STUDY AND COMPARATIVE ANALYSIS OF DEEP LEARNING TECHNIQUES FOR EMOTION DETECTION IN TEXTUAL DATA

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CANDIDATE'S DECLARATION

I, Purvak Baliyan, Roll No's –2K23/DSC/20 students of M.Tech (Department of Software Engineering), hereby certify that the work which is being presented in the thesis entitled "Study and Comparative Analysis of Deep Learning Techniques for Emotion Detection in Textual Data" in partial fulfilment of the requirements for the award of degree of Master of Technology, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from Jan 2025 to May 2025 under the supervision of Dr. Sonika Dahiya.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Signature of Supervisor **Signature of External Examiner**

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CERTIFICATE

I hereby certify that the Project Dissertation titled "Study and Comparative Analysis of Deep Learning Techniques for Emotion Detection in Textual Data" which is submitted by Purvak Baliyan, Roll No – 2K23/DSC/20, Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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Abstract

Detecting emotions from textual data is increasingly significant in various domains such as mental health support, customer experience enhancement, and social media analysis. As digital communication grows, understanding the emotional tone of written content has become essential for building responsive and human-centric applications. This study explores recent developments in deep learning techniques that aim to improve the accuracy and efficiency of emotion classification in text. In-depth analysis is conducted on a variety of deep learning architectures from basic ones like Bi-LSTM, Bi-GRU, ANN, CNN to complex transformer-based models like BERT, RoBERTa, and GPT. The models are evaluated on three widely used datasets—ISEAR, GoEmotion, and MELD—chosen for their diversity in the use of language as well as emotion categories. For the sake of comparison, the three datasets went through the same preprocessing including text cleaning, normalization, tokenization, and encoding. The aim of this research work is to analyze and compare the performance of the models under uniform training conditions and metric parameters like accuracy and F1-score. Experimentation outcomes show that transformer models provide enhanced performance by efficiently comprehending the contextually suitable sense of emotion in words. This comparative review not only unveils the potential of existing models but also reveals where more can be gained, the keys to even more sophisticated and sensitive emotion recognition systems.

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Chapter 1

INTRODUCTION

Emotion recognition from text has become an important task in Natural Language Processing (NLP). Its value can be witnessed in a variety of real-world applications such as evaluation of mental wellbeing, social media trend detection, customer opinion extraction, and human-computer interaction. Detection of happiness, anger, fear, or sadness in text material helps systems to have a better comprehension of human actions. This, consequently, enables applications in domains like adaptive mental health care, content personalization, and live sentiment analysis for customer service.

Compared to general sentiment analysis that usually marks text as either negative or positive, emotion detection is directed towards more in-depth and subtle understanding of emotional expression. It facilitates the subtlety of context, culture, and language-driven emotions—factors that matter while interacting with various groups or multilingual content. It is required to preserve such subtleties to support applications that require a more natural, human-like response. [1]

Deep learning has taken the field leaps forward. Bi-LSTM, CNN, and other advanced transformer-based models such as BERT, RoBERTa, and GPT have shown promising results in recognizing emotion from text. They can capture the semantic and contextual depth required to understand how emotions are being expressed. There are still issues, however. Sarcasm, idioms, cultural references, and nuanced emotional cues continue to pose difficulties due to their ambiguities. Practical issues such as unbalanced datasets, high resource consumption, and the limitations of text-only input—lacking visual or vocal context—further complicate the task. [2]

Moreover, most existing research tends to focus on isolated components, such as the performance of a single model or a particular dataset. There is a lack of comprehensive studies that jointly consider multiple model architectures, preprocessing approaches, dataset characteristics, and linguistic diversity.

This study addresses that gap by combining an in-depth review of textual emotion detection strategies with a practical comparison of several deep learning models. We examine and evaluate seven key architectures—Bi-LSTM, Bi-GRU, ANN, CNN, BERT, RoBERTa, and GPT—using three widely used datasets: ISEAR, GoEmotions, and MELD. Each dataset offers unique properties: ISEAR focuses on psychological responses, GoEmotions includes nuanced emotions from online discussions, and MELD provides conversational data from a multimodal dialogue setting. This combination allows for a robust evaluation of model performance in diverse contexts. [3]

Our findings show that transformer-based models, particularly BERT and

RoBERTa, consistently perform better in capturing emotional nuances, with F1-scores reaching up to 70.95% on ISEAR and 63.95% on GoEmotions. But they are not without sacrifice: these models tend to be computationally demanding and require big training data, so are less suitable for application with processing limitations or in real-time scenarios. They are also constrained by emotion class imbalance and unavailability of other modalities (such as voice or facial expression) to further restrict their application in the real world.

By the integration of theoretical insights with empirical analysis, this study highlights the importance of strong model design, effective preprocessing pipelines, and context-aware training techniques. It also hints at future research directions in emotion detection studies such as designing light transformer models, knowledge integration with domain knowledge, and multimodal learning approaches. Finally, the research also strives to help researchers and developers create more adaptive, accessible, and efficient emotion-aware systems to cater to the diverse needs of real-world application environments.

1.1 Problem Statement

Emotion detection from text has evolved into an essential area of research in natural language processing since it is finding more and more applications in mental health screening, social media monitoring, customer opinion analysis, and interactive systems. Despite progress made through sophisticated deep learning models like Bi-GRU, ANN, Bi-LSTM, CNNs, and transformer architectures (e.g., BERT, RoBERTa, and GPT), there are still enormous problems in detecting the subtleties and oftentimes multivariate emotional expressions in language. Much of what has been conducted has a tendency to focus on individual factors—e.g., specific data or model structures—without regard for the general interplay among linguistic, cultural, and contextual forces. This limiting trend limits developing emotion detection systems that are truly adaptive and functional across settings. Additionally, most of the current models are plagued with a lack of sensitivity to idioms, cultural language, or inter-language variations, thus causing a drop in performance when used in multilingual or cross-cultural text.

Another major hindrance is the excessive computational expense of modern models, which makes them impractical for real-time or low-resource applications. Models based on the Transformer architecture are computationally intensive and require enormous amounts of labeled data and deep hardware resources, which may not always be available. Moreover, datasets with unbalanced distributions skew results toward the dominant emotion classes and yield biased results. Most models also disregard the importance of multimodal signals—like tone, facial expression, or gesture—that play a central role in real emotional communication. In addition, models learned from formal corpora do not generalize to domain-specific texts like social media posts in an informal setting or clinical notes. This dissertation addresses these issues by starting with an overview of past emotion detection approaches in order to identify common flaws and missed potential, and afterwards comparing seven deep models on three differing datasets (ISEAR, GoEmotions, MELD). The aim is to achieve the way in which emotional nuances can be extracted more effectively through model design and data handling in line with insights, and the foundation for more extensive, effective, and real-world-compatible emotion detection systems.

1.2 Overview of the research objectives

This dissertation attempts to improve the real-world usability, adaptability, and accuracy of emotion recognition from text by overcoming the most significant challenges found in current research. The main goal is to perform a detailed review of methods, datasets, and deep learning models used in this field of study and describe the most significant challenges like cultural bias, class imbalance, and lack of interdisciplinary integration. With the contrast of generic models such as Bi-LSTM, CNNs, and transformer models such as BERT and RoBERTa, the paper aims to create a systematic approach to bringing to light how different methods cope with emotional subtlety in a variety of scenarios. While doing so, the research conducts an exhaustive empirical comparison of seven deep learning models across three benchmark datasets (ISEAR, GoEmotions, MELD) with differing linguistic style, emotion intensity, and source domain. This assists in comparing how well such models tend to do on emotional depth across platforms like social media, psychological literature, and conversational dialogue.

Besides benchmarking performance, the dissertation also makes a mention of the practical real-world constraint of deploying the likes of such models, specifically the performance vs. computational efficiency trade-offs. Model compression and optimization techniques are investigated to enable transformer models to be deployable in low-resource settings. Further, the paper deals with the challenge of cultural and domain difference by investigating the extent to which the models are generalizable over languages, cultural expressions, and domains such as mental illness and customer service. Lastly, the research discovers it essential that the systems get explainable and multimodal since the combination of text with other cues like voice or face may provide more effective emotion detection. Through the provision of empirical evidence, technical approaches, as well as ethical concerns, the dissertation is meant to provide the ground for secure generation and inclusive emotion detection systems.

1.3 Overview of the Study

This study investigates the task of emotion recognition from text by the combination of two complementary methodologies: a critical analysis of the existing paradigms and an experiential comparison of state-of-the-art deep learning models. The first half of the study is devoted to combining trends within the field from 2021 to 2024, analyzing a number of studies utilizing various deep learning paradigms, preprocessing methods, and corpora. The review indicates a general flaw of previous research—i.e., the tendency to treat models, data, and preprocessing in isolation. In response, this research emphasizes a more holistic perspective, highlighting how cultural context, multilingual challenges, and ambiguous emotional expressions complicate emotion detection. Well-known datasets like ISEAR, GoEmotions, and MELD are examined, alongside techniques for preparing data, such as tokenization and lemmatization. The review also notes the growing popularity of transformer-based models, particularly BERT, for their ability to capture nuanced emotional context, though it points out ongoing challenges like high computational requirements and limited model interpretability.

Building on these insights, the second phase of the study conducts a practical evaluation of seven deep learning models—including Bi-LSTM, Bi-GRU, ANN, CNN, BERT, RoBERTa, and GPT—using consistent preprocessing techniques across the ISEAR, GoEmotions, and MELD datasets. The transformer models, especially BERT and RoBERTa, delivered stronger performance due to their ability to understand context in both directions, achieving higher F1-scores compared to more traditional models. But these models were far more computationally expensive, with a preference for requiring a number of orders of computational capability compared to light models. Class imbalance in data also led to unfairness at the cost of fairness. Models also were unable to generalize to expert settings, like clinical discussion, where emotional signals were of mixed complexity. Finally, the research anticipates better models, more abundant cultural data, and multimodal techniques that marry text with other forms such as speech or images. The research ends by requesting honest and ethical AI that is equally scalable and sensitive to affective nuances of human communication.

Chapter 2

RELATED WORK

Emotion detection from text has become a strengthening core topic in natural language processing (NLP), especially due to its use in areas such as mental health tracking, sentiment analysis in a business setting, and enhancing human-computer interactions. Initial research in this direction used to largely rely on lexicon-based techniques and basic machine learning models classifiers. These approaches employed hand-designed features, including emotion lexicons and syntactic templates, which supported rudimentary sentiment classification (e.g., positive, negative, neutral). Their performance was limited when dealing with managing the sophistication and frequency of cultural bias prevalent in emotional expression in text.

Deep learning brought significant progress, as models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) generated more powerful results. CNNs excelled at local textural feature extraction, particularly in shorter formats such as tweets or status updates, while bidirectional implementations of LSTMs and GRUs improved sequential dependency understanding by reading the text in both directions. Despite these advances, these models struggled with maintaining long-term dependencies and repeating on languages or conversational datasets like MELD and GoEmotions, both of which contain rich context and emotionally diverse content.

The emergence of transformer models like BERT, RoBERTa, and GPT was a revolution in the field. These models utilize self-attention mechanism whereby they are able to attend to word relations in a whole text instead of word pairs, hence better at identifying implicit emotions, sarcasm, and culturally embedded cues. BERT's pretraining on huge texts and bidirectional context understanding have both resulted in improved performance on emotion detection tasks, such as scoring over 70% F1-scores on data sets like ISEAR. A further improved model, RoBERTa, additionally boosted performance by altering pretraining dynamics and boosting training data. However, there are drawbacks to these models—they require significant computational resources, require big labeled data, and yield little transparency in the decision process. [10], [11],

More and more studies also indicate the effect of dataset diversity and preprocessing methods on model performance. Benchmark datasets like ISEAR, GoEmotions, and MELD all have their own unique characteristics and challenges. ISEAR provides data across cultures but has broader emotion categories. GoEmotions offers detailed emotion labels but is skewed by imbalanced class distribution. MELD brings in multimodal elements, incorporating text, audio, and visual input, but it is constrained by its scripted nature. Preprocessing plays a critical role here—methods like removing noise (e.g., emojis, links), tokenizing text, or lemmatizing words are widely used, yet inconsistent implementations across studies lead to reproducibility issues.

Table 2.1. Research Questions and Focus Areas in Emotion Detection Studies.

Q. No.	Research Question
1	Is an interdisciplinary survey done in emotion detection studies?
2	What are effective DL techniques used in detecting emotions from text in multiple languages?
3	What preprocessing techniques were elucidated in the studies?

While these studies address individual aspects of emotion detection, this work covers all of the multilingual, interdisciplinary approaches and pre-processing done in the studies, offering a more holistic view of recent advancements in this field. Table 2.2 compares research focus areas across studies on emotion detection, highlighting whether each study addresses the research questions from Table 2.1.

Table 2.2. Comparative Analysis of Research Focus Areas Across Studies.

Research Questions	[1]	[2]	[3]	[4]
RQ1	Yes	No	No	Yes
RQ2	No	Yes	No	Yes
RQ3	No	No	Yes	No

One of the persistent limitations in prior literature is the narrow focus on either modeling techniques or dataset-specific findings, with minimal effort to bridge insights across disciplines. Psychological theories, such as Ekman's six basic emotions, offer useful classification schemes but rarely align with scalable computational models. On the other hand, NLP-focused research often prioritizes algorithmic innovation without adequately addressing cultural, linguistic, or ethical concerns. Hybrid models that merge transformers with graph-based or attention-enhanced architectures offer potential in unifying these approaches, though they remain underexplored in real-world applications.

Issues such as class imbalance and the lack of multimodal context still hinder emotion recognition accuracy. Imbalanced datasets such as GoEmotions also favor dominant emotions such as joy or anger and underrepresent less evident ones such as grief or remorse. Solutions such as resampling, class-weighting adjustments, and hybrid approaches (e.g., CNN and Bi-LSTM layers combination) have been promising but need to be further evaluated. Moreover, emotion is rarely conveyed through text alone—there is intonation, facial expression, and body language typically engaged in full emotional expression. Failure to provide such cues in strictly text-based systems hinders their useful deployment.

In order to bridge these limitations, this study contributes in two ways. Firstly, it presents a systematic review of the latest trends in emotion recognition, such as deep learning models, preprocessing pipeline, and dataset characteristics, with special focus on cross-cultural and multilingual issues. Secondly, it presents a comparative analysis of seven deep learning models—Bi-LSTM, Bi-GRU, CNN, ANN, BERT, RoBERTa, and GPT—deployed on three prominent datasets: ISEAR, GoEmotions, and MELD. This comparison not only confirms the strong performance of transformer models but also sheds light on their computational demands and fairness issues.

By combining literature review with experimental validation, this work aims to move the field toward more inclusive, efficient, and context-sensitive emotion-aware technologies. The insights gained here have practical implications for domains such as healthcare, online communication platforms, and adaptive user interfaces.

Table 2.3. Summary of Related Work

Title of the Paper	**Year**	**Authors**	**Findings**
Emotion Detection of Textual Data: An Interdisciplinary Survey	2021	S. Zad et al.	Provides a comprehensive survey of text-based emotion detection methods and their interdisciplinary relevance. Highlights challenges and open research issues.
A Survey of Textual Emotion Recognition and Its Challenges	2023	J. Deng and F. Ren	Reviews existing approaches and challenges in textual emotion recognition, with emphasis on linguistic ambiguity and context handling.
A review of multimodal emotion recognition from datasets, preprocessing, features, and fusion methods	2023	B. Pan et al.	Reviews multimodal emotion recognition; discusses datasets, preprocessing methods, and fusion strategies for textual, visual, and audio features.
A systematic review of applications of natural language processing and future challenges with special emphasis in text-based emotion detection	2023	S. Kusal et al.	Presents NLP applications in emotion detection and identifies future challenges such as data scarcity, bias, and explainability.
A BERT-based dual-channel explainable text emotion recognition system	2022	P. Kumar and B. Raman	Proposes a BERT-based explainable model with dual channels for improved accuracy and interpretability.
A Comparative Study of CNNs and DNNs for Emotion Detection from text using TF-IDF	2023	A. K. Jadon and S. Kumar	Compares CNN and DNN models using TF-IDF; CNN outperforms DNN in terms of accuracy and training efficiency.

A Deep Neural Network Model for the Detection and Classification of Emotions from Textual Content	2022	M. Z. Asghar et al.	Proposes a DNN model for emotion classification; demonstrates effectiveness across multiple datasets.
Advancing Text Emotion Recognition: BERT and BiLSTM Integration	2024	P. Gethsia et al.	Combines BERT and BiLSTM for enhanced context-aware emotion detection, showing performance improvements.
Bert-cnn: A deep learning model for detecting emotions from text	2022	A. R. Abas et al.	Integrates BERT and CNN for effective emotion detection; achieves high performance on benchmark datasets.
An Enhanced Context-based Emotion Detection Model using RoBERTa	2022	R. Kamath et al.	Introduces a RoBERTa-based model leveraging context to improve emotion classification accuracy.
Emotion Classification in Texts Over Graph Neural Networks: Semantic Representation is Better Than Syntactic	2023	I. Ameer et al.	Demonstrates that semantic graph representations outperform syntactic ones for emotion detection using GNNs.
Textual emotion detection utilizing a transfer learning approach	2023	M. H. Mozhdehi and A. M. Eftekhari Moghadam	Uses transfer learning techniques to improve generalization in emotion detection tasks.
Transformer models for text-based emotion detection: a review of BERT-based approaches	2021	F. A. Acheampong et al.	Reviews BERT and its variants for emotion detection, emphasizing their superiority over traditional models.
Emotion Detection in Twitter Social Media Using Long Short-Term Memory (LSTM) and Fast Text	2021	M. A. Riza and N. Charibaldi	Uses LSTM and FastText for Twitter-based emotion detection; demonstrates effectiveness on informal texts.
EMOCOV: Machine learning for emotion detection, analysis and visualization using COVID-19 tweets	2021	M. Y. Kabir and S. Madria	Proposes a system for emotion analysis and visualization in COVID-19 tweets using ML techniques.

Chapter 3

RESEARCH METHODOLOGY

In this section, we present a chapter explicating an in-depth analysis including the dataset, preprocessing of our methodology for Emotion detection from text.

3.1 Dataset Collection

This section reviews commonly used public datasets in emotion detection, highlighting their applications as noted in related studies, as detailed in Table 3.1.

Table 3.1: Datasets Summary of Emotion Detection for comparison of Deep Learning methods.

Datasets	Description	Size
Isear	An open dataset consisting of emotional responses related to seven emotions was compiled from (approx.) 3000 individuals, aiming to support multicultural analysis of emotional expression [4].	7,666
GoEmotion	It is a Reddit comments dataset labeled with 27 emotions is ideal for fine-grained emotion classification tasks [5].	58,000
Meld	Multimodal dataset with visual, text, and audio emotion labels from the Friends TV series for emotion recognition in dialogue [6].	13,708

text	emotion
My favourite food is anything I didn't have to cook myself.	27
Now if he does off himself, everyone will think hes having a la	27
WHY THE FUCK IS BAYLESS ISOING	2
To make her feel threatened	14
Dirty Southern Wankers	3
OmG pEyToN iSn'T gOoD eNoUgH tO hElP uS iN tHe PlAyOfFs!	26
Yes I heard abt the f bombs! That has to be why. Thanks for yc	15

Figure 3.1: Dataset

3.2 Data Preprocessing

In the preprocessing stage to ensure data quality and consistency for emotion detection models, the following preprocessing steps were applied: [3], [5], [7], [8], [9], [10], [11], [12], [13], [14], [15]

- **Emoji Removal:** Emojis were removed from the text as they may introduce noise and inconsistencies, especially due to their varied interpretations and lack of linguistic structure. Example: *Before*: "I'm feeling great 😂!", *After*: "I'm feeling great !".

- **Lowercasing:** All text was converted to lowercase to treat words like “Happy,” “HAPPY,” and “happy” as the same token, reducing vocabulary size and improving consistency. Example: *Before*: "Happy HAPPY happy" .*After*: "happy happy happy".

- **Non-Textual Element Removal:** Elements such as URLs, HTML tags, and content within brackets were stripped out, as they typically do not contribute meaningfully to emotional analysis. Example: *Before*: "Visit us at https://fun.com [laughs]", *After*: "Visit us at".

- **Punctuation and Number Removal:** Punctuation marks and numeric values were eliminated since they rarely carry emotional meaning in isolation. This helps avoid tokenization issues. Example: *Before*: "Wow! I got 100 on my test!", *After*: "Wow I got on my test".

- **Language Filtering:** Only English text was retained. Multilingual or non-English content was excluded to maintain uniformity and avoid translation or interpretation challenges. Example: *Before*: "I am happy aujourd’hui", *After*: "I am happy".

- **Contraction Expansion:** Contractions like "don’t" or "you’re" were expanded to their full forms ("do not", "you are") to ensure consistent representation and improve model understanding. Example: *Before*: "She can’t do this because she’s tired", *After*: "She cannot do this because she is tired".

- **Spell Correction:** Misspelled words were corrected to their nearest valid English counterparts to avoid out-of-vocabulary (OOV) issues and improve input clarity. Example: *Before*: "I am so hapy and exctied", *After*: "I am so happy and excited".

- **Whitespace Normalization:** Extra spaces, tabs, and line breaks were standardized to single spaces to support consistent tokenization and avoid fragmented words. Example: *Before*: "I feel good ", *After*: "I feel good".

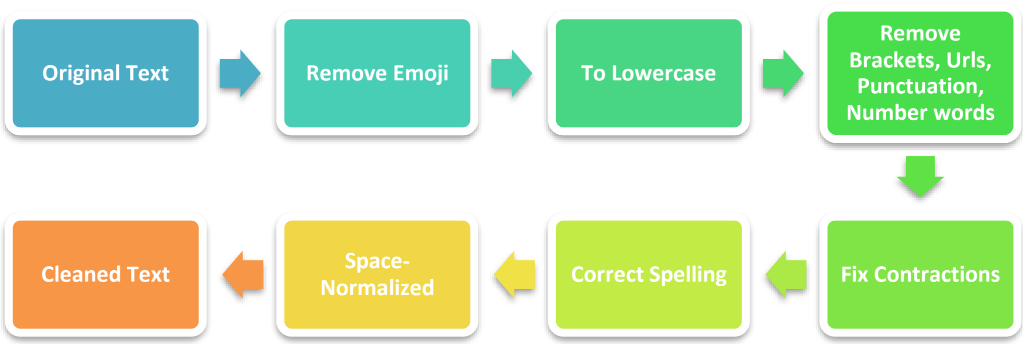

Figure 3.2: Preprocessing Pipeline

3.3 Methods

This section describes multiple DL models that are used to compare and analyze within this paper.

3.3.1 Bi-LSTM (Bidirectional Long Short-Term Memory)

Bidirectional LSTMs are a unique type of neural network that is particularly designed to learn word sequences in two directions—start to end and end to start. This means that not only does the model learn from the words that come before a particular word, but also from the words that follow. This two-way transfer of information helps the model determine the meaning of a sentence as a whole, especially useful when performing emotion or sentiment analysis with words that are contextually involved. [8]

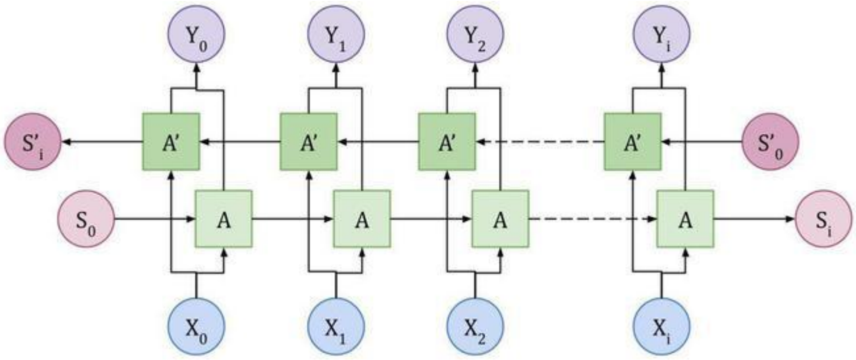

Figure 3.3: Bi-LSTM architecture

3.3.2 Bi-GRU (Bidirectional Gated Recurrent Unit)

The Bi-GRU is very much the same as the Bi-LSTM but slightly less complex inner structure. It's a faster and leaner model that still processes text bidirectionally. Because of its light architecture, Bi-GRU typically comes in when there is minimal computational power to spare. Although Bi-GRU has less number of parameters than LSTM models, it is just as effective in processing the flow of language, especially when used for short texts where being capable of processing the prior and subsequent context is most critical. [3]

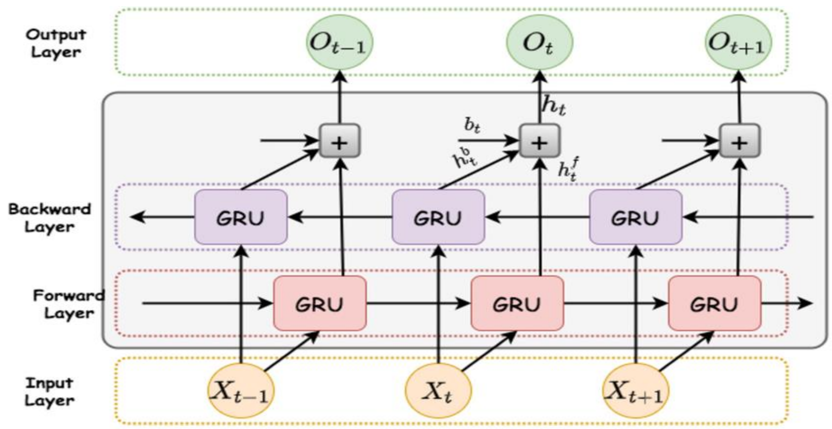

Figure 3.4: Bi-GRU architecture

3.3.3 ANN (Artificial Neural Network)

An artificial neural network is one of the most basic and oldest types of neural models. It is created by many layers of neurons in a feed-forward-only sequence. ANNs do not store earlier inputs like sequence models. ANNs are applied in problems where data is more structured or does not have a temporal or sequential nature. ANNs, despite being simple, are of great assistance in classification problems such as discovering categories or making simple predictions from data. [3]

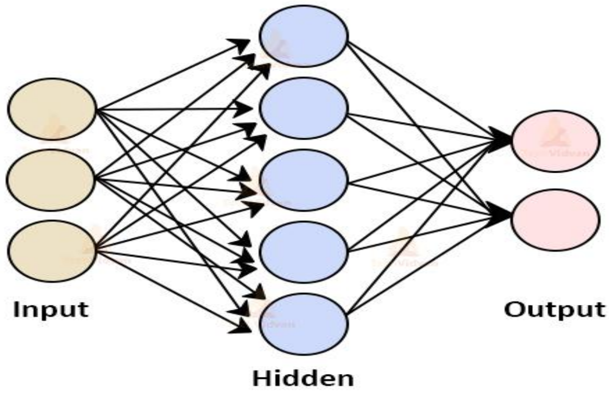

Figure 3.5: ANN architecture

3.3.4 CNN (Convolutional Neural Network)

Although CNNs are generally associated with picture recognition, they're even highly beneficial for text data. CNNs in natural language processing read words or groups of words of a sentence to identify local patterns which aid in determining meaning or tone. The local patterns, once identified, assist in sentence classification or the identification of emotion. CNNs are fast and efficient and thus perform best if they're dealing with large data that needs to be processed immediately. [16]

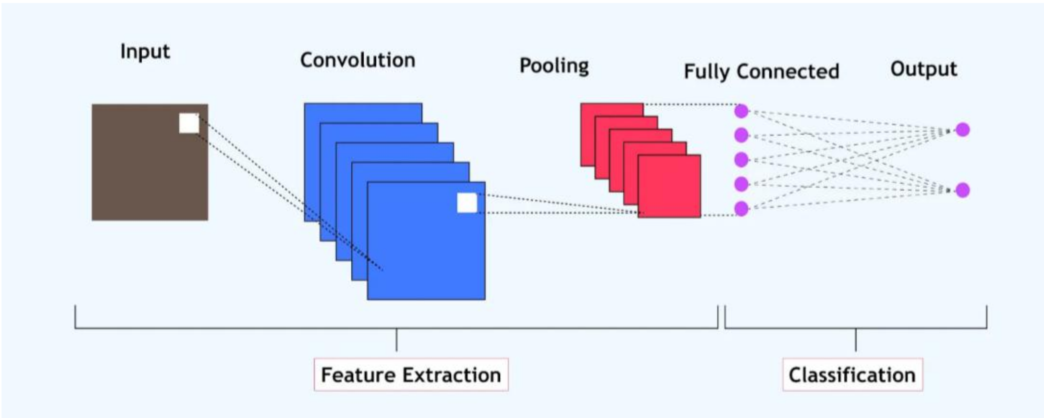

Figure 3.6: CNN architecture

3.3.5 BERT (Bidirectional Encoder Representations from Transformers)

BERT is a robust language model that processes sentences from both directions at once. This allows it to see entirely how words relate to each other, no matter where they appear in a sentence. BERT is trained on vast quantities of text and acquires the meaning of words and the syntax of sentences, which can be adapted for specific tasks such as question-answering or locating emotions in text. Its deep understanding of context has made it a popular model across many language-focused applications. [3]

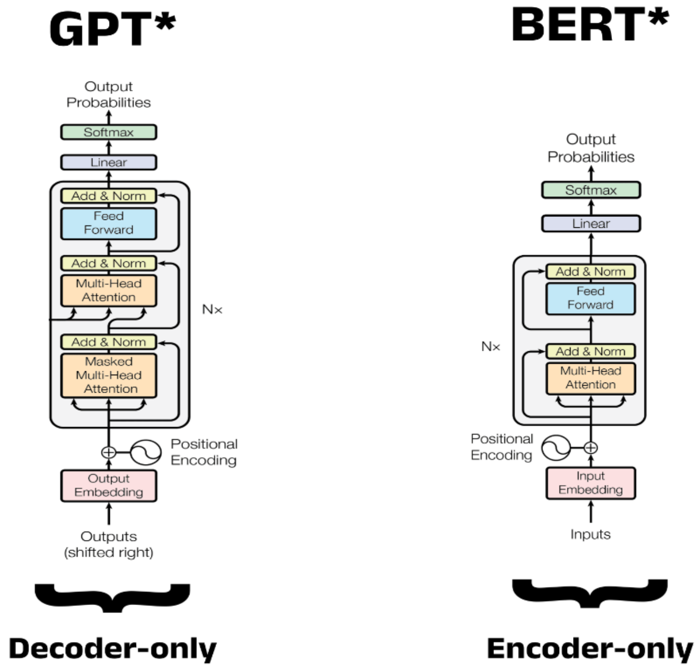

Figure 3.7: Bert and GPT architecture

3.3.6 RoBERTa (Robustly Optimized BERT Pretraining Approach)

RoBERTa builds upon the success of BERT with larger data and better training techniques. It removes some of the limitations of the initial BERT model, such as predicting the next sentence, and only focuses on learning word relationships. This develops a model more precise in language patterns. RoBERTa outperformed BERT on many tasks and is now a very popular option for high-accuracy language comprehension projects. [5]

3.3.7 GPT (Generative Pretrained Transformer)

GPT is special in that it cares more about generating language than just understanding it. It is trained to forecast the next word in a sentence, and this does well to instruct it in a wonderful sense of sentence flow. This is very apt when writing text that sounds extremely natural. It's most commonly used in chatbots, story generation, or anything when there's a demand to create new text. GPT models are particularly well-known for their ability to produce coherent and often very human-sounding responses when asked. [17], [18]

3.4 Pipeline Overview

The process of emotion detection from text starts with the numerical conversion of the emotion labels using a process called label encoding. The reason for this is that machine learning algorithms operate on numbers and not words. For instance, if the data include emotions "joy," "anger," and "sadness," each one of them is allocated a unique number like 0, 1, or 2.

Once the labels are encoded, the information is cleaned to remove redundant symbols, special characters, and inconsistencies like numerous spaces or misspellings. This improves the text quality and prevents the model from being misled by unnecessary information.

The dataset is divided into three sets after it has been cleaned: training, validation, and testing. The training set is employed to assist the model in learning patterns. The validation set is employed while training to ensure that the model is learning appropriately and not overfitting. The testing set is then held back to see how accurate the model is at being with new, unseen data.

Each block of text is subsequently sent through a tokenizer—the very same one BERT employs, a fantastically powerful language model. Tokenization is the process of breaking a sentence down into discrete items (tokens) on which the model can be applied. Tokens, along with them, attention masks are created. The masks instruct the model which words to attend to and which words are padding or filler.

For instance, the sentence "I feel happy" is converted to a series of numbers like [101, 1045, 2514, 3407, 102]. The tokens are referring to each token of the BERT vocabulary. Special tokens 101 and 102 are employed by BERT to indicate the start and the end of the sentence.

Following tokenization, the data—token IDs, attention masks, and encoded labels—is wrapped in TensorFlow datasets, data structures purpose-built to provide batches of data into the model while it is learning.

At this phase, various model architectures are trained on this pre-trained knowledge. They may range from transformer architectures such as BERT to Bi-LSTM, Bi-GRU layers for emotional context. On training these models, various test metrics such as accuracy and F1-score are utilized to test them with various test datasets to see how well they recognize various different emotions.

It is this process that is used step by step and in careful detail to make sure that the models are being trained equally, on clean data, and that their performance can be rightfully compared.

3.5 Performance Metrics

Performance metrics play an important role in the measurement of the performance of emotion detection techniques. For the identification of the performance of DL models, important metrics like F1-Score and Accuracy were utilized.

Accuracy. It establishes the right predictions (correct identification and correct rejection) based on all predictions of a model.[13].

Accuracy = (True Positives + True Negatives) / (Total Predictions)

F1-score. It gauges model performance by achieving a trade-off between precision (making correct predictions for one class) and recall (able to detect all occurrences of a class). [13].

*F1-Score = 2 * (Precision * Recall) / (Precision + Recall)*

Chapter 4

Results and Discussion

Below, we will introduce several pre-trained models that have been applied in HAR dataset. Comparison of different deep learning approaches to emotion recognition in text shows that transformer-based models such as BERT and RoBERTa outperform traditional architecture models such as Bi-LSTM, Bi-GRU, and CNN. Transformers attained the highest F1-scores of 70.95% when compared against cross-cultural narrative datasets and 63.95% for fine-grained emotion classification tasks. This dramatic enhancement—somewhere between 8% to 15% above base models—is the ability of the transformers to read input text bidirectionally and utilize self-attention mechanisms. These capabilities enable them to grasp sophisticated emotional clues that are often implicit, such as sarcasm buried in speech or culturally embedded emotive expressions. In dialogue-imitation datasets, transformers were able to capture emotional development across sequences of conversational turns, which models such as Bi-LSTM were unable to do effectively since they do not excel in maintaining long-range context.

The success of such models also highly depended on the preprocessing technique used on the text input. Operations like lowercasing all the characters, removing emojis, and expanding contractions helped the data to become simplified, removing inconsistency and tightening the token alignment with pre-trained embeddings. Especially in social media or casual text, spell-checking was particularly helpful by correcting common typographical mistakes like "happpy" to "happy," thus reducing the number of unknown tokens and stabilizing predictions. But over-normalization had a tendency to have side effects sometimes. For example, removing punctuation indiscriminately reduced the emotional weight of certain statements—"I'm fine!" carries a distinctly different sentiment than "I'm fine."—and eliminating case distinctions could blur meaning in instances like "Python" (the programming language) versus "python" (the snake). Despite these drawbacks, preprocessing was found to be indispensable for improving classification performance, especially in datasets characterized by informal or user-generated content. [2], [20], [21], [22]

Properties inherent in the datasets themselves also had significant effects on model performance. Class imbalance was certainly the most common problem. Joy and anger would comprise more than a majority of the labeled examples, with other emotions—grief, remorse, or shame—strongly underrepresented. This bias resulted in models learning to be disproportionately biased in favor of predicting the most common classes at the expense of their capacity to be attuned to the less frequent emotional expressions. This bias

This bias not only hurts the overall generalizability of a model but also causes fairness issues when applied in real-world situations. In applications like mental health counseling or online harassment identification, the inability to recognize less common but vital emotions could weaken substantially. Further, the emotional displays in the many forms of cultures added another level of uncertainty. An expression that would constitute one of sarcasm or irony in some cultural context might literally be understood in another, so cross-cultural data sets are inherently difficult. Data sets created out of scripted media, such as television scripts, were also said not to be spontaneous, reducing the ecological validity of the models being trained on them.

On the computational side, transformers delivered great accuracy but at the cost of using more resources, thus a practical limitation. Training models such as RoBERTa took about three to five times more GPU memory and processing than smaller models such as Bi-GRU. This drastic difference in computational cost generates a serious impediment for using these models in time-sensitive or resource-constrained environments. For example, real-time customer support apps or real-time sentiment monitoring across social media need to be low latency and scalable—domains where transformers are currently behind. Interestingly, even while GPT models were promising much for generative tasks, their one-way models were limiting them from being top performers in emotion classification tasks as they weren't yet leveraging context on both sides of a sentence sufficiently. They were limited by their one-way architecture. This constraint negatively impacted their capacity for decoding implicit emotional meaning, particularly in emotionally charged or ambiguous statements.

A further significant limitation of the present study was dependence on text-only data. Emotions tend to be communicated not merely via words, but also voice tone, face, and body posture—none of which are accessible in written modes. For example, the expression "That's just great" can express sincere gratitude or caustic sarcasm, depending on how one says it or the facial expression one accompanies the statement with. Without such further cues, even sophisticated models can err. This issue was particularly noticeable in ambiguous examples from social media or informal communication, where brevity and irony are common. Moreover, the performance of these models often declined when tested on data from non-Western cultures. This discrepancy can be attributed to the fact that most pretraining datasets are skewed toward Western linguistic patterns and idioms, leading to poorer generalization across diverse cultural contexts. Ethical issues also surfaced—especially regarding under-detection of minority or less-expressed emotions—which could lead to harmful biases if these systems are used in sensitive domains like therapy or education.

4.1 Hyperparameter Tuning

Hyperparameter tuning is done for each model in this comparative study to achieve the best accuracy and efficiency for DL models. Table 3 displays the hyperparameters of the models used in this paper.

Table 4.1: Hyperparameters are used to build DL models.

Models	Hyperparameters
Bi-LSTM	Units = 64(forward) + 64(backward) = 128 units, Iterations=10, Batch size=64.
Bi-GRU	Units = 64(forward) + 64(backward) = 128 units, Iterations=10, Batch size=64.
ANN	Dropout=0.25, Activation='RELU' for hidden layer and 'SOFTMAX' for output, Layers=64, 64, output units, Iterations=10, Batch size=64
CNN	Dropout=0.25, Filters=64, Kernel size=3, 4, 5, Activation='RELU' for hidden layer and 'SOFTMAX' for output, Layers= 64, 64, 64, 64, output units, Pool = GlobalMaxPooling, Iterations=10, Batch size=64.
BERT	Hidden units = 768(Bert base), Output Activation = 'None'(logits used), Pretrained Model = 'bert-base-uncased', Iteration=10, Batch size=64
RoBERTa	Hidden units = 768(RoBerta base), Output Activation = 'None'(logits used), Pretrained Model = 'roberta-base', Iteration=10, Batch size=64
GPT	Hidden units = 768(GPT-2 small), Output Activation = 'None'(logits used), Pretrained Model = 'gpt2', Iteration=10, Batch size=64

4.2 Comparative Analysis

The performance of seven DL models – Bi-LSTM, Bi-GRU, ANN, CNN, BERT, RoBERTa, and GPT was evaluated on three emotion detection datasets: MELD, ISEAR, and GoEmotions. Using a 75:25 train-test split, metrics revealed distinct trends (Table 4.2). Transformer-based models dominated across datasets, achieving the highest scores on ISEAR and MELD. For GoEmotions, BERT outperformed all models, followed by Roberta and CNN. Despite its scale, GPT trailed BERT and RoBERTa, while ANN, Bi-LSTM, and Bi-GRU underperformed consistently. These results highlight the superiority of contextualized embeddings (e.g., BERT) across diverse textual contexts, as shown in Table 4.2 and Table 4.3, with architectural choice significantly impacting emotion detection accuracy [3], [8], [11], [14], [18], [19].

Table 4.2: Models Performance Metric f1-score on MELD, ISEAR, and GoEmotion Datasets

Models	F1-Score		
	MELD	ISEAR	GoEmotion
Bi-LSTM	44.19	54.03	59.19
Bi-GRU	43.66	51.24	59.66
ANN	40.46	54.51	57.81
CNN	44.26	61.28	62.02
BERT	50.78	70.95	63.95
RoBERTa	52.20	70.18	62.13
GPT	48.67	66.22	62.78

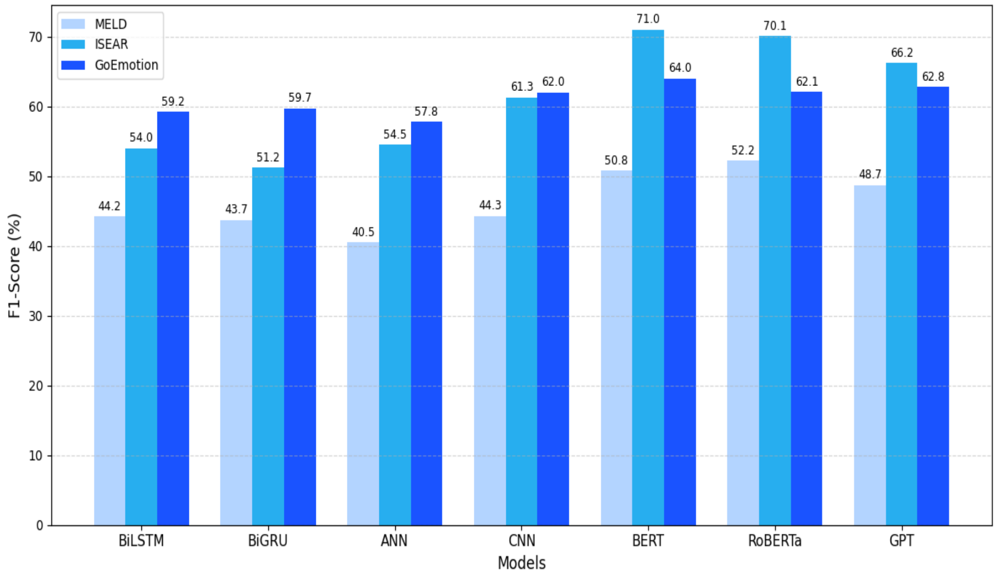

Figure 4.1: Comparison of model F1-scores across MELD, ISEAR, and GoEmotion datasets.

Table 4.3: Models Performance Metric Accuracy on MELD, ISEAR, and GoEmotion Datasets

Models	Accuracy		
	MELD	ISEAR	GoEmotion
Bi-LSTM	50.20	53.19	59.99
Bi-GRU	51.60	49.36	60.37
ANN	51.31	53.93	59.00
CNN	52.18	60.95	62.47
BERT	51.07	70.42	63.68
RoBERTa	53.18	70.10	62.04
GPT	50.67	66.38	62.63

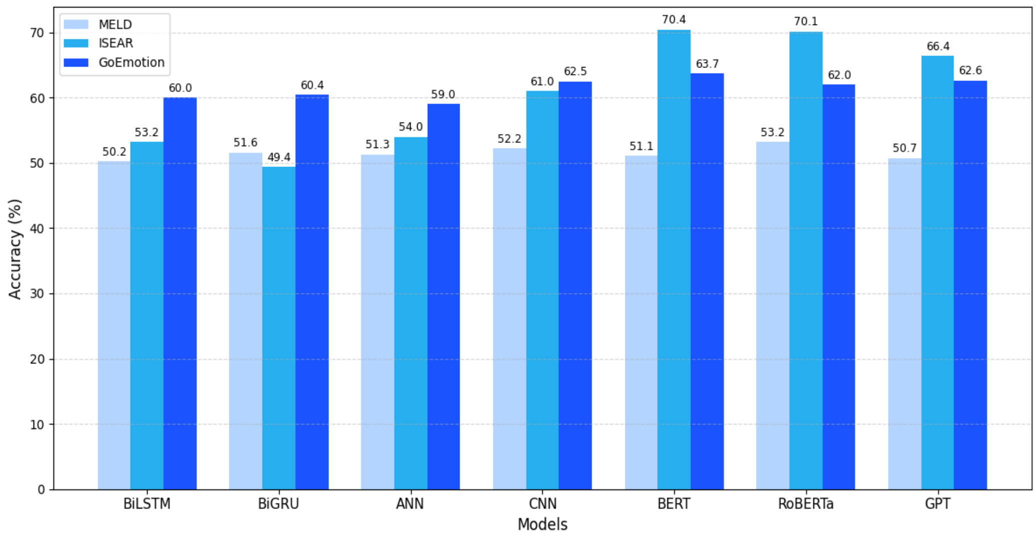

Figure 4.2: Comparison of model Accuracy across MELD, ISEAR, and GoEmotion datasets.

Figure 4.1-4.2 shows a comparison of model F1-scores and Accuracy across MELD, ISEAR, and GoEmotion datasets, highlighting performance variations using F1-Score and accuracy for each dataset.

Chapter 5

CONCLUSION, LIMITATIONS and FUTURE SCOPE

5.1 Conclusion

In The findings of this study confirm that transformer-based models represent a major leap forward in the field of emotion detection from text. Tools like BERT and RoBERTa have outperformed older architectures—such as Bi-LSTM, CNN, and GRU—particularly due to their ability to understand context from both directions and pick up on subtle emotional cues embedded within complex language patterns. They have all consistently been shown to work best on an overwhelmingly vast majority of datasets, both multiculturality and conversationality-wise.

Preprocessing played a crucial role in results improvement as well. Applying standard cleaning operations such as lowercasing, spell correction, and unwanted character elimination removed noise from input and enhanced token matching. Such operations proved particularly beneficial in chat or user-generated content where spelling differences or colloquial language would otherwise confuse the model.

But despite all these developments, there are still formidable hurdles to be overcome. Heavy resource consumption by the giant transformer models and they are hence still less practical for light applications. Data constraint—i.e., bias towards certain types of emotions and Western cultural conditions—still comes in the way of fairness and generalizability. Multimodal data availability, which very possibly might introduce more contextual information using voice, facial expressions, or body language, also limits the scope of emotional perception attainable in text-based models.

In total, while BERT and RoBERTa have established new state-of-the-art points of accuracy and contextual comprehension, deployment in the real world still has to continue solving efficiency, fairness, domain robustness, and transparency problems.

5.2 Limitations

The largest problem with transformer-based models such as BERT and RoBERTa is that they use excessive computational complexity. They usually demand high-end equipment as well as longer training time, which reduces their attractiveness to low-resource environments or real-time processing needs.

Another pressing issue is that emotion datasets are unbalanced, in particular ones like GoEmotions or MELD. These capture a preponderance by a limited collection of large emotions like happiness or rage with hardly any influence on more subtle emotional feelings like regret or sorrow. This type of imbalance has the result of causing the models to become skewed in favor of the more abundant labels, which lowers the performance on the less abundant ones.

The only text-based data reliance is the other significant disadvantage. Lacking audio or visual data, those models are prone to misinterpretation of words that are heavy in context—mostly in detecting sarcasm, irony, or emotionally laden messages from tone or facial expression.

Moreover, the majority of training sets feature very obvious cultural and linguistic bias. For example, MELD draws extensively on Western material, which is predominantly scripts of TV shows like Friends. As such, models trained on such data did not perform well when applied to non-Western environments whose emotional expression patterns differ. Nevertheless, the company only acknowledges that it has a "bias issue.".

Second, the majority of these models do not possess generalization capability across domains. A model that has been fine-tuned using academic or benchmark corpora will not fare well if applied to chat in domains like healthcare conversations or customer service conversations, where linguistic and emotional signals can be significantly different.

Finally, there is an issue of interpretability. Transformer models are typically "black boxes" and opaque, which create issues of trust, particularly in high-stakes use cases like mental health evaluation or support systems where knowing the reasoning behind predictions is crucial.

5.3 Future Scope

With the aim to overcome current boundaries and take the field forward, certain high-level strategic goals would need to be resolved:

- **Light-Weight Model Design:** Mode optimization of small but effective models of transformer models can reduce system resource loading by considerable amounts without altering performance quality, making them ideal for use in real-time or mobile systems.

- **Multimodal Emotion Detection:** Including voice, face, or even physical signals such as heart rate would make model comprehension even more sensitive and richer as far as detecting subtle and ambiguous claims is concerned. Including such other signals as inputs to text completes and improves emotional analysis.

- **Multiculturally Distributed Datasets:** Emotion dataset sharing across languages and cultures would geographically generalize the models. This would reduce variation in performance and make equal emotion recognition possible for more people.

- **Bias Handling Methods:** Synthetic generation of data, bias reduction through adversarial training, and application of fairness-aware loss functions must be explored to offset emotional class distribution imbalances and smooth probabilities of biased output.

- **Domain-Specific Adaptation:** Fine-tuning model-based transfer learning or domain adaptation method will improve performance for domains such as medical text processing or customer relationship systems. Fine-tuning the models with usual domain-specific data such as that would be most likely to make them more relevant and accurate.

- **Enhancing Model Explainability:** Incorporation of features such as attention heatmaps, LIME (Local Interpretable Model-Agnostic Explanations), or SHAP may allow action disentanglement from the model and generate human-interpretable explanations. It is especially useful in high-stakes domains where understanding why something is predicted is just as critical as prediction.

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APPENDIX A

A.1 LIST OF PUBLICATION

1. Dr. Sonika Dahiya, Purvak Baliyan & Priyanka Arora (2025). A Systematic Review on Recent Advancements in Emotion Detection from Text Using Deep Learning Techniques. **[Scopus Indexed] [Accepted]**

2. Dr. Sonika Dahiya & Purvak Baliyan (2025). Comparative analysis of deep learning techniques for emotion detection in textual dataset. **[Scopus Indexed] [Accepted]**

A.2 PAPER ACCEPTANCE PROOF

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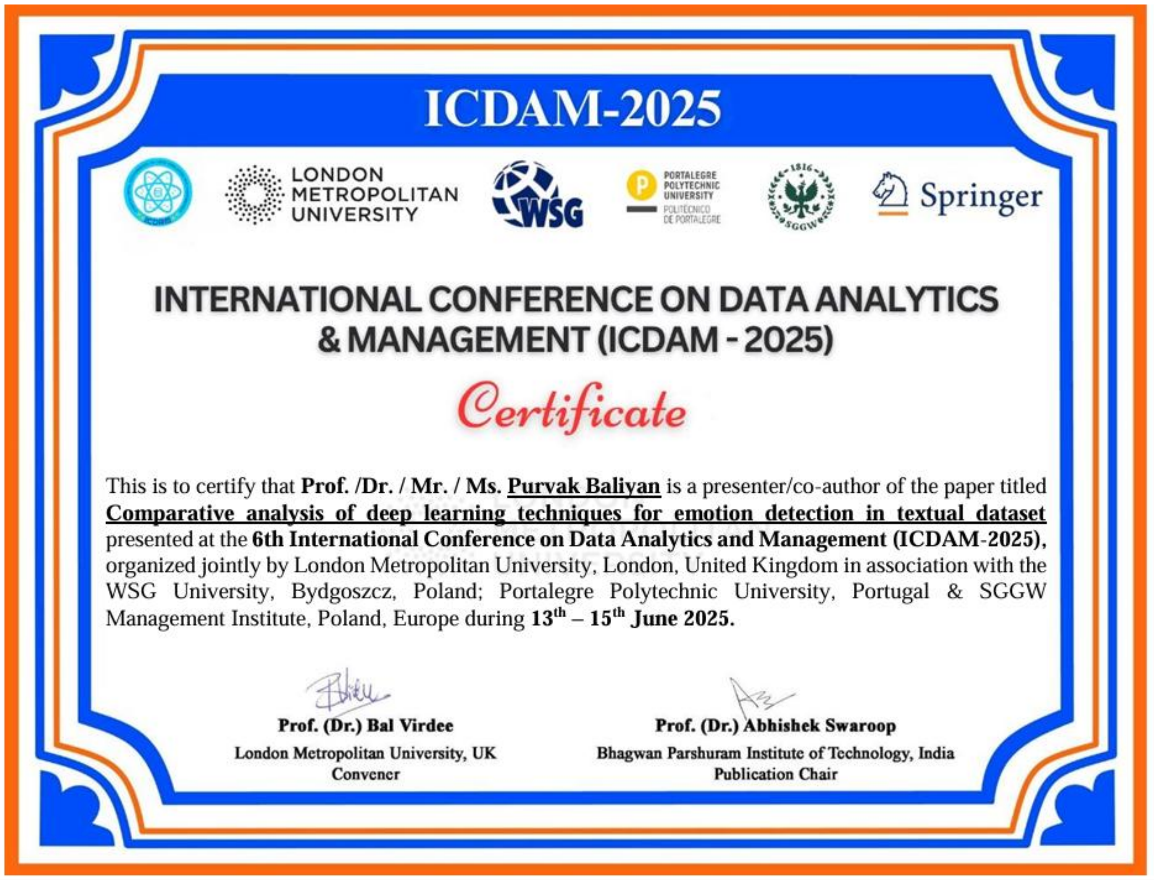

ICDAM-2025

INTERNATIONAL CONFERENCE ON DATA ANALYTICS & MANAGEMENT (ICDAM - 2025)

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This is to certify that **Prof. /Dr. / Mr. / Ms. Purvak Baliyan** is a presenter/co-author of the paper titled **Comparative analysis of deep learning techniques for emotion detection in textual dataset** presented at the **6th International Conference on Data Analytics and Management (ICDAM-2025)**, organized jointly by London Metropolitan University, London, United Kingdom in association with the WSG University, Bydgoszcz, Poland; Portalegre Polytechnic University, Portugal & SGGW Management Institute, Poland, Europe during **13th – 15th June 2025.**

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