PSI technique was introduced by Maniya and Bhatt [185]. Developed to address complex and often subjective decision scenarios, PSI offers a unique approach by focusing on the relative preferences and similarities between alternatives rather than relying solely on explicit criteria weights. This technique helps decision-makers make informed choices by considering both the importance of criteria and the preference relationships among alternatives.

5.1.2 Methodology of SOTM

The proposed method of SOTM is divided into three steps. In the first step, we generate a decision matrix with three alternatives and three criteria. The three alternatives are positive, negative, and neutral which correspond to the three criteria viz context, rating, and emotion. We apply the SAW technique in the second step to evaluate the ranking scores of each alternative. Further, in the third step, games are played among reviews to deduce the correct sentiment tag. The SOTM model's pipeline is shown in *Fig. 5.1.*

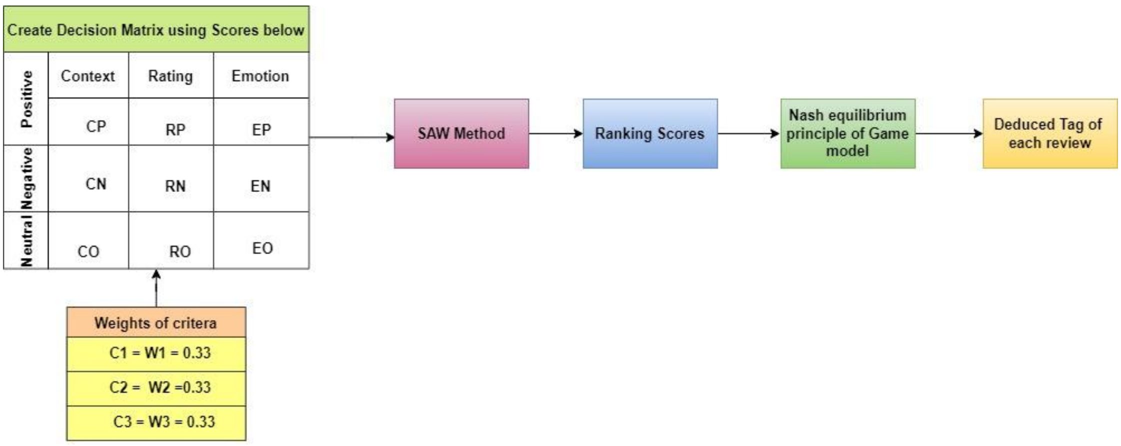

Fig. 5.1: Pipeline of the SOTM model for sentiment tagging

Step 1: Construct a decision matrix: A decision matrix of order 3×3 is generated where the columns correspond to the criteria and rows represent the alternatives. To generate the decision matrix following steps are taken.

i) Evaluation of Rating Scores: The rating given with the review ranges from 1 star to 5 stars. We use these star ratings to evaluate rating scores for positive, negative, and neutral sentiments of a review. The degree of positive rating (*DRP*) is the given value of the star rating in the review (*p*) (refer to *Equation (5.1)*). In *Equation (5.2),* we calculate the degree of negative rating (*DRN*). In this equation, we use *5* because *5* is the maximum rating of a review. We calculate the degree of neutral rating (*DRO*) using *Equation (5.3)*. Further, we normalize *DRP, DRN,* and *DRO* to nullify the dominance of one over the other. After normalization, all the scores lie between *0* and *1*. The calculations of normalized rating scores (*RP, RN, and RO*) are given in *Equations (5.4) to* (*5.6*).

$$DRP = p \tag{5.1}$$

$$DRN = (5 - DRP) \tag{5.2}$$

$$DRO = (5 - |DRP - DRN|) \tag{5.3}$$

$$RP = \frac{DRP}{DRP + DRN + DRO} \tag{5.4}$$

$$RN = \frac{5 - DRP}{DRP + DRN + DRO} \tag{5.5}$$

$$RO = \frac{5 - |DRP - DRN|}{DRP + DRN + DRO} \tag{5.6}$$

ii) Evaluation of Emotion Scores: Emotions are classified as Happy (*H*), Angry (*A*), Sad (*S*), Surprise (S_p), or fear. In the current study, we neglect the fear emotion. *Equation (5.7)* shows the set of four emotions (*E*). We evaluate emotion scores using the text2emotion[13] Python library. Then, we categorize emotions *E* into three sub-categories: positive emotion (*EP*), negative emotion (*EN*), and neutral emotion (*EO*) using *Equations (5.7)* to *(5.10).* These values lie between 0 and 1.

$$E = \{H, A, S, S_p\} \tag{5.7}$$

$$EP = H + S_P \tag{5.8}$$

$$EN = A + S + S_P \tag{5.9}$$

$$EO = \frac{H + S + S_P + A}{2} \tag{5.10}$$

iii) Evaluation of Context Scores: We generate context scores for a review to provide numerical values to the textual reviewer feedback. The three context scores generated for each review are positive (*CP*), negative (*CN*), and neutral (*CO*). To determine the context scores, we use *SWN* [186]. The context scores range between *0* and *1*. We calculate the normalized context scores by following *Algorithm 4.1* in Chapter 4.

Once all the scores are evaluated, we construct a decision matrix. *Table 5.1* shows a decision matrix. It consists of three alternatives viz. positive, negative, and neutral, and three criteria viz. context, rating, and emotion.

Table 5.1: Decision matrix for the SAW method

Criteria → **Alternative ↓**	**Context**	**Rating**	**Emotion**
Positive	*CP*	*RP*	*EP*
Negative	*CN*	*RN*	*EN*
Neutral	*CO*	*RO*	*EO*

[13] https://pypi.org/project/text2emotion/

Step 2: SAW Technique: In this step, we apply the SAW MCDM technique to rank each alternative (positive, negative, and neutral) for the given three criteria. Since each criterion has equal relevance and prominence, we chose weight (*W*) = *0.33.* We follow *Algorithm 5.1* to generate the ranking scores of each alternative using the *SAW* method.

Algorithm 5.1: SAW technique to retrieve ranking scores

Input: *positive, negative, and neutral score of rating (RP, RN, RO), emotion (EP, EN, EO), and context (CP, CN, CO)*

Output: *The combined score is the ranking Score (λ_i) of each review R_i.*

1: *Construct decision matrix* $M = [M_{ij}]_{3\times3}$ *using the input scores.*

2: *Calculate normalized value (θ_{ij}).*

$$\theta_{ij} = \begin{cases} \dfrac{m_{ij}}{m_j^{\max}} = \wp \in BC \\ \dfrac{m_j^{\min}}{m_{ij}} = \xi = 0 \in NBC \end{cases} \quad \forall i, j \in \{1,2,3\}$$

3: *Assign weight,* $w_j = 0.33$.

4: *Calculate ranking scores for each review (λ_i).*

$$\lambda_i = \sum_{j=1}^{n} w_j . (\theta_{ij})$$

Table 5.2: Ranking scores of three sentiments

Orientation	Ranking Scores
Positive	λ_1
Negative	λ_2
Neutral	λ_3

Step 3: Sentiment orientation tagging using the Game model: A non-cooperative game is played between reviews (R_1 and R_2). Ranking scores given in *Table 5.2* are taken as the payoff for the players. Ranking scores of R_1 are denoted by $\lambda_1, \lambda_2, \lambda_3$, and ranking scores of R_2 are denoted by $\omega_1, \omega_2, \omega_3$. The payoffs of R_1 and R_2 are shown in *Table 5.3*. To achieve the Nash Equilibrium, we apply dominant strategies (DR_i) Following *Algorithm 5.2* The strategies corresponding to the payoffs of the Nash Equilibrium are the deduced tag of each review.

Table 5.3: Normal form representation of the game played between two reviews.

Players → ↓	**R2**			
	Strategies↓ →	**Positive**	**Negative**	**Neutral**
R1	**Positive**	(λ_1, ω_1)	(λ_1, ω_2)	(λ_1, ω_3)
	Negative	(λ_2, ω_1)	(λ_2, ω_2)	(λ_2, ω_3)
	Neutral	(λ_3, ω_1)	(λ_3, ω_2)	(λ_3, ω_3)

Algorithm 5.2: Deduce sentiment tag for review

Input: *Ranking scores* $\{\lambda_1, \lambda_2, \lambda_3\}$ *for review* R_i *and* $\{\omega_1, \omega_2, \omega_3\}$ *of review* R_j.

Output: *Sentiment Tag for* R_i *and* R_j, *i.e.,* $R_i, R_j \in \{P, N, O\}$.

1: *Generate a normal form matrix for players* R_i *and* R_j *using the Ranking scores.*

2: *Compute dominant strategies* DR_i *for* R_i *and* R_j *respectively*

3: *Compute Nash equilibrium (NE), where NE =* $DR_i \bigcap DR_j$.

4: *The strategies corresponding to NE are the sentiment tags for reviews* R_i *and* R_j.

5.1.3 Methodology of ABRM

The ABRM model is proposed to rank the different aspects of food reviews. The ABRM is designed to rank aspects so that customers can conveniently get help making the right decision. *Fig. 5.2* shows the pipeline of the ABRM model. We used the PSI technique to rank the alternatives based on the criteria. There are two steps involved in this model. First, we evaluate the aspect scores of different aspects of food reviews and construct a decision matrix. In the second step, we apply the PSI technique to rank these aspects.

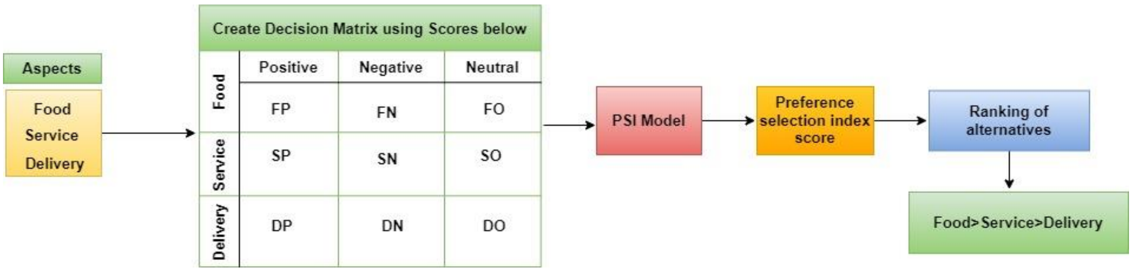

Fig. 5.2: Pipeline of the ABRM model for aspects ranking

Step 1: Evaluation of Aspect-based scores: We consider three aspects to improve restaurants' performance: food quality, service quality, and delivery quality. To implement PSI, we need numeric scores for these aspects. So, the first step in ABRM is the evaluation of these scores.

i) Evaluation of Food Quality Score: We fetch the food quality of the restaurant using written feedback. We use the SWN to evaluate whether the sentiment behind the food quality is positive (*FP*), negative (*FN*), or neutral (*FO*). We follow *Algorithm 5.1* to compute these scores.

ii) Evaluation of Service Quality Score: The service quality of restaurants is evaluated using emotions in the written feedback. We use the Python-based library[14] to calculate the emotions. We compute the three scores for service quality viz. positive (*SP*), negative (*SN*), and neutral (*SO*) using *Equations (5.11)* to *(5.13)*.

$$SP = H + S_P \tag{5.11}$$

$$SN = S + A + S_P \tag{5.12}$$

$$SO = \frac{S + A + S_P + H}{2} \tag{5.13}$$

[14] https://pypi.org/project/text2emotion/

(iii) Evaluation of Delivery Quality Score: To evaluate the delivery quality score, we use the delivery rating given by customers to the delivery services. The sentiment about the delivery service can be positive (*DP*), negative (*DN*), or neutral (*DO*). The values are evaluated using *Equations (5.14)* to *(5.16)*. In the given equations, *p* is the rating given for the delivery service by the reviewer. The range of *DP, DN,* and *DO* is between *0* and *1*.

$$DP = p \tag{5.14}$$

$$DN = 5 - DP \tag{5.15}$$

$$DO = 5 - |DP - DN| \tag{5.16}$$

Once we receive all the desired scores, we construct a decision matrix. In the matrix, alternatives are aspects, and criteria are the sentiment tags. The decision matrix contains the three alternatives viz. Food, Service, and Delivery and three criteria viz. Positive, Negative, and Neutral. as given in *Table 5.4*.

Table 5.4: The decision matrix consists of alternatives and criteria

Criteria → Alternative ↓	Positive	Negative	Neutral
Food	FP	FN	FO
Service	SP	SN	SO
Delivery	DP	DN	DO

Step 2: Implement PSI Technique: We apply the PSI technique to rank the aspects. These rankings help us prioritize while ordering food from an online service. This step is implemented in *Algorithm 5.3*. Depending upon the ranking, the alternative with the highest rank gets the excellent tag, and the least-ranked alternative gets the worst tag.

Algorithm 5.3: PSI for Aspect based ranking

Input: *positive, negative, and neutral scores of food (FP, FN, FO), Service (SP, SN, SO), and Delivery (DP, DN, DO)*

Output: *Tagging and ranking of aspects of food, service, and delivery with excellent, average, and worst tags.*

1: *Construct a decision matrix* $M = [m_{ij}]_{3\times 3}$.

2: *Calculate the normalized decision matrix (m^*_{ij}).*

$$m^*_{ij} = \begin{cases} m_{ij}^* = \dfrac{m_{ij}}{m_{ij\,\max}} = \chi \in BC \\ m_{ij}^* = \dfrac{m_{ij\,\min}}{m_{ij}} = \tau = 0 \in NBC \end{cases} \quad \forall i, j \in \{1,2,3\}$$

3: *Calculate the mean of the normalized matrix (N)*

$$N = \frac{1}{n}\sum_{i=1,j=1}^{3} m^*_{ij} \qquad \text{// Where n is the no. of alternative.}$$

4: *Calculate the value of the preference (Π_j).* $\Pi_j = \sum_{i=1}^{m} (m^*_{ij} - N)^2$

5: *Calculate the deviation of values (Ω_j),* $\Omega_j = 1 - \Pi_j$

6: *Calculate criteria weights (Ψ_j).*

$$\Psi_j = \frac{\Omega_j}{\sum_{j=1}^{n}\Omega_j}$$

7: *Calculate the preference selection index* (I_i), $I_i = \sum_{j=1}^{p} m_{ij}^* . \Psi_j \quad \forall i, j \in \{1,2,3\}$

8: *Ranking of different aspects,* $I_1 \langle I_2 \langle I_3$

9: *Tagging of aspects*

$$\begin{aligned} &I_1 \rightarrow Excellent \\ &I_2 \rightarrow Average \\ &I_3 \rightarrow Worst \end{aligned}$$

Table 5.5: Preference Selection Index of three aspects

Aspects	Preference Selection Indexes (I_i)
Food	I_1
Service	I_2
Delivery	I_3

After applying *Algorithm 5.4,* we receive ranks for the different aspects and thus accordingly provide the tags. *Table 5.5* illustrates the aspects and their corresponding ranks. *Equation (5.17)* shows the ranking and the corresponding tag.

$$I_1 > I_2 > I_3 \qquad and \qquad \begin{aligned} &I_1 \rightarrow Excellent \\ &I_2 \rightarrow Average \\ &I_3 \rightarrow Worst \end{aligned} \tag{5.17}$$

5.1.4 Illustrative Example

Let us consider the following two reviews.

R_1 (1 star): *"Very bad service provides by swiggy no any customer care help and very rude answer given by riders very poor service."*

R_2 (4 stars): *"Absolutely fantastic platform for online food ordering & delivery within estimate time. have a great deal with every time to give better & best satisfaction."*

5.1.4.1 SOTM Algorithm Implementation

The SOTM algorithm gives the sentiment tag to the reviews given by the customers. We first construct a decision matrix as shown in *Table 5.6* by following *Algorithm 5.1*. Next, we apply the SAW methodology given in *Algorithm 5.2* to get the ranking scores received in *Table 5.7* for R_1 and R_2. We apply the non-cooperative game model using *Algorithm 5.3*. *Table 5.8* shows the normal form representation of the game model. Then, using the principle of Nash equilibrium, we deduce the sentiment orientation of both reviews highlighted in bold in *Table 5.9*.

Table 5.6: The decision matrix of R_1.

R_1 (1 star)			
Alternatives	**Context**	**Rating**	**Emotion**
Positive	0.0127	0.1250	0.0000
Negative	0.0706	0.5000	0.1100
Neutral	0.0579	0.3750	0.0825

Table 5.7: The decision matrix of R_2.

R₂ (4 stars)			
Alternatives	**Context**	**Rating**	**Emotion**
Positive	0.1266	0.5000	0.6600
Negative	0.0588	0.1250	0.3300
Neutral	0.0678	0.3750	0.1650

Table 5.8: Ranking scores of R_1 and R_2.

	R_1	R_2
Alternatives	**Ranking score**	**Ranking score**
Positive	0.0127	0.8010
Negative	0.0706	0.1667
Neutral	0.0579	0.4166

Table 5.9: Non-cooperative game played between R_1 and R_2.

		R_2		
		Positive	**Negative**	**Neutral**
R_1	**Positive**	(0.0127,0.8010)	(0.0127, 0.1667)	(0.0127, 0.4166)
	Negative	**(0.0706, 0.8010)**	(0.0706, 0.1667)	(0.0706, 0.4166)
	Neutral	(0.0579, 0.8010)	(0.0579, 0.1667)	(0.0579, 0.4166)

5.1.4.2 ABRM Algorithm Implementation

The objective of constructing ABRM is to rank the different aspects of restaurants viz. Food, Service, and Delivery. From *Table 5.6* and *Table 5.7*, we first evaluate the numeric scores of R_1 and R_2 using *Table 5.6* and *Table 5.7.* Following *Algorithm 5.4,* we generate PSI scores illustrated in *Table 5.10*, then we rank them, and using *Algorithm 5.4*.

Table 5.10: Preference Selection index values of different aspects of the delivery app.

	R_1 (1 stars)		R_2 (4 stars)	
Alternatives	**PSI**	**Rank**	**PSI**	**Rank**
Service	0.6480	3	0.1622	2
Delivery	0.8520	1	1.0000	1
Food	0.7397	2	0.1356	3

$$Delivery > Food > Service \text{ and } \begin{array}{l} Delivery \rightarrow Excellent \\ Food \rightarrow Average \\ Service \rightarrow Worst \end{array} \text{ for } R_1 \tag{5.18}$$

$$Delivery > Service > Food \text{ and } \begin{array}{l} Delivery \rightarrow Excellent \\ Service \rightarrow Average \\ Food \rightarrow Worst \end{array} \text{ for } R_2 \tag{5.19}$$

Equation (5.18) shows the ranking of different aspects according to R_1. We deduce that delivery is excellent, food quality is average, and service is worst. Similarly, *Equation (5.19)*. shows that according to reviewer R_2, delivery is excellent, service is average, and food is worst.

5.2 TOPSIS-based Game Theory Sentiment Tagger (TOGT-ST)

This section introduces a novel mathematical optimization framework designed to conduct sentiment and emotion analysis of reviews. Our model accomplishes two primary tasks: firstly, it identifies the positive and negative sentiment polarities within each review, and secondly, it determines whether the customer's satisfaction level is satisfactory or unsatisfactory based on the review content.

This section is further categorized as follows: In *subsection 5.2.1*, we briefly introduce the TOPSIS method. The proposed methodology of TOGT-ST is described in *subsection 5.2.2*. In *subsection 5.2.3*, we demonstrate the illustrative example of the proposed approach. The experimentation and results are explained in *subsection 5.2.4*.

5.2.1 TOPSIS Method

TOPSIS, one of the MCDM techniques is a widely used method in decision analysis. It serves as a systematic approach for evaluating and ranking a set of alternatives based on multiple criteria. The TOPSIS technique is particularly valuable in situations where decision-makers need to choose the most suitable alternative among several options while considering various conflicting criteria.

5.2.2 Proposed Methodology of TOGT-ST

To fetch the sentiment from review feedback, we derive three scores - context, rating, and emotion scores for each review. The flowchart for carrying out the suggested method is shown in *Fig. 5.3*.

The framework comprises two main stages. In the first stage, we combine the context, rating, and emotion scores of each review to generate performance scores using the TOPSIS method. These performance scores serve as a representation of the review's overall sentiment and emotional content. In the second stage, we apply a non-cooperative game on these performance scores to achieve the Nash Equilibrium. This step helps us deduce the final sentiment of the review and extract the customer's satisfaction feedback.

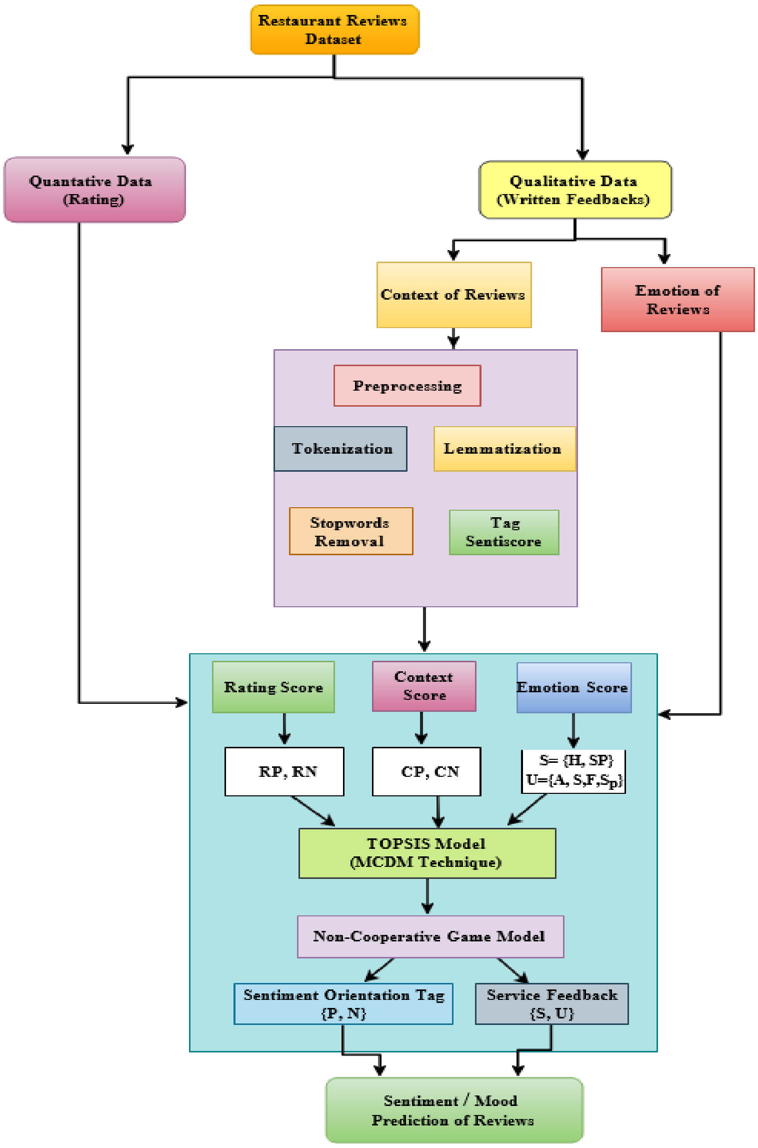

Fig. 5.3: Flowchart of the implementation of the TOGT-ST model

Step 1: Determine context scores of a review comment using SWN: In this step, we use SWN to determine the context scores of textual comments using *Algorithm 3.1* in *Chapter 3.*

Step 2: Evaluate Rating Scores: The rating of a review is between 1 and 5. We calculate two rating scores, named Positive rating (*RP*) and Negative rating (*RN*). *RP* is equal to the rating given with a review, and *RN* is (*5 - RP*). *RP* ranges between 1 and 5, and *RN* is between 0 and 4.

Step 3: Determine the service feedback of the review comment: We evaluate the service feedback based on the sentiments expressed in the reviews. The service feedback for the restaurant can be either satisfactory (*S*) or unsatisfactory (*U*). The Python library[15] Python library is used to evaluate emotion scores. This library classifies emotions as Happy (*H*), Angry (*A*), Surprised (S_p), Sad (*S*), or Fearful (*F*). Satisfactory service feedback includes

[15] text2emotion

happy and surprising emotions, and unsatisfactory service feedback includes anger, surprise, sadness, and fear. After step 3, we have six scores, viz. positive context (*CP*), negative context (*CN*), positive rating (*RP*), negative rating (*RN*), Satisfactory feedback (*S*), and unsatisfactory feedback (*U*). The values of these six scores have different ranges. In the next step, we pass these scores to the TOPSIS model and receive performance scores.

Step 4: Performance score of each review using TOPSIS: In TOPSIS, each evaluation consists of two strategies: polarity and service feedback. Polarity can be either positive (*P*) or negative (*N*) and is determined using *Equation (5.20)* and *(5.21)*.

$$P = RP + CP \tag{5.20}$$

$$N = RN + CN \tag{5.21}$$

Similarly, service feedback can be either satisfactory or unsatisfactory, as determined by the *Equations (5.22)* and *(5.23)*.

$$S = H + S_P \tag{5.22}$$

$$U = S_p + F + A + S \tag{5.23}$$

PS, *PU*, *NS*, and *NU* are the possible combinations of strategies between polarity and service feedback. *Table 5.11* outlines four possible strategies for each evaluation.

Table 5.11: Polarity and Service Feedback values of a review R_i

Strategies			
Polarity		**Service Feedback**	
P	α_i	***S***	γ_i
N	β_i	***U***	δ_i

The numeric values corresponding to four strategies are - *PS*, *PU*, *NS*, and *NU*, for review R_i is given in *Table 5.11*. Here α_i and β_i represent numeric values for the positive and negative polarities of R_i, respectively. Similarly, γ_i and δ_i depict the numeric values of satisfactory and unsatisfactory service feedback of R_i, respectively. The matrix formed from the various combinations is shown in *Table 5.12*.

Table 5.12: Numeric score corresponding to four strategies of review R_i

	PS	***PU***	***NS***	***NU***
$\boldsymbol{R_i}$	$\alpha_i.\gamma_i$	$\alpha_i.\delta_i$	$\beta_i.\gamma_i$	$\beta_i.\delta_i$

Then, the TOPSIS algorithm is applied to evaluate the performance scores (λ_1, λ_2, λ_3, λ_4) of each strategy in a review. The *Algorithm 5.4* illustrates the TOPSIS approach for calculating performance scores.

Algorithm 5.4: Calculate the Performance Score (P_i)

Input: *Polarity* $\{\alpha_i, \beta_i\}$ *and Service Feedback score* $\{\gamma_i, \delta_i\}$ *of each review.*

Output: *Performance Score* (P_j^+) *of PS, PU, NS, and NU of players R_i and R_j.*

1: *Construct a normalized decision matrix* (S_{ij}).

$$S_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \forall i, j$$

where, S_{ij} *and* x_{ij} *are the elements of normalized and original decision matrix, respectively.*

2: *Construct a weighted normalized decision matrix* (V_{ij}) $V_{ij} = S_{ij} * W_j$ $\forall i, j$*, where,* W_j *is the assigned weight to an attribute j.*

3: *Determine positive ideal* (A^+) *and negative ideal* (A^-) *solutions, i.e.,*

$$A^+ = \{(\max V_{ij} \mid i \in l), (\min V_{ij} \mid i \in l^{'}); \forall j\} = \{V_1^+, V_2^+ ....\}$$

$$A^- = \{(\min V_{ij} \mid i \in l), (\max V_{ij} \mid i \in l^{'}); \forall j\} = \{V_1^-, V_2^- ....\}$$

l and l' are associated with benefits and cost attributes, respectively.

4: *Calculate separation measure* (M_i^+, M_i^-).

$$M_i^+ = \sqrt{\sum_{i=1}^{n} (V_{ij} - V_i^+)^2} \quad \forall j, \text{ and } \quad M_i^- = \sqrt{\sum_{i=1}^{n} (V_{ij} - V_i^-)^2} \quad \forall j.$$

5: *Calculate relative closeness to the ideal solution, i.e., Performance Score* (P_j^+),

$$P_j^+ = \frac{M_j^+}{M_j^+ + M_j^-}$$

Step 5: Play Non-cooperative games among the reviews: In this final step, we take two reviews (say, R_i and R_j) and four strategies - *PS*, *PU*, *NS*, and *NU* corresponding to each review. Then, we engage them in a non-cooperative game. The performance scores determined in the preceding step are used as payoffs of the players as shown in *Table 5.13.*

Table 5.13: Performance scores corresponding to four strategies of players R_i and R_j.

R_i		***R_j***	
PS	ψ_1	***PS***	θ_1
PU	ψ_2	***PU***	θ_2
NS	ψ_3	***NS***	θ_3
NU	ψ_4	***NU***	θ_4

The matrix of non-cooperative games is represented in *Table 5.14*. It demonstrates the payoff values for the two players. A row indicates the payoff for the first player for a specific strategy. The column displays the payoff for the second participant for a player strategy. The intersection of both competitors' dominant strategies is known as the Nash Equilibrium. We evaluate the Nash equilibrium and derive a sentiment tag for both reviews. *Algorithm 5.5* illustrates the methodology used to derive sentiment tags by playing games among reviews.

Table 5.14: Payoffs of the different strategies for the players R_i and R_j

Players $\longrightarrow\downarrow$	R_i				
	Strategies $\longrightarrow\downarrow$	***PS***	***PU***	***NS***	***NU***
	PS	$\{\psi_1,\theta_1\}$	$\{\psi_1,\theta_2\}$	$\{\psi_1,\theta_3\}$	$\{\psi_1,\theta_4\}$
R_j	***PU***	$\{\psi_2,\theta_1\}$	$\{\psi_2,\theta_2\}$	$\{\psi_2,\theta_3\}$	$\{\psi_2,\theta_4\}$
	NS	$\{\psi_3,\theta_1\}$	$\{\psi_3,\theta_2\}$	$\{\psi_3,\theta_3\}$	$\{\psi_3,\theta_4\}$
	NU	$\{\psi_4,\theta_1\}$	$\{\psi_4,\theta_2\}$	$\{\psi_4,\theta_3\}$	$\{\psi_4,\theta_4\}$

Table 5.14 represents the normal form representation of the game played between two players R_i and R_j. Now we evaluate the Nash equilibrium of the game which is basically the sentiment tag of the text.

In game theory, the Nash equilibrium is a concept that describes a situation in a game where each player's strategy is at its best response given the strategies chosen by all the other players. It's a point where no player has an incentive to change their strategy, assuming all other players' strategies remain unchanged. Then we evaluate the strategies corresponding to that Nash equilibrium which is basically the sentiment tag of the text. For evaluating the sentiment tag we used *Algorithm 5.5* to sentiment tag to the text.

Algorithm 5.5: Deduce sentiment tag for review.

***Input**: Reviews data file with performance scores PS, PU, NS, and NU of players R_i and R_j.*

***Output**: Tagged Sentiment of reviews, i.e.,* $\{R_i, R_j\} \in \{PS, PU, NS, NU\}$.

***1:** Generate a Normal form matrix for players R_i, and R_j using the performance scores.*

***2:** Compute dominant strategies for R_i, i.e. (DR_i) and R_j, i.e. (DR_j)*

$$\{DR_i, DR_j\} \in \{PS, PU, NS, NU\}.$$

***3:** Compute Nash equilibrium (NE), where NE = DR_i intersection DR_j.*

***4:** The strategies corresponding to NE are the sentiment tags for reviews R_i and R_j.*

***5:** Repeat steps 1 to 5 will get the sentiment tag of R_1 and R_2, i.e.,*

$$\{R_i, R_j\} \in \{PS, PU, NS, NU\}.$$

5.2.3 Illustrative Example of TOGT-ST

Let us consider the two reviews R_1 and R_2.

***R_1* (4 Star):** *"Came here for lunch, and the food was good and tasty. We tried buffet and all the items in veg and non-veg were tasty."*
***R_2* (2 Star):** *"Food quality and taste is not good. Super slow service. Nice ambience but very poor in customer handling. Lot of items not available even if in the menu."*

In the first step, we use *Algorithm 3.1* to calculate the context scores of the written review comment. Next, we calculate emotion scores to evaluate customer service feedback. Using these scores, we categorize service feedback into two categories:

satisfactory (S) and unsatisfactory (U). *Table 5.15* and *Table 5.16* displays the numeric scores associated with the six parameters CP, CN, RP, RN, S, and U, as well as the four strategies (PS, PU, NS, NU) for reviews R_1 and R_2.

Table 5.15: Values of different parameters of reviews and possible strategies of R_1 and R_2.

	R_1			R_2		
Criteria's → Alternatives ↓	**Context (*CP, CN*)**	**Rating (*RP, RN*)**	**Service (*S, U*)**	**Context (*CP, CN*)**	**Rating (*RP, RN*)**	**Service (*S, U*)**
PS	0.11	4.00	1.00	0.16	2.00	0.27
PU	0.11	4.00	0.00	0.16	2.00	0.18
NS	0.02	1.00	1.00	0.21	3.00	0.27
NU	0.02	1.00	0.00	0.21	3.00	0.18

The TOPSIS model described in *Algorithm 5.5* is then applied. We obtain one performance score for each player's strategy. The calculated performance scores for R_1 and R_2 are shown in *Table 5.16*.

Table 5.16: Performance Score of R_1 and R_2.

Players →	R_1	R_2
Strategies ↓	**Performance Score**	**Performance Score**
PS	1.00	0.45
PU	0.52	0.00
NU	0.47	1.00
NS	0.00	0.65

Now, we play the non-cooperative game with four strategies between R_1 and R_2. The comprehensive form representation of the game is depicted in *Fig. 5.4*.

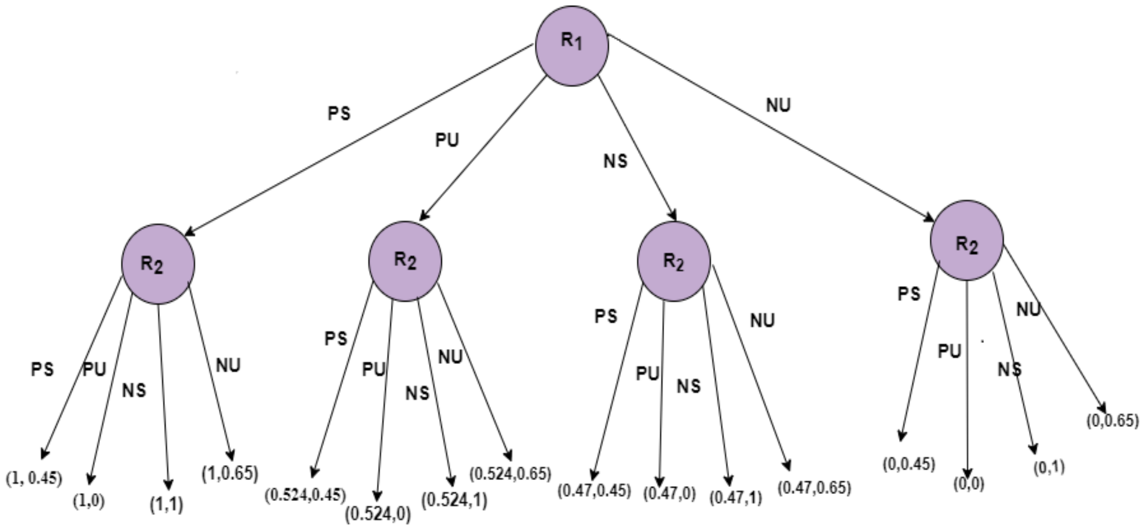

Fig. 5.4: Extensive Form Representation of game played between R_1 and R_2.

In *Table 5.17*, for player R_1, the payoffs in the first row outweigh those in the other rows and the corresponding strategy is PS. Similarly, for R_2, the payoff corresponding to the third column dominates other columns, and the strategy corresponding to this column is *NU*. The Nash equilibrium is the intersection of the dominant strategies of R_1 and R_2, i.e., *PS* and *NU*, respectively. The *PS* annotation for R_1 allows us to infer that the review has positive polarity (*P*) and positive service feedback (*S*). The *NU* marker denotes that R_2 has both negative polarity (*N*) and unsatisfactory service feedback (*U*). The equilibrium of R_1 and R_2, as well as the physical interpretation of the identifiers, are depicted in *Fig. 5.5.*

Table 5.17: Non-Cooperative game between players R_1 and R_2.

Players ⟶ ↓		***R₂***			
	Strategies ⟶ ↓	***PS***	***PU***	***NU***	***NS***
R₁	***PS***	(1.00,0.45)	(1.00,0.00)	**(1.00,1.00)**	(1.00,0.65)
	PU	(0.52,0.45)	(0.52,0.00)	(0.52,1.00)	(0.52,0.65)
	NS	(0.47,0.45)	(0.47,0.00)	(0.47,1.00)	(0.47,0.65)
	NU	(0.00,0.45)	(0.00,0.00)	(0.00,1.00)	(0.00,0.65)

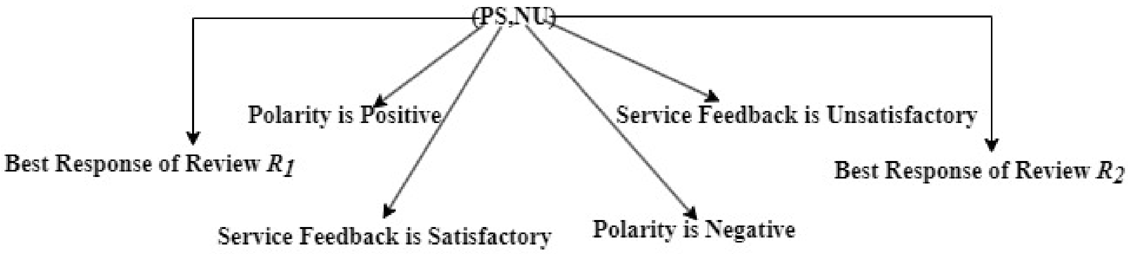

Fig. 5.5: Nash Equilibrium of R_1 and R_2.

Fig 5.5 is the Nash equilibrium of the game played between two players. Nash equilibrium also implies best response of the game. The best response implies dominant strategy of the game. A dominant strategy refers to a strategy that provides the best outcome for a player regardless of the strategy chosen by the other players. If a player has a dominant strategy, it means that this strategy is always the best choice, irrespective of what the opponents do. On the other hand, a Nash equilibrium occurs when each player's strategy is the best response to the strategies chosen by all the other players. While a dominant strategy implies a player always has one clear best option, a Nash equilibrium focuses on the point where no player wants to change their strategy, given the strategies of others. In some cases, a Nash equilibrium might involve dominant strategies, but not all Nash equilibria involve dominant strategies. Nash equilibrium can exist without dominant strategies, and not every game with dominant strategies necessarily has a unique Nash equilibrium. (PS, NU) is the Nash equilibrium and is also the best response of the game which is also implies that *PS* is the best response of R_1 and *NU* is the best response of reviewer R_2.

5.2.4 Experimentation & Evaluation

In this section, we discuss the experimentation and results of SOTM (discussed in *Section 5.1*) and TOGT-ST models *(Section 5.2).*

In this section, our focus is divided into several subsections, each serving a distinct purpose. In *subsection 5.2.4.1*, we commence by outlining our data collection process. Moving forward, *subsection 5.2.4.2* involves a comparative analysis between the

SOTM and TOGT-ST models using the Zomato + Swiggy Dataset. This comparison is further extended to *subsection 5.2.4.3,* where we apply these models to assess the Trip Advisor Dataset. In *subsection 5.2.4.4*, our attention shifts to the evaluation of the proposed models, particularly in the context of the Yelp Dataset. Lastly, in *section 5.2.4.5*, we delve into a comprehensive assessment of the Macro and Micro performance of both the SOTM and TOGT-ST models.

5.2.4.1 Datasets

To evaluate the effectiveness and efficiency of the proposed models, three datasets were used. *Table 5.18* gives the details about the data statistics of the datasets.

Table 5.18: Data statistics

Dataset	Language	Positive	Negative	Neutral
Zomato+Swiggy	English	1644	1145	1211
Yelp	English	1567	1245	1188
TripAdvisor	English	1369	1456	1175

5.2.4.2 Comparison over Zomato + Swiggy Dataset

In this subsection, we compare the proposed models with various approaches by Anas and Kumari [187], Gojali and Khodra [188], Al Omari et al. [189], and Jagdale and Deshmukh [190]. Anas and Kumari [187] used Naïve Bayes and the random forest method for opinion mining of reviews. Gojali and Khodra [188] used the WordNet approach to predict the reviews' orientation and aspect of the reviews, and the recorded F-measure is 0.783 over the Zomato dataset. The author[191] proposed sentiment attribution analysis with hierarchical classification and automatic aspect categorization to improve social listening for diligent marketing. He proposed five models, out of which SVM on Hierarchical Classification (Hybrid) gives the best result. Al Omari et al. [189] performed a logistic regression algorithm on the Zomato dataset and performed a sentiment orientation task (*P, N, O*). Jagdale and Deshmukh [190] performed sentiment analysis on the Zomato dataset using a supervised machine learning classification algorithm like gradient boosting. All the comparisons based on four evaluation metrics are depicted in Fig. 5.6 The SOTM model outperforms with 0.9 accuracy, 0.88 F1-measure, 0.86 precision, and 0.87 recall. Similarly, the TOGT-ST model achieved an accuracy of 0.9 precision of 0.86, and an F1 score of around 0.88.

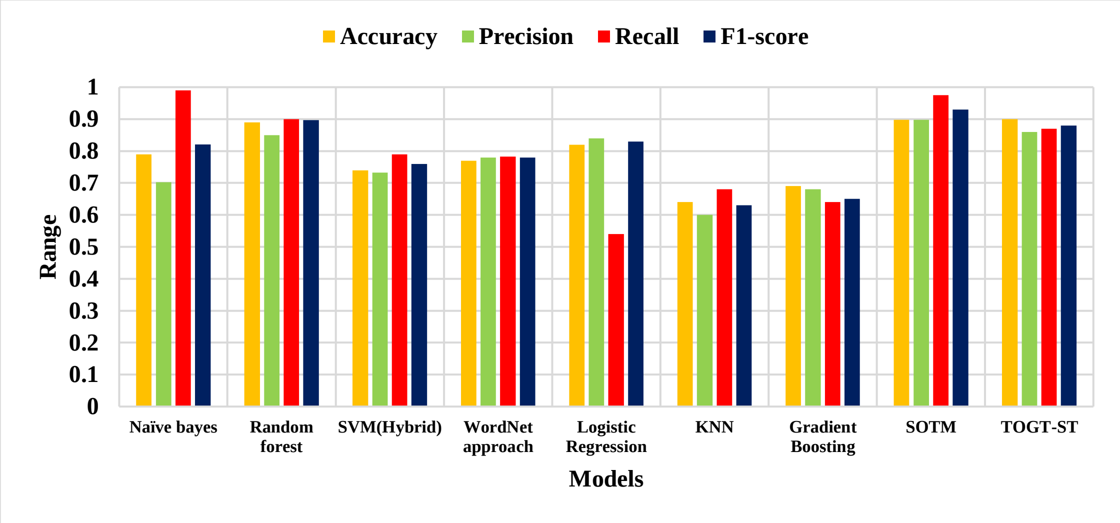

Fig. 5.6: Performance comparison of the proposed model with existing approaches.

5.2.4.3 Comparison on Trip Advisor Dataset

In this subsection, we compare the performance of the SOTM and TOGT-ST with other techniques over the Trip Advisor dataset. Afzaal et al. [192] suggested a fuzzy logic model named Fuzzy Lattice Reasoning (FLR) constituted of fuzzy lattice rules. One of the unsupervised approaches, called POST-VIA360 [175], utilized sentiment analysis and contextual information to suggest eateries and places of interest. The DOC-ABSADeepL SA-MpMcDM methodology model, which included expert evaluations based on natural language reviews and numerical ratings, was another cutting-edge decision aid that Zuheros et al. [9] introduced. The comparison is illustrated in *Fig. 5.7*, where our proposed models consistently outperformed the other unsupervised models, achieving an accuracy of 0.90. The SOTM model achieved an accuracy of around 0.9 and F1-score of around 0.93. The recall and precision are around 0.97 and 0.89. TOGT-ST achieved an accuracy of 0.91.

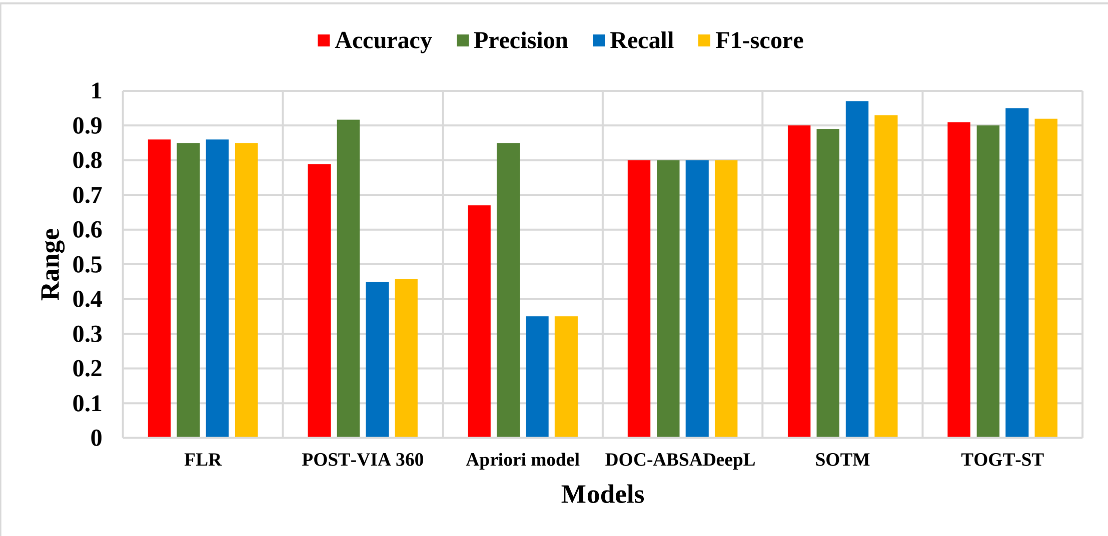

Fig. 5.7: Evaluation of the proposed model in comparison to an unsupervised method.

5.2.4.4 Comparison on Yelp Dataset

We compared our polarity classification results with JST+ [193], ASUM [194], HASM [195], TSM [196], and ASUM+ [197]. To assess the performance of the suggested models, we used two samples of the dataset - a smaller sample of 1000 reviews (all of which were awarded 1 or 5 stars), and a bigger sample of 1000 reviews (all of which were given 2 or 4 stars). The range of maximum and lowest accuracy for various models across large and small datasets is shown in Fig. 5.8. The ranges for ASUM are 0.76 - 0.79, ASUM+ is 0.84 - 0.86, JST+ is 0.60 - 0.61, TSM+ is 0.52 - 0.54, SOTM is 0.87 - 0.90 and the TOGT-ST model is 0.85 - 0.89. The proposed model performed better than those shown in *Fig. 5.8* when compared to existing unsupervised methods. The suggested model's increased accuracy is a result of its independence from training and language.

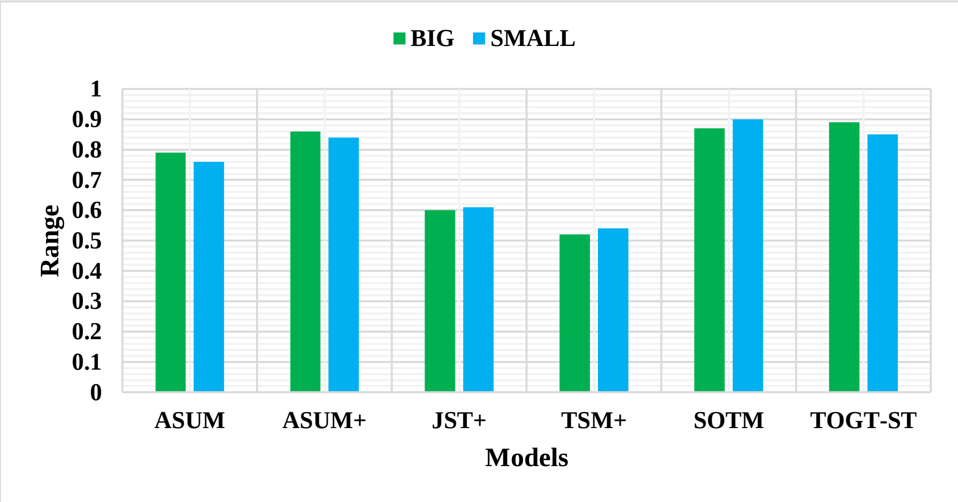

Fig. 5.8: Performance evaluation on the Yelp datasets of different sentiment classification methods

5.2.4.5 Macro, Micro Evaluation on SOTM and TOGT-ST

In this subsection, we evaluate the macro and micro performance of two models i.e. SOTM and TOGT-ST. To measure the overall performance, we calculate macro and micro averages. To treat all classes equally, the macro-average computes metrics for each class separately before averaging them. Each category's contributions are added together to determine the micro-average. This statistic helps understand performance across datasets of varying sizes. From *Equation (1.13) - (1.19)* we can see how the accuracy, F1-score, and recall averaged across all datasets look on a global and local scale, respectively. *Fig. 5.9* depicts the overall performance of the suggested model. Macro precision, recall, and F1-score for SOTM are 0.86, 0.85 and 0.89. The micro-precision, recall, and F1-score for SOTM are 0.87, 0.92, and 0.9. Similarly, in the case of TOGT-ST macro precision is 0.9, recall is 0.98 and F1-score is 0.93.

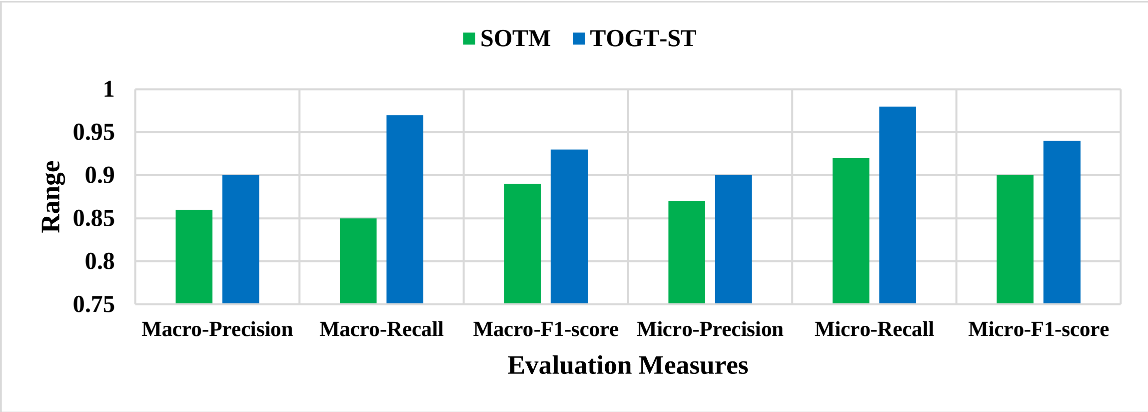

Fig. 5.9: Macro and micro performance evaluation metrics over three datasets

5.3 Language-independent EDAS-based Sentiment Tagging using Game Theory (LESTG)

Within this section, we present a novel approach for conducting sentiment analysis. This approach seamlessly blends the Evaluation Based on Distance from Average Solution (EDAS) MCDM technique with a non-cooperative game model.

The section unfolds as follows: In *subsection 5.3.1*, we provide a concise introduction to the EDAS MCDM technique. Moving on to *subsection 5.3.2,* we expound upon the details of the proposed methodology. To offer a tangible understanding, *subsection 5.3.3* is dedicated to numerical illustrations of the proposed model, supported by examples. In *subsection 5.3.4* we discuss the experiments and results.

5.3.1 EDAS

The EDAS approach was developed by Keshavarz Ghorabaee et al. [198]. EDAS is a valuable technique in the realm of MCDM. It offers a straightforward and structured approach for evaluating and ranking alternatives in complex decision scenarios with multiple criteria. EDAS stands out by considering not only the criteria values but also how alternatives deviate from the average performance on these criteria. This method assists decision-makers in identifying and selecting preferred alternatives based on both objective data and their relative importance. It finds practical applications across various domains, providing transparency and systematic decision support.

5.3.2 Proposed Methodology of the LESTG Model

The LESTG model aims to classify the sentiment behind the reviews according to their emotional content. *Fig. 5.10* depicts the LESTG model's pipeline. The first step is to clean the data involving processes such as preprocessing, tokenization, lemmatization, and stopword removal. Next, we calculate the context scores and emotion scores from a written review comment. Further, we build a 3 × 2 decision matrix with three feasible alternatives and three criteria. The three alternatives are positive, negative, and neutral, and the two criteria are context and emotion. The EDAS technique calculates the review appraisement scores after establishing a decision matrixes. Following the non-cooperative game, the model determines the Nash equilibrium, and the final sentiment tag for a review is inferred.

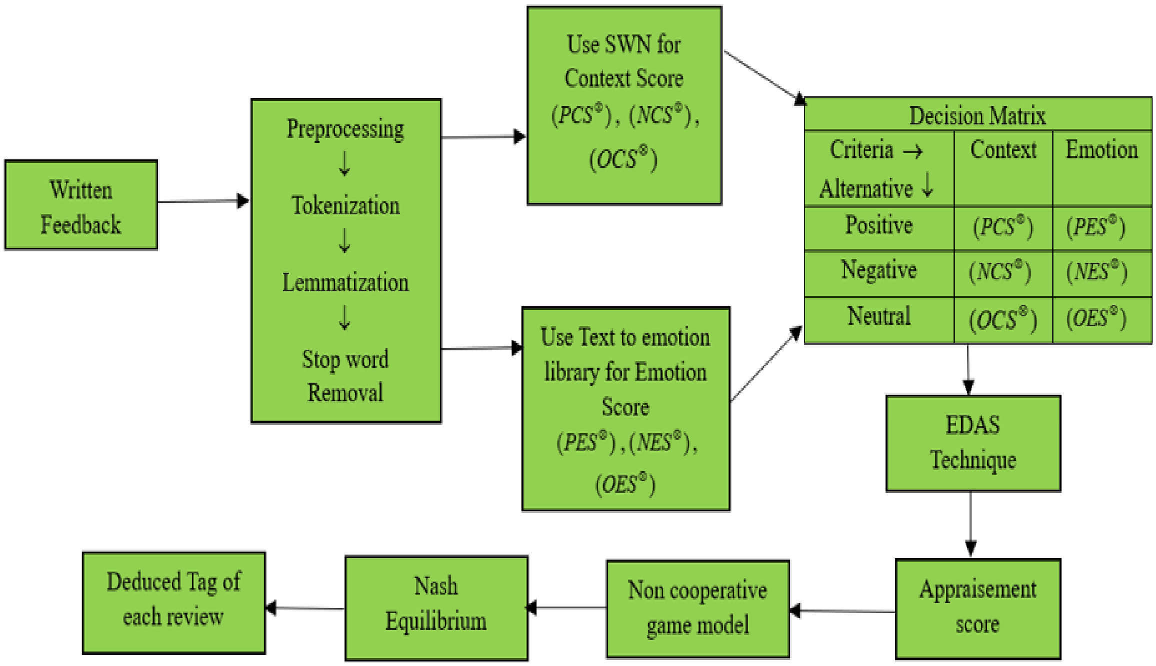

Fig. 5.10: The LESTG model framework for sentiment analysis of reviews.

Step 1: Evaluate Context Scores of Reviews: Context scores are objective numerical measures allocated to assess the sentiment analysis of a given textual feedback. They effectively quantify the magnitude of positive, negative, or neutral sentiment conveyed within a review. These scores are calculated by, leveraging the capabilities of SWN for accurate computation. The resulting context scores exhibit values that reside within the closed interval [0, 1]. We denote $(PCS^{\circledR})$ as the positive polarity, $(NCS^{\circledR})$ as the negative polarity and $(OCS^{\circledR})$ as the neutral polarity of the context. To accomplish this, *Algorithm 5.1* (*Section 5.1.2*) is employed.

Step 2: Evaluate the emotion scores of reviews: After obtaining the emotion scores, the emotions E are further categorized into three groups: positive emotions $(PES^{\circledR})$ negative emotions $(NES^{\circledR})$ score, and neutral emotion $(OES^{\circledR})$ scores. The categorization of emotions into three categories is performed using *Algorithm 4.2* in *Chapter 4* The resulting values of $(PES^{\circledR})$, $(NES^{\circledR})$ and $(OES^{\circledR})$ fall within the range of 0 to 1.

Step 3: Calculate Appraisement Scores: We follow *Algorithm 5.6* to calculate the appraisement score, which is taken as a payoff for a player in a game. Considering that all of the criteria are equally relevant, W=0.5 is used. Finally, we assess the appraisement score. In a non-cooperative game, players are compensated with the appraisement scores of each review as payoffs.

Algorithm 5.6: Calculate Appraisement Score

Input: *Positive, negative, and neutral scores of context* $(PCS^{\circledR})$, $(NCS^{\circledR})$, $(OCS^{\circledR})$ *and Emotion* $(PES^{\circledR})$, $(NES^{\circledR})$, $(OES^{\circledR})$ *scores.*

Output: *Appraisement score of each review.*

1: *Construct a decision matrix having 3 alternatives and 2 criteria* $[A_{3\times 2}]_{3\times 2}$.

2: *Calculate the Average solution,* $Av_j = \frac{\sum_{i=1}^{n} A_{ij}}{n} \quad \forall i \in \{1,2,3\}\ \&\ j \in \{1,2\}$

3: *Calculate* PDA_{ij} *and* $NPDA_{ij}$

$$PDA_{ij} = \begin{cases} \dfrac{\max(0,(X_{ij} - Av_j)}{Av_j} = \lambda \rightarrow FC \\ \dfrac{\max(0,(Av_j - X_{ij})}{Av_j} = \wp = 0 \rightarrow NFC \end{cases}, \quad NDA_{ij} = \begin{cases} \dfrac{\max(0,(Av_j - X_{ij})}{Av_j} = \psi \rightarrow FC \\ \dfrac{\max(0,(X_{ij} - Av_j)}{Av_j} = \zeta = 0 \rightarrow NFC \end{cases}$$

4: *Calculate the weighted sum* SP_i *and* SN_i, $SP_i = \sum_{j=1}^{m} w_j.PDA_{ij} \quad \& \quad SN_i = \sum_{j=1}^{m} w_j.NDA_{ij}$

5: *Calculate* NSP_i *and* NSN_i, $NSP_i = \frac{SP_i}{\max(SP_i)} \quad \& \quad NSN_i = 1 - \frac{SN_i}{\max(SN_i)}$

6: *Calculate the Appraisement score,* $AS_i = \alpha_i = \frac{1}{2}\left(NSP_i + NSN_i\right)$

Step 4: Play Non-cooperative games amongst the reviews: The appraisement score*s* for reviews R_1 and R_2 are used as the payoffs for players. *Table 5.19* shows the three strategies and corresponding appraisement scores $\{\alpha_1, \alpha_2, \alpha_3\}$ of R_1 and $\{\beta_1, \beta_2, \beta_3\}$ R_2 for positive, negative, and neutral, respectively. We implement *Algorithm 5.10* to play the non-cooperative game between R_1 and R_2 to reach the Nash Equilibrium.

Table 5.19: Normal Form Representation of game showing payoffs corresponding to different strategies evaluated from the appraisement scores.

Players $\rightarrow$ $\downarrow$	**R1**			
R2	**Strategies** $\downarrow\rightarrow$	P (β_1)	N (β_2)	O (β_3)
	P (α_1)	$\{\alpha_1, \beta_1\}$	$\{\alpha_1, \beta_2\}$	$\{\alpha_1, \beta_3\}$
	N (α_2)	$\{\alpha_2, \beta_1\}$	$\{\alpha_2, \beta_2\}$	$\{\alpha_2, \beta_3\}$
	O (α_3)	$\{\alpha_3, \beta_1\}$	$\{\alpha_3, \beta_2\}$	$\{\alpha_3, \beta_3\}$

Algorithm 5.7: Determine sentiment tag for assessment

Input*: Appraisement scores* $\{\alpha_1, \alpha_2, \alpha_3\}$ *for review* R_1 *and* $\{\beta_1, \beta_2, \beta_3\}$ *review* R_2

Output*: Sentiment Tag for* R_1 *and* R_2 *i.e.,* $\{R_1, R_2\} \in \{P, N, O\}$.

1: *Generate a normal form matrix for players* R_i, R_j *using the appraisement scores.*

2: *Compute dominant strategies for* R_i *i.e.* (DR_i) *and* R_j *i.e.* (DR_j), *where* DR_i, DR_j *belongs to {P, N, O}*

3: *Compute Nash equilibrium (NE), where NE =* DR_i *intersection* DR_j.

4: *The strategies corresponding to NE are the sentiment tags for reviews* R_i *and* R_j.

5.3.3 Numerical Illustration on LESTG Model

This subsection discusses numerical examples to demonstrate the LESTG model. We consider two English reviews - R_1 and R_2.

English Reviews
R$_1$ (*2 Stars*): *"Very nice monitor! Great vibrant color and clarity A very usable 16:10 aspect that works much better for applications than the common 16:9 that is great for movies, but not much else.*
R$_2$ (*4 Stars*): *"This Blu Ray player is defective. It won't play Blu rays from universal studios or other companies like Sony. The WIFI connection is pretty much non-existent. I tried everything humanly possible in order to get the wireless connection on this Player to no avail. All of the wifi compatible electronic devices in my apartment connect easily except this Player. I will be purchasing a Samsung BD J7500 and will stay away from panasonic once and for all !!!".*

First, we calculate the context scores and emotion scores of reviews using *Algorithm 4.1* and *Algorithm 4.2* (Chapter 4), respectively. The obtained values are shown in Table 5.20. Next, we apply the *Algorithm 5.9. Table 5.21* shows the average of the three alternatives for both criteria.

Table 5.20: Context scores and emotion scores of R_1 and R_2

	Orientation	Context Score of R_1	Emotion Score of R_1
R$_1$	**Positive**	0.2	0.33
	Negative	0.8	0.5
	Neutral	0.1	0.17
R$_2$	**Positive**	0.89	0.571
	Negative	0.21	0.143
	Neutral	0.11	0.43

Table 5.21: Calculate the average of all the criteria.

Orientation	Context Score of R_1	Emotion Score of R_1	Context Score of R_2	Emotion Score of R_2
Positive	0.2	0.33	0.89	0.571
Negative	0.8	0.5	0.21	0.143
Neutral	0.1	0.17	0.11	0.43
AV_j	0.366667	0.333333	0.403333	0.381333

Table 5.22 and *Table 5.23* evaluate the positive (*PDA)* and negative (*NDA*) distance from the average.

Table 5.22: Positive Distance from Average (PDA) of R_1 *and* R_2

	Context		Emotion	
Weightage = 0.5	R_1	R_2	R_1	R_2
Positive *(P)*	0.455041	0	0	0.498688
Negative (*N*)	0	0.478908	0.515152	0
Neutral (*O*)	0.72752	0.727047	0	0.128609

Table 5.23: Negative Distance from Average (NDA) of R_1 *and* R_2

	Context		Emotion	
Weightage = 0.5	R_1	R_2	R_1	R_2
Positive *(P)*	0.455041	0	0	0
Negative (*N*)	0	0.478908	0	0.623684
Neutral (*O*)	0.72752	0.727047	0.484848	0

Next, we calculate the positive and negative distance from the average of both reviews. Then we evaluate the weighted sum of positive, negative, and neutral distance using *Algorithm 5.9* shown in *Table 5.24* and *Table 5.25*.

Table 5.24: Weighted sum of *PDA* of R_1 *and* R_2

	Context		Emotion		*SPi*	
Weightage = 0.5	R_1	R_2	R_1	R_2	R_1	R_2
Positive *(P)*	0.22752	0	0	0.249344	0.228	0.249
Negative (*N*)	0	0.239454	0.2578	0	0.258	0.239
Neutral (*O*)	0.36376	0.363524	0	0.064304	0.364	0.428

Table 5.25: Weighted sum of *NDA* of R_1 *and* R_2

	Context		Emotion		*SNi*	
Weightage = 0.5	R_1	R_2	R_1	R_2	R_1	R_2
Positive *(P)*	0.2275	0	0	0	0.228	0.000
Negative (*N*)	0	0.239454	0	0.311842	0.000	0.551
Neutral (*O*)	0.3637	0.363524	0.24242	0	0.606	0.364

Table 5.26 shows the standard values of *NSPi*, *NSNi,* and *ASi* for all the selected alternatives. In the end, we calculate the AS_i for all the selected alternatives, as shown in *Table 5.27*.

Table 5.26: Standard values of R_1 *and* R_2.

	SP_i		SN_i		*NSPi*		*NSNi*		*ASi*	
Weightage = 0.5	R_1	R_2	R_1	R_2	R_1	R_2	R_1	R_2	R_1	R_2
Positive *(P)*	0.23	0.249	0.23	0	0.626	0.582	0.624	1	0.625	0.791
Negative (*N*)	0.26	0.239	0	0.551	0.7088	0.558	1	0	0.854	0.279
Neutral (*O*)	0.36	0.428	0.61	0.364	1	1	0	0.339	0.500	0.670

Table 5.27: Appraisement scores of both reviews R_1 and R_2.

	R_1	R_2
	Appraisement Scores *(ASi)*	**Appraisement Scores *(ASi)***
Positive (*P*)	0.625	0.791
Negative (*N*)	0.854	0.279
Neutral (*O*)	0.500	0.670

Now we play the non-cooperative game between the two reviews following *Algorithm 5.10*. *Table 5.28* shows the 3 strategies, positive, negative, and neutral, and each player's payoff corresponding to the three strategies. The game is played with appraisement scores as payoffs of R_1 and R_2. *Fig. 5.11* is an extensive form representation of *Table 5.30*.

Table 5.28: Normal form representation of the non-cooperative game

Players → ↓		R_2		
	Strategies → ↓	**Positive (*P*)**	**Negative (*N*)**	**Neutral (*O*)**
R_1	**Positive (*P*)**	(0.625,0.791)	(0.625,0.279)	(0.625,0.670)
	Negative (*N*)	**(0.854,0.791)**	(0.854,0.279)	(0.854,0.670)
	Neutral (*O*)	(0.500,0.791)	(0.500,0.279)	(0.500,0.670)

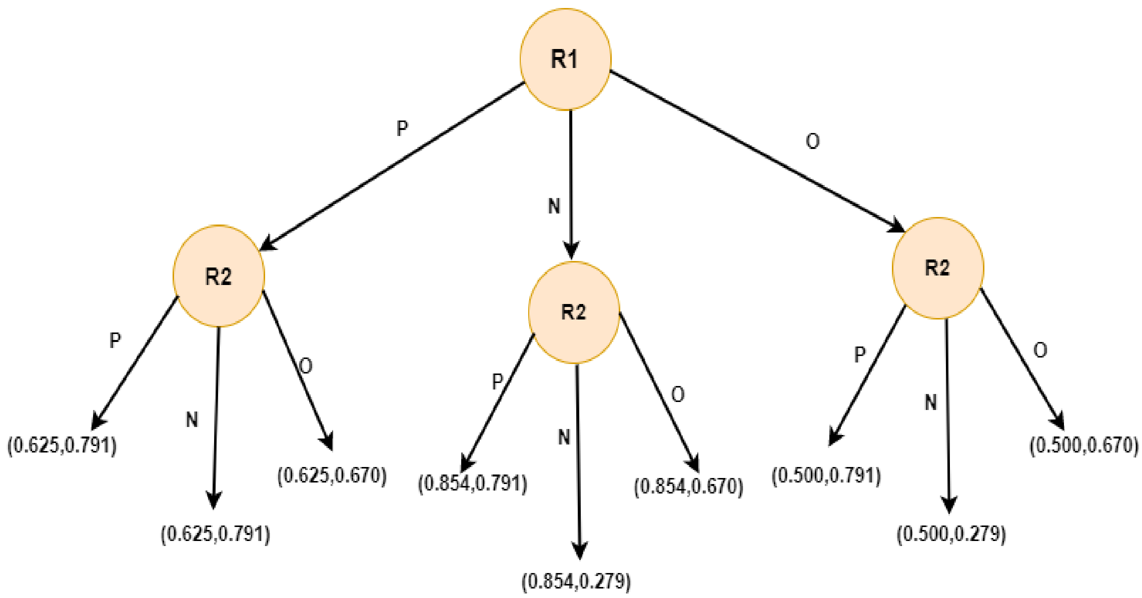

Fig. 5.11: Extensive form representation of players R_1 and R_2 with their respective strategies

We reach the Nash equilibrium and deduce the appropriate tag for the reviews. Here Nash Equilibrium is (0.854,0.791), and strategies corresponding to these payoffs are (*N, P*), where *N* is the deduced tag of review R_1 and *P* is the deduced tag of R_2. *Table 5.29* shows the Nash equilibrium of the LESTG model for the given reviews. *Fig. 5.12* gives a physical interpretation of deduced tags of R_1 and R_2.

Table 5.29: Nash equilibrium of the non-cooperative game

Players → ↓	***R₂***	
	Strategies → ↓	Positive (*P*)
R₁	Negative (*N*)	(0.854,0.791)

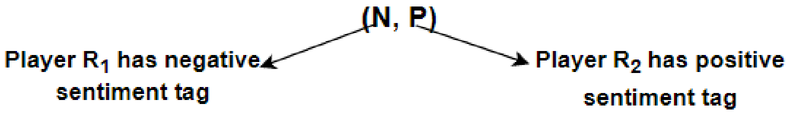

Fig. 5.12: Deduced tag of each review from the non-cooperative game model.

5.3.4 Experimentation & Evaluation

In this subsection, the LESTG model's resilience was evaluated across diverse domains with English and Hindi-language datasets. The datasets cover different domains viz. movies, hotels, electronics, and IMBD movie reviews.

Subsection 5.3.4.1 is dedicated to elucidating the datasets we utilize. Moving forward, in *subsection 5.3.4.2*, we delve into evaluating the efficiency of the proposed model on TripAdvisor datasets. Similarly, *subsection 5.3.4.3* is reserved for the comparative analysis of electronic datasets. Transitioning to *subsection 5.3.4.4,* we shift our focus to a comparison involving the IMBD model. Subsequently, in *section 5.3.4.5,* we pivot to the evaluation conducted on the Hindi hotel reviews dataset. In *subsection 5.3.4.6* follows, where we assess the model's performance on Hindi electronic reviews. Lastly, in *Section 5.3.4.7*, we undertake an evaluation or discussion which is yet to be specified.

5.3.4.1 Datasets

The proposed technique is applied to six datasets containing English and Hindi reviews. Data statistics of the datasets are presented in *Table 5.30.*

Table 5.30: Data statistics of different datasets

Data Set	Language	Positive	Negative	Neutral
TripAdvisor reviews[16]	English	256	387	344
Electronic reviews[17]	English	287	249	394
IMBD reviews[18]	English	278	213	178
Hotel reviews[19]	Hindi	512	350	138
Electronic reviews[20]	Hindi	337	266	246

[9] *https://www.kaggle.com/code/residentmario/exploring-tripadvisor-uk-restaurant-reviews/notebook*

[17] *https://www.kaggle.com/code/prakharprasad/mobile-reviews-topic-modeling*

[18] *http://www.imdb.com"*

[19] *http://www.imdb.com"*

[20] *https://www.kaggle.com/datasets/datafiniti/amazon-and-best-buy-electronics*

5.3.4.2 Evaluation of the TripAdvisor Dataset

We assessed the performance of the LESTG model in comparison to five distinct unsupervised models as shown in *Fig. 5.13.* The unsupervised approach POST-VIA360 [175] utilized sentiment analysis and contextual information to suggest eateries and places of interest. LESTG model outperformed POST-VIA360 significantly in terms of evaluation metrics. The DOC-ABSADeepL SA-MpMcDM methodology model, which included expert evaluations based on natural language reviews and numerical ratings, was another cutting-edge decision aid that Zuheros et al.[9] introduced. Our LESTG model demonstrated superior precision, recall, and f-measure when compared to DOC-ABSADeepL. Additionally, our model exhibited better performance in terms of precision, recall, and f-measure compared to Buon Appetito. We compared the LESTG model with Bayesian game model-based *(chapter 3)* mathematical framework was proposed for sentiment classification of reviews, achieving an accuracy of approximately 0.87 and an F1 score of approximately 0.88 on the Tripadvisor dataset. However, our LESTG model surpassed this performance with an accuracy of 0.93 and an F1 score of 0.94, indicating its superiority. Based on these results, it is evident that the LESTG model offers better accuracy and performance compared to the existing unsupervised approaches evaluated in our study.

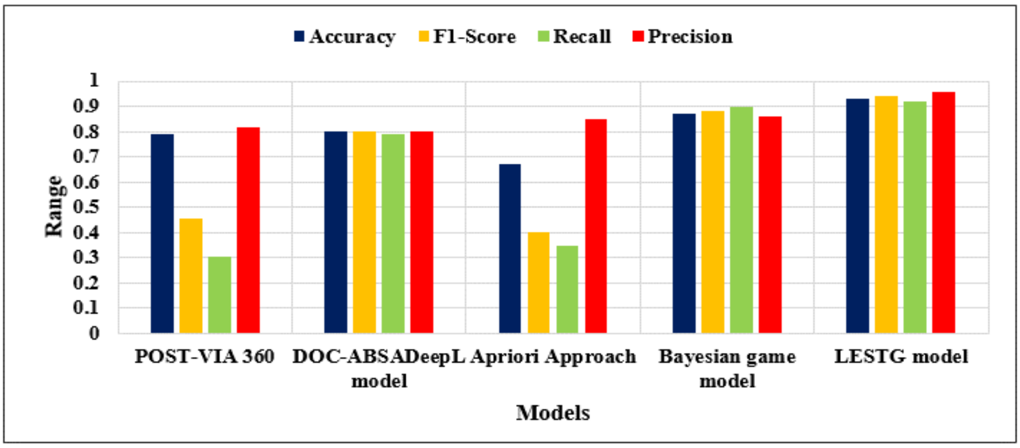

Fig. 5.13: Comparative analysis of the LESTG model and unsupervised methods.

5.3.4.3 Evaluation of Amazon Electronic Reviews

To evaluate the effectiveness of the proposed model, we compared it with various methods on the Amazon Electronic Reviews dataset as shown in *Fig. 5.14.* Daniel & Meena[178] introduced the LSVM classifier approach, which achieved accuracy and MCC scores of around 0.77 and 0.633. Next, we compared the proposed model with W2VLDA [55] which achieved an accuracy over the electronic dataset of 0.834 and the MCC score of 0.658. The next comparison is made with a mathematical optimization model. We proposed a Bayesian game model (*Chapter 3*) based sentiment analysis of reviews whose accuracy and MCC score were recorded as 0.94 and 0.781, respectively. The author [179] presented a novel approach called selective domain adaptation (SDA), which focuses on selectively transferring private knowledge from the source domain that is closest to the target domain at the feature level. The accuracy of electronic reviews is .856, and the MCC score is 0.699. The investigation presented the BERT-MultiLayer Convolutional Neural

Network (B-MLCNN) as an integrated deep learning paradigm. B-MLCNN adopted a holistic approach by considering the entire textual review as a singular document and conducting sentiment classification accordingly. Notably, the accuracy achieved for electronics reviews is approximately 0.95. The obtained accuracy is about 0.95 [180] and the MCC score is 0.781. Hence, the proposed model shows a superior accuracy of 0.96, and an MCC score of 0.781, which is higher than the existing approaches.

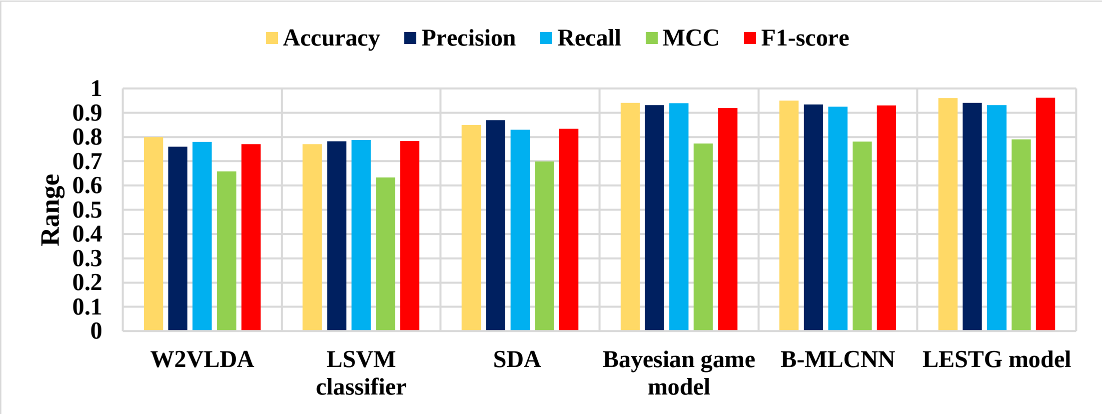

Fig. 5.14: Efficiency of the LESTG model in comparison to unsupervised methods

5.3.4.4 Comparison on IMBD Movie Reviews

Vashishtha et al. [56] presented an unsupervised sentiment classification system that utilized the SentiWordNet lexicon and fuzzy linguistic hedges to comprehensively analyze phrases, compute their sentiment scores (senti-scores), and determine their polarity. By combining unigrams, bigrams, and trigrams on the same scale, their approach achieved the highest accuracy of 0.693 and the highest f-score of 0.691. In another study, Sentiment Analysis Based on Sentiment Clustering (SASC) was introduced, achieving an accuracy of .7542 [75]. Furthermore, a computationally efficient integrated deep learning paradigm called BERT-MultiLayered Convolutional Neural Network (B-MLCNN) was proposed for sentiment classification. B-MLCNN treated the entire textual review as a single document and achieved an accuracy of approximately 0.95 for IMDB movie reviews [180]. In the Bayesian game model, the accuracy obtained is 0.92, with an F1 score of 0.94, recall of 0.91, and precision of 0.93 [181]. The LESTG model achieved an accuracy of 0.96 and has an MCC score of 0.7812 as shown in *Fig. 5.15.*

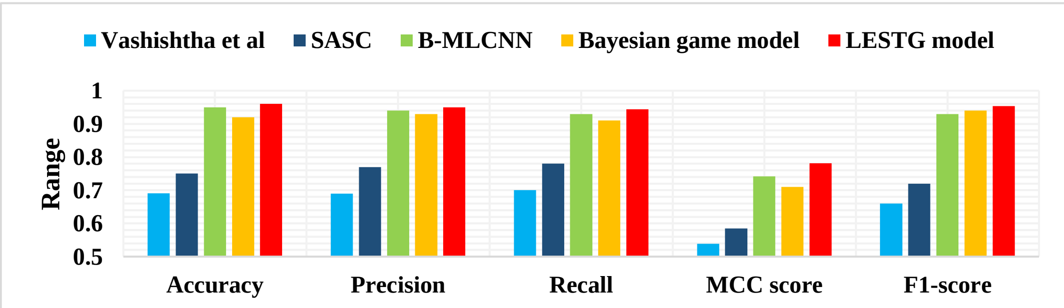

Fig. 5.15: Comparison of the LESTG model with other unsupervised algorithms.

5.3.4.5 Evaluation on the Hindi Hotel Dataset

Mishra et al. [199] introduced the HSWN, CSPL+HSWN, and CSPLE, with respective accuracy rates of 0.46, 0.85, and 0.825, Akhtar et al.[83] embedded vectors from the CNN. The sentiment-augmented optimized vector obtained at the end is used for SVM training for the model's sentiment classification accuracy of 0.77. LESTG achieved an accuracy of 0.84 for hotel reviews with the recorded F1-score is 0.81 as shown in *Fig. 5.16.*

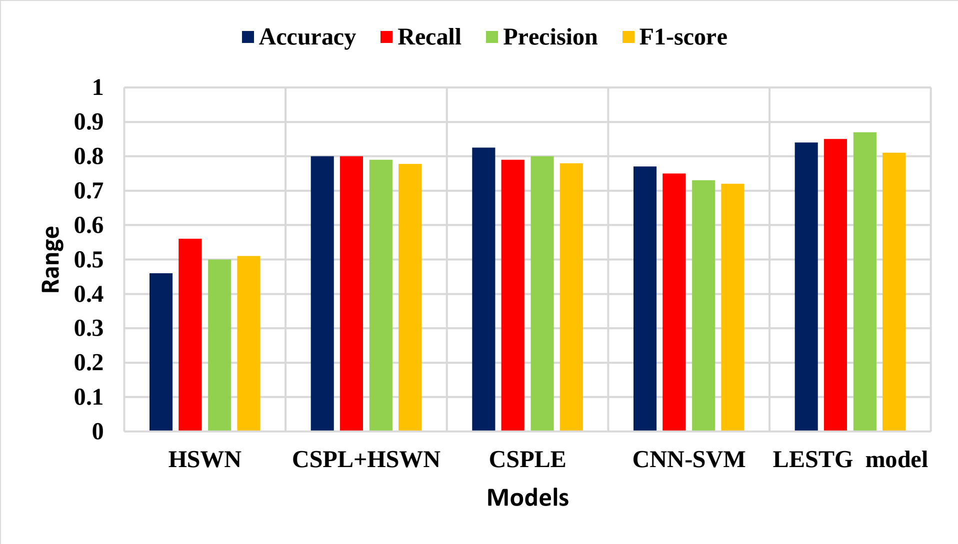

Fig. 5.16: Comparison of existing approaches with the proposed model

5.3.4.6 Evaluation on the Hindi Electronic Dataset

Fig. 5.17 depicts the performance comparison of the proposed approach with other models on the same dataset. Jha et al. [20] proposed the HMDSAD dictionary-based approach to classify unlabelled reviews from the target domain into positive, negative, and neutral categories. This approach had an accuracy of 0.56. HSWN [77] is a comprehensive lexicon covering the polarity of words in the Hindi language. The accuracy recorded for this lexicon-based method proposed by Akhtar et al. [83] developed the embedded vectors from a Convolutional Neural Network(CNN). The sentiment-augmented optimized vector is used to train the SVM for sentiment classification, and the supervised CNN-SVMS model has an accuracy of 0.68. Singh et al. [200] pre-processed the Hindi texts and identified their English equivalents, and a summary review was then calculated using the HSWN database. The technique had an accuracy of .48. The classification accuracy of the decision trees classifier was 0.54 [201]. COGT-ST *(Section 5.4)* model achieved the accuracy, recall, and F1-score for electronic reviews as 0.82, 0.87, and 0.84. Similarly, MOOGT-ST achieved the recall of around 0.87.

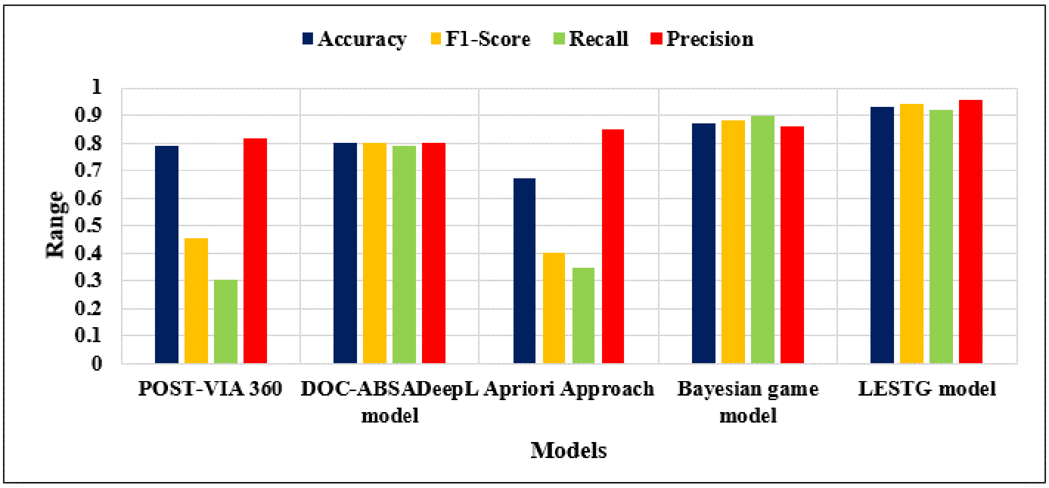

Fig. 5.17: Comparison of existing approaches with the proposed models in terms of evaluation measures.

5.3.4.7 Macro and Micro Evaluation on LESTG Model

The comprehensive evaluation encompassing distinct data sets is illustrated in *Fig. 5.18 Equations (1.13)* to *(1.19)* give the accuracy, F1-score, and recall metrics. Remarkably, the results demonstrate substantial comparability between the macro and micro averages. Thus, signifying the stability of the proposed approach irrespective of the domain and the language of the datasets.

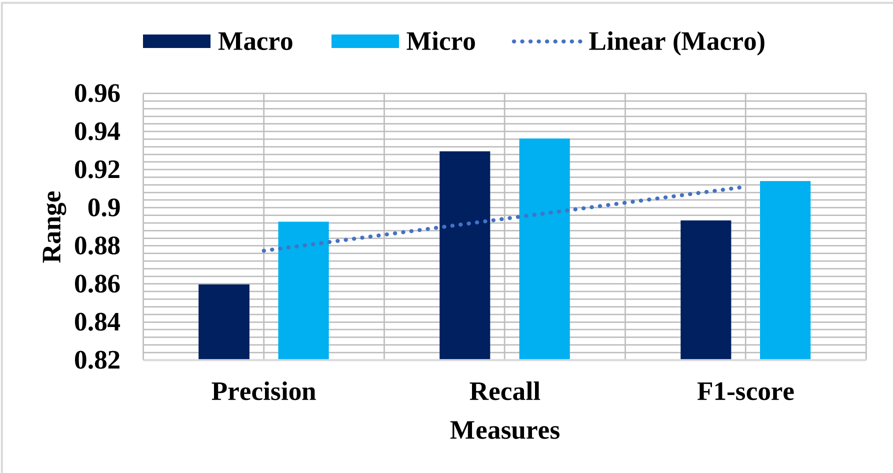

Fig. 5.18: The LESTG model's Macro and Micro averaged performance over six evaluation datasets.

5.4 CODAS and Game Theory-based Sentiment Tagger (CODGT-ST) and Grey Relational Analysis & Game Theory-based Sentiment Tagger (GRAGT-ST)

In this section, we introduce two sentiment classification models named the CODGT-ST and the GRAGT-ST model. The organization of the section is as follows.

The CODGT-ST and GRAGT-ST methodologies are explained in *subsection 5.4.1.* Experimentation and evaluation of the proposed techniques are discussed in *section 5.4.2.* The Dataset Collected is introduced in *subsection 5.4.2.1.* We assess the CODGT-ST and GRAGT-ST model performance in *subsection 5.4.2.2.*

5.4.1 CODAS Technique

The CODAS technique, which stands for "Complex Proportional Assessment" is a powerful method in the realm of MCDM. It provides a structured approach for evaluating and ranking alternatives in complex decision scenarios. By considering multiple criteria and their respective weights, CODAS allows decision-makers to systematically assess and compare options, making it a valuable tool for tackling intricate decision-making problems across various fields, from business and engineering to environmental planning and healthcare. CODAS aids in achieving well-informed decisions that balance diverse criteria and objectives, ultimately leading to more effective and rational choices.

5.4.1.1 Methodology of CODGT-ST Model

Fig. 5.19 illustrates the pipeline of the CODGT-ST model. The dataset is pre-processed to clean the data. First, we evaluate the context and emotion scores and then feed this numerical data into the CODAS algorithm. This gives us the assessment score. Last, we apply the zero-sum game to deduce the sentiment tag for news headlines.

Step 1: Evaluate the context scores and emotion scores of the text: We evaluate the context scores of each news headline by using *Algorithm 4.1* in Chapter 4. To evaluate the emotion scores of the text, we follow *Algorithm 4.2* in Chapter 4. The values obtained from these two algorithms are arranged as a decision matrix and fed to the CODAS technique to generate the assessment scores.

Step 2: Calculate Assessment scores*:* The CODGT-ST model employs two types of distances—Euclidean and Taxicab. The Euclidean distance is preferred as the primary measure, while the Taxicab distance serves as the secondary metric. The negative-ideal-solution distances are used here. Thus, alternatives with longer distances are preferred as a result. *Algorithm 5.8* is used to calculate the assessment scores.

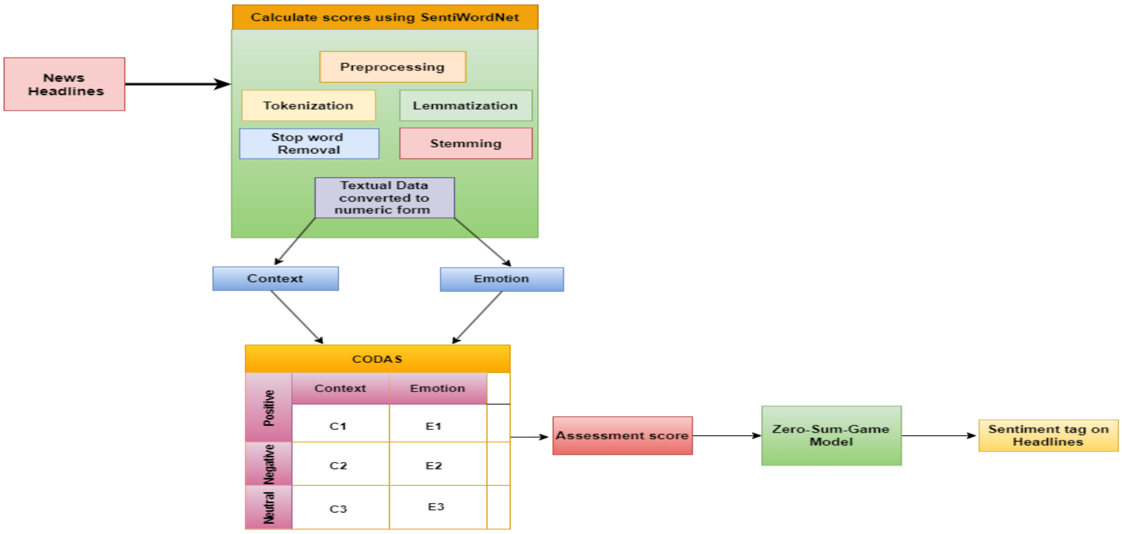

Fig. 5.19: The pipeline of the CODGT-ST model

Algorithm 5.8: Assessment Score Evaluation

Input: *Decision matrix having alternatives and criterions.*

Output: *Assessment score of each review*

1: *Construct a decision matrix* (X).

$$(X) = [c_{ij}]_{n \times m} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nm} \end{bmatrix} \qquad \forall (i,\ j \in Natural\ \ No.)$$

where c_{ij} $(c_{ij} \geq 0)$ *denoted the performance value of* i^{th} *alternative on* j^{th} *criterion.*

2*: Calculate the normalized decision matrix.*

$$n_{ij} = \begin{cases} \dfrac{x_{ij}}{\max\limits_{i} x_{ij}} \ if\ \ j \ \in \ N_b \\ \dfrac{\min\limits_{i} x_{ij}}{x_{ij}} \ if\ \ j \ \in \ N_c \end{cases}$$

where N_b and N_b denote benefit and cost criteria respectively

3: *Calculate the weighted normalized decision matrix* $s_{ij} = w_\tau n_{ij}$ *, where*

$w_\tau\ (0 < w_\tau < 1)$ *denotes the weight of the* j^{th} *criteria* $\sum\limits_{\tau=1}^{m} w_\tau = 1$.

4: *Evaluate the negative-ideal solution* (Ins_j).

$$\left. \begin{aligned} Ins &= [Ins_j]_{1 \times m} \\ Ins_j &= \min_i s_{ij} \end{aligned} \right\}$$

5: *Evaluate Euclidean* (κ_i) *and Taxicab distance* (ξ_i) *from the* (Ins_j).

$$\left. \begin{aligned} \kappa_i &= \sqrt{\sum_{j=1}^{m} (s_{ij} - Ins_j)^2} \\ \xi_i &= \sum_{j=1}^{m} |s_{ij} - Ins_j| \end{aligned} \right\}$$

6: *Evaluate the relative assessment matrix* (R_a). $\quad R_a = [\hbar_{ik}]_{n \times n}$

7: Calculate each alternative's assessment score.

$$\hbar_{ik} = (\kappa_i - \kappa_k) + (\psi(\kappa_i - \kappa_k) \times (\xi_i - \xi_k)) \qquad where \qquad \psi(x) = \begin{cases} 1 & if \quad |x| \geq \tau \\ 0 & if \quad |x| < \tau \end{cases}$$

$$H_i = \sum_{k=1}^{n} \hbar_{ik}$$

Step 3: Play the zero-sum game between each headline: Now we apply the zero-sum game for sentiment tagging. The sentiment analysis task is completed by applying *Algorithm 5.9* and categorizing the strategies as positive, negative, and neutral. Then we give a sentiment tag to each headline and complete the sentiment analysis task. Hence the efficiency of the COGT-ST model on different datasets is presented in *section 5.6.*

Algorithm 5.9: Zero-Sum-Game Algorithm

Input: *Context and emotion score of R_1 and R_2*
Output: *Sentiment tag to each review.*

If(R_1=Positive) then
If (R_2=Positive) print Draw
If (R_2=Negative) print Lost
If (R_2=Neutral) print Win

If(R_1= Negative) then
If (R_2=Positive) print Win
If (R_2=Negative) print Draw
If (R_2=Neutral) print Lost

If(R_1= Neutral) then
If (R_2=Positive) print Lost
If (R_2=Negative) print Win
If (R_2=Neutral) print Draw
Report the error and exit
Draw: display cancel output
Succeed: announce victory and exit.
exist: the program exists

5.4.2 Grey Relational Analysis & Game Theory-based Sentiment Tagger (GRAGT-ST)

In this section, we introduce an approach for sentiment analysis by integrating the Grey Relational Analysis (GRA) MCDM technique and zero-sum game. First, we extract the context and emotion scores of the reviews using *Algorithm 5.1* and *Algorithm 5.8*, respectively. Then we apply the GRA technique that provides GRC scores to each criterion. We follow *Algorithm 5.10* to calculate the GRC scores. Once the grades are received, a zero-sum game (*Algorithm 5.9*) is played among the players to deduce the correct sentiment.

5.4.2.1 GRA Method

The GRA technique is a data analysis and decision-making method widely used in engineering, economics, and various fields where complex systems or processes need to be studied and optimized. GRA is particularly valuable for scenarios involving multiple influencing factors and a limited dataset.

In GRA, data is analyzed to establish relationships or correlations between variables, even when the data is incomplete or uncertain. This technique is based on the concept of "grey systems theory," which allows for the analysis of systems with incomplete information or when data is only partially available. GRA quantifies the relationships between variables by measuring the degree of similarity or proximity between data series, often employing mathematical models and algorithms. The GRA technique offers several advantages, such as its ability to handle uncertainties and incomplete data, making it suitable for real-world problems where precise information may be lacking. It provides insights into the relative importance and influence of various factors, aiding in decision-making, optimization, and prediction tasks. Overall, GRA is a valuable tool for decision-makers, analysts, and researchers seeking to understand complex systems, identify key factors, and make informed choices in situations characterized by ambiguity and limited data. Step-wise procedure is given by *Algorithm 5.10*.

Algorithm 5.10: GRA MCDM Technique

Input: *Decision matrix having alternatives and criteria's.*

Output: *Grey relational grade. Of each headline*

1: *Data normalization between [0 1].*

$$x_i^*(k) = \begin{cases} \dfrac{x_i^\vartriangle(k) - \min x_i^\vartriangle(k)}{\max x_i^\vartriangle(k) - \min x_i^\vartriangle(k)} \rightarrow \textit{For Higher the better} \\ \dfrac{\max x_i^\vartriangle(k) - x_i^\vartriangle(k)}{\max x_i^\vartriangle(k) - \min x_i^\vartriangle(k)} \rightarrow \textit{For Lower the better} \end{cases}$$

2: *Evaluate the deviation sequence by using the formula below*

$$x_i^*(k) = 1 - \frac{|\, x_i^\vartriangle(k) - x_i^\vartriangle \,|}{\max x_i^\vartriangle(k) - x_i^\vartriangle}$$

3: *Evaluate grey relational coefficient (GRC)*

$$\xi_i(k) = \frac{\Omega_{\min} + \xi.\Omega_{\max}}{\Omega_{\Delta i}(k) + \xi.\Omega_{\max}}$$

Where, $\Omega_{\Delta i}(k) = |\, x_i^\vartriangle(k) - x_i^\vartriangle \,|$ *and* $\Omega_{\max} = 1, \Omega_{\min} = 0$

4: *Estimate grey relational grade.*

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \omega_k \xi_i(k)$$

5.4.3 Performance Evaluation

In this section, we first discuss the datasets and compare the performances with existing approaches as shown in further subsections.

5.4.3.1 Datasets

For a comparison of the proposed model, we used four datasets. Data statistics of the datasets are mentioned in *Table 5.31*.

Table 5.31: Data statistics of the collected Dataset

S. No.	Data Set	Positive Class	Negative Class
1	SemEval 2017 Task 5	450	550
2	S&P CNX NIFTY	655	345
3	WIPRO and INFOSYS news dataset	549	451

5.4.3.2 Evaluation of the proposed models with existing approaches

We conducted a comparative analysis of the CODGT-ST and GRAGT-ST models against existing approaches, as depicted in *Fig. 5.20*, using three different datasets. Atzeni et al. [30] introduced an N-gram method for sentiment classification, achieving an accuracy of approximately 0.78, which is notably lower than the performance of the CODGT-ST and GRAGT-ST models. Furthermore, the author [32] conducted a comparison between the SVM and CNN [33] models, with reported accuracies of 0.68 and 0.3127, respectively. Dridi et al. [31] employed Ridge regression with Stochastic Gradient Descent (SGD) on the dataset, achieving an accuracy of 0.68 across the three datasets. In contrast, both CODGT-ST and GRAGT-ST models achieved higher accuracies of 0.78 and 0.82, respectively. As depicted in *Fig. 5.20,* these results demonstrate the promising accuracy of the CODGT-ST and GRAGT-ST models on these Datasets.

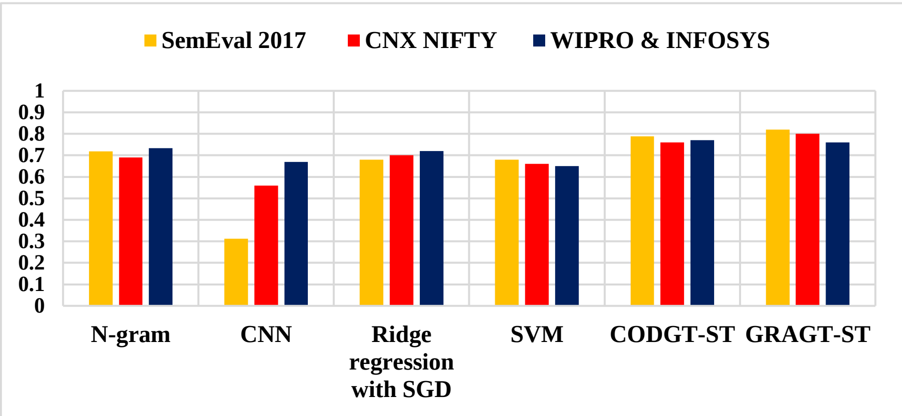

Fig. 5.20: Comparison of supervised approaches with a proposed model

5.5 Discussion

In this section, we first validate the results of approaches discussed in this chapter using the statistical z-test method. Later, we discuss the challenges posed by the proposed models.

i) Statistical validation of the algorithms: We perform the statistical Z-test on two proportions to verify the effectiveness of the SOTM, TOGT-ST, LESTG, CODGT-ST, and GRAGT-ST models. Two distinct samples are extracted from datasets of different domains.

To apply the test, we first define the null hypothesis (H_o) and alternate hypothesis (H_a) as given below:

H_o: $p_1 = p_2$, i.e., the accuracy of *sample* 1 (*S1*) is equal to the accuracy of *sample* 2 (*S2*)
H_a: $p_1 \neq p_2$, i.e., the accuracy of *sample* 1 (*S1*) is not equal to the accuracy of *sample* 2 (*S2*)

Two population proportions are analyzed using a two-tailed test given by *Equation* (*5.20*) and a z-test. The z-statistic is computed using *Equation* (*5.32*).

$$P = \frac{X_1 + X_2}{N_1 + N_2} \tag{5.20}$$

$$z = \frac{p_1 - p_2}{\sqrt{P(1-P)(1/n_1 + 1/n_2)}} \tag{5.21}$$

Table 5.32: Two Proportion Z-Test statistics across different models

Models →	SOTM		TOGT-ST		LESTG		CODGT-ST		GRA-GT-ST	
Parameters ↓	**S1**	**S2**	**S1**	**S2**	**S1**	**S2**	**S1**	**S2**	**S1**	**S2**
Sample Size (n_1)	450	356	378	786	1000	500	1565	1878	1987	1289
Sample Proportion (p_1/p_2)	0.97	0.89	0.735	0.876	0.923	0.9	0.957	0.95	0.945	0.922
Favorable cases (X_1)	437	320	278	689	923	450	1498	1789	1879	1189
P	0.9355		0.8308		0.915		0.953		0.923	
Z	4.564		-6.00		1.5084		0.968		1.23	
Hypothesis Status	H_o is not rejected		H_o is not rejected		H_o is not rejected		H_o is not rejected		H_o is not rejected	

The obtained results are tabulated in *Table 5.32*. Based on the statistical analysis results, the null hypothesis (H_o) is not rejected, indicating a lack of sufficient evidence to support the claim that the population proportions p_1 and p_2 are different at the 0.05 significance level. Hence, it can be concluded that there is insufficient statistical support to assert a significant disparity between the two proportions. This suggests that the percentage of correctly classified reviews remains consistent across datasets with different sample sizes. As a result, it can be inferred that the proposed models consistently produce reliable outcomes.

ii) Challenges of the Proposed Model for Text: For sentiment analysis of text the lexicon database used is either SWN for English or HSWN for Hindi. The incompleteness of these lexicon databases is a significant contributor to the algorithm's diminished efficacy. The word inventories are not exhaustive, and a few words have incorrect sentiment evaluations as well. The proposed systems are also incapable of correctly analyzing statements containing sarcasm or irony. *Table 5.33* contains the examples where the proposed models failed to detect the correct sentiment tags.

Table 5.33: Examples where the proposed models fail.

Reviews	Challenges	Actual	Predicted
"I do not dislike noodles."	Phrases with negation	Positive	Negative
"Thnk u 4 the treat in @ Phonenix Palladium. "	Special characters and slang	Neutral	Negative
"Someone who works as a pizza man does not like pizza?"	Irony	Neutral	Positive
"Pizza is tasty but not at that price."	Tone	Positive	Negative

5.6 Summary

This chapter presents a model for text sentiment classification using Multiple Criteria Decision Making (MCDM) and non-cooperative game models. The goal is to provide a strong framework for textual sentiment analysis and classification. In this chapter, we introduced numerous sentiment tagger models like SOTM, ABRM, TOGT-ST, LESTG, CODGT-ST, and GRAGT-ST. All these proposed methodologies use either the parameters of the reviews, like context, emotion, or rating scores, to generate the combined performance score that can be used as a payoff for playing a game between reviews. We used datasets from numerous domains in either of the two languages (Hindi and English). The macro F1-score of SOTM is 0.89. where ABRM ranks different aspects of the customer reviews. TOGT-ST's average F1 score on different datasets is 0.93. Similarly, the LESTG model is implemented on a two-language dataset. LESTG archived an accuracy of 0.96 on English electronic reviews and 0.84 on Hindi hotel reviews. The highest accuracy of the CODGT-ST model is 0.78 on the SemEval-2017 task dataset. The last model, GRAGT-ST, has an accuracy of 0.87 on the INFOSYS dataset. As a result, the LESTG model displays the best performance out of five. We summarize that an integrated framework paves the path to different NLP tasks to enhance accuracy.

Chapter 6

Sentiment Classification of Hindi Written Reviews

This chapter focuses on generating a sentiment tagger for the Hindi language. According to the survey, Hindi is the third most spoken language after English and Mandarin. As a result, the amount of Hindi content available on the internet continues to rise through weblogs, blogs, reviews, and recommendations. In this work, we targeted Hindi languages for sentiment classification we focus on providing a framework to perform unsupervised sentiment analysis using MCDM and game theory optimization techniques. This chapter aims to generate unsupervised techniques for Hindi reviews.

The organization of this chapter is as follows. In *section 6.1* we introduce MOORA & Game theory model Sentiment Tagger (MOOGT-ST) for Hindi Text and discuss its methodology and its comparison with existing approaches. In *Section 6.2* we presented COPRAS and Game Theory-Based Sentiment Tagger (COGT-ST). COGT-ST uses COPRAS and a non-cooperative game model for the text. In *section 6.3* we collected the Hindi dataset and implemented these models on these datasets of numerous domains. Results are compared with the existing approaches. In *section 6.4* we discuss various aspects of these models and validate them statistically. In *section 6.5* we conclude the chapter paving its future scope.

6.1 MOORA & Game Theory Model-based Sentiment Tagger (MOOGT-ST)

This section introduces integrated MCDM and Game theory framework. We used integrated MOORA and non-cooperative game models. We named this integrated mathematical framework "*MOORA & Game Theory Model Based Sentiment Tagger"* (*MOOGT-ST*). The MOORA technique is proposed by Brauers [202]. Multi-objective (or programming) optimization, also known as multi-criteria or multiple-attribute optimization, is improving two or more competing attributes (goals) simultaneously while adhering to given constraints.[202]. The MOORA technique begins with constructing the problem's decision matrix. The columns and rows of the decision matrix contain the criteria and alternatives, respectively. The complete procedure of MOORA is explained in *Algorithm 6.2*. At the end, we get the ranking score of each alternative. To calculate the performance of each review and then allowed to play the game model between two players, which at the end reached an optimal point known as Nash equilibrium. Then we get the deduced sentiment tag to the Hindi reviews dataset. We identify a review's sentiment's positive, negative, and neutral orientations. We leverage context scores derived from textual comments utilizing the HSWN lexicon and star rating scores to acknowledge a review.

6.1.1 Proposed Methodology

The MOOGT-ST model generally consists of four phases. Each of these phases' steps is described below in *Fig. 6.1*.

(i) Extracting data characteristics, such as customer evaluations and ratings.
(ii) Creating a decision matrix using alternatives and criteria.
(iii) Assigned each criterion an equal weight of 0.5.
(iv) Carrying out a MOORA MCDM analysis to evaluate the performance score of each review.
(v) Performance scores evaluated from the MOORA technique will be considered as a payoff for playing a game between two players.

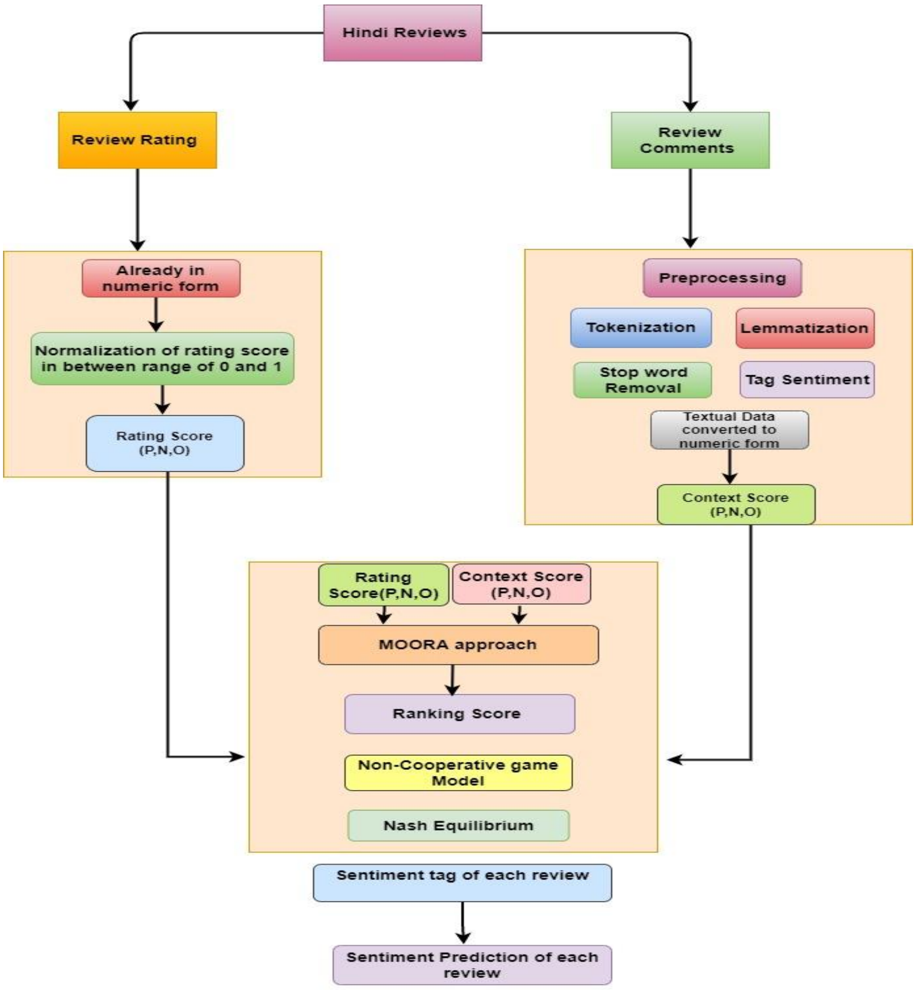

Fig. 6.1: A pipeline of the proposed model for sentiment analysis of reviews

6.1.2 Payoff Computation

For generating the payoffs for playing a game between two players, we calculate context and rating scores using steps 1 and step 2 for generating a decision matrix. Initially for constructing a decision matrix, we have three alternatives and two criteria. Alternatives are positive, negative, and neutral. Similarly, two criteria rating and context are evaluated using *step 1* and *step 2.*

Step 1: Context Score evaluation (Criteria 1): The first criterion in this case is context score. Determine the context score of the review comment using HSWN. First, we use HSWN [203] to assign a context score to the textual comments using *Algorithm 6.1.*

Algorithm 6.1: Contextualizing the reviews' scores.

Input: *W – Set of words in each review, HSWN – HindiSentiWordNet.*

Output: *Context Score of i^{th} review C = {CP, CN, CO}, where CP = positive sentiment value, CN = negative sentiment value, CO = neutral sentiment value.*

1: *Initialize CP = CN = CO = 0.*

2: *Take $W = \{w_1, w_2, \ldots, w_n\}$* // *where w_i represents the i^{th} ($1 \leq i \leq n$) word in the review.*

3: *Calculate_Context_Score*
If ($w_i \in$ HSWN) then

$$CP = \frac{\text{Positive sentiment score of } w_i}{n} \rightarrow \gamma_1$$

$$CN = \frac{\text{Negative sentiment score of } w_i}{n} \rightarrow \gamma_2$$

$$CO = \frac{(1-(CP+CN))}{n} \rightarrow \gamma_3$$

// *Word count (n) in collection W*

Step 2: Rating Score Evaluation (Criteria 2): The second criterion for constructing a decision matrix is rating score. We aggregate all the criteria and alternative numeric values in this step. There are two criteria for context and rating; each criterion has three alternative degrees positive, degree of negative, and degree of neutral. The alternative scores pertaining to context criteria are evaluated using the HSWN lexicon, which ranges between 0 and 1. The alternative scores for rating criteria are evaluated using *Equations (6.1) - (6.6)* Where *p* is the given rating of the product, we consider a positive rating (*P*). Similarly, following *Equations (6.1) - (6.3*), we evaluate negative (N) and neutral ratings (O). We normalized these alternative scores using *Equations (6.4) - (6.6*) and renamed them *dP, dN,* and *dO.* Now, these values lie between *0* and *1.*

$$\text{Positive rating (P)} = p \tag{6.1}$$

$$\text{Negative rating (N)} = 5\text{-}p \tag{6.2}$$

$$\text{Neutral rating (O)} = 5 - (P\text{-}N) \tag{6.3}$$

$$\text{Degree of Positive rating,} \quad dP = \frac{p}{P+N+O} \tag{6.4}$$

$$\text{Degree of Negative rating,} \quad dN = \frac{5-p}{P+N+O} \tag{6.5}$$

$$\text{Degree of Neutral rating,} \quad dO = \frac{5-(P-N)}{P+N+O} \tag{6.6}$$

6.1.3 Deducing Sentiment Tag using MCDM Techniques

Now to create a decision matrix for the MOORA technique we have three alternatives and two criteria. Alternatives are the degree of positive (*dP*), negative (*dN*), and neutral (*dO*) and criteria are context and rating of the review denoted by *V*. We follow *Algorithm 6.2* for evaluating payoff from MOORA and evaluate the ranking score by passing the decision matrix through *Algorithm 2. Equation (6.7)* represents the decision matrix for the MOORA technique where *dP, dN*, and *dO* are alternatives. Where C_1, C_2, and C_3 are the numeric values of context criteria Similarly E_1, E_2, and E_3 are the numeric values of emotion criteria corresponding to these three alternatives.

$$V = \begin{array}{c} dP \\ dN \\ dO \end{array} \begin{bmatrix} C_1 & E_1 \\ C_2 & E_2 \\ C_3 & E_3 \end{bmatrix}_{3\times 2} \tag{6.7}$$

Algorithm 6.2: MOORA Method for Sentiment Tagging of Reviews

Input: *Decision matrix* $V = [v_{ij}]_{3\times 2}$

Output*: Ranking of alternatives.*

1: *Calculate the score* v_{ij} *of two criteria against three alternatives.*

2: *Normalize the score.*

$$v_{ij}^{*} = \frac{v_{ij}}{\sqrt{\sum_{i=1}^{m} v_{ij}^{2}}} \quad \forall\ i,\ j \in \{1, 2\}$$

3: *Take the weight w_i=0.5 for both criteria.*

4: *Sum of the weighted beneficial criteria.*

$$p_i = \sum_{j=1}^{g} w_j v_{ij}^{*}$$

5: *Sum of the weighted non-beneficial criteria.*

$$r_i = \sum_{j=g+1}^{n} w_j v_{ij}^{*}$$

6: *Calculate* y_i^* *for each alternative.*

$$y_i^* = p_i - r_i$$

7: *Ranking* $A_i > A_j$ *if* $y_i^* > y_j^*$.

6.1.4 Sentiment Orientation Tagging using the Non-Cooperative Game Model

Now, we can play the non-cooperative game between two players (R_1 and R_2) using *Algorithm 6.3*. The payoff for playing the non-cooperative game, we need two players

(R_1 and R_2), and these players have three strategies (Positive, Negative, and Neutral). Ranking scores calculated using *Algorithm 6.2* will be taken as a payoff for R_1 and R_2. Ranking scores of R_1 is ψ_1, ψ_2, ψ_3, and ranking scores of R_2 is π_1, π_2, π_3. So, possible combinations of ranking scores of R_1 and R_2 in normal form representation are shown in *Table 6.1*. We follow *Algorithm 6.3* to reach the Nash equilibrium. After getting Nash equilibrium, the strategies corresponding to these payoffs of Nash Equilibrium are the deduced tag to each review.

Table 6.1: Normal form representation of the game played between R_1 and R_2.

Players → ↓		***R₂***		
	Strategies → ↓	***P***	***N***	***O***
R₁	***P***	(ψ_1, π_1)	(ψ_1, π_2)	(ψ_1, π_3)
	N	(ψ_2, π_1)	(ψ_2, π_2)	(ψ_2, π_3)
	O	(ψ_3, π_1)	(ψ_3, π_2)	(ψ_3, π_3)

Algorithm 6.3: Deduce sentiment tag for review

Input: *Appraisement scores* $\{\psi_1, \psi_2, \psi_3\}$ *for review* R_i *and* $\{\pi_1, \pi_2, \pi_3\}$ *for review* R_j

Output: *Sentiment Tag for* R_i *and* R_j, *i.e.,* $\{R_1, R_2\} \in \{P, N, O\}$.

1. *Generate a Normal form matrix for players* R_i *and* R_j *using the appraisement scores.*

2. *Compute dominant strategies for* R_i, *i.e.* (DR_i) *and* R_j *i.e.* (DR_j), *where* DR_i, DR_j *belongs to {P, N, O}*

3. *Compute Nash equilibrium (NE), where NE =* DR_i *intersection* DR_j.

4. *The strategies corresponding to NE are the sentiment tags for reviews* R_i *and* R_j.

6.1.5 Illustrative Example on MOOGT-ST Model

We take a Hindi review comment and rating from the online review dataset depicted below and use the MOORA method to generate a sentiment tag, which is in detail below.

Illustrative Example 1

R_1: (*4 star*) *" मुझे यह पसंद है! मेरे फोन का हेडसेट जैक छोटा है, इसलिए यह वास्तव में एक अलग एडेप्टर की आवश्यकता के बिना फिट बैठता है। यह सीधे जैक में जुड़ा। वाह! मैं आकार भूल जाता हूं, लेकिन मुझे यकीन है कि यह इस उत्पाद की जानकारी के विनिर्देश अनुभाग में है। यह वही करता है जो मैं चाहता था। "*

"I am liking this! My phone's headset jack is small, so this actually fit WITHOUT needing a separate adapter. It connected right into the jack. Yay! I forget the sizes, but I am sure it is in the specification section of this product's information. It does just what I wanted."

"mujhe yah pasand hai! mere phon ka hedaset jaik chhota hai, isalie yah vaastav mein ek alag edeptar kee aavashyakata ke bina phit baithata hai. yah seedhe jaik mein juda. vaah! main aakaar bhool jaata hoon, lekin mujhe yakeen hai ki yah is utpaad kee jaanakaaree ke vinirdesh anubhaag mein hai. yah vahee karata hai jo main chaahata tha."

R_2: (1 star)" हमने कॉर्न चीज़ बॉल्स, मैंचो सूप और पनीर शशलिक सिज़लर ऑर्डर किए। सिज़लर बासी था। पनीर की महक आ रही थी और वेटर इतनी बदतमीजी कर रहा था कि गलती तक स्वीकार नहीं कर सका। फिर कभी नहीं जा रहा |"

"We ordered Corn Cheese Balls, Mancho Soup and Paneer Shashlik Sizzler. The sizzler was stale. The smell of cheese was coming and the waiter was so abusive that he could not even admit the mistake. never going again"

"hamane korn cheez bols, maincho soop aur paneer shashalik sizalar ordar kie. sizalar baasee tha. paneer kee mahak aa rahee thee aur vetar itanee badatameejee kar raha tha ki galatee tak sveekaar nahin kar saka. phir kabhee nahin ja raha"

MOORA requires criteria that affect the alternatives in their computations. *Table 6.2* shows that the criteria and alternatives chosen in this study are context (C_1) and rating (C_2). Both criteria are equally important. We considered equivalent weights, i.e., 0.5 for context and 0.5 is rating. We follow *Algorithm 6.3* to perform sentiment tagging of reviews.

Table 6.2: Criteria description of the reviews.

Criteria	Weights	Type
Context (C_1)	0.5	Beneficial
Rating (C_2)	0.5	Beneficial

We first construct the decision matrix shown in *Table 6.3*. Following *Algorithm 6.2,* we get the ranking score mentioned in *Table 6.2* of R_1 and R_2. Then following *Algorithm 6.3*, we apply the non-cooperative game model. *Table 6.5* is the normal form representation of the game model; then, using the principle of Nash equilibrium, we deduce the sentiment orientation of both reviews, as mentioned in *Table 6.6*.

Table 6.3: Numeric Scores of Criteria and Alternative.

Criteria →	Context		Rating	
Alternative ↓	R_1	R_2	R_1	R_2
Positive (A_1)	0.075949	0.89	0	0.571
Negative (A_2)	0.047059	0.21	1	0.143
Neutral (A_3)	0.971109	0.11	0	0.43

Table 6.4: Final performance score of both the reviews.

R_1 (4 stars)		R_2 (1 star)
Alternative ↓	Performance Score	Performance Score
Positive (A_1)	0.00161	-0.03797
Negative (A_2)	-0.00664	0.476471
Neutral (A_3)	-0.30510	-0.48555

Table 6.5: Non-cooperative game model for deducing sentiment tag.

	R_2			
R_1		**Positive (A_1)**	**Negative (A_2)**	**Neutral (A_3)**
	Positive (A_1)	(0.00161, -0.3797)	**(0.00161,0.476471)**	(0.00161, 0.48555
	Negative (A_2)	(-0.00664, -0.3797	(-0.00664,0.476471)	(-0.00664,0.48555)
	Neutral (A_3)	(-0.30510, -0.3797)	(-0.30510, 0.476471)	(-0.30510, -0.48555)

Table 6.6: Deduced tag using the game model.

	R_2		
R_1		**Positive (A_1)**	**Negative (A_2)**
	Positive (A_1)	(0.00161, -0.3797)	**(0.00161,0.476471)**

The Nash equilibrium of the game model played between two players is (0.00161,0.476471), and the strategies corresponding to the payoff are positive and negative. Tag deduction shows that R_1 is positive while R_2 is negative. In the following way, we deduced the sentiment tag of each review. We deduced the sentiment tag using the MOOGT-ST model.

We implemented the proposed model by collecting data from the Hindi reviews dataset. The results were then compared to conventional approaches. Several metrics were analyzed, and their efficacies were inspected. To demonstrate the model's language independence, we applied it to an English dataset and analyzed the encouraging results.

6.2 COPRAS and Game Theory-Based Sentiment Tagger (COGT-ST)

In this subsection, we introduce "*COPRAS and Game Theory-Based Sentiment Tagger* (*COGT-ST*)". We use the COPRAS MCDM technique to present a framework for tagging reviews with sentiment based on ratings and customer comments. The model generally consists of three phases: **(i)** extracting data characteristics, such as customer evaluations and ratings; **(ii)** creating a decision matrix based on attributes; and **(iii)** carrying out an MCDM analysis. This is the first step in extracting features from competitors' products. The extracted characteristics are transformed into a decision matrix in the second phase. In the third phase, we assigned each criterion an equal weight of 0.5 and then ranked the reviews using the COPRAS method. The final tag for this review is the alternative that receives the highest rank. Each of these phases' steps is described below in *Fig. 6.2*. Below are the steps from step 1 to step 3 for sentiment tagging of the Hindi reviews.

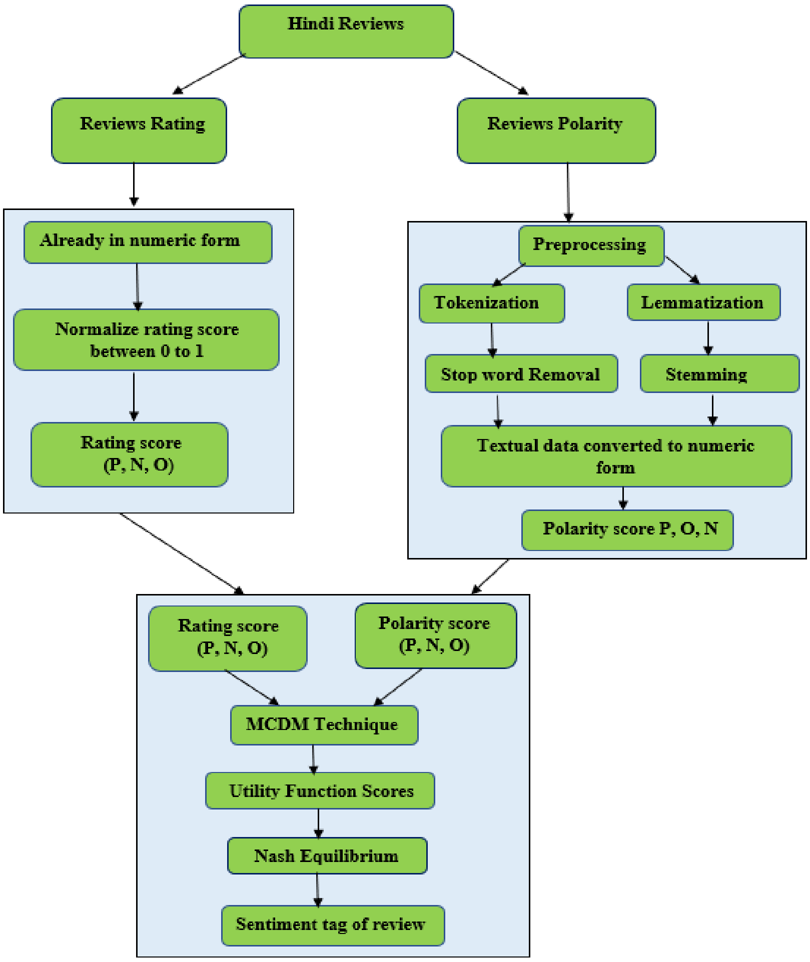

Fig 6.2: A pipeline of the COGT-ST model for sentiment analysis of reviews.

Step 1: Polarity/Context & Rating Score Evaluation (Criteria 1 & 2): In this step, we create and construct a decision matrix using two criteria and three alternatives. For COGT-ST the two criteria which we had considered are polarity and rating. To determine the polarity/context score of textual comments using (HSWN)[203]. We follow *Algorithm 6.1* to generate the sentiscores of the Hindi comments. Similarly, we evaluate rating scores following *subsection 6.1.2* for generating a decision matrix of the reviews. Then we get the rating and polarity/context score from this step for constructing the decision matrix.

Step 2: COPRAS MCDM Technique: We perform the COPRAS method following *Algorithm 6.4*. It generates the utility value by integrating rating and polarity scores which will work as a payoff for the non-cooperative game model.

Algorithm 6.4: MCDM Method for sentiment tagging of reviews

Input: *Rating and Polarity scores of the review.*

Output: *Utility value of the reviews.*

1: *Construct a decision matrix* x_{ij}.

2: *Normalize the decision matrix* (X^*_{ij}), $X^*_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$

3: Calculate Normalized Decision-Making (d_{ij}), $d_{ij} = X^{*}_{ij}.w_j$

4: Calculate Maximum (S_{i+}) *and Minimum Indexes* (S_{i-}) *for each alternative.*

$$S_{i+} = \sum_{j=1}^{k} d_{ij} \quad and \quad S_{i-} = \sum_{j=k+1}^{n} d_{ij}$$

5: Calculate Weighted averages (Q_i), $Q_i = S_{+i} + \dfrac{\min S_{-i} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \dfrac{\min S_{-i}}{S_{-i}}} \cong S_{+i} + \dfrac{\sum_{i=1}^{m} S_{-i}}{\sum_{i=1}^{m}\left(\dfrac{1}{S_{-i}}\right)}$

6: Calculate the order of alternatives $(A^{\otimes})$, $A^{\otimes} = \{A_i \mid \max_i Q_i\}$

7: Calculate the Utility value (U_i), $U_i = \dfrac{Q_i}{Q_{\max}} \times 100\%$

Step 3: Non-cooperative Game played between R_1 and R_2: The non-cooperative game between two players (R_1 and R_2) is now played. Two players (R_1 and R_2) with three different strategies (Positive, Negative, and Neutral) are required to play the non-cooperative game. Utility values are calculated using *Algorithm 6.4* and will be taken as a payoff for R_1 and R_2. Utility value of R_1 is $\lambda_1, \lambda_2, \lambda_3$, and Utility value of R_2 is $\omega_1, \omega_2, \omega_3$.So possible combinations of the Utility value of R_1 and R_2 are shown in *Table 6.7*. We follow *Algorithm 6.5* to reach the Nash equilibrium. After achieving Nash equilibrium, each review's determined tag is comprised of the strategies that correlate to these payoffs of Nash equilibrium.

Table 6.7: Normal form representation of game played between two reviews.

	Positive	**Negative**	**Neutral**
Positive	(λ_1, ω_1)	(λ_1, ω_2)	(λ_1, ω_3)
Negative	(λ_2, ω_1)	(λ_2, ω_2)	(λ_2, ω_3)
Neutral	(λ_3, ω_1)	(λ_3, ω_2)	(λ_3, ω_3)

Algorithm 6.5: Deduce sentiment tag for review

***Input**: Utility value* $\{\lambda_1, \lambda_2, \lambda_3\}$ *for review R_i and* $\{\omega_1, \omega_2, \omega_3\}$ *for review R_j*

***Output**: Sentiment Tag for R_i and R_j, i.e.,* $\{R_1, R_2\} \in \{P, N, O\}$.

***1:** Generate a normal form matrix for players R_i and R_j using the appraisement scores.*

***2:** Compute dominant strategies for R_i, i.e. (DR_i) and Rj i.e. (D_j), where DR_i, DR_j belongs to {P, N, O}*

***3:** Compute Nash equilibrium (NE), where NE = DR_i intersection DR_j.*

***4:** The strategies corresponding to NE are the sentiment tags for reviews R_i and R_j.*

6.2.1 Illustrative Example on COGT-ST Model

We take a Hindi review comment and rating from the online review dataset depicted below and use the COPRAS method to generate a sentiment tag, which is discussed in illustrative *example 1* in *section 6.1.5.* Then we apply the COGT-ST model. Initially, we apply the COPRAS MCDM technique. COPRAS requires criteria that affect the alternatives in their computations. Table 6.8 shows that the criteria chosen in this study are polarity (C_1) and rating (C_2). Both criteria are equally important. We considered equivalent weights, i.e. 0.5 for polarity and 0.5 is rating. Numeric scores of criteria and alternatives are shown in *Table 6.9.*

Table 6.8: Criteria description

Criteria	Weights	Type
Polarity (C_1)	0.5	Beneficial
Rating (C_2)	0.5	Beneficial

First, we calculate the numeric score of alternatives and criteria as shown in *Table 6.9.* Using *Algorithm 6.4*, we obtain the utility value for R_1 and R_2 which is shown in *Table 6.10.* The non-cooperative game concept is then put into practice using Algorithm 3. The game model is presented in *Table 6.11* in normal form. Using the idea of Nash equilibrium, we next ascertained the sentiment orientation of both reviews, which is presented in *Table 6.12.*

Table 6.9: Numeric Scores of Criteria and Alternative

Criteria →	**Context**		**Rating**	
Alternative ↓	**R_1**	**R_2**	**R_1**	**R_2**
Positive (A_1)	0.075949	0.89	0	0.571
Negative (A_2)	0.047059	0.21	1	0.143
Neutral (A_3)	0.971109	0.11	0	0.43

Table 6.10: Utility value score from MCDM

R_1 (4 stars)		**R_2 (1 star)**
Alternative ↓	**Performance Score**	**Performance Score**
Positive (A_1)	0.6102	0.07594
Negative (A_2)	0.01328	0.9528
Neutral (A_3)	0.00322	0.9711

Table 6.11: Non-cooperative game model for deducing sentiment tag

	R_2			
R_1		**Positive (A_1)**	**Negative (A_2)**	**Neutral (A_3)**
	Positive (A_1)	(0.6102, 0.07594)	(0.6102, 0.9528)	(0.6102, 0.9711)
	Negative (A_2)	(0.01328, 0.07594)	(0.01328, 0.9528)	(0.01328, 0.9711)
	Neutral (A_3)	(0.00322, 0.07594)	(0.00322, 0.9528)	(0.00322, 0.9711)

Table 6.12: Deduced tag using the game model

	R_2			
R_1		**Positive (A_1)**	**Negative (A_2)**	**Neutral (A_3)**
	Positive (A_1)	(0.6102, 0.07594)	(0.6102, 0.9528)	**(0.6102, 0.9711)**

The Nash equilibrium of the game model played between two players is (0.6102, 0.9711) and the strategies corresponding to the payoff are positive and negative. The deduced tag of the R_1 is positive, and R_2 is negative. In the following way, we deduced the sentiment tag of each review. We deduced the sentiment tag using the COGT-ST model. We combined the polarity and rating scores of reviews, evaluated the performance score, and deduced each review's sentiment orientation.

6.3 Experimentation & Evaluation

In this section, we collected Hindi reviews of different domains and then compared them with various approaches then in the discussion section we address various aspects of this chapter like macro-micro, statistical validation, and various challenges of the proposed approaches for the Hindi language dataset.

6.3.1 Data Collection

We applied the suggested technique to three sets of data that included ratings and comments written in Hindi. The first dataset was the movie reviews dataset crawled from online sources[21]. Second, we crawled hotel reviews and ratings from online[22] sources. The third dataset is the subset of the Amazon electronics[23] dataset. Each dataset contains 1000 reviews and ratings. *Table 6.13* shows the data statistics of the three collected datasets.

Table 6.13: Data statistics of different datasets.

Data Set	Language	Positive	Negative	Neutral
Movies reviews	Hindi	512	350	138
Hotel reviews	Hindi	657	132	211
Electronics reviews	Hindi	576	292	132

6.3.2 Evaluation on the Movie Dataset

We calculated accuracy, precision, recall, and the F-measure on movie review datasets to compare performance. Essentially, all of these measures assess the same qualities and, as a result, generate remarkably similar values for a dataset.

[21] *"Internet Movie Database, http://www.imdb.com"*

[22] *"https://www.tripadvisor.in/Restaurants"*

[23] *"https://jmcauley.ucsd.edu/data/amazon/"*

Table 6.14: Comparison of different approaches with the proposed approaches.

S. No.	Unsupervised Method	Accuracy	F-measure	Precision	Recall
1	SWN(VS+APS)[204]	0.63	0.64	0.63	0.63
2	Naïve bayes[205]	0.71	0.75	0.75	75
3	HSWN[206]	0.60	0.46	0.60	37.5
4	RNN[207]	0.72	0.70	0.72	0.71
5	CNN-SVM[84]	0.65	0.64	0.6	0.66
6	CSPL+HSWN[199]	0.76	0.73	0.75	0.74
7	LSTM+CNN[208]	0.78	0.76	0.77	0.76
8	COGT-ST	0.8	0.85	0.87	0.81
9	MOOGT-ST	0.82	0.87	0.84	0.84

Singh et al. [204] proposed SentiWordNet techniques for sentiment classification of Hindi movie reviews with an accuracy of 63.42 %, shown in Table 6.14. Bhoir et al. [205] proposed two models, Naïve Bayes, having an accuracy of 71%. Joshi et al. [206] developed the Hindi-SentiWordNet (HSWN) lexical resource for sentiment analysis of a Hindi movie dataset, with an accuracy of 60%. Seshadri et al. [207] proposed an RNN model whose accuracy is 72%. Akhtar et al. [84] proposed a CNN-SVM model whose accuracy is 65.96%. Mishra et al. [199] created the (CSPLE + HSWN) model with 76.5% accuracy. Jain et al.[208] has introduced the Hindi Text classification using optimization techniques. COGT-ST archives an accuracy of around 80% whereas MOOGT-ST accuracy is 82%. Hence both proposed models outperform the existing approaches as illustrated in *Table 6.14*.

6.3.3 Evaluation on the Hotel Dataset

Mishra et al., [199] introduced the HSWN, CSPL+HSWN, and CSPLE, with respective accuracy rates of 46 %, 85 %, and 82.5 %, and error rates of 54 %, 15 %, and 17.5 %; among these models, CSPL+HSWN had the greatest accuracy rate of 85 %. Akhtar et al.[83] embedded vectors from the CNN. The sentiment-augmented optimized vector obtained at the end is used for SVM training for the proposed model's sentiment classification accuracy of 77.16%. Below, *Fig. 6.15* depicts the accuracy and error rate of all the approaches where green bars denote these models' accuracy in predicting the sentiment tagging and red bars denote the error rate compared to the proposed model. Fig. 6.15 illustrates that the proposed model's accuracy is 91 %, greater than the other approaches, and recorded the lowest error rate of 9 %, indicating that the results predicted by the proposed MCDM method are more accurate. COGT-ST model archives the F1-score of around 81% whereas the MOOGT-ST archives an accuracy of around 82%. Hence both the proposed models produced a state-of-art comparison with other approaches as shown in the *Fig. 6.3*.

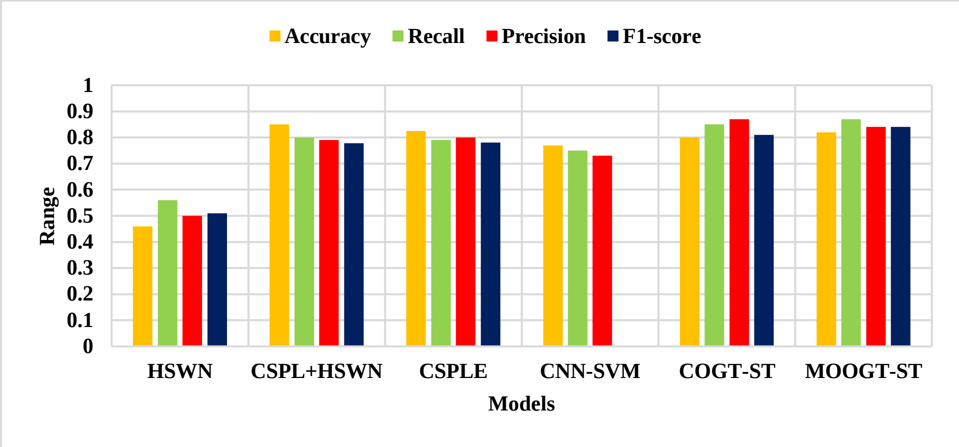

Fig. 6.3: Comparison of existing approaches with proposed models in terms of evaluation measures.

6.3.4 Evaluation on the Electronic Dataset

Fig. 6.4 depicts the performance comparisons of the proposed approach with other models on the same dataset that outperform the other model in all respects. Jha et al.[20] proposed the HMDSAD dictionary-based approach to classify unlabelled reviews from the target domain into positive, negative, and neutral categories. This approach had an accuracy of 56%, and the error rate recorded was 44% over the electronics reviews[24] dataset. HSWN [77] is a comprehensive lexicon covering the polarity of words in the Hindi language. It contains the following fields: POS tag, Synset ID (WordNet ID in Hindi), Positive score, Negative score, and Related Terms (separated by a comma). The accuracy recorded for this lexicon-based method is 31% and 69%, which is higher than the existing approaches. Akhtar et al.[83] developed the embedded vectors from a Convolutional Neural Network(CNN). The sentiment-augmented optimized vector is used to train the SVM for sentiment classification, and the supervised CNN-SVMS model has an accuracy of 68.04 %, and an error rate is around 32%. Singh et al. [200] pre-processed the Hindi texts and identified their English equivalents, and a summary review was then calculated using the HSWN database. As is evident from the table, the technique offered by Singh et al. is 31.48 % less effective than the proposed model with 48% accuracy. The classification accuracy of the decision trees classifier is 54%, and this supervised method is 25% less efficient than the proposed model, and the recorded rate is 45% [201]. COGT-ST model archive the accuracy, recall and F1-score for electronic reviews are as 82%, 87% and 84%. Similarly, MOOGT-ST archive the recall of around 87% as shown in *Fig. 6.4*.

[24] "*https://jmcauley.ucsd.edu/data/amazon/*"

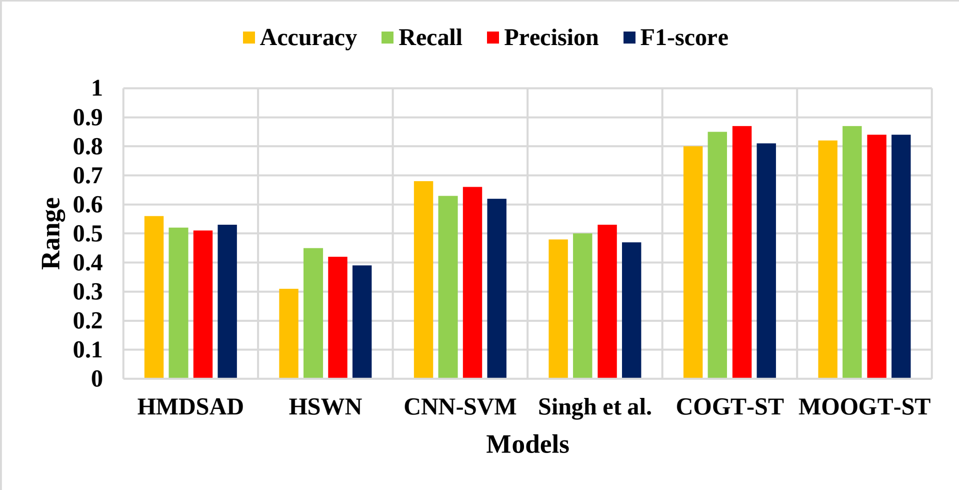

Fig. 6.4: Comparison of existing approaches with the proposed models in terms of evaluation measures.

6.4 Discussion

Here we discuss various aspects of the proposed models such as macro -micro assessment, statistical validation of both approaches, and various challenges of the proposed framework.

i) Macro and Micro Assessment: We used macro and micro averages to evaluate progress across multiple data sets. Macro-average first calculates metrics for each class individually, then takes their average (thus treating all classes equally). The F1 score, Macro recall, and Macro precision are all 0.78, 0.87, and 0.89, respectively. Micro-average determines the mean measure by summing the contributions of each class. When the quantity of datasets varies, this statistic helps assess performance. Micro achieves a precision of 0.87, a recall of 0.92, and an F1-score of 0.90. Macro and micro level descriptions of accuracy, F-score, and recall over all n datasets may be found in *Equations (1.13)* to *(1.18)*. When estimating overall performance, we consider both bilateral and multilateral averages as we explore various data sets. *Fig. 6.5*. displays the combined outcomes from the three data sets.

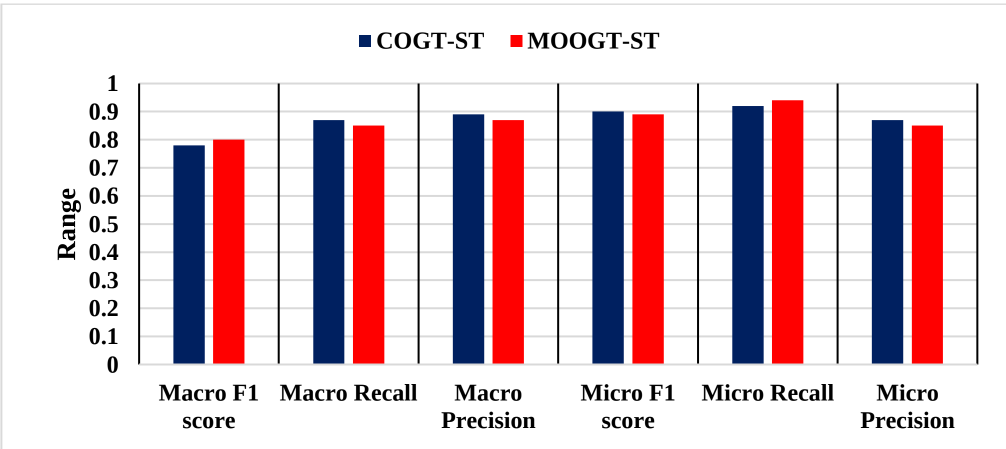

Fig. 6.5: Macro and Micro performance across three datasets of reviews.

ii) Statistical validation of the Game Model algorithms: We performed the statistical Z test on two proportions to verify the effectiveness of the COGT-ST and MOOGT-ST models. The dataset for the review was divided into two samples of various sample sizes. Two distinct samples were extracted from datasets containing different domains as illustrated in *Table 6.15*. A Z-test was conducted to analyze the proportions of two populations (p_1 and p_2) while examining the alternative null hypotheses H_o and H_a. The data provided has been condensed and presented in a tabular format as *Table 6.15*.

Table 6.15: Two Proportion Z-Test statistics across datasets

	COGT-ST Model		**MOOGT-ST Model**	
Parameters	**Sample 1**	**Sample 2**	**Sample 1**	**Sample 2**
Sample Size(n_1)	160	175	1000	500
Sample Proportion (p_1)	0.975	0.84	0.900	0.906
Favorable cases (X_1)	156	147	900	453
P	0.9015		0.9013	
Z	3.988		-0.245	
Hypothesis status	H_o is not rejected		H_o is not rejected	

H_o: $p_1 = p_2$ i.e, the accuracy of *sample* 1 is equal to the accuracy of *sample* 2
H_a: $p_1 \neq p_2$ i.e accuracy of *sample* 1 is not equal to the accuracy of *sample* 2

$$P = \frac{X_1 + X_2}{N_1 + N_2} \tag{6.7}$$

Two population proportions were analyzed using a two-tailed test evaluated using *Equation (6.7)* and a z-test. The z-statistic was computed utilizing *Equation (6.8)*.

$$z = \frac{p_1 - p_2}{\sqrt{P(1-P)(1/n_1 + 1/n_2)}} \tag{6.8}$$

Based on the statistical analysis results, the null hypothesis (H_o) was not rejected, indicating a lack of sufficient evidence to support the claim that the population proportions p_1 and p_2 are different at the 0.05 significance level. Hence, it can be concluded that there is insufficient statistical support to assert a significant disparity between the two proportions. This suggests that the percentage of correctly classified reviews remains consistent across datasets with different sample sizes. As a result, it can be inferred that the proposed model consistently produces reliable outcomes.

iii) Challenges of the Proposed Model: The HSWN lexicon is the foundation for the sentiment scoring of opinion words of Hindi text. HSWN's main flaw is that not enough words are covered, and some words are not given the proper HSWN score. One significant drawback of the lexicon-based approach is that the system cannot correctly classify customer feedback if a word or polarity shifter is not included in the sentiment lexicon. The proposed system cannot properly classify certain sentiment words and polarity shifters. *Table 6.16* presents a few examples.

Table 6.16: Examples where the proposed model fails

Reviews	Actual	Predicted
"मुझे ट्रिलर और हॉरर फिल्म नापसन्द नहीं है।" *("Mujhe triller aur horror film napasand hai")* *("I do not dislike triller and horror movies")* ***(Phrases with negation)***	Positive	Negative
("अंतिम एपिसोड अंत में एक भयानक मोड़ के साथ आश्चर्यजनक था।") *("Antim episode ant me ek bayanak mor ke sath ashchrajanak tha")* *("The final episodes was surprising with a terrible twist at the end ")* ***(Negative term used in positive way)***	Neutral	Positive
("कातिल और जहरीली दिख रही हैं एक्ट्रेस ") *(" katil aur jahreli dikh rahi hai actress")* *("Actress is looking killer and poison")* ***(Irony)***	Positive	Negative
("Thnk u 4 ट्रीट इन @ Phonenix पैलेडियम") *("Thank u for treat in @ Phonenix Paledium")* *("Thnk u 4 the treat in @ Phonenix Palladium ")* ***(Special characters and slang terms)***	Neutral	Negative

6.5 Summary

In this study, we introduced two unsupervised techniques for Hindi text. The first model is MOOGT-ST in which we used the MOORA MCDM technique for aggregating the context and rating scores of reviews. By combining these scores, the ranking score is determined for each review. Then, a two-person game is played between pairs of reviews, and the Nash equilibrium is calculated. This iterative process is applied to all reviews in the dataset, resulting in an overall accuracy of 82% when applied to Hindi review datasets. Similarly, the next model we used is the COGT-ST model which consists of the COPRAS technique which integrates the context and rating scores of reviews. Hence the proposed framework established the mathematical foundation of the sentiment analysis. MOOGT-ST and COGT-ST models are implemented on numerous Hindi datasets of various domains. The results are compared with existing state of art approaches. Hence the proposed model is a sentiment tagger for the Hindi language. Hence both mathematical frameworks can be adaptable to another AI task.

Chapter 7

Application of Sentiment Analysis for Designing Recommendation Systems

Sentiment analysis, an integral task of NLP, boasts a wide array of applications spanning numerous domains. In the realm of marketing[209], it facilitates the extraction of valuable insights from customer feedback, social media mentions, and product reviews, thereby empowering enterprises to refine their strategies and elevate customer satisfaction[175]. Within the financial sector[210], sentiment analysis plays a critical role in forecasting stock market trends through the analysis of news articles and social media content, offering invaluable guidance to investors in their decision-making processes. In the healthcare domain[211], it contributes to the monitoring and comprehension of patient sentiments, while in the political arena, it assists in the objective assessment of public opinion during electoral campaigns and policy deliberations. Across various industries, sentiment analysis serves as a cornerstone for effective brand management, customer support optimization, and informed product development, ultimately fostering evidence-based decision-making and the enhancement of user experiences[144].

Better recommendations may be made by having a deeper understanding of user preferences and emotional states. Sentiment analysis offers a sophisticated approach to enhance the recommendations proposed by the recommendation systems. In this chapter, we discuss two techniques to recommend mobile brands. We rank mobile brands by analyzing their sentiments about their various features.

The organization of this chapter is as follows. In *section 7.1*, we briefly introduce recommendation systems. In *section 7.2*, we introduce the COPRAS [212]and the PROMTHEE-I MCDM techniques, which we use to rank the alternatives. *Section 7.3* presents the implementation of these methodologies. In *section 7.4*, we conclude the chapter.

7.1 Recommendation system

A recommendation system, often referred to as a recommender system, that utilizes algorithms and data analysis techniques to provide personalized suggestions and recommendations to users. These systems are commonly employed by various online platforms, such as e-commerce[213] websites, streaming services, and social media platforms, to enhance user experiences. By analyzing user preferences, browsing history, purchase behavior, and demographic information, recommendation systems can predict and suggest items, products, content, or connections that align with a user's interests and needs. There are different types of recommendation systems, including collaborative filtering, content-based filtering, and hybrid approaches, each with its own set of methodologies. Ultimately, recommendation systems play a pivotal role in improving user engagement, increasing sales, and assisting users in discovering relevant content from the overwhelming sea of options available in today's digital landscape.

7.2 MCDM-based Recommendation Systems

MCDM-based recommendation systems use decision-making algorithms to provide consumers with personalized choices. Unlike conventional recommendation systems that depend on user preferences and historical data[214], MCDM-based systems consider various criteria and aspects that affect user decision-making. These include user preferences, item characteristics, cost, quality, and other factors. This gives users more accurate and personalized suggestions that meet their complicated needs. Product selection, portfolio management, and service suggestions benefit from MCDM-based[215] recommendation systems, which provide informed and customized decision-making. Recommending the best product is combined in this study for ranking alternatives based on ratings. Initially, recommendations were made based on consumers' stated preferences concerning the items' core characteristics. Online sources were then used to extract product performance scores based on their feature ratings [216].

An MCDM consists of *n* alternatives and *m* criteria that form a decision matrix of order *m x n*. Out of the *m* criteria, some are beneficial and some are non-beneficial. Depending upon the priority, we assign weights to these criteria. There are various techniques to give weights to these criteria. One of the techniques is Shannon entropy for weight estimation. In this chapter, we use Shannon entropy for weight estimation by assigning weights to the different features of a product. The two MCDM techniques that we have used for product recommendation are COPRAS and PROMTHEE-1.
Within this section, we introduce a recommendation system based on Multi-Criteria decision-making (MCDM). *Subsection 7.2.1* outlines our method for estimating weights using Shannon entropy. In *subsection 7.2.2*, we delve into the COPRAS method, a specific MCDM technique. Subsequently, in *subsection 7.2.3,* we introduce yet another MCDM technique known as the PROMETHEE-I Method.

7.2.1 Weight Estimation by Shannon Entropy

The Shannon entropy method can be used to assign weights to criteria in MCDM based on the principle of diversity or uncertainty among the criteria. This method is particularly useful when decision-makers want to avoid bias and ensure that the selected criteria reflect a balanced representation of their preferences. We follow *Algorithm 7.1* to assign the weights to each criterion.

Algorithm 7.1: Weight estimation using Shannon Entropy

1: *Construct a decision matrix* x_{ij} .

2: *Normalize the decision matrix.* (ω_{ij}), $\omega_{ij} = \dfrac{x_{ij}}{\sum_{j=1}^{m} x_{ij}}$

3: *Calculate entropy* (E_i). $E_i = -E_o \sum_{j=1}^{m} \omega_{ij} . \ln \omega_{ij}$

4: *Calculate the degree of diversification* (D_i). $D_i = 1 - E_i$.

5: *Calculate the degree of importance* (I_{ij}).

$$I_{ij} = \frac{D_i}{\sum_{S=1}^{n} D_S} \approx \frac{1 - E_i}{\sum_{S=1}^{n} (1 - E_s)}$$

7.2.2 COPRAS Method

The Complex Proportional Assessment technique (COPRAS) is a multi-criteria decision-making approach designed to facilitate the ranking and selection of alternatives across various criteria. COPRAS addresses the intricacies of real-world decision scenarios by considering both favourable and unfavourable impacts associated with each alternative across a spectrum of criteria. The method involves a sequence of steps encompassing criteria normalization, determination of preference coefficients, and computation of overall rankings. By evaluating net flow values for individual alternatives, which encapsulate the weighted disparities between positive and negative evaluations, COPRAS provides a systematic mechanism to manage complex and interrelated criteria. Its versatility extends to diverse domains, including project assessment, supplier choice, and resource distribution, enhancing the quality and comprehensiveness of decision-making processes. The stepwise procedure is shown in *Algorithm 6.4* in Chapter 6.

7.2.3 PROMTHEE-I Method

PROMETHEE-I is a decision-making technique used to compare and rank a set of alternatives based on multiple criteria. It assesses the preferences by considering both positive and negative aspects of each alternative with the criteria. PROMETHEE-I employs pairwise comparisons to generate preference indices and preference flows for each alternative. The method calculates net flows, which represent the difference between positive and negative flows, and then ranks the alternatives accordingly. PROMETHEE-I's flexibility in handling qualitative and quantitative data, along with its ability to capture intricate preference relationships, makes it valuable. It helps in delivering refined and comprehensive suggestions by considering a multitude of criteria simultaneously. *Algorithm 7.2* shows the procedure of PROMTHEE-I to rank the alternatives.

Algorithm 7.2: *Rank the alternatives using the PROMETHEE-I method*

1: *Determine the deviations based on pairwise comparisons which $d_i(a,b)$ denotes the difference between the evaluation of a and b on each criterion.* $d_i(a,b) = g_j(a) - g_j(b)$

2: *Calculate the Preference function* $P_j(a,b) = F_j[d_i(a,b)] \ \forall\ j = 1,......k$

3: *Formulation of a Global Preference Index* $\pi(a,b)$.

$$\pi(a,b) = \sum_{j=1}^{k} P_j(a,b) w_j \quad \forall\ a,b \in A \qquad \textit{where,}\ 0 \le \pi(a,b) \le 1$$

4: *Calculation of PROMETHEE-I partial positive and negative ranking.*

$$\phi^+(a) = \frac{1}{(n-1)} \sum_{x \in A} \pi(a,x) \quad \textit{and} \quad \phi^-(a) = \frac{1}{(n-1)} \sum_{x \in A} \pi(a,x)$$

5: *Estimate net outranking rate flow.* $\phi(a) = \phi^+(a) - \phi^-(a)$

6: *Rank the alternatives.*

7.3 Proposed Methodologies and Experimentation

In this section, we evaluate the proposed methodology by implementing it on the dataset at hand. We provide a detailed explanation of our methodology as it is put into practice with the collected dataset in *subsection 7.3.1*. Moving forward to *subsection 7.3.2,* we assess the resilience and stability of the proposed methodology, followed by a sensitivity analysis in *subsection 7.3.3*. Lastly, in *subsection 7.3.4*, we perform a comparative analysis of different methods, focusing on their correlation.

7.3.1 Datasets

The dataset used to verify the efficacy of the proposed approaches contains mobiles of different brands. The features like battery life, storage capacity, cost-effectiveness, and customer rating are analyzed for each brand. *Table 7.1* shows the five smartphones treated as alternatives for ranking.

Table 7.1: Alternatives used to rank the products using the proposed models

S. No.	Alternatives	Mobile Brand
1	Al_1	*"Samsung Galaxy A50, A505G, 64GB"*
2	Al_2	*"Google – Pixel 3a with 64GB."*
3	Al_3	*"Xiaomi Redmi Note 81 Pro 128GB"*
4	Al_4	*"Moto G7 with Alexa Hands- 64 GB"*
5	Al_5	*"LG G8 ThinQ with Alexa Hands-128 GB"*

The features of the listed alternatives are displayed in *Table 7.2*. *Table 7.2* displays the features and the criteria nomenclature. We use eight mobile features to rank the alternatives.

Table 7.2: Criteria used to rank the products using the proposed model

S. No.	Criteria Numbering	Mobile features	B/NB
1	$(\vartheta)_1$	Battery Life	Beneficial
2	$(\vartheta)_2$	Value for money	Cost
3	$(\vartheta)_3$	Face recognition	Beneficial
4	$(\vartheta)_4$	Fingerprint reader	Beneficial
5	$(\vartheta)_5$	Easy to use	Beneficial
6	$(\vartheta)_6$	Screen quality	Beneficial
7	$(\vartheta)_7$	Camera quality	Beneficial
8	$(\vartheta)_8$	Customer reviews	Beneficial

7.3.2 Methodologies

This subsection presents two frameworks for product ranking. We use ratings of various features of products and overall customer ratings. We use Shannon entropy for the weight estimation of each criterion. Then we apply COPRAS and PROMTHEE-I to recommend the best product. The framework is divided into three phases and the block diagram is shown in *Fig. 7.1.*

(i) Extract product features and customer ratings
(ii) Design a decision matrix with criteria
(iii) Implement MCDM techniques

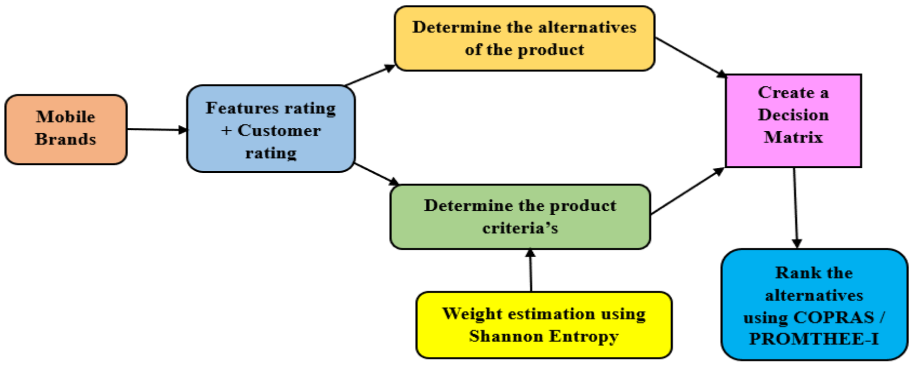

Fig. 7.1: Proposed model's pipeline of COPRAS.

During the initial phase of feature extraction, we assess consumer satisfaction with the features of alternative products. Information on product features was collected at the feature level. We transform the obtained features into a decision matrix in the next step. Lastly, feature weights are retrieved using the Shannon entropy method, and the COPRAS / PROMTHEE-I method is used to rank the products. To ensure the framework's dependability and efficacy, a sensitivity analysis is performed at the Summary. *Fig. 7.1* depicts the processing steps of the proposed model. The procedures involved in completing each stage are outlined below. For the above dataset first, we create the decision matrix as shown in *Table 7.3* Then we use *Algorithm 7.1* to calculate the weights for each criterion using Shannon entropy on the alternatives and criteria of *Table 7.3.* The degree of importance (I_j) is the weight of the criteria is illustrated in *Table 7.4.*

Table 7.3: Decision Matrix along with criteria and alternatives

	Criteria ↓							
Alternatives ↓	$(\vartheta)_1$	$(\vartheta)_2$	$(\vartheta)_3$	$(\vartheta)_4$	$(\vartheta)_5$	$(\vartheta)_6$	$(\vartheta)_7$	$(\vartheta)_8$
Al_1	4.2	4	4.5	3.9	4.1	4	4	4.3
Al_2	4.3	4.8	3.7	4.5	4.4	4.4	4.7	4.4
Al_3	4.7	4.7	4	4.6	4	4.1	4.3	4.6
Al_4	4	4.5	4	4.4	5	4.6	1	4.3
Al_5	4.4	4.6	4.2	4.5	4	4.4	4.8	4.4

Table 7.4: Degree of Diversification ($1 - E_j$) and Degree of importance (I_j)

Criteria →	$(\vartheta)_1$	$(\vartheta)_2$	$(\vartheta)_3$	$(\vartheta)_4$	$(\vartheta)_5$	$(\vartheta)_6$	$(\vartheta)_7$	$(\vartheta)_8$
$1 - E_j$	-0.15993	-0.15956	-0.15946	-0.15978	-0.15823	-0.16003	-0.09493	-0.16074
I_j	0.13188	0.13158	0.131497	0.131757	0.130483	0.131962	0.07828	0.132553

Then we follow *Algorithm 7.2* and evaluate the utility value as illustrated in *Table 7.5* after applying the COPRAS technique. *Algorithm 7.3* evaluates the net ranking rate from PROMTHEE-I and ranks the alternatives based on eight criteria as shown in *Table 7.6*.

Table 7.5: Index Values using COPRAS Technique: Maximizing and Minimizing and Each Alternative's Relative Weight (Q_i) and Ultimate ranking of alternative and Utility Value Index (U_i)

Alternatives ↓	S_{i-}	S_{i+}	Q_i	**Rank**	**Recommendation Rate**	U_i
Al_1	0.11987	0.07794	0.20917	1	Highly recommended	100
Al_2	0.13138	0.07805	0.19779	5	Least Recommended	94.5589
Al_3	0.12745	0.08185	0.20527	3	Average recommendation	98.1346
Al_4	0.11953	0.07641	0.20801	2	Highly Recommended	99.4449
Al_5	0.12937	0.08072	0.20232	4	Weakly Recommended	96.725

Table 7.6: Net ranking rate $\varphi(a)$ evaluated from PROMTHEE-I

Alternatives ↓	$\varphi(a)$	**Rank**	**Recommendation Rate**
Al_4	0.9275	2	Highly recommended
Al_2	0.5933	5	Least Recommended
Al_3	0.7581	3	Average recommendation
Al_1	0.9786	1	Highly Recommended
Al_5	0.6069	4	Weakly Recommended

The alternatives with ranks one and two are highly recommended for purchase by customers, the alternatives with rank three have an average recommendation, the alternatives with rank four are weakly recommended, and the alternatives with rank five are the least recommended to buy or sell because they are the least popular among consumers. The utility (U_i) value index is calculated in *Table 7.5*. After that, the products were ranked utilizing the COPRAS method. We used it to rank and select the best smartphone to evaluate the framework's effectiveness. *Table 7.6* evaluates the net ranking rate from the PROMTHEE-I MCDM technique.

7.3.3 Sensitivity Analysis

A sensitivity analysis (Sen_{ij}) is performed to examine the ranking's stability and consistency concerning the criteria weights. The study aims to improve a model's output in terms of quality and quantity, showing the sensitivity of decision-making when confronted with uncertain input values. Reduce subjectivity by creating a series of filter selections and guiding the selection of complex alternatives with the help of the multi-criteria approach. The same problem can have multiple solutions because different MCDM methods use different mathematical procedures. The researchers' MCDM method determines which alternatives to consider. Despite this, there is no consensus regarding the quality of the decision-making technique known as sensitivity analysis. *Table 7.7* shows three weighted scenarios for testing the proposed model's robustness. The values of weights of the three cases corresponding to 8 criteria are given in *Table 7.8* The proposed model is implemented using these weights in three different cases, and the final ranking of alternatives was done in all three cases in *Table 7.9.*

Table 7.7: Weight estimation in different cases

S. No	Weighting Methods	Description
Case 1	Entropy Method	For this, we evaluate using the entropy method
Case 2	B-50%, NB-50%	50% weightage is given to beneficial criteria and 50% to non-beneficial criteria
Case 3	B-60%, 40%-NB	60% weightage is given to beneficial criteria and 40% to non-beneficial criteria

Table 7.8: Criteria with different weights

Criteria	Entropy Method (Case 1)	B-50%, NB-50% (Case 2)	B-60%, 40%-NB (Case 3)
$(\vartheta)_1$	0.13188628	0.125	0.15
$(\vartheta)_2$	0.13158042	0.125	0.15
$(\vartheta)_3$	0.13149667	0.125	0.1
$(\vartheta)_4$	0.13175688	0.125	0.1
$(\vartheta)_5$	0.13048336	0.125	0.15
$(\vartheta)_6$	0.13196213	0.125	0.1
$(\vartheta)_7$	0.078281	0.125	0.1
$(\vartheta)_8$	0.13255326	0.125	0.15

Table 7.9: Ranking of alternatives in three different cases

	COPRAS Technique	PROMTHEE-I Technique
Different Cases	**Alternatives Ranking**	**Alternatives Ranking**
Case 1	$Al_1 > Al_4 > Al_3 > Al_5 > Al_2$	$Al_1 > Al_4 > Al_3 > Al_2 > Al_5$
Case 2	$Al_2 > Al_5 > Al_3 > Al_1 > Al_4$	$Al_1 > Al_4 > Al_3 > Al_2 > Al_5$
Case 3	$Al_2 > Al_5 > Al_3 > Al_1 > Al_4$	$Al_2 > Al_5 > Al_3 > Al_1 > Al_4$

COPRAS and PROMTHEE-I MCDM techniques are implemented on the dataset as discussed in *Section 7.3.1* and then rank the alternatives following *Algorithm 7.1* and *Algorithm 7.2* as shown in *Table 7.9*.

In case 1 we ranked the alternatives and Al_1 got the highest rank followed by Al_4. Whereas, in case 2, the rank of Al_3 remained the same as in case 1, but the rank of Al_1 and Al_2 get exchanged with the variation in the weights same follow in case 3 as it is in case 2. Only alternatives with consecutive ranks get exchanged, which is quite evident that the ranks of the two best alternatives can get exchanged as we did not see much difference in the ranks of alternatives in different cases of weight estimation. Whereas in PROMTHEE-I in case 1 the alternatives ranking is as $Al_1 > Al_4 > Al_3 > Al_2 > Al_5$. In Case 2 the ranking is $Al_1 > Al_4 > Al_3 > Al_2 > Al_5$ similarly in Case 3 we $Al_2 > Al_5 > Al_3 > Al_1 > Al_4$. Therefore, this shows the robustness of our method.

Criteria characteristics and weighting distribution among criteria both have an impact on MCDM ranking outcomes [212]. We examine the effect of varying the weight of criteria on the ranking results obtained by each method and the robustness of the employed MCDM methods. To accomplish this, the MCDM methods depicted in *Fig. 7.2* and *Fig. 7.3* demonstrate the variation of criterion weights and observe the changes in the final ranking of alternatives. There are significant changes in the weights of criteria, and this panel shows how those changes affect the rankings of alternatives. Furthermore, the sensitivity coefficient (Sen_{ij}) for the ith method has been calculated using the jth criterion. *Equation (7.1)* determines the average change in alternative ranking results when the COPRAS/PROMTHEE-I techniques alter the criterion weight. (Sen_{ij}) for COPRAS method is 0.5 evaluated using *Equation (7.2)* and for PROMTHEE-I is 0.75 evaluated using *Equation (7.3)*.

$$Sen_{ij} = \frac{\sum_{w=1}^{W} D_{ij}^{w}}{H} \forall i, j, w \in \{0.1, 0.2, 0.3, ...0.9, 1\} \tag{7.1}$$

$$Sen_{ij} = \frac{2}{4} = 0.5 \rightarrow COPRAS\ Method \tag{7.2}$$

$$Sen_{ij} = \frac{3}{4} = 0.7 \rightarrow PROMTHEE - I\ Method \tag{7.3}$$

Where D_{ij}^{w} is the number of changes in method I's alternative ranking result when the weight of criterion j changes within a specific range, and H stands for how often the criteria weights change. The weight of each criterion changes between 0.1 and 1.

PROMETHEE-I Sensitivity Coefficient is 0.75 which implies a change of 1% in criteria weights or values will result in a 0.75% change in outranking flows and rankings. This suggests that PROMETHEE-I is moderately sensitive to changes in input parameters.

A small change in weights or values can lead to a noticeable, but not overly dramatic, change in the decision outcomes.

COPRAS Sensitivity Coefficient is 0.5 which implies a change of 1% in criteria weights or values will lead to a 0.5% change in the decision scores or rankings. This indicates that COPRAS is also sensitive to changes but to a slightly lesser extent compared to PROMETHEE-I. Changes in input parameters will still have an impact on the decision outcomes, but the impact might be relatively smaller compared to PROMETHEE-I. Variation in ranking model is illustrated in *Fig. 7.2* and *Fig. 7.3.*

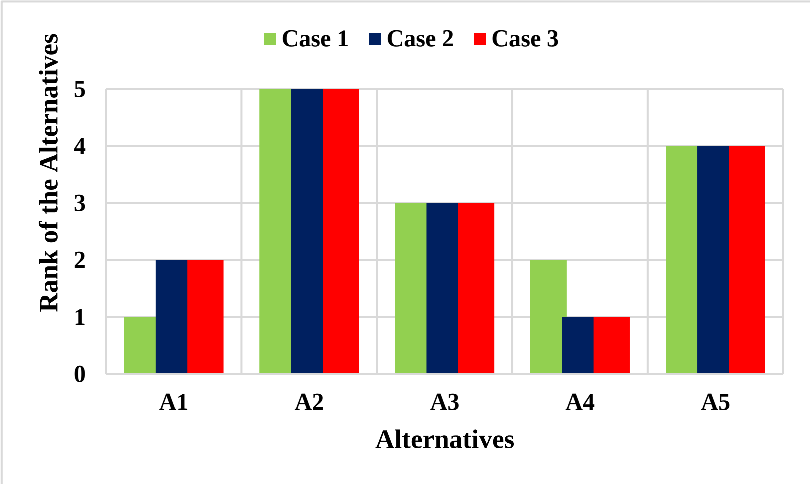

Fig. 7.2: Rank of Alternatives through COPRAS techniques.

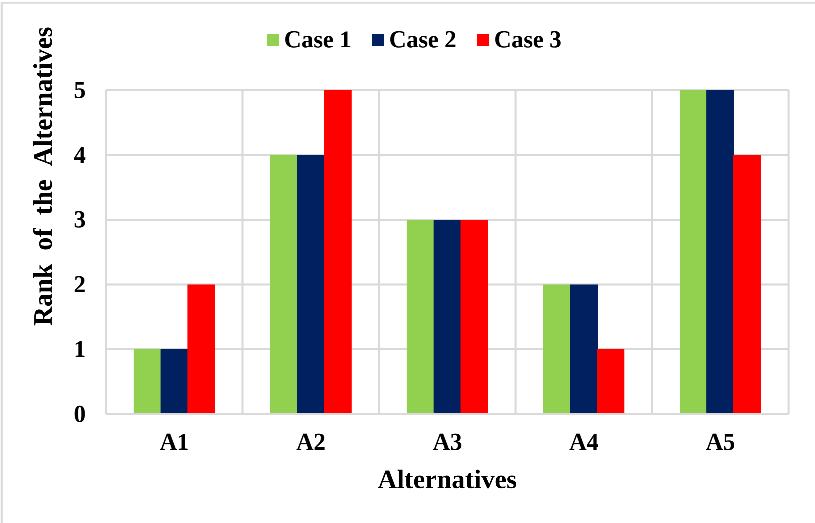

Fig. 7.3: Rank of Alternatives through PROMTHEE-I techniques.

Hence, it is clear from *Fig. 7.2* and *Fig. 7.3* ranking pattern that irrespective of different weights in three cases, the variation comes in the ranking of alternatives. Two changes were made in the consecutive ranks of the alternatives due to the different weights (*case 1*, *case 2*, and *case 3*). Al_1 and Al_2 ranks are affected due to variations in the weight in the three cases. However, only the rank of two consecutive alternative changes, i.e., Al_1 and Al_2, get exchanged, whereas the rank of three alternatives, Al_3, Al_4, *and* Al_5, *is* unaffected by the variation in weights. This implies that the proposed MCDM model is robust in the decision-making process. In the case of PROMTHEE-I in both case1 and 2 Al_1 has the rank 1 followed by Al_4.

7.3.4 Comparison based on Correlation

The comparative analysis of the proposed model with other existing models is shown in this section. For this objective, the proposed work is contrasted with a few MCDM approaches, including (IF-Multi-MOORA)[32], (IF-TOPSIS) [217], (IF-TODIM)[218], (IF-VIKOR)[219]. The advantages of the proposed work over alternative MCDM techniques are discussed in more depth below. A sensitivity analysis of the criteria weights is conducted to comprehend the consequences of changing the weight values in the ranking order. This examination demonstrates the suggested work's robustness. The proposed work's consistency is further evaluated using Spearman correlation. Correlation coefficients have been used extensively for comparing rankings from different decision-making methods. This coefficient value can be calculated using *Equation (7.4)*[220].

$$r_{coeff} = \frac{\sum_{i=1}^{n}(a_{ij} - a_{ij}^*)(b_{ij} - b_{ij}^*)}{\sqrt{\sum_{i=1}^{n}(a_{ij} - a_{ij}^*) \times \sum_{i=1}^{n}(b_{ij} - b_{ij}^*)^2}}, \quad j = 1, 2, ...n \tag{7.4}$$

This study found that all correlation coefficients greater than 0.6 indicated that the method developed in this paper is compatible with other techniques. However, it is essential to note that our method and the IF-TOPSIS method have a higher correlation coefficient than (0.98).

Table 7.10: Results from different methods and Spearman's Correlation Coefficients

Methods	Score	Ranking	Ranking Correlation				
			COPRAS	IF-Multi MOORA	IF-TOPSIS	IF-TODIM	IF-VIKOR
COPRAS	Q(Al_1) =0.20917, Q(Al_2) =0.19779, Q(Al_3) =0.20527, Q(Al_4) =0.20801, Q(Al_5) =0.20232	$Al_1 > Al_4 > Al_3 > Al_5 > Al_2$	1	0.6	0.98	0.5	0.6
IF-Multi-MOORA	-	$Al_1 > Al_4 > Al_2 > Al_5 > Al_3$	-	1	0.6	0.3	0.9
IF-TOPSIS	CI (Al_1) = 0.53, CI (Al_4) = 0.41, CI (Al_3) = 0.23, CI (Al_5) = 0.22, CI (Al_2) = 0.16	$Al_1 > Al_4 > Al_3 > Al_5 > Al_2$	-	-	1	0.5	0.6
IF-TODIM	CI (Al_1) = 0.53, CI (Al_4) = 0.41, CI (Al_3) = 0.23, CI (Al_5) = 0.22, CI (Al_2) = 0.16	$Al_1 > Al_3 > Al_2 > Al_4 > Al_5$	-	-	-	1	0.3
IF-VIKOR	δ (Al_1) = 0.87, δ(Al_4) = 0.8, δ(Al_2) = 0.63, δ(Al_5) = 0.25, δ(Al_3) = 0	$Al_1 > Al_4 > Al_2 > Al_5 > Al_3$	-	-	-	-	1

According to *Table 7.10*, The rankings produced by the proposed model are compared to those produced by existing MCDM approaches MCDM methods (IF-Multi-MOORA) [32], (IF-TOPSIS) [217], (IF-TODIM) [218], (IF-VIKOR) [219] offered in this field to determine the validity of the proposed model's ranking. Comparative studies were conducted using data previously used in similar studies. Our method shows a positive correlation with all other previously proposed methods, and our result is at par with this method. Similarly, we made the comparison of correlation for the PROMTHEE-I MCDM technique as illustrated in *Table 7.11*.

Table 7.11: Spearman's Correlation Coefficients of various methods

Methods	Ranking Correlation				
	PROMETHEE	**IF-Multi MOORA**	**IF-TOPSIS**	**IF-TODIM**	**IF-VIKOR**
PROMETHEE	1	0.6	0.98	0.5	0.6
IF-Multi-MOORA	-	1	0.6	0.3	0.9
IF-TOPSIS	-	-	1	0.5	0.6
IF-TODIM	-	-	-	1	0.3
IF-VIKOR	-	-	-	-	1

According to *Table 7.10*, the rankings produced by the proposed model are compared to those produced by existing MCDM approaches like (IF-Multi-MOORA) [32], (IF-TOPSIS) [217], (IF-TODIM) [218], (IF-VIKOR) [219] offered in this field to determine the validity of the proposed model's ranking. The PROMETHEE-I technique will help suggest picking the top brand. Because it takes into account customer happiness through evaluations provided to specific aspects of mobile brands, customers may find the suggested practical approach to be a decision support system. This framework can be used to recommend a suitable product in knowledge-based recommendation systems.

7.4 Summary

This chapter focuses on employing the PROMETHEE-1 and COPRAS techniques from MCDM to enhance product recommendations, thereby aiding customers in making well-informed purchase decisions. To ensure the robustness of our approach, we employ the Shannon entropy weighting technique to assign appropriate weights to each criterion, thereby maintaining their relative significance within the decision-making process.

This chapter introduces an advanced alternative recommendation system that draws upon the power of two MCDM methodologies: COPRAS and PROMETHEE-I. This system is designed to identify the optimal alternatives, providing customers with valuable insights for selecting the most suitable products. The evaluation process involves assessing various attributes of mobile brands, which serve as the evaluation criteria. Additionally, different mobile brands are considered as alternatives, and diverse attributes of the mobiles are treated as criteria for evaluation.

Significantly, this chapter not only presents the immediate findings but also paves the way for future research. We highlight the promising avenue of using public opinions in recommendation systems to enhance the selection of the best products. This approach holds the potential to contribute to the field of sentiment analysis as it guides individuals towards superior alternatives, ultimately refining the sentiment analysis process.

Chapter 8

Contribution, Summary & Future Work

This chapter marks the contribution of this thesis, encompassing the outcomes and implications of our research efforts, as presented in *section 8.1*. Within *section 8.2*, we comprehensively list and elaborate on the valuable contributions made during the execution of our proposed research, specifically focusing on the problem of sentiment classification for written text. Subsequently, in *section 8.3,* we delve into the findings derived from our research work, highlighting the results and insights obtained from our experiments and analyses in the domain of sentiment classification for Hindi text. Finally, in *section 8.4*, we discuss potential avenues for future research and extensions that can be explored based on the groundwork and discoveries reported in this thesis. We provide valuable recommendations and directions for advancing and building upon our research to further enhance the field of sentiment classification for Hindi text.

8.1 Contribution

This research work represents a significant advancement in the field of Natural Language Processing, specifically focusing on the area of sentiment analysis. The thesis makes several noteworthy contributions, which are summarized below:

i) Application of Mathematical Optimization Techniques: This research introduces novel mathematical optimization techniques for sentiment categorization of written text. By employing these techniques, the sentiment analysis process becomes more robust and efficient.

ii) Unsupervised Approach: The proposed sentiment analysis approach is unsupervised, eliminating the need for extensive training data. This not only simplifies the implementation but also makes it more adaptable to various domains and languages.

iii) Lexicon-Based Adaptability: The approach relies on lexicon-based methods, enabling it to be applied to any language with an available lexicon database. This adaptability enhances its versatility and applicability across different linguistic contexts.

iv) Time and Space Efficiency: The mathematical optimization techniques employed in this work exhibit minimal time and space complexity. As a result, the sentiment categorization process becomes faster and requires fewer computational resources.

v) Generalizability of Mathematical Optimization Models: The proposed mathematical optimization models can be easily adapted to solve complex problems and offer a clear interpretation of their solutions in a physical or understandable form. This enhances the transparency and interpretability of the sentiment analysis results.

vi) Addressing Negation Handling Challenges: The research work presents innovative mathematical techniques to effectively handle challenges related to negation in sentiment analysis. By tackling this issue, the accuracy and reliability of sentiment categorization are greatly improved.

8.2 Summary

This thesis introduces innovative unsupervised approaches for sentiment analysis, encompassing both sentiment categorization and recommendation systems. The study explores the application of mathematical models to achieve these objectives. Initially, a game theory model is employed for binary class sentiment classification, followed by an investigation of Multiple Criteria Decision Making (MCDM) techniques for the same task. Subsequently, an integrated framework combining game theory and MCDM is developed for sentiment analysis.

The research focuses on both Hindi and English review datasets, demonstrating the adaptability of the proposed approaches to multiple languages. The obtained accuracy from these models shows promising results. To validate the model's performance, a Z-test hypothesis is conducted, corroborating the efficacy of the unsupervised approaches.
An essential advantage of the proposed approaches is their independence from training data, making them more flexible and resource-efficient than supervised models. Remarkably, the achieved results are comparable with those obtained from supervised models, highlighting the potential of the unsupervised methods in sentiment analysis.

Overall, this research contributes valuable insights into unsupervised sentiment analysis techniques, showcasing the effectiveness of mathematical models in sentiment analysis. The successful application of these approaches to Hindi and English datasets reinforces their versatility and holds promising implications for sentiment analysis tasks across various languages and domains.

8.3 Findings

We list the major findings of the thesis below.

i) Adaptability of MCDM Techniques: The study showcases the ease with which MCDM techniques can be adapted to the sentiment categorization task, both in terms of handling different alternatives and criteria. This adaptability extends to multiclass sentiment analysis as well, making MCDM a versatile tool for sentiment-related tasks.

ii) Integration of MCDM and Game Theory: Combining MCDM with game theory yields superior solutions for sentiment analysis, leading to improved accuracy. In this integration, the performance scores derived from MCDM techniques serve as payoffs for the game played between two players. This novel approach enhances the understanding of sentiments and offers more accurate results.

iii) Versatility Across Languages and Domains: The models developed in this research exhibit adaptability to various languages and domains. This cross-language and cross-domain compatibility makes them valuable assets for sentiment analysis applications in diverse contexts.

iv) Comparable Performance to Supervised Models: The results obtained from the mathematical optimization models are on par with those from supervised models. This indicates that the proposed unsupervised approach based on game theory and MCDM techniques can deliver competitive performance without the need for extensive training data.

v) Reduction in Time and Space Complexity: Implementing the mathematical optimization models leads to reduced time and space complexity, making the approach more computationally efficient. This efficiency is achieved through deterministic steps, facilitating practical application and scalability.

In Summary, the study's major findings underscore the significance of game theory models, particularly Nash equilibrium, in sentiment analysis. The integration of MCDM techniques enhances the accuracy of sentiment categorization, while also highlighting the models' adaptability to different languages and domains. The research demonstrates that the proposed mathematical optimization approach can deliver competitive results compared to supervised methods, all while significantly reducing time and space complexity. These findings contribute valuable insights and methodologies to advance sentiment analysis research and its practical applications in various fields.

8.4 Future Work

This thesis represents a sincere effort to conduct sentiment analysis on text written in both Hindi and English languages. However, it is important to acknowledge that the model discussed in this study has certain limitations that have impacted its overall performance. In light of these challenges, we have identified several tasks that we plan to pursue in our future research.

- **Handling Challenges:**

Our future strategies involve integrating sophisticated NLP methodologies capable of managing slang, irony, and various linguistic intricacies. This integration aims to boost accuracy and elevate the capabilities of our automated system significantly.

- **Generate Multimodal for Sentiment Analysis:**

Multimodal sentiment analysis involves utilizing multiple modalities, such as text, images, audio, and video, to understand and predict sentiment or emotions. Integrating various data types allows for a more comprehensive understanding of the sentiment expressed in a given context.

- **Expanded Polarity Classifications:**

  The model discussed in this thesis performs only binary and tertiary class classification. We plan to extend classification to multiclass classification such as “strongly positive,” “positive,” “weakly positive,” “neutral,” “strong negative,” “negative,” and “weak negative”.

- **Extending Applicability to Low-Resource Languages:**

  The proposed models are lexicon-based we intend to make necessary adjustments to the models for low-resource languages like Hindi, Bengali, and Urdu.

- **Creation of dataset of low resources languages:**

  In our upcoming research endeavors, we aim to create SentiWordNet resources tailored to the local languages of India, specifically focusing on Pahadi languages such as Garhwali, Kumaoni, Himachali, Jaunsari, Bhotia Languages, and others. This initiative aims to foster increased research and development in these regional languages, providing essential sentiment analysis tools and resources that can facilitate deeper investigations and analyses in the linguistic landscape of these lesser-represented languages.

- **Exploring Mathematical Optimization in Other NLP Tasks:**

Extending mathematical optimization techniques to tasks like Word Sense Disambiguation (WSD) and query expansion.Fostering innovation in broader NLP applications by leveraging optimization approaches.

The thesis proves to be a template for the efficient application of mathematical optimization methods for sentiment analysis tasks. In the near future, we would like to explore more applications of mathematical optimization methods to other NLP tasks like WSD, query expansion, etc. The overall objective is to create a more powerful, adaptable, and scientifically rigorous model that revolutionizes sentiment analysis and enhances decision-making while unveiling deeper insights into human sentiment and opinion across diverse contexts.

*****

Bibliography

[1] B. Agarwal, N. Mittal, P. Bansal, and S. Garg, “Sentiment analysis using common-sense and context information,” *Computational Intelligence and Neuroscience*, vol. 2015, 2015, doi: 10.1155/2015/715730.

[2] V. Vyas, V. Uma, and K. Ravi, “Aspect-based approach to measure performance of financial services using voice of customer,” *Journal of King Saud University - Computer and Information Sciences*, 2020, doi: 10.1016/j.jksuci.2019.12.009.

[3] Z. Bu, H. Li, J. Cao, Z. Wu, and L. Zhang, “Game theory based emotional evolution analysis for Chinese online reviews,” *Knowledge-Based Systems*, vol. 103, pp. 60–72, 2016, doi: 10.1016/j.knosys.2016.03.026.

[4] R. Ahuja and S. C. Sharma, “Transformer-Based Word Embedding With CNN Model to Detect Sarcasm and Irony,” *Arabian Journal for Science and Engineering*, pp. 1–14, Sep. 2021, doi: 10.1007/S13369-021-06193-3/TABLES/8.

[5] J. Liang and J. Yang, “Application of the AHP method on the optimization with undesirable priorities,” *Engineering with Computers 2021*, vol. 1, pp. 1–17, Mar. 2021, doi: 10.1007/S00366-021-01359-X.

[6] D. Kang and Y. Park, “Review-based measurement of customer satisfaction in mobile service: Sentiment analysis and VIKOR approach,” *Expert Systems with Applications*, vol. 41, no. 4, pp. 1041–1050, Mar. 2014, doi: 10.1016/J.ESWA.2013.07.101.

[7] B. Ozyurt and M. A. Akcayol, “A new topic modeling based approach for aspect extraction in aspect based sentiment analysis: SS-LDA,” *Expert Systems with Applications*, vol. 168, p. 114231, Apr. 2021, doi: 10.1016/J.ESWA.2020.114231.

[8] M. Atzeni, A. Dridi, and D. Reforgiato Recupero, “Fine-grained sentiment analysis on financial microblogs and news headlines,” *Communications in Computer and Information Science*, vol. 769, pp. 124–128, 2017, doi: 10.1007/978-3-319-69146-6_11.

[9] C. Zuheros, E. Martínez-Cámara, E. Herrera-Viedma, and F. Herrera, “Sentiment Analysis based Multi-Person Multi-criteria Decision Making methodology using natural language processing and deep learning for smarter decision aid. Case study of restaurant choice using TripAdvisor reviews,” *Information Fusion*, vol. 68, pp. 22–36, Apr. 2021, doi: 10.1016/J.INFFUS.2020.10.019.

[10] M. M. Queiroz, R. Telles, and S. H. Bonilla, “Blockchain and supply chain management integration: a systematic review of the literature,” *Supply Chain Management*, vol. 25, no. 2, pp. 241–254, Feb. 2020, doi: 10.1108/SCM-03-2018-0143/FULL/HTML.

[11] A. Alwehaibi, M. Bikdash, M. Albogmi, and K. Roy, “A study of the performance of embedding methods for Arabic short-text sentiment analysis using deep learning approaches,” *Journal of King Saud University - Computer and Information Sciences*, 2021, doi: 10.1016/j.jksuci.2021.07.011.

[12] R. Pradhan and D. K. Sharma, “An ensemble deep learning classifier for sentiment analysis on code-mix Hindi–English data,” *Soft Computing*, pp. 1–18, Apr. 2022, doi: 10.1007/S00500-022-07091-Y/TABLES/13.

[13] Z. Nasim and S. Haider, “ABSA Toolkit: An Open Source Tool for Aspect Based Sentiment Analysis,” *International Journal on Artificial Intelligence Tools*, vol. 26, no. 6, 2017, doi: 10.1142/S0218213017500233.

[14] Z. Nasim and S. Ghani, “Sentiment Analysis on Urdu Tweets Using Markov Chains,” *SN Computer Science*, vol. 1, no. 5, Sep. 2020, doi: 10.1007/S42979-020-00279-9.

[15] V. Yadav, P. Verma, and V. Katiyar, “Long short term memory (LSTM) model for sentiment analysis in social data for e-commerce products reviews in Hindi languages,” *International Journal of Information Technology 2022*, pp. 1–14, Jun. 2022, doi: 10.1007/S41870-022-01010-Y.

[16] T. Daudert, “Exploiting textual and relationship information for fine-grained financial sentiment analysis,” *Knowledge-Based Systems*, vol. 230, p. 107389, Oct. 2021, doi: 10.1016/J.KNOSYS.2021.107389.

[17] K. Jindal and R. Aron, “A systematic study of sentiment analysis for social media data,” *Materials Today: Proceedings*, Feb. 2021, doi: 10.1016/J.MATPR.2021.01.048.

[18] M. N. Win, S. D. R. Ravana, and L. Shuib, “SENTIMENT ATTRIBUTION ANALYSIS WITH HIERARCHICAL CLASSIFICATION AND AUTOMATIC ASPECT CATEGORIZATION ON

ONLINE USER REVIEWS," *Malaysian Journal of Computer Science*, vol. 35, no. 2, pp. 89–110, Apr. 2022, doi: 10.22452/mjcs.vol35no2.1.

[19] S. Baccianella, A. Esuli, and F. Sebastiani, "SENTIWORDNET 3.0: An enhanced lexical resource for sentiment analysis and opinion mining," *Proceedings of the 7th International Conference on Language Resources and Evaluation, LREC 2010*, pp. 2200–2204, 2010, Accessed: Sep. 23, 2021. [Online]. Available: http://lrec-conf.org/proceedings/lrec2010/pdf/769_Paper.pdf.

[20] V. Jha, R. Savitha, P. D. Shenoy, V. K R, and A. K. Sangaiah, "A novel sentiment aware dictionary for multi-domain sentiment classification," *Computers and Electrical Engineering*, vol. 69, pp. 585–597, 2018, doi: 10.1016/j.compeleceng.2017.10.015.

[21] J. Hartmann, M. Heitmann, C. Siebert, and C. Schamp, "More than a Feeling: Accuracy and Application of Sentiment Analysis," *International Journal of Research in Marketing*, vol. 40, no. 1, pp. 75–87, Mar. 2023, doi: 10.1016/J.IJRESMAR.2022.05.005.

[22] C. Liu, P. Rani, and K. Pachori, "Sustainable circular supplier selection and evaluation in the manufacturing sector using Pythagorean fuzzy EDAS approach," *Journal of Enterprise Information Management*, vol. 35, no. 4–5, pp. 1040–1066, 2022, doi: 10.1108/JEIM-04-2021-0187.

[23] N. Savela, A. Oksanen, M. Pellert, and D. Garcia, "Emotional reactions to robot colleagues in a role-playing experiment," *International Journal of Information Management*, vol. 60, 2021, doi: 10.1016/j.ijinfomgt.2021.102361.

[24] D. Gräbner, M. Zanker, G. Fliedl, and M. Fuchs, "Classification of Customer Reviews based on Sentiment Analysis," *Information and Communication Technologies in Tourism 2012*, pp. 460–470, 2012, doi: 10.1007/978-3-7091-1142-0_40.

[25] Z. Wang, Z. Hu, S. B. Ho, E. Cambria, and A. H. Tan, "MiMuSA—mimicking human language understanding for fine-grained multi-class sentiment analysis," *Neural Computing and Applications*, 2023, doi: 10.1007/s00521-023-08576-z.

[26] N. Jain and S. Mittal, "Bayesian Nash Equilibrium based Gaming Model for Eco-safe Driving," *Journal of King Saud University - Computer and Information Sciences*, no. xxxx, 2021, doi: 10.1016/j.jksuci.2021.07.004.

[27] N. Jain and S. Mittal, "Bayesian Nash Equilibrium based Gaming Model for Eco-safe Driving," *Journal of King Saud University - Computer and Information Sciences*, 2021, doi: 10.1016/j.jksuci.2021.07.004.

[28] K. Wang, W. C. Sun, and Q. Du, "A non-cooperative meta-modeling game for automated third-party calibrating, validating and falsifying constitutive laws with parallelized adversarial attacks," *Computer Methods in Applied Mechanics and Engineering*, vol. 373, 2021, doi: 10.1016/j.cma.2020.113514.

[29] Y. Wang, Z. Bu, H. Yang, H. J. Li, and J. Cao, "An effective and scalable overlapping community detection approach: Integrating social identity model and game theory," *Applied Mathematics and Computation*, vol. 390, 2021, doi: 10.1016/j.amc.2020.125601.

[30] D. Sznycer and A. W. Lukaszewski, "The emotion–valuation constellation: Multiple emotions are governed by a common grammar of social valuation," *Evolution and Human Behavior*, vol. 40, no. 4, pp. 395–404, Jul. 2019, doi: 10.1016/J.EVOLHUMBEHAV.2019.05.002.

[31] R. Mahmoudi and M. Rasti-Barzoki, "Sustainable supply chains under government intervention with a real-world case study: An evolutionary game theoretic approach," *Computers and Industrial Engineering*, vol. 116, pp. 130–143, 2018, doi: 10.1016/j.cie.2017.12.028.

[32] J. Heidary Dahooie, R. Raafat, A. R. Qorbani, and T. Daim, "An intuitionistic fuzzy data-driven product ranking model using sentiment analysis and multi-criteria decision-making," *Technological Forecasting and Social Change*, vol. 173, p. 121158, Dec. 2021, doi: 10.1016/j.techfore.2021.121158.

[33] S. S. Goswami, S. Jena, and D. Kumar Behera, "Implementation of CODAS MCDM Method for the Selection of Suitable Cutting Fluid; Implementation of CODAS MCDM Method for the Selection of Suitable Cutting Fluid," 2021, doi: 10.1109/SASM51857.2021.9841150.

[34] J. Tamošaitiene and E. Gaudutis, "COMPLEX ASSESSMENT OF STRUCTURAL SYSTEMS USED FOR HIGH-RISE BUILDINGS," *Vilnius Gediminas Technical University*, vol. 19, no. 2, pp. 305–317, Apr. 2013, doi: 10.3846/13923730.2013.772071.

[35] P. Wang, Z. Zhu, and Y. Wang, "A novel hybrid MCDM model combining the SAW, TOPSIS and GRA methods based on experimental design," *Information Sciences*, vol. 345, pp. 27–45, 2016, doi:

10.1016/j.ins.2016.01.076.

[36] P. Akhavan, S. Barak, H. Maghsoudlou, and J. Antuchevičienė, “FQSPM-SWOT for strategic alliance planning and partner selection; case study in a holding car manufacturer company,” *Technological and Economic Development of Economy*, vol. 21, no. 2, pp. 165–185, 2015, doi: 10.3846/20294913.2014.965240.

[37] D. Petković, M. Madić, M. Radovanović, and V. Gečevska, “Original scientific paper APPLICATION OF THE PERFORMANCE SELECTION INDEX METHOD FOR SOLVING MACHINING MCDM PROBLEMS,” *FACTA UNIVERSITATIS Series: Mechanical Engineering*, vol. 15, pp. 97–106, 2017, doi: 10.22190/FUME151120001P.

[38] M. Masdari and H. Khezri, “Service selection using fuzzy multi-criteria decision making: a comprehensive review,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 2, pp. 2803–2834, Feb. 2021, doi: 10.1007/S12652-020-02441-W/FIGURES/32.

[39] S. Çalı and Ş. Y. Balaman, “Improved decisions for marketing, supply and purchasing: Mining big data through an integration of sentiment analysis and intuitionistic fuzzy multi criteria assessment,” *Computers & Industrial Engineering*, vol. 129, pp. 315–332, Mar. 2019, doi: 10.1016/J.CIE.2019.01.051.

[40] K. Madani and J. R. Lund, “California’s Sacramento–San Joaquin Delta Conflict: From Cooperation to Chicken,” *Journal of Water Resources Planning and Management*, vol. 138, no. 2, pp. 90–99, 2012, doi: 10.1061/(asce)wr.1943-5452.0000164.

[41] W. Jiang, K. Zhou, C. Xiong, G. Du, C. Ou, and J. Zhang, “KSCB: a novel unsupervised method for text sentiment analysis,” *Applied Intelligence*, pp. 1–11, Apr. 2022, doi: 10.1007/S10489-022-03389-4/FIGURES/2.

[42] H. Kang, S. J. Yoo, and D. Han, “Senti-lexicon and improved Naïve Bayes algorithms for sentiment analysis of restaurant reviews,” *Expert Systems with Applications*, vol. 39, no. 5, pp. 6000–6010, Apr. 2012, doi: 10.1016/J.ESWA.2011.11.107.

[43] M. Li, L. Chen, J. Zhao, and Q. Li, “Sentiment analysis of Chinese stock reviews based on BERT model,” *Applied Intelligence*, vol. 51, no. 7, pp. 5016–5024, Jul. 2021, doi: 10.1007/S10489-020-02101-8/TABLES/5.

[44] A. Ahmad and T. Ahmad, “A Game Theory Approach for Multi-document Summarization,” *Arabian Journal for Science and Engineering*, vol. 44, no. 4, pp. 3655–3667, Apr. 2019, doi: 10.1007/s13369-018-3619-y.

[45] N. Capuano, L. Greco, P. Ritrovato, and M. Vento, “Sentiment analysis for customer relationship management: an incremental learning approach,” *Applied Intelligence*, vol. 51, no. 6. pp. 3339–3352, 2021, doi: 10.1007/s10489-020-01984-x.

[46] D. K. Kirange and R. R. Deshmukh, “Sentiment Analysis of News Headlines for Stock Price Prediction,” *An international journal of advanced computer technology*, vol. 5, no. 3, 2016, doi: 10.13140/RG.2.1.4606.3765.

[47] A. Tripathy, A. Anand, and S. K. Rath, “Document-level sentiment classification using hybrid machine learning approach,” *Knowledge and Information Systems*, vol. 53, no. 3, pp. 805–831, Dec. 2017, doi: 10.1007/S10115-017-1055-Z/FIGURES/5.

[48] A. Ligthart, C. Catal, and B. Tekinerdogan, “Systematic reviews in sentiment analysis: a tertiary study,” *Artificial Intelligence Review 2021 54:7*, vol. 54, no. 7, pp. 4997–5053, Mar. 2021, doi: 10.1007/S10462-021-09973-3.

[49] M. E. Basiri, S. Nemati, M. Abdar, E. Cambria, and U. R. Acharya, “ABCDM: An Attention-based Bidirectional CNN-RNN Deep Model for sentiment analysis,” *Future Generation Computer Systems*, vol. 115, pp. 279–294, Feb. 2021, doi: 10.1016/J.FUTURE.2020.08.005.

[50] F. A. Gers, J. Schmidhuber, and F. Cummins, “Learning to forget: Continual prediction with LSTM,” *Neural Computation*, vol. 12, no. 10, pp. 2451–2471, 2000, doi: 10.1162/089976600300015015.

[51] M. Birjali, M. Kasri, and A. Beni-Hssane, “A comprehensive survey on sentiment analysis: Approaches, challenges and trends,” *Knowledge-Based Systems*, vol. 226, Aug. 2021, doi: 10.1016/J.KNOSYS.2021.107134.

[52] J. Hu, X. Zhang, Y. Yang, Y. Liu, and X. Chen, “New doctors ranking system based on VIKOR method,” *International Transactions in Operational Research*, vol. 27, no. 2, pp. 1236–1261, Mar. 2020, doi: 10.1111/itor.12569.

[53] A. Mee, E. Homapour, F. Chiclana, and O. Engel, “Sentiment analysis using TF–IDF weighting of UK MPs’ tweets on Brexit,” *Knowledge-Based Systems*, vol. 228, p. 107238, Sep. 2021, doi: 10.1016/J.KNOSYS.2021.107238.

[54] D. N. Nguyen, T. T. Phan, and P. Do, “Embedding knowledge on ontology into the corpus by topic to improve the performance of deep learning methods in sentiment analysis,” *Scientific Reports*, vol. 11, no. 1, 2021, doi: 10.1038/s41598-021-03011-6.

[55] A. García-Pablos, M. Cuadros, and G. Rigau, “W2VLDA: Almost unsupervised system for Aspect Based Sentiment Analysis,” *Expert Systems With Applications*, vol. 91, pp. 127–137, 2017, doi: 10.1016/j.eswa.2017.08.049.

[56] S. Vashishtha and S. Susan, “Highlighting keyphrases using senti-scoring and fuzzy entropy for unsupervised sentiment analysis,” *Expert Systems with Applications*, vol. 169. 2021, doi: 10.1016/j.eswa.2020.114323.

[57] M. Song, H. Park, and K. shik Shin, “Attention-based long short-term memory network using sentiment lexicon embedding for aspect-level sentiment analysis in Korean,” *Information Processing & Management*, vol. 56, no. 3, pp. 637–653, May 2019, doi: 10.1016/J.IPM.2018.12.005.

[58] A. Zhao and Y. Yu, “Knowledge-enabled BERT for aspect-based sentiment analysis,” *Knowledge-Based Systems*, vol. 227, p. 107220, Sep. 2021, doi: 10.1016/J.KNOSYS.2021.107220.

[59] I. Perikos, S. Kardakis, and I. Hatzilygeroudis, “Sentiment analysis using novel and interpretable architectures of Hidden Markov Models[Formula presented],” *Knowledge-Based Systems*, vol. 229, p. 107332, 2021, doi: 10.1016/j.knosys.2021.107332.

[60] K. Fiok, W. Karwowski, E. Gutierrez, and M. Wilamowski, “Analysis of sentiment in tweets addressed to a single domain-specific Twitter account: Comparison of model performance and explainability of predictions,” *Expert Systems with Applications*, vol. 186. 2021, doi: 10.1016/j.eswa.2021.115771.

[61] B. Liang, H. Su, L. Gui, E. Cambria, and R. Xu, “Aspect-based sentiment analysis via affective knowledge enhanced graph convolutional networks,” *Knowledge-Based Systems*, vol. 235, p. 107643, Jan. 2022, doi: 10.1016/j.knosys.2021.107643.

[62] T. Swathi, N. Kasiviswanath, and A. A. Rao, “An optimal deep learning-based LSTM for stock price prediction using twitter sentiment analysis,” *Applied Intelligence*, vol. 52, no. 12, pp. 13675–13688, Mar. 2022, doi: 10.1007/s10489-022-03175-2.

[63] R. Chiha, M. Ben Ayed, and C. da C. Pereira, “A complete framework for aspect-level and sentence-level sentiment analysis,” *Applied Intelligence*, pp. 1–19, Apr. 2022, doi: 10.1007/S10489-022-03279-9/TABLES/11.

[64] J. Wu, X. Ma, F. Chiclana, Y. Liu, and Y. Wu, “A consensus group decision making method for hotel selection with online reviews by sentiment analysis,” *Applied Intelligence*, vol. 52, no. 9, pp. 10716–10740, Jul. 2022, doi: 10.1007/S10489-021-02991-2/FIGURES/7.

[65] J. W. Lin and R. G. Chang, “Chinese story generation of sentence format control based on multi-channel word embedding and novel data format,” *Soft Computing*, vol. 26, no. 5, pp. 2179–2196, Mar. 2022, doi: 10.1007/S00500-021-06548-W/FIGURES/13.

[66] D. Wang, X. Guo, Y. Tian, J. Liu, L. H. He, and X. Luo, “TETFN: A text enhanced transformer fusion network for multimodal sentiment analysis,” *Pattern Recognition*, vol. 136, 2023, doi: 10.1016/j.patcog.2022.109259.

[67] S. Kardakis, I. Perikos, F. Grivokostopoulou, and I. Hatzilygeroudis, “Examining Attention Mechanisms in Deep Learning Models for Sentiment Analysis,” *mdpi.com*, 2021, doi: 10.3390/app11093883.

[68] I. Perikos, S. Kardakis, and I. Hatzilygeroudis, “Sentiment analysis using novel and interpretable architectures of Hidden Markov Models,” *Knowledge-Based Systems*, vol. 229, p. 107332, Oct. 2021, doi: 10.1016/J.KNOSYS.2021.107332.

[69] D. Zhang, Z. Zhu, S. Kang, G. Zhang, and P. Liu, “Syntactic and semantic analysis network for aspect-level sentiment classification,” *Applied Intelligence*, vol. 51, no. 8, pp. 6136–6147, Aug. 2021, doi: 10.1007/S10489-021-02189-6/FIGURES/9.

[70] R. Liang and J. qiang Wang, “A Linguistic Intuitionistic Cloud Decision Support Model with Sentiment Analysis for Product Selection in E-commerce,” *International Journal of Fuzzy Systems 2019 21:3*, vol. 21, no. 3, pp. 963–977, Jan. 2019, doi: 10.1007/S40815-019-00606-0.

[71] Y. Peng, T. Xiao, and H. Yuan, “Cooperative gating network based on a single BERT encoder for aspect term sentiment analysis,” *Applied Intelligence*, vol. 52, no. 5, pp. 5867–5879, Mar. 2022, doi: 10.1007/S10489-021-02724-5/TABLES/7.

[72] Q. Zhang, L. Shi, P. Liu, Z. Zhu, and L. Xu, “ICDN: integrating consistency and difference networks by transformer for multimodal sentiment analysis,” *Applied Intelligence*, vol. 53, no. 12, pp. 16332–16345, Mar. 2023, doi: 10.1007/s10489-022-03343-4.

[73] T. Gu, H. Zhao, and M. Li, “Effective inter-aspect words modeling for aspect-based sentiment analysis,” *Applied Intelligence*, pp. 1–14, Jun. 2022, doi: 10.1007/S10489-022-03630-0/TABLES/6.

[74] L. Li, J. Johnson, W. Aarhus, and D. Shah, “Key factors in MOOC pedagogy based on NLP sentiment analysis of learner reviews: What makes a hit,” *Computers & Education*, vol. 176, p. 104354, Jan. 2022, doi: 10.1016/J.COMPEDU.2021.104354.

[75] Y. Wang, H. Han, X. He, and R. Zhai, “A two-stage unsupervised sentiment analysis method,” *Multimedia Tools and Applications*, 2023, doi: 10.1007/s11042-023-14864-6.

[76] A. Das, A. Ghosh, and S. Bandyopadhyay, *Semantic Role Labeling for Bengali Noun using 5Ws Who, What, When, Where and Why*. 2010.

[77] A. Das, … S. B. the eighth workshop on A., and undefined 2010, “SentiWordNet for Indian languages,” *aclanthology.org*, pp. 21–22, 2010, Accessed: Apr. 18, 2022. [Online]. Available: https://aclanthology.org/W10-3208.pdf.

[78] B. A.R., A. Joshi, and P. Bhattacharyya, “Cross-Lingual Sentiment Analysis for Indian Languages using Linked WordNets,” *Proceedings of COLING 2012: Posters*, vol. 1, no. December 2012, pp. 73–82, 2012, Accessed: Apr. 30, 2022. [Online]. Available: http://www.aclweb.org/anthology/C12-2008.

[79] P. Arora, A. Bakliwal, and V. Varma, “Hindi Subjective Lexicon Generation using WordNet Graph Traversal,” *International Journal of Computational Linguistics and Applications*, vol. 3, no. Jan-Jun 2012, pp. 25–29, 2012, Accessed: Apr. 30, 2022. [Online]. Available: https://www.academia.edu/download/44138556/inproceedings.pdf.a951328a48178e4d.3136322e706466.pdf.

[80] V. Jha, N. Manjunath, P. D. Shenoy, K. R. Venugopal, and L. M. Patnaik, “HOMS: Hindi opinion mining system,” *2015 IEEE 2nd International Conference on Recent Trends in Information Systems, ReTIS 2015 - Proceedings*, pp. 366–371, Aug. 2015, doi: 10.1109/ReTIS.2015.7232906.

[81] B. Patra, D. Das, A. Das, R. P.-I. C. on Mining, and undefined 2015, “Shared task on sentiment analysis in indian languages (sail) tweets-an overview,” *Springer*, vol. 9468, pp. 650–655, 2015, doi: 10.1007/978-3-319-26832-3_61.

[82] Deepa Modi and Neeta Nain, “Part-of-Speech Tagging of Hindi Corpus Using Rule-Based Method,” *Proceedings of the International Conference on Recent Cognizance in Wireless Communication & Image Processing*, pp. 241–247, 2016, doi: 10.1007/978-81-322-2638-3_28.

[83] M. S. Akhtar, A. Kumar, A. Ekbal, and P. Bhattacharyya, “A hybrid deep learning architecture for sentiment analysis,” *COLING 2016 - 26th International Conference on Computational Linguistics, Proceedings of COLING 2016: Technical Papers*, pp. 482–493, 2016, Accessed: Apr. 18, 2022. [Online]. Available: https://aclanthology.org/C16-1047/.

[84] M. S. Akhtar, A. Ekbal, and P. Bhattacharyya, “Aspect based sentiment analysis in Hindi: Resource creation and evaluation,” *Proceedings of the 10th International Conference on Language Resources and Evaluation, LREC 2016*, pp. 2703–2709, 2016, Accessed: Apr. 20, 2022. [Online]. Available: https://aclanthology.org/L16-1429/.

[85] S. Pandey, M. S. Akhtar, and T. Chakraborty, “Syntactically Coherent Text Augmentation for Sequence Classification,” *IEEE Transactions on Computational Social Systems*, vol. 8, no. 6, pp. 1323–1332, Dec. 2021, doi: 10.1109/TCSS.2021.3075774.

[86] Y. Sharma, V. Mangat, and M. Kaur, “A practical approach to Sentiment Analysis of Hindi tweets,” *Proceedings on 2015 1st International Conference on Next Generation Computing Technologies, NGCT 2015*, pp. 677–680, 2016, doi: 10.1109/NGCT.2015.7375207.

[87] V. Jha, S. R. P. Deepa Shenoy, and K. R. Venugopal, “Reputation system: Evaluating reputation among all good sellers,” *Proceedings of the 7th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, WASSA 2016 at the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 115–121, 2016, doi: 10.18653/v1/w16-0419.

[88] V. Jha, S. G. R, P. Deepa Shenoy, and V. K. R, "Generating Multilingual Subjectivity Resources using English Language," *International Journal of Computer Applications*, vol. 152, no. 9, pp. 975–8887, 2016, Accessed: Apr. 30, 2022. [Online]. Available: http://www.internetworldstats.com/stats7.htm,.

[89] K. Garg, "Sentiment analysis of Indian PM's 'Mann Ki Baat,'" *International Journal of Information Technology 2019 12:1*, vol. 12, no. 1, pp. 37–48, Jul. 2019, doi: 10.1007/S41870-019-00324-8.

[90] D. Kakwani *et al.*, "IndicNLPSuite: Monolingual Corpora, Evaluation Benchmarks and Pre-trained Multilingual Language Models for Indian Languages," *Findings of the Association for Computational Linguistics Findings of ACL: EMNLP 2020*, vol. 3, pp. 4948–4961, 2020, doi: 10.18653/V1/2020.FINDINGS-EMNLP.445.

[91] "Score based sentiment analysis of book reviews in... - Google Scholar." https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Score+based+sentiment+analysis+of+book+reviews+in+hindi+languages&btnG= (accessed Apr. 30, 2022).

[92] A. Sotoudeh-Anvari, S. J. Sadjadi, S. M. H. Molana, and S. Sadi-Nezhad, "A new MCDM-based approach using BWM and SAW for optimal search model," *Decision Science Letters*, vol. 7, no. 4, pp. 395–404, 2018, doi: 10.5267/j.dsl.2018.2.001.

[93] H. Li, W. Wang, L. Fan, Q. Li, and X. Chen, "A novel hybrid MCDM model for machine tool selection using fuzzy DEMATEL, entropy weighting and later defuzzification VIKOR," *Applied Soft Computing Journal*, vol. 91, 2020, doi: 10.1016/j.asoc.2020.106207.

[94] R. Krishankumar, J. Premaladha, K. S. Ravichandran, K. R. Sekar, R. Manikandan, and X. Z. Gao, "A novel extension to VIKOR method under intuitionistic fuzzy context for solving personnel selection problem," *Soft Computing*, vol. 24, no. 2, pp. 1063–1081, 2020, doi: 10.1007/s00500-019-03943-2.

[95] J. Qi, J. Hu, and Y. H. Peng, "Integrated rough VIKOR for customer-involved design concept evaluation combining with customers' preferences and designers' perceptions," *Advanced Engineering Informatics*, vol. 46, 2020, doi: 10.1016/j.aei.2020.101138.

[96] A. Guleria and R. K. Bajaj, "A robust decision making approach for hydrogen power plant site selection utilizing (R, S)-Norm Pythagorean Fuzzy information measures based on VIKOR and TOPSIS method," *International Journal of Hydrogen Energy*, vol. 45, no. 38, pp. 18802–18816, 2020, doi: 10.1016/j.ijhydene.2020.05.091.

[97] A. E. Youssef, "An integrated MCDM approach for cloud service selection based on TOPSIS and BWM," *IEEE Access*, vol. 8, pp. 71851–71865, 2020, doi: 10.1109/ACCESS.2020.2987111.

[98] B. D. Rouyendegh, A. Yildizbasi, and P. Üstünyer, "Intuitionistic Fuzzy TOPSIS method for green supplier selection problem," *Soft Computing*, vol. 24, no. 3, pp. 2215–2228, 2020, doi: 10.1007/s00500-019-04054-8.

[99] S. S. Raju, G. B. Murali, and P. K. Patnaik, "Ranking of Al-CSA composite by MCDM approach using AHP–TOPSIS and MOORA methods," *Journal of Reinforced Plastics and Composites*, vol. 39, no. 19–20, pp. 721–732, 2020, doi: 10.1177/0731684420924833.

[100] C. S. Dhanalakshmi, P. Madhu, A. Karthick, M. Mathew, and R. Vignesh Kumar, "A comprehensive MCDM-based approach using TOPSIS and EDAS as an auxiliary tool for pyrolysis material selection and its application," *Biomass Conversion and Biorefinery*, vol. 12, no. 12, pp. 5845–5860, 2022, doi: 10.1007/s13399-020-01009-0.

[101] K. Kiracı and E. Akan, "Aircraft selection by applying AHP and TOPSIS in interval type-2 fuzzy sets," *Journal of Air Transport Management*, vol. 89, 2020, doi: 10.1016/j.jairtraman.2020.101924.

[102] H. Dhumras and R. K. Bajaj, "Modified EDAS method for MCDM in robotic agrifarming with picture fuzzy soft Dombi aggregation operators," *Soft Computing*, 2023, doi: 10.1007/s00500-023-07927-1.

[103] M. Akram and R. Bibi, "Multi-criteria group decision-making based on an integrated PROMETHEE approach with 2-tuple linguistic Fermatean fuzzy sets," *Granular Computing*, 2023, doi: 10.1007/s41066-022-00359-6.

[104] J. Ye and T. Y. Chen, "Pythagorean Fuzzy Sets Combined with the PROMETHEE Method for the Selection of Cotton Woven Fabric," *Journal of Natural Fibers*, vol. 19, no. 16, pp. 12447–12461, 2022, doi: 10.1080/15440478.2022.2072993.

[105] R. A. da Cunha, L. A. D. Rangel, C. A. Rudolf, and L. dos Santos, "A decision support approach employing the PROMETHEE method and risk factors for critical supply assessment in large-scale projects," *Operations Research Perspectives*, vol. 9, 2022, doi: 10.1016/j.orp.2022.100238.

[106] “Evaluation of Private Banks using PROMETHEE Method,” *REST Journal on Banking, Accounting and Business*, vol. 1, no. 3, pp. 42–50, 2022, doi: 10.46632/jbab/1/3/6.

[107] S. Burak, F. Samanlioglu, and D. Ülker, “Evaluation of irrigation methods in Söke Plain with HF-AHP-PROMETHEE II hybrid MCDM method,” *Agricultural Water Management*, vol. 271, 2022, doi: 10.1016/j.agwat.2022.107810.

[108] A. Ulutaş, F. Balo, and A. Topal, “Identifying the Most Efficient Natural Fibre for Common Commercial Building Insulation Materials with an Integrated PSI, MEREC, LOPCOW and MCRAT Model,” *Polymers*, vol. 15, no. 6, p. 1500, 2023, doi: 10.3390/polym15061500.

[109] L. Y. Peng, L. Y. Pan, J. Lu, and Y. M. Long, “A combination of FDM, EWM, and GRA to measure performance in higher vocational college: An empirical case from China,” *Heliyon*, vol. 9, no. 2, 2023, doi: 10.1016/j.heliyon.2023.e13134.

[110] N. A. Maidin, S. M. Sapuan, M. M. Taha, and M. Z. M. Yusoff, “Material Selection of Natural Fibre Using a Grey Relational Analysis (GRA) Approach,” *BioResources*, vol. 17, no. 1, pp. 109–131, 2022, doi: 10.15376/biores.17.1.109-131.

[111] M. Riaz, H. Garg, M. T. Hamid, and D. Afzal, “Modelling uncertainties with TOPSIS and GRA based on q-rung orthopair m-polar fuzzy soft information in COVID-19,” *Expert Systems*, vol. 39, no. 5, 2022, doi: 10.1111/exsy.12940.

[112] Z. Hua, X. Jing, and L. Martínez, “An ELICIT information-based ORESTE method for failure mode and effect analysis considering risk correlation with GRA-DEMATEL,” *Information Fusion*, vol. 93, pp. 396–411, 2023, doi: 10.1016/j.inffus.2023.01.012.

[113] M. Liang *et al.*, “Evaluating the Comprehensive Performance of 5G Base Station: A Hybrid MCDM Model Based on Bayesian Best-Worst Method and DQ-GRA Technique,” *Mathematical Problems in Engineering*, vol. 2022, 2022, doi: 10.1155/2022/4038369.

[114] V. Chodha, R. Dubey, R. Kumar, S. Singh, and S. Kaur, “Selection of industrial arc welding robot with TOPSIS and Entropy MCDM techniques,” *Materials Today: Proceedings*, vol. 50, pp. 709–715, 2021, doi: 10.1016/j.matpr.2021.04.487.

[115] S. S. Lin, A. Zhou, and S. L. Shen, “Safety assessment of excavation system via TOPSIS-based MCDM modelling in fuzzy environment,” *Applied Soft Computing*, vol. 138, p. 110206, 2023, doi: 10.1016/j.asoc.2023.110206.

[116] Z. Bu, H. Li, J. Cao, Z. Wu, and L. Zhang, “Game theory based emotional evolution analysis for Chinese online reviews,” *Knowledge-Based Systems*, vol. 103, pp. 60–72, 2016, doi: 10.1016/j.knosys.2016.03.026.

[117] R. Tripodi, M. P.-C. Linguistics, and undefined 2017, “A game-theoretic approach to word sense disambiguation,” *direct.mit.edu*, Accessed: Oct. 29, 2021. [Online]. Available: https://direct.mit.edu/coli/article-abstract/43/1/31/1562.

[118] F. Liu and M. Li, “A game theory-based network rumor spreading model: based on game experiments,” *International Journal of Machine Learning and Cybernetics*, vol. 10, no. 6, pp. 1449–1457, Jun. 2019, doi: 10.1007/S13042-018-0826-5/FIGURES/5.

[119] S. Ruseti, M. D. Sirbu, M. A. Calin, M. Dascalu, S. Trausan-Matu, and G. Militaru, “Comprehensive exploration of game reviews extraction and opinion mining using nlp techniques,” *Advances in Intelligent Systems and Computing*, vol. 1041, pp. 323–331, 2020, doi: 10.1007/978-981-15-0637-6_27/COVER.

[120] M. Jain, A. Jaswani, A. Mehra, and L. Mudgal, “Rumour Source Detection Using Game Theory,” *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 6, no. 4, p. 49, 2020, doi: 10.9781/ijimai.2020.10.003.

[121] L. Jain, R. Katarya, and S. Sachdeva, “Recognition of opinion leaders coalitions in online social network using game theory,” *Knowledge-Based Systems*, vol. 203, p. 106158, Sep. 2020, doi: 10.1016/j.knosys.2020.106158.

[122] D. W. Huang, L. X. Yang, P. Li, X. Yang, and Y. Y. Tang, “Developing Cost-Effective Rumor-Refuting Strategy through Game-Theoretic Approach,” *IEEE Systems Journal*, vol. 15, no. 4, pp. 5034–5045, Dec. 2021, doi: 10.1109/JSYST.2020.3020078.

[123] A. Saxena, M. Mangal, and G. Jain, “KeyGames: A Game Theoretic Approach to Automatic Keyphrase Extraction,” pp. 2037–2048, Jan. 2021, doi: 10.18653/v1/2020.coling-main.184.

[124] M. Jain, A. Suvarna, and A. Jain, “An evolutionary game theory based approach for query expansion,”

Multimedia Tools and Applications 2021, pp. 1–25, Oct. 2021, doi: 10.1007/S11042-021-11297-X.

[125] G. Jain and D. K. Lobiyal, "Word Sense Disambiguation using Cooperative Game Theory and Fuzzy Hindi WordNet based on ConceptNet," *Transactions on Asian and Low-Resource Language Information Processing*, vol. 21, no. 4, pp. 1–25, Mar. 2022, doi: 10.1145/3502739.

[126] S. Xia, F. Lin, Z. Chen, C. Tang, Y. Ma, and X. Yu, "A Bayesian Game Based Vehicle-to-Vehicle Electricity Trading Scheme for Blockchain-Enabled Internet of Vehicles," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 6856–6868, Jul. 2020, doi: 10.1109/TVT.2020.2990443.

[127] R. Sharma and M. T. J. Spaan, "Bayesian-Game-Based Fuzzy Reinforcement Learning Control for Decentralized POMDPs," *IEEE Transactions on Computational Intelligence and AI in Games*, vol. 4, no. 4, 2012, doi: 10.1109/TCIAIG.2012.2212279.

[128] A. Dahiya and B. B. Gupta, "A reputation score policy and Bayesian game theory based incentivized mechanism for DDoS attacks mitigation and cyber defense," *Future Generation Computer Systems*, vol. 117, pp. 193–204, Apr. 2021, doi: 10.1016/J.FUTURE.2020.11.027.

[129] S. Abapour, B. Mohammadi-Ivatloo, and M. Tarafdar Hagh, "A Bayesian game theoretic based bidding strategy for demand response aggregators in electricity markets," *Sustainable Cities and Society*, vol. 54, 2020, doi: 10.1016/j.scs.2019.101787.

[130] Y. Xiao, W. Li, S. Qiang, Q. Li, H. Xiao, and Y. Liu, "A Rumor & Anti-Rumor Propagation Model Based on Data Enhancement and Evolutionary Game," *IEEE Transactions on Emerging Topics in Computing*, vol. 10, no. 2, pp. 690–703, 2022, doi: 10.1109/TETC.2020.3034188.

[131] M. Abedian, A. Amindoust, R. Maddahi, and J. Jouzdani, "A game theory approach to selecting marketing-mix strategies," *Journal of Advances in Management Research*, vol. 19, no. 1, pp. 139–158, 2022, doi: 10.1108/JAMR-10-2020-0264.

[132] N. Smirnov, Y. Liu, A. Validi, W. Morales-Alvarez, and C. Olaverri-Monreal, "A game theory-based approach for modeling autonomous vehicle behavior in congested, urban lane-changing scenarios," *Sensors*, vol. 21, no. 4, pp. 1–20, 2021, doi: 10.3390/s21041523.

[133] S. Zhang, S. Zhang, W. Yuan, and T. Q. S. Quek, "Rate-Splitting Multiple Access-Based Satellite-Vehicular Communication System: A Noncooperative Game Theoretical Approach," *IEEE Open Journal of the Communications Society*, vol. 4, pp. 430–441, 2023, doi: 10.1109/OJCOMS.2023.3240163.

[134] M. Asvial, A. F. S. Admaja, and M. A. Laagu, "Non-cooperative Game Leach for Cluster Distribution Routing Method on Wireless Sensor Network (WSN)," *Journal of Communications*, pp. 198–206, 2023, doi: 10.12720/jcm.18.3.198-206.

[135] N. T. Boyd, S. A. Gabriel, G. Rest, and T. Dumm, "Generalized Nash equilibrium models for asymmetric, non-cooperative games on line graphs: Application to water resource systems," *Computers and Operations Research*, vol. 154, 2023, doi: 10.1016/j.cor.2023.106194.

[136] P. Zhang, C. Li, M. Zhou, W. Huang, A. Abusorrah, and O. O. Bamasag, "Transaction transmission model for blockchain channels based on non-cooperative games," *Science China Information Sciences*, vol. 66, no. 1, 2023, doi: 10.1007/s11432-021-3362-9.

[137] J. Zhao *et al.*, "Peer-to-Peer electricity trading of interconnected flexible distribution networks based on Non-Cooperative games," *International Journal of Electrical Power and Energy Systems*, vol. 145, 2023, doi: 10.1016/j.ijepes.2022.108648.

[138] Y. Liu, C. Zong, C. Dai, H. Zheng, and D. Zhang, "Behavioral Decision-Making Approach for Vehicle Platoon Control: Two Noncooperative Game Models," *IEEE Transactions on Transportation Electrification*, pp. 1–1, 2023, doi: 10.1109/tte.2023.3237929.

[139] J. Yang, Z. Cai, Q. Fu, and Z. Xu, "The Shapley Value Based on Hesitant Fuzzy Linguistic Comprehensive Entropy and its Application in Noncooperative-Cooperative Biform Game," *SSRN Electronic Journal*, 2022, doi: 10.2139/ssrn.4295240.

[140] X. Liu, J. Zhang, P. Zhu, Q. Tan, and W. Yin, "Quantitative cyber-physical security analysis methodology for industrial control systems based on incomplete information Bayesian game," *Computers & Security*, vol. 102, p. 102138, Mar. 2021, doi: 10.1016/J.COSE.2020.102138.

[141] K. C. Lalropuia and V. Gupta, "A Bayesian game model and network availability model for small cells under denial of service (DoS) attack in 5G wireless communication network," *Wireless Networks*, vol. 26, no. 1, pp. 557–572, 2020, doi: 10.1007/s11276-019-02163-8.

[142] M. Tian, Z. Dong, and X. Wang, "Analysis of false data injection attacks in power systems: A dynamic

Bayesian game-theoretic approach," *ISA Transactions*, vol. 115, pp. 108–123, 2021, doi: 10.1016/j.isatra.2021.01.011.

[143] G. Chen, K. Cao, and Y. Hong, "Learning implicit information in Bayesian games with knowledge transfer," *Control Theory and Technology*, vol. 18, no. 3, pp. 315–323, 2020, doi: 10.1007/s11768-020-0086-2.

[144] R. Bi, Q. Chen, L. Chen, J. Xiong, and D. Wu, "A Privacy-Preserving Personalized Service Framework through Bayesian Game in Social IoT," *Wireless Communications and Mobile Computing*, vol. 2020, 2020, doi: 10.1155/2020/8891889.

[145] L. T. Maccarone and D. G. Cole, "Bayesian games for the cybersecurity of nuclear power plants," *International Journal of Critical Infrastructure Protection*, vol. 37, 2022, doi: 10.1016/j.ijcip.2021.100493.

[146] S. Sawadsitang, D. Niyato, P. S. Tan, P. Wang, and S. Nutanong, "Shipper Cooperation in Stochastic Drone Delivery: A Dynamic Bayesian Game Approach," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 8, pp. 7437–7452, 2021, doi: 10.1109/TVT.2021.3090992.

[147] Y. Zhang, P. Hang, C. Huang, and C. Lv, "Human-Like Interactive Behavior Generation for Autonomous Vehicles: A Bayesian Game-Theoretic Approach with Turing Test," *Advanced Intelligent Systems*, vol. 4, no. 5, p. 2100211, 2022, doi: 10.1002/aisy.202100211.

[148] L. Govindaraj, B. Sundan, and A. Thangasamy, "An Intrusion Detection and Prevention System for DDoS Attacks using a 2-Player Bayesian Game Theoretic Approach," *Proceedings of the 2021 4th International Conference on Computing and Communications Technologies, ICCCT 2021*, pp. 319–324, 2021, doi: 10.1109/ICCCT53315.2021.9711773.

[149] Z. Shi, H. Zhou, C. de Laat, and Z. Zhao, "A Bayesian game-enhanced auction model for federated cloud services using blockchain," *Future Generation Computer Systems*, vol. 136, pp. 49–66, 2022, doi: 10.1016/j.future.2022.05.017.

[150] Y. Yu, G. Li, Y. Liu, and Z. Li, "V2V Energy Trading in Residential Microgrids Considering Multiple Constraints via Bayesian Game," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–12, 2023, doi: 10.1109/tits.2023.3250649.

[151] L. D. Christensen, "A Bayesian game of resource exploitation in hinterland regions: modelling scenarios for sustainable development," *Environment, Development and Sustainability*, vol. 25, no. 1, pp. 277–296, 2023, doi: 10.1007/s10668-021-02052-1.

[152] S. Abapour, B. Mohammadi-Ivatloo, and M. Tarafdar Hagh, "A Bayesian game theoretic based bidding strategy for demand response aggregators in electricity markets," *Sustainable Cities and Society*, vol. 54, p. 101787, Mar. 2020, doi: 10.1016/J.SCS.2019.101787.

[153] A. Antoci, S. Borghesi, and M. Galeotti, "Environmental options and technological innovation: An evolutionary game model," *Journal of Evolutionary Economics*, vol. 23, no. 2, pp. 247–269, 2013, doi: 10.1007/s00191-011-0238-0.

[154] M. Chica, R. Chiong, M. T. P. Adam, and T. Teubner, "An Evolutionary Game Model with Punishment and Protection to Promote Trust in the Sharing Economy," *Scientific Reports*, vol. 9, no. 1, 2019, doi: 10.1038/s41598-019-55384-4.

[155] Z. Zhang and H. Zhang, "A variable-population evolutionary game model for resource allocation in cooperative cognitive relay networks," *IEEE Communications Letters*, vol. 17, no. 2, pp. 361–364, 2013, doi: 10.1109/LCOMM.2012.122012.122676.

[156] B. Wölfl *et al.*, "The Contribution of Evolutionary Game Theory to Understanding and Treating Cancer," *Dynamic Games and Applications*, vol. 12, no. 2, pp. 313–342, 2022, doi: 10.1007/s13235-021-00397-w.

[157] M. Alam, K. M. A. Kabir, and J. Tanimoto, "Based on mathematical epidemiology and evolutionary game theory, which is more effective: Quarantine or isolation policy," *Journal of Statistical Mechanics: Theory and Experiment*, vol. 2020, no. 3, 2020, doi: 10.1088/1742-5468/ab75ea.

[158] P. García-Victoria, M. Cavaliere, M. A. Gutiérrez-Naranjo, and M. Cárdenas-Montes, "Evolutionary game theory in a cell: A membrane computing approach," *Information Sciences*, vol. 589, pp. 580–594, 2022, doi: 10.1016/j.ins.2021.12.109.

[159] Z. Zhu, X. Wang, L. Liu, and S. Hua, "Green sensitivity in supply chain management: An evolutionary game theory approach," *Chaos, Solitons and Fractals*, vol. 173, 2023, doi: 10.1016/j.chaos.2023.113595.

[160] Z. Tian, X. Gao, S. Su, J. Qiu, X. Du, and M. Guizani, “Evaluating Reputation Management Schemes of Internet of Vehicles Based on Evolutionary Game Theory,” *IEEE Transactions on Vehicular Technology*, vol. 68, no. 6, pp. 5971–5980, 2019, doi: 10.1109/TVT.2019.2910217.

[161] P. ZongJie, G. Xin, C. LinYan, and L. JingHua, “The new path to improve construction safety performance in China: an evolutionary game theoretic approach.,” *International Journal of Environmental Research and Public Health*, vol. 16, no. 13, p. 2443, 2019.

[162] A. A. Khan, M. Abolhasan, and W. Ni, “An evolutionary game theoretic approach for stable and optimized clustering in vanets,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 5, pp. 4501–4513, 2018, doi: 10.1109/TVT.2018.2790391.

[163] X. Zhou, R. Zhao, L. Cheng, and X. Min, “Impact of policy incentives on electric vehicles development: a system dynamics-based evolutionary game theoretical analysis,” *Clean Technologies and Environmental Policy*, vol. 21, no. 5, pp. 1039–1053, 2019, doi: 10.1007/s10098-019-01691-3.

[164] Y. Yang, B. Che, Y. Zeng, Y. Cheng, and C. Li, “MAIAD: A multistage asymmetric information attack and defense model based on evolutionary game theory,” *Symmetry*, vol. 11, no. 2, 2019, doi: 10.3390/sym11020215.

[165] C. L. Hall, M. A. Porter, and M. S. Dawkins, “Dominance, sharing, and assessment in an iterated Hawk–Dove game,” *Journal of Theoretical Biology*, vol. 493, 2020, doi: 10.1016/j.jtbi.2019.110101.

[166] Y. Lei, B. Guo, and X. Li, “Research on development countermeasures of new energy automobile industry based on hawk-dove game,” *Proceedings - 2021 International Conference on E-Commerce and E-Management, ICECEM 2021*, pp. 12–15, 2021, doi: 10.1109/ICECEM54757.2021.00010.

[167] T. Sakiyama, “Population Dynamics and Its Instability in a Hawk-Dove Game on the Network,” *Studies in Computational Intelligence*, vol. 1015, pp. 405–410, 2022, doi: 10.1007/978-3-030-93409-5_34.

[168] A. Maruotti, M. Fabbri, and M. Rizzolli, “Multilevel Hidden Markov Models for Behavioral Data: A Hawk-and-Dove Experiment,” *Multivariate Behavioral Research*, vol. 57, no. 5, pp. 825–839, 2022, doi: 10.1080/00273171.2021.1912583.

[169] T. E. Galanthay, V. Křivan, R. Cressman, and T. A. Revilla, “Evolution of Aggression in Consumer-Resource Models,” *Dynamic Games and Applications*, 2023, doi: 10.1007/s13235-023-00496-w.

[170] G. Zhou and X. Wu, “Hawk-dove game study on green railway alignment selection,” *International Journal of Applied Decision Sciences*, vol. 10, no. 4, pp. 315–326, 2017, doi: 10.1504/IJADS.2017.087187.

[171] A. Moussaoui and P. Auger, “Effects of Fast Hawk-Dove-Bully Game on the Dynamics of a Stage-structured Population,” *Mathematical Modelling of Natural Phenomena*, vol. 11, no. 4, pp. 135–153, 2016, doi: 10.1051/mmnp/201611410.

[172] T. Sakiyama, “A power law network in an evolutionary hawk–dove game,” *Chaos, Solitons and Fractals*, vol. 146, 2021, doi: 10.1016/j.chaos.2021.110932.

[173] B. Biswas, P. Sengupta, A. Kumar, D. Delen, and S. Gupta, “A critical assessment of consumer reviews: A hybrid NLP-based methodology,” *Decision Support Systems*, vol. 159, p. 113799, Aug. 2022, doi: 10.1016/j.dss.2022.113799.

[174] Y. Narahari, R. Narayanam, D. Garg, and H. Prakash, “Foundations of Mechanism Design,” *Game Theoretic Problems in Network Economics and Mechanism Design Solutions*, pp. 1–131, 2009, doi: 10.1007/978-1-84800-938-7_2.

[175] R. Colomo-Palacios, F. J. García-Peñalvo, V. Stantchev, and S. Misra, “Towards a social and context-aware mobile recommendation system for tourism,” *Pervasive and Mobile Computing*, vol. 38, pp. 505–515, Jul. 2017, doi: 10.1016/J.PMCJ.2016.03.001.

[176] M. Trevisiol, L. Chiarandini, and R. Baeza-Yates, “Buon appetito: Recommending personalized menus,” *HT 2014 - Proceedings of the 25th ACM Conference on Hypertext and Social Media*, pp. 327–329, 2014, doi: 10.1145/2631775.2631784.

[177] Y. Yiran and S. Srivastava, “Aspect-based Sentiment Analysis on mobile phone reviews with LDA,” *ACM International Conference Proceeding Series*, pp. 101–105, 2019, doi: 10.1145/3340997.3341012.

[178] D. A. J. Daniel and M. J. Meena, “A Novel Sentiment Analysis for Amazon Data with TSA based Feature Selection,” *Scalable Computing: Practice and Experience*, vol. 22, no. 1, pp. 53–66, Feb. 2021, doi: 10.12694/scpe.v22i1.1839.

[179] Y. Dai, J. Liu, J. Zhang, H. Fu, and Z. Xu, “Unsupervised Sentiment Analysis by Transferring Multi-source Knowledge,” *Cognitive Computation*, vol. 13, no. 5, pp. 1185–1197, 2021, doi: 10.1007/s12559-020-09792-8.

[180] P. Atandoh, F. Zhang, D. Adu-Gyamfi, P. H. Atandoh, and R. E. Nuhoho, “Integrated deep learning paradigm for document-based sentiment analysis,” *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 7, p. 101578, Jul. 2023, doi: 10.1016/J.JKSUCI.2023.101578.

[181] N. Punetha and G. Jain, “Bayesian game model based unsupervised sentiment analysis of product reviews,” *Expert Systems with Applications*, vol. 214, p. 119128, Mar. 2023, doi: 10.1016/j.eswa.2022.119128.

[182] A. S. Ghadikolaei, S. K. Esbouei, and J. Antuchevičienė, “Applying fuzzy MCDM for financial performance evaluation of Iranian companies,” *Technological and Economic Development of Economy*, vol. 20, no. 2, pp. 274–291, Jun. 2014, doi: 10.3846/20294913.2014.913274.

[183] S. R. Savanur and R. Sumathi, “SentiNeg: Algorithm to Process Negations at Sentence Level in Sentiment Analysis,” *International Journal of Software Innovation*, vol. 11, no. 1, 2023, doi: 10.4018/IJSI.315741.

[184] K. Almutairi, S. J. Hosseini Dehshiri, S. S. Hosseini Dehshiri, A. Mostafaeipour, A. X. Hoa, and K. Techato, “Determination of optimal renewable energy growth strategies using SWOT analysis, hybrid MCDM methods, and game theory: A case study,” *International Journal of Energy Research*, vol. 46, no. 5, pp. 6766–6789, Apr. 2022, doi: 10.1002/ER.7620.

[185] K. Maniya and M. G. Bhatt, “A selection of material using a novel type decision-making method: Preference selection index method,” *Materials & Design*, vol. 31, no. 4, pp. 1785–1789, Apr. 2010, doi: 10.1016/J.MATDES.2009.11.020.

[186] A. Esuli and F. Sebastiani, “SENTIWORDNET: A publicly available lexical resource for opinion mining,” *Proceedings of the 5th International Conference on Language Resources and Evaluation, LREC 2006*, pp. 417–422, 2006, Accessed: Sep. 23, 2021. [Online]. Available: http://nmis.isti.cnr.it/sebastiani/Publications/2007TR02.pdf.

[187] S. M. Anas and S. Kumari, “Opinion Mining based Fake Product review Monitoring and Removal System,” *Proceedings of the 6th International Conference on Inventive Computation Technologies, ICICT 2021*, pp. 985–988, 2021, doi: 10.1109/ICICT50816.2021.9358716.

[188] S. Gojali and M. L. Khodra, *Aspect based sentiment analysis for review rating prediction; Aspect based sentiment analysis for review rating prediction*. 2016.

[189] M. Al Omari, M. Al-Hajj, N. Hammami, and A. Sabra, “Sentiment classifier: Logistic regression for Arabic services’ reviews in Lebanon,” *2019 International Conference on Computer and Information Sciences, ICCIS 2019*, 2019, doi: 10.1109/ICCISci.2019.8716394.

[190] R. S. Jagdale and S. S. Deshmukh, “Sentiment Classification on Twitter and Zomato Dataset Using Supervised Learning Algorithms,” *Proceedings of the 2020 International Conference on Smart Innovations in Design, Environment, Management, Planning and Computing, ICSIDEMPC 2020*, pp. 330–334, 2020, doi: 10.1109/ICSIDEMPC49020.2020.9299582.

[191] M. N. Win, S. D. R. Ravana, and L. Shuib, “SENTIMENT ATTRIBUTION ANALYSIS WITH HIERARCHICAL CLASSIFICATION AND AUTOMATIC ASPECT CATEGORIZATION ON ONLINE USER REVIEWS,” *Malaysian Journal of Computer Science*, vol. 35, no. 2, pp. 89–110, Apr. 2022, doi: 10.22452/MJCS.VOL35NO2.1.

[192] M. Afzaal, M. Usman, A. C. M. Fong, S. Fong, and Y. Zhuang, “Fuzzy Aspect Based Opinion Classification System for Mining Tourist Reviews,” *Advances in Fuzzy Systems*, vol. 2016, 2016, doi: 10.1155/2016/6965725.

[193] C. Lin, Y. He, R. Everson, and S. Rüger, “Weakly supervised joint sentiment-topic detection from text,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 24, no. 6, pp. 1134–1145, 2012, doi: 10.1109/TKDE.2011.48.

[194] Y. Jo and A. Oh, “Aspect and sentiment unification model for online review analysis,” *Proceedings of the 4th ACM International Conference on Web Search and Data Mining, WSDM 2011*, pp. 815–824, 2011, doi: 10.1145/1935826.1935932.

[195] S. Kim, J. Zhang, Z. Chen, A. Oh, and S. Liu, “A hierarchical aspect-sentiment model for online reviews,” *Proceedings of the 27th AAAI Conference on Artificial Intelligence, AAAI 2013*, pp. 526–533, 2013, doi: 10.1609/aaai.v27i1.8700.

[196] Q. Mei, X. Ling, M. Wondra, H. Su, and C. Zhai, "Topic sentiment mixture: Modeling facets and opinions in weblogs," *16th International World Wide Web Conference, WWW2007*, pp. 171–180, 2007, doi: 10.1145/1242572.1242596.

[197] X. Xu, X. Cheng, S. Tan, Y. Liu, and H. Shen, "Aspect-level opinion mining of online customer reviews," *China Communications*, vol. 10, no. 3, pp. 25–41, 2013, doi: 10.1109/CC.2013.6488828.

[198] M. Keshavarz Ghorabaee, E. Kazimieras Zavadskas, L. Olfat, and Z. Turskis, "Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS)," *content.iospress.com*, vol. 26, no. 3, pp. 435–451, 2015, doi: 10.15388/Informatica.2015.57.

[199] D. Mishra, M. Venugopalan, and D. Gupta, "Context Specific Lexicon for Hindi Reviews," *Procedia Computer Science*, vol. 93, no. September, pp. 554–563, 2016, doi: 10.1016/j.procs.2016.07.283.

[200] J. P. Singh, N. P. Rana, and W. Alkhowaiter, "Sentiment analysis of products' reviews containing English and Hindi texts," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9373, pp. 416–422, 2015, doi: 10.1007/978-3-319-25013-7_33/TABLES/6.

[201] D. S. Kulkarni and S. S. Rodd, "Sentiment Analysis in Hindi—A Survey on the State-of-the-art Techniques," *Transactions on Asian and Low-Resource Language Information Processing*, vol. 21, no. 1, Nov. 2021, doi: 10.1145/3469722.

[202] W. K. Brauers, "Optimization Methods for a Stakeholder Society," *Nonconvex Optimization and Its Applications*, vol. 73, 2004, doi: 10.1007/978-1-4419-9178-2.

[203] N. Mittal, B. Agarwal, G. Chouhan, N. Bania, and P. Pareek, "Sentiment Analysis of Hindi Review based on Negation and Discourse Relation," pp. 14–18, 2013.

[204] V. K. Singh, R. Piryani, A. Uddin, P. Waila, and Marisha, "Sentiment analysis of textual reviews: Evaluating machine learning, unsupervised and sentiwordnet approaches," *Proceedings of the 2013 5th International Conference on Knowledge and Smart Technology, KST 2013*, pp. 122–127, 2013, doi: 10.1109/KST.2013.6512800.

[205] P. Bhoir and S. Kolte, "Sentiment analysis of movie reviews using lexicon approach," *2015 IEEE International Conference on Computational Intelligence and Computing Research, ICCIC 2015*, Mar. 2016, doi: 10.1109/ICCIC.2015.7435796.

[206] A. Joshi, B. A. R, and P. Bhattacharyya, "A Fall-back Strategy for Sentiment Analysis in Hindi: a Case Study," *Proceedings of the 8th ICON*, 2010, [Online]. Available: www.censusindia.gov.in/CensusData2001.

[207] A. Kumar, "SUPPLEMENT ISSUE ARTICLE ANALYZING SENTIMENT IN INDIAN LANGUAGES MICRO TEXT USING RECURRENT NEURAL NETWORK," Accessed: Apr. 18, 2022. [Online]. Available: www.iioab.org.

[208] V. Jain and K. L. Kashyap, "Ensemble hybrid model for Hindi COVID-19 text classification with metaheuristic optimization algorithm," *Multimedia Tools and Applications*, 2022, doi: 10.1007/s11042-022-13937-2.

[209] S. Sigari and A. H. Gandomi, "Analyzing the past, improving the future: a multiscale opinion tracking model for optimizing business performance," *Humanities and Social Sciences Communications*, vol. 9, no. 1, 2022, doi: 10.1057/s41599-022-01325-y.

[210] J. Li, G. Li, M. Liu, X. Zhu, and L. Wei, "A novel text-based framework for forecasting agricultural futures using massive online news headlines," *International Journal of Forecasting*, vol. 38, no. 1, pp. 35–50, Jan. 2022, doi: 10.1016/J.IJFORECAST.2020.02.002.

[211] P. K. Jain, R. Pamula, and G. Srivastava, "A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews," *Computer Science Review*, vol. 41, p. 100413, Aug. 2021, doi: 10.1016/J.COSREV.2021.100413.

[212] V. Maliene, R. Dixon-Gough, and N. Malys, "Dispersion of relative importance values contributes to the ranking uncertainty: Sensitivity analysis of Multiple Criteria Decision-Making methods," *Applied Soft Computing Journal*, vol. 67, pp. 286–298, 2018, doi: 10.1016/j.asoc.2018.03.003.

[213] G. Kumar and N. Parimala, "A weighted sum method MCDM approach for recommending product using sentiment analysis," *International Journal of Business Information Systems*, vol. 35, no. 2, pp. 185–203, 2020, doi: 10.1504/IJBIS.2020.110172.

[214] A. Nasir, M. A. Shah, U. Ashraf, A. Khan, and G. Jeon, "An intelligent framework to predict socioeconomic impacts of COVID-19 and public sentiments," *Computers & Electrical Engineering*,

vol. 96, p. 107526, Dec. 2021, doi: 10.1016/J.COMPELECENG.2021.107526.

[215] J. S. Preethi, A. M. Abirami, A. Askarunisa, G. S. Priya, and E. Sankaragomathy, "Applying MCDM Techniques for Ranking Products Based on Online Customer Feedback," *International Journal of Knowledge Based Computer Systems*, vol. 3, no. 2, 2015, doi: 10.21863/ijkbcs/2015.3.2.009.

[216] V. K. Chawra and G. P. Gupta, "Optimized coverage-aware trajectory planning for AUVs for efficient data collection in underwater acoustic sensor networks," *Evolutionary Intelligence*, 2021, doi: 10.1007/s12065-021-00667-x.

[217] F. E. Boran, S. Genç, M. Kurt, and D. Akay, "A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method," *Expert Systems with Applications*, vol. 36, no. 8, pp. 11363–11368, Oct. 2009, doi: 10.1016/j.eswa.2009.03.039.

[218] C. Wu and D. Zhang, "Ranking products with IF-based sentiment word framework and TODIM method," *Kybernetes*, vol. 48, no. 5, pp. 990–1010, 2019, doi: 10.1108/K-01-2018-0029.

[219] G. Büyüközkan, O. Feyzioğlu, and F. Gocer, "Evaluation of hospital web services using intuitionistic fuzzy AHP and intuitionistic fuzzy VIKOR," *IEEE International Conference on Industrial Engineering and Engineering Management*, vol. 2016-Decem, pp. 607–611, Dec. 2016, doi: 10.1109/IEEM.2016.7797947.

[220] N. Chitsaz and M. E. Banihabib, "Comparison of Different Multi Criteria Decision-Making Models in Prioritizing Flood Management Alternatives," *Water Resources Management*, vol. 29, no. 8, pp. 2503–2525, Jun. 2015, doi: 10.1007/s11269-015-0954-6.