Sentiment Analysis and Sarcasm Detection

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by

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CANDIDATE'S DECLARATION

I, Manali Bhat, Roll No. 2K19/SPD/10 student of M.Tech (Signal Processing and Digital Design), hereby declare that the project titled "**Sentiment Analysis and Sarcasm Detection**" which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associate ship, Fellowship or other similar title or recognition.

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I hereby certify that the Project Dissertation titled "Sentiment Analysis and Sarcasm Detection" which is submitted by Manali Bhat, Roll No. 2K19/SPD/10, Electronics and Communication Engineering Department, 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 to this University or elsewhere.

Place: Delhi **PROF. RAJIV KAPOOR**

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ABSTRACT

The study of sentiment analysis for this work began by going through the present research conducted by different researchers. While performing the thorough literature review, comparative and qualitative analysis of different research papers were performed keeping in mind the datasets used by various researchers, the method used to derive the sentiment, categories of the outcome, areas in which sentiment analysis and others was studied. The summary of the entire study is culminated in a tabular format in the upcoming chapters. After going through the literature, it was found that there is a huge area for studying and understanding sarcasm which is on the textual format. Also, since, detecting sarcasms can further pave way for understanding the hidden sentiment or the true sentiment, Sarcasm detection was further studied. In the study for detecting sarcasm, we design a model that takes care of the fine sentiments and the coarse sentiments in the comment / statements under the study. This model is also tested on state of art models and also on 3 different datasets and it gives good results.

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CHAPTER 1

INTRODUCTION TO SENTIMENT ANALYSIS

Under natural language processing, we have Sentiment analysis which aims at categorizing or classifying pieces of text according to the intutional sentiment which is derived from it [79]. Sentiment is expression of emotion and opinions by individuals, communities or groups based upon events, topics or issues pertaining to different fields. Sentiment analysis is analysis of the text and its linguistics for identification and segregation of views put forward by a user / author. This would, thereby, summarize the major intent of the author pertaining to the context or the polarity of the context. Thereby being able to guide brands of the sentiment for their product in the market, the brand reputation etc. The intent of the text could be a suggestion, assertion, judgment.

Opinion mining as well as Sentiment analysis are many a times used in place of each other. However, some argue it to be a slightly variant from one another. Any opinion that one holds is subjective, it could rely on facts or on feelings and judgments [66]. The process of extracting subjective information from the data or text is sentiment analysis [66]. While opinion mining suggest the process of extracting opinions and then analyzing them is different.

Analysis could be done for varied reasons as shown in the figure 1. The sentiment analysis which is based on aspect heavily depends on attributes or properties of an object, product or a service. This helps to understand performance of a particular aspect and the value it has generated. Emotion classification is done with the purpose of identifying the emotion. It is based on machine learning algorithms and lexicon analysis. Consumer Intent, this involves tracking consumer likes, dislikes to build a pattern which would develop an understanding of the kind of approach consumers have for a particular entity or topic, their behavioral patterns. This could help companies in branding their commodities and services to target a particular kind of audience and cater their requirements for a larger purpose. Polarity of text for understanding views of the author. This purely tries to divide a text into one of the binary or ternary options.

The views of many people for certain events, brands and product can be known by performing sentiment analysis. Thus, the data is gathered and modified for improvements by researchers to do the evaluations. This makes data for analysis a crucial part for analyzing the sentiment. Objective or Subjective data may or may not contain opinions or intent. Thus, in order to perform sentiment analysis, it becomes essential to recognize and extract the features from the source material. This makes feature selection and extraction an important aspect of analyzing sentiment.

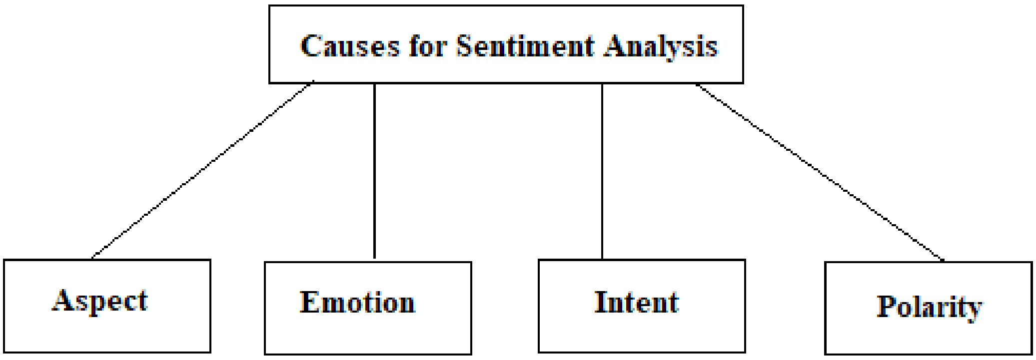

Fig 1: Reasons for sentiment Analysis

Data could possibly be from surveys, social media, microblogging sites, user reviews from shopping sites like Amazon, Shopify, Flipkart etc. It is obtained by crawling the websites using the Application Programming Interface provided by the platforms or using the evaluated and labelled datasets especially for twitter posts or amazon products or movie reviews etc.

Data collected could be analyzed in varied quantities. By looking onto the entire document at once we would be able to derive the summarized polarity of the writer. This polarity could be classified in 2 or 3 categories namely, positive, negative (for datasets which are bipolar like yes / no, spam / not spam etc) and/or both along with neutral. Taking a look at the different statements in the document block one could conclude whether there are or are not any sentiment polarities that oppose each other. As the analyzes of only one statement is performed, one might not get the clear picture but would surely get a more detailed idea of what is been communicated within the sentence. Another way to study the data could be by fixating on certain parameters or aspects and considering only that part of the entire document that discusses it. This could help derive emotions people are associating to that particular parameter of the device or news etc.

Analyzing sentiments is challenging due to issues like use of slang, grammatical errors or spelling mistakes or even sarcasm. Understanding if the text is genuine or not is also a challenge. As there are various factors like social, political circumstances etc that drive sentiments of a user or author.

In general, a sarcastic spoken word or a sarcastic written sentence is hard to find. With the rise of social media, it has become essential to identify and isolate such sarcastic views so that it does not create misunderstandings and chaos in real life. With this in our minds, we have look into detection of sarcasm. Since, sarcasm detection is a binary problem, we can say that it is a part of sentiment classification. Sentiment classification involves categorizing the statements into one of the pre-defined categories. In this paper, we put forward a deep learning-based model that looks into the coarse and fine aspects of the statements under study. The model is also facilitated with attention thereby ensuring only the words which are of more importance are considered in the final decision making to deduce the outcome for the statement under consideration. The model has been tested on different datasets which are meant for detecting sarcasm. It has also been tested on the state-of-art models and the outcome is compared and presented.

Ever since the entire world has been connected via internet, we have audio, image, video, text are the four major modes for communicating with one another. This has opened up another realm for researching and deducing on sentiment analysis and emotion recognition. The study for understanding human emotions is a widely researched area. Emotions could be understood in a wide variety of ways, be it spoken word or unspoken gestures or even written text, there is elaborate research that is needed to decipher the correct and true sentiment that is being reflected from the source. Since, communicating online relating to specific issues like politics, religion etc can turn into sarcasm and irony [19] Sentiment analysis is also a widely popularized area for researchers and industries to experiment and carry out their study. Sentiment analysis which aims at categorizing or classifying pieces of text according to the intuitional sentiment which is derived from it [14]. The intent put forward by the creator could be any of suggestion, assertion or judgement. However, the deduced sentiment heavily relies on the perception of the person who is consuming it. This complicates the task of sentiment classification. Since, the words could convey a mixture of sentiments it becomes challenging to figure out the inclination of a sentiment towards a particular emotion. This could be looked at from a different perspective as well. By understanding the meaning derived from the group of words and understanding the hidden intent within the group of words. These are two different things and may or may not be in line with one another every time. This is also where sarcasm comes into play. Sarcasm is subjective, it is based on way we preserve. Any opinion that one holds is subjective, it could rely on facts or on feelings and judgments [13]. So, understanding whether or not a statement or document is sarcastic is challenging in itself. With the bloom in the social media, and availability of a variety of platforms like Facebook, Twitter, Instagram, Tiktok, LinkedIn etc, communicating ideas, thoughts and opinions as become easy for everyone. This has led to drastic rise in social crimes like cyber-bullying, preaching offensive and hate speeches, spreading rumors for personal or political gains, spamming and much more, despite, the term of service which disallows such speech [12]. This makes it really very essential to identify and isolate such sarcastic pieces of content.

Sarcastic statements often contain a blend of emotions or shift of emotions, thus, clearly, making it a special instance of sentiment analysis. Like for example, this statement – "It is been hours since I am waiting for the boutique to open, the employees seem so dedicated". This clearly shows the contrast between the part of statement before the comma – 'It is been hours since I am waiting for the boutique to open', and the one after it – 'the employees seem so dedicated'. Detecting such kind of sarcasm would truly enhance and automate detection of sarcasm as a part of sentiment analysis.

Detecting Sarcasm relies on extraction of features and learning techniques. We can also say, that, sarcasm detection comes under text-classification. So that the performance of sentiment analysis task is improved we propose a model which is based on deep learning. The model is build up of bidirectional LSTM and attention. The features are extracted using the FastText and Glove embeddings thereby ensuring that we cover both the global co-occurrence between the words from the entire corpus also take care of the unknown words or words which are not a part of the vocabulary. The model is trained and evaluated for the test dataset.

CHAPTER 2

CLASSIFYING SENTIMENT ANALYSIS

Results from the study pertaining to sentiment analysis largely rely on the cause for which analysis is being performed. This makes categorizing sentiment analysis a vital task. Broadly, in order to categorize sentiment analysis, we have considered three major aspects viz., Method based, result based and application based. These categories are narrowed down by categorizing them further.

Classifying sentiment analysis based on outcome can be categorized as opinion mining and affective analysis. Opinion mining deals with the polarity of the text. These polarities could be dual (positive or negative) or triple (positive, neutral, negative) Emotion based analysis is majorly based on the 8 emotions of human sentiments like happiness, sadness, anger, fear, anticipation, surprise, disgust, trust.

Sentiment analysis can also be classified as Lexicon-based, Machine learning based, and mixture of both the methods. The figure 2 shows all possible ways in which sentiment analysis could be categorized for better understanding.

Lexicon based classification considers words and marks their intensity and polarity. Approaches which are based on Lexicon have low utility when worked on unseen data [75]. Polarity defines if the word is biased towards a positive side or negative side or neutral side and intensity defines the degree to which the word is biased towards the polarity. For example, the words sad and very sad have the same polarity but the intensity of the words could differ.

When the text to be analyzed is feed, the words of the input text are compared and weighed to those of the sentiment lexicon to get the output sentiment. Glove [86], Word2Vec [85], and FastText [87] can also be used to get the word vector features, embeddings. More often lexicon-based approach deals with opinion mining type of classification. English language has a huge number well-structured lexicons but that isn’t the case for other commonly used languages. Recently, there have been studies pertaining to analysis for non-English languages particularly Arabic, Chinese, Urdu, Russian etc.

Machine Learning Models are divided as unsupervised and supervised algorithms. There could also be a blend of both of these algorithms to form a hybrid or a semi-supervised algorithm. The supervised algorithms are efficient enough for labelled training datasets. A huge amount of annotated data is required for performing supervised learning [80]. Various types of supervised machine learning methods such as Naive Bayes (NB) [81], Support Vector Machines (SVM) [84], Maximum Entropy (ME), Logistic Regression (LR) [83], etc. and feature combinations have been applied in sentiment analysis research [74]. Classifiers and Regression models all are part of supervised learning models with labelled data. Unsupervised algorithms perform well for real-time data that is not classified or labelled. Here, text is at first converted in form of vectors to obtain the features of the text. Clustering based models like K-means or K-clustering or dimensionality reduction techniques for feature selection and features extraction are unsupervised.

Major drawback of the Lexicon-based classification is that there could be less values assigned or inappropriate values assigned to words. Although, Machine learning algorithms deal with this quite well they need to have a huge training data to correctly classify the sentiments.

Sentiment analysis has varied applications. Web 2.0 upgrade facilitated blogging and social networking sites which has increased the applications of sentiment analysis in many folds. Thus, by considering all of these as categories we would be able to view from a broader perspective the areas to which sentiment analysis is applied and the areas to which it could be applied in further studies.

Sentiment analysis has applications ranging in diverse areas. Namely, it’s been used for marketing and sales by companies and brands for brand managements, understanding voice of costumer, market research, product analytics eyeing the competitors etc. Social media platforms and online shopping sites could be used for this purpose as these are platforms where consumers and potential consumers from different demographics come together and discuss their experience, intent regarding the product or service and influence each other to form an overall perception of the product or the company.

Apart from this sentiment analysis could be used for understanding the public opinions on a certain government policy or a particular news event etc. This would help the public to express their feelings and believes as well as the policy makers on how the new policies are being perceived. It could also be used to predict the election poll results and know the public choice well in advance. Further advanced study in this regard could even replace the traditional polling system the way we know it today.

Analyzing sentiments could also help in performing surveillance to detect criminal intelligence on various social media platforms. Currently, there is need for performing surveillance, detecting and isolating cyber-trafficking [63]. A study dealing with this issue monitors cyber-trafficking social media discussions, the authors proposed a system that collects, analysis, and visualizes social media content, the linkage among users and their temporal features. This would help in keeping cyber bullying and cybercrime in check. Also, at times many the social media users knowingly or unknowingly put up sensitive information which could be misused or traded by various organizations such as advertising companies, or criminals. [64]. This makes it an essential task to focus on identifying privacy leaks in the content of texts put out on social media.

Sentiment analysis could also be used to study trends of a particular share in share market or market sentiment as a whole. Alongside this it would also be helpful for stock prediction and thereby guide buyers on the most promising shares.

Thus, we could broadly classify sentiment analysis applications in a few categories, namely, prediction, detection, creation / study, analysis. Here, the creation / study deals with all the works which have put their focus on building of corpus / lexicon or some kind of a dataset. Analysis group deals with all the study performed to analysis some data and derive something out of it. Detection group deals with all the researches which have worked to detect emotions or sentiments and so on, whereas, Prediction categories all the study which culminates to forecasting and predicting.

Apart from all of this there is a method which lets researchers utilize the efforts of their fellow researchers. This is transfer learning [90] which takes one type of training data /

knowledge and utilizes it for data of a different type which shares some commonalities. This helps in generalizing the outcome and lowers the labeling effort [64].

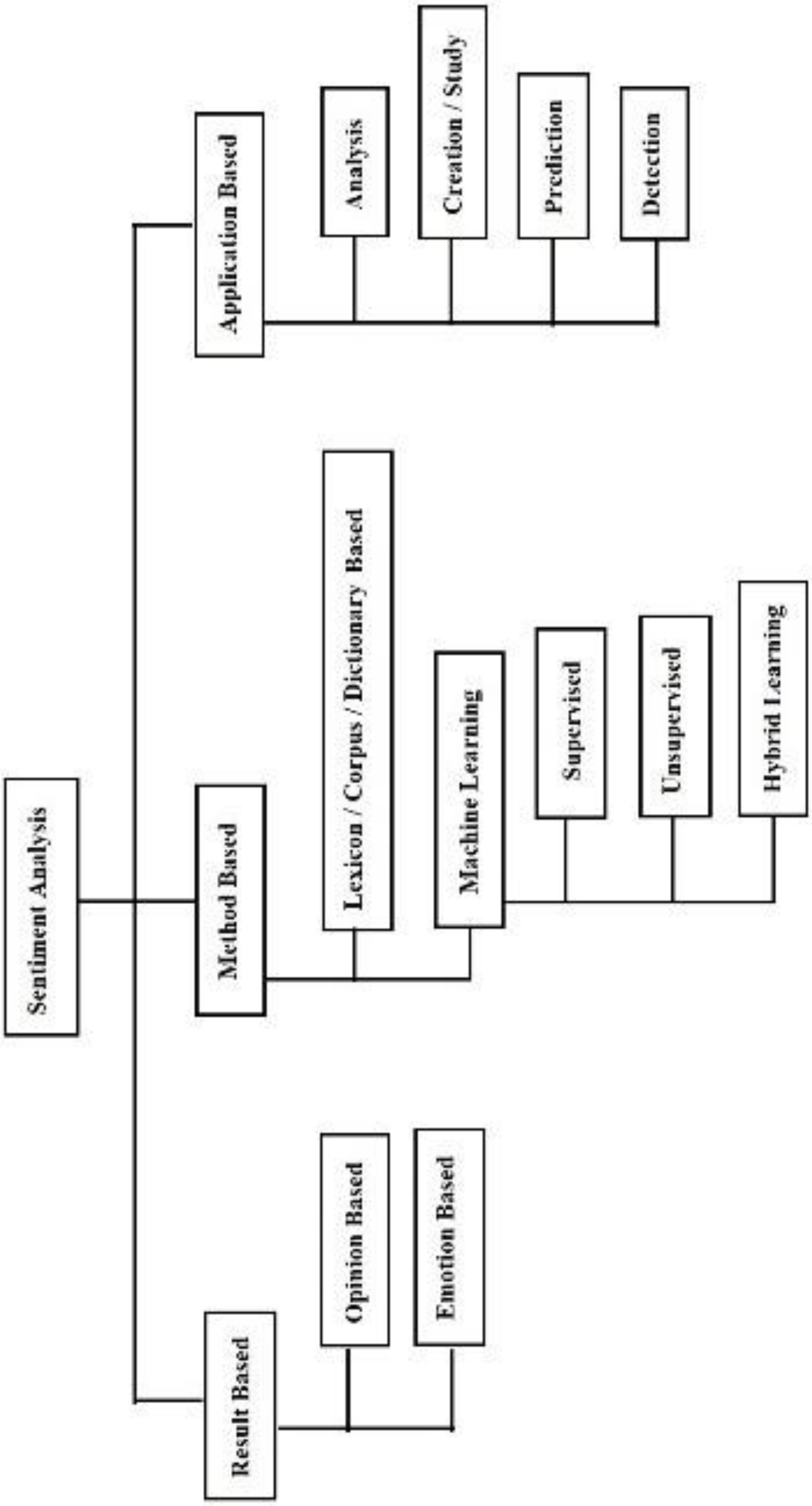

Fig 2: Classification of Sentiment Analysis

CHAPTER 3

GENERALIZED FLOW FOR ANALYZING SENTIMENT

Majorly the sentiment analysis happens in a format as shown in the flow diagram. However, based on kind of dataset used, model parameters and desired output there could be slight changes in the flow mentioned. The type of machine learning model also determines the flow of the process.

At first, data is procured from a well-known dataset or by the means of web scrapping. As per study of papers it is been found that a lot of papers heavily relied on the data gathered by user generated content (UGC) that comes from the social networking sites and social media. The UGC data on the social media and user reviews commonly showcase subjective texts as the writers freely post their opinions, the most popular one being twitter [79]. Data collected from twitter is preferred for it being user generated, contains a variety of opinions from people of different demographics, huge choices of topics for data scrapping. Other than twitter, data pertaining to e-commerce websites, movie reviews etc is chosen.

By making use of different data sources, some studies have managed to cover a wider range of materials [79]. The data which is gathered has to be converted to a usable format. For this purpose, it is cleaned, preprocessed to desirable format that can be used for further processing. This stage incorporates a number of minor tasks. Tasks like tokenizing viz., breaking text into pieces of smaller size text, stop word filtration (words that don't contribute to final goal example, repeating characters etc are discarded) and stemming or lemmatizing (converting word to a base word) and splitting dataset. Dataset can be split into 2 to 3 kinds namely, training and testing dataset and / or validation dataset. In order to train the sentiment classifiers, sentiment reversal prediction model training dataset is used, for testing the performance of the classifiers as well as the sentiment reversal prediction model, the validation data is used, for evaluating the blind performance test dataset is used [67]. In short, the training dataset is used by the model for learning purposes while the testing dataset is used for getting an unbiased result from the trained or learned model. Validation dataset is used to guide while the model is getting tuned to the hyperparameters.

Now we discuss a crucial step for sentiment analysis which is responsible to decide what parameters to lookout for while deciding on a sentiment. For supervised learning, we carefully choose features that would be enough to correctly distinguish between various categories of classification. While for unsupervised learning, feature extraction is performed prior to passing the data to the model. The features could be any of the parts of speech like the adjectives or the adverbs that would add on the emotion being put out, it could even be words that voice out opinions like don't, dislike, never, ugly, bad good, like etc or even negation words or phrases which completely change meaning put forward by the statement, the phrases whose meaning could even suggest irony.

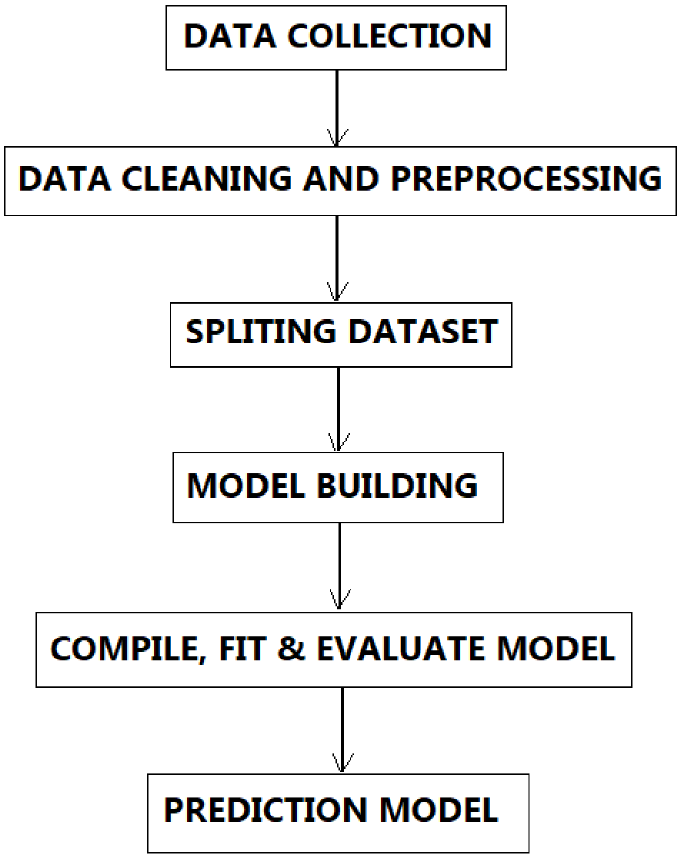

Fig 3: Generalized Program Flow

Before one could do feature selection a major step of feature extraction needs to be performed. It is responsible for the performance of the model. While feature selection is selection of features which would contribute maximum to the output or the ones with have maximum chances of driving a particular kind of output in which we might be interested, feature extraction creates a brand-new feature set that has the essence of the most useful data.

One can perform these by means of applying unsupervised methods like the PCA or the supervised methods like the LDA. Text-based features include the Bag-of-Words model (BoW) and N-gram Language Model extracted using the Term Frequency-Inverse Document Frequency (TF-IDF) weighting scheme [36] could be used for this purpose. One could also visualize the results as well in order to get a pictorial insight into the data worked upon.

After this, the vector of words with label is formed and then the model is built. Then, the training data is passed through it. Later on, we decide a model architecture, which means deciding the number of hidden layers, the activation functions, embedding sizes etc. This is called compilation. After deciding the model architecture, we train the model to get all the parameters to the best value in order to map the inputs and outputs. This is data fitting. Lastly, the model is used for feed-forward passes for the prediction of new inputs. This being done the results are evaluated on various parameters.

CHAPTER 4

STUDY RELATING SENTIMENT ANALYSIS

In order to truly understand the direction of recent study revolving around sentiment analysis, careful selection of publications over the past few years is looked upon.

While going through all of the chosen papers it has been found that the study is divergent across various issues that still prevail and bother the researchers, the industry and at times, the content consumers. Vivid areas which have been a recent target of study among researchers across the globe is as shown in the figure 4. Broadly we happen to categorize the area of study based on the major focus performed by the authors.

4.1 Areas touched by papers under this study

The categories under which the classification is done are prediction, detection, analysis and creation / study. The areas which have been put under the category of prediction majorly focus on forecasting the outcome of a particular task or an event; including prediction of a stock or stock market sentiment, results of an election, trying to predict the data which might interest a user and suggesting it etc. For those categorized under detection are driving to find out a particular kind of behavior or pattern. Be it sarcasm detection, rumor detection, detection of hate speech found online or recognizing a contributor based on a given topic etc. Identifying the role of a social edia user to analyze and understand social media relations, understanding and forecasting user behavior and the interactions users conduct with one another [95].

Another group is formed comprising of methods for building or modifying the corpus, lexicon, dictionary as well as studies performed relating to understanding sentiment based on different languages like Russian, Arabic, Urdu, Chinese, Japanese etc. This study could comprise of building a dataset that could be used for analysis or using methods to detect sentiment and so on. We also have come across studies which propose CONCEPTVECTOR, an analytics aide which helps users to interactively build a lexicon for custom concepts [96]; Social media users put up many spatial and temporal-based data including texts, images and videos which had given rise to big data[68]. We came across a foresighted tweet analysis platform NeedFull, which was developed in order to help the government authorities to understand psychological needs of the people by creating this tweet analysis platform during the tough times

Apart from these categories a collection of all the study performed with intention for analysis is grouped together. Analysis could be done considering the length of the text. By considering entire text document at once or by considering the sentences one after the other or by analyzing text based on topics or by considering a particular aspect or feature. Analysis could also be done to figure out the context of the text. Analysis of polarity is also a vividly researched topic. Polarity analysis could be binary or ternary or based on 7 or 8 emotion classification. Another hot topic is cross domain analysis which aims at facilitating a labeled source domain for an unlabeled target domain.

Different kinds of methods were proposed by researchers to tackle these issues. All of these are discussed in brief in table 2.

4.2 Dataset:

The kind of dataset chosen has a crucial importance in the study. As the dataset is chosen for training of the model, validation and testing as well data selection heavily impacts the performance of the model and the kind of prediction it makes. Thus, choosing dataset is one essential step.

The data could be coming from sources of different kinds, namely, user generated content from the social media, reviews for services or products, news from tv or websites, mix of data from different resources. From the study of different kind of works pertaining to sentiment analysis, a few kinds of datasets dominate majority of the researches. In this section such datasets have been discussed.

There are several ways to obtain a dataset. Either by using the usual datasets built by previous studies or by web scrapping social media sites or websites or datasets from various competitions. The datasets commonly used are the datasets by Stanford University like the twitter sentiment dataset, Stanford sentiment treebank dataset, IMDB movie review datasets, Movie review datasets etc.

Datasets for stock market prediction and analysis are obtains by scrapping financial sites like Yahoo finance and stock exchanges like Shanghai, Hong Kong etc. Dataset for analyzing sentiments associated with products, services or brands are obtained by scrapping websites. The most popular one being Amazon.com for sentiment analysis in English language. For Chinese language, Dangdang.com- e-commerce website, Ctrip - travel agency company website, Danmaku videos’s live commenting etc. The app stores like Google’s play store and apple store also are scraped to draw reviews. Datasets are also procured from microblogging websites like Twitter for procuring tweets in English language, Sina Wiebo -Chinese microblogging website etc.

Twitter has an application programming interface (API) that allows researchers, students to collect tweets. However, the limit is upto the previous seven days for data collection. A premium account, which charges a lot can provide data older than seven days [69]. Also, Twitter has features for filtration to get the data required.

A generalized way for scaping data from websites begins by choosing the target website which needs to be crawled for scraping the data. After that it is essential to collect the URL of all the pages in that website. This helps fixating the exact location from where the data would be collected to build up the dataset. Now, to procure the data a request to these URLs is made. The request is responded by providing HTML of the page. In order to find the data in HTML locators are used and the data that is found is saved in structured formats like JSON or CSV formats.

Competitions and workshops like SemEval (Semantic Evaluation) which aim at advancing semantic analysis and help in creating annotated datasets for different challenging problems pertaining to NLP semantics. Every year’s workshop consists of group of tasks worked on by different teams are presented and compared. The SemEval dataset has now become the extremely popular dataset for the analysis of sentiment[80]. Of all the papers under study, datasets from different tasks of SemEval-2014 are the most frequent ones followed by SemEval-2015 and 2016.

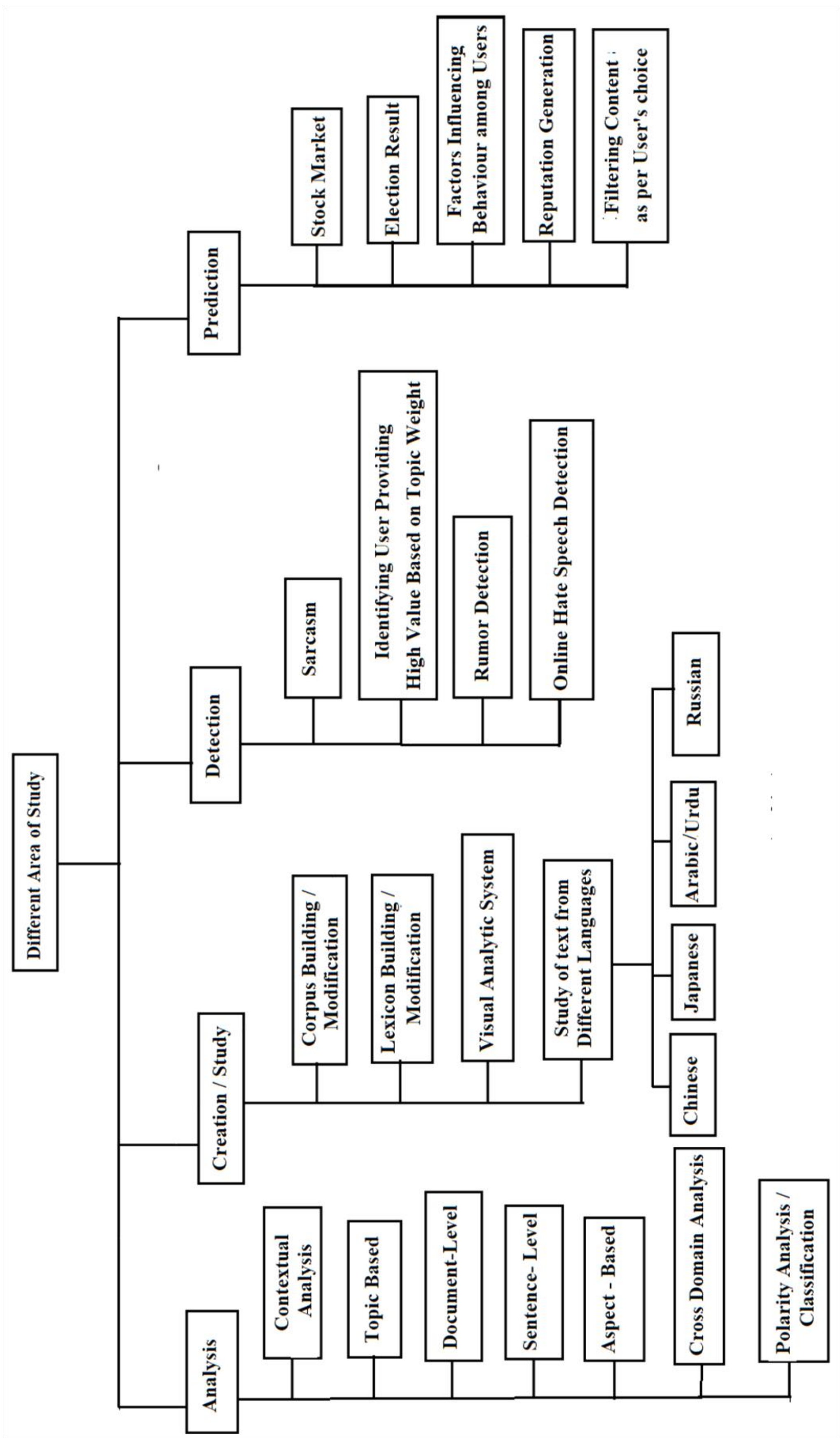

Fig 4.1: Different Area Of Study

4.3 Features and feature processing

Certain keywords or words play an important role in driving the sentiment of the entire text. Grouping them together would ease the process of deriving the sentiment. These are identified as features. Of the variety of features which could be derived from the text, picking the ones which have the most impact in analysis of the sentiment is a big task. Reducing the number of input variables to only the most useful ones for a model in order to predict a target is feature selection. Thus, feature extraction and selection are of utmost importance. Feature selection is also related to dimensionality reduction wherein the input data is projected to a lower dimensional feature space. This could also be done by choosing a smaller set of important features [70]. Some of such methods are discussed briefly namely, chi-square, information gain, LASSO, etc.

The Chi-square test method tests independence of 2 events. It is calculated between each feature and target and the features which give the best chi-square scores are chosen.
The information gain measures information that we could get from a feature of the class. Using this we could know about the features which can meaningfully discriminate between the classes which are to be learned.

LASSO stands as Least Absolute Shrinkage and Selection Operator and is a linear L1 regularisation technique that estimates sparce coefficients. It is useful in contexts where solutions with fewer parameter values are preferred.

Correlation coefficients are also used for feature selection as good variables are well correlated with the target. The variables however must not be correlated among themselves. If they are correlated then they don’t add information so one of them must be utilised for selection. Heatmaps can be used for this purpose.

The feature selection methods build focus on the existing dataset and throw away the not so important ones. The existing features are looked into and no new features are created. The Feature extraction techniques discards the original features after creating brandnew features from the features present, thus, reducing the overall number of features in the dataset. The new dataset which consists of reduced features has a gist of the information which was present int the original data. In feature selection, the new feature set is formed by taking a part of the original one. The new feature space of feature extraction can be transformed from the original space by applying linear or nonlinear combinations [70]. Some vividly used feature extraction methods like PCA, LDA, bag of words, TF-IDF are discussed briefly.

PCA removes redundancy that exists between correlated features in the dataset[71]. Principle Components Analysis (PCA), a dimensionality reduction linear technique and an unsupervised learning algorithm. The higher dimensional data is mapped to data in a lower dimension but the data in the lower dimension ought to have maximum variance. New orthogonal features are linear combination of all input features. These are identified and ranked depending upon the amount of variance of the input data they can explain.

Linear Discriminant Analysis (LDA), is one of the most popular unsupervised algorithms. It is a dimensionality reduction technique which is responsible for modelling each document as a mixture of topics [72]. It tries to increase the distance in between mean of class and reduce the spreading in the class itself. Maximizing distance between means of each class after the data is projected in lower dimensional reduces overlap between different classes.
Bag of words uses words as features for training the classifier. After text processing a vocabulary of unique words is formed. A matrix of features is created, each entry in the matrix shows the absence or presence of the word, this is called as text vectorisation. Feature representation based on bag of words aproach faces the problem of data sparsity [75]. Like bag-of-words we also have n-grams were a group of words are considered.

Another feature extraction technique is TF-IDF viz. term frequency-inverse document frequency which is a widely used statistical technique for measuring the importance of a term in a given text from a document corpus [73]. It raises proportionality of TF-IDF value according to the amount of times a word appears in the text and decreases with total number of documents in corpus that consists of that word. Term frequency specifies the count of the term in the text. Inverse document frequency measures if a term is unfrequent of frequent across the corpus document.

4.4 Models:

To perform sentiment analysis on a variety of datasets, applications it is essential to model the framework so that correct outcome is achieved. Authors and researchers have been keen on working out several model which could bring an apt solution to this problem. Over the years of research, various findings have been put out to facilitate growth in this realm of study. It is however interesting to note that a few of these Machine learning methods have been vividly used and are found to be effective. This segment of the study aims at throwing light on these methods. The kinds of such methods which have been discussed further are jotted in the figure 5.

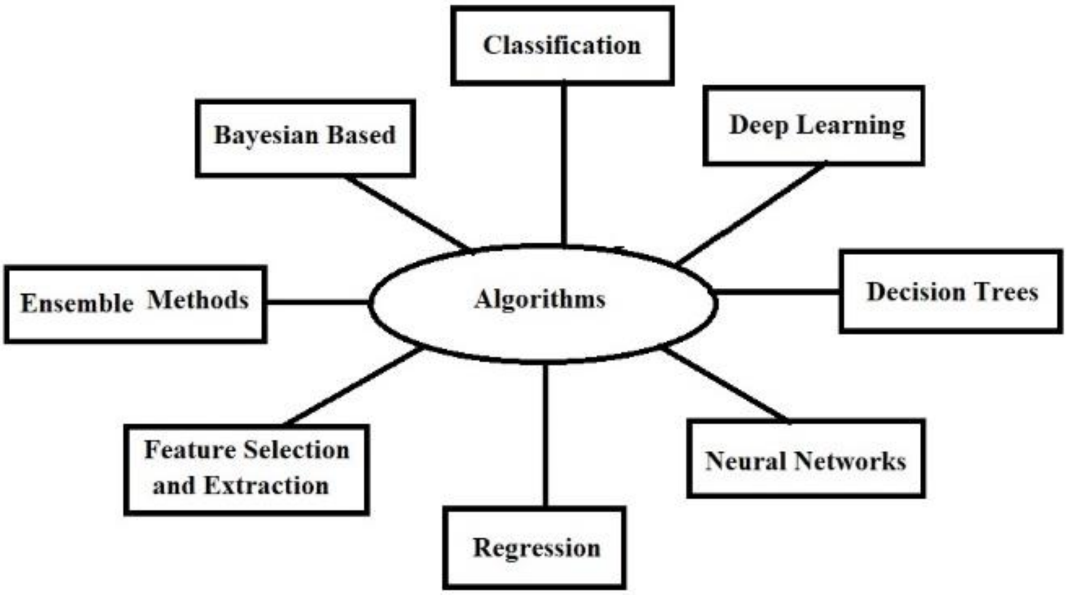

Fig 4.2: Types of vividly used algorithms

The most frequently used algorithms from the recent studies are classified in eight different groups namely, classification, regression, Bayesian based, neural networks, ensemble methods, decision trees [82], feature selection and extraction (also includes dimensionality reduction), deep learning. Of these, classification algorithms like SVM [84], Naïve Bayes [81] etc, regression algorithms like logistic regression [83], ordinary least square regression etc, decision trees [82] algorithms are a kind of supervised algorithms. Some of the Ensemble methods are random forest, boosting, adaboosting etc, whereas the Bayesian methods are naïve Bayes, Multinomial naïve Bayes, Bayesian network, Gaussian naïve Bayes etc. The feature selection as well as extraction methods have been discussed in a brief. Neural network and deep learning algorithms are also amongst the most vividly used algorithms for sentiment analysis, namely, feedforward neural network (FFNN), Radial Basis Network (RBF), Long Short Term Memory (LSTM), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU) etc.

Support Vector Machines (SVM) [84], a supervised learning method focuses on finding a hyperplane in a P-dimensional space (P is the number of features) which distinctively classifies the data points. The chosen hyperplane must provide maximum distance between datapoints of different classes. The datapoints which are near the hyperplane greatly influence its location and tilt. The overall goal is to increase distance between these support vectors and hyperplane that is, to find the optimal hyperplane. This technique has been widely utilized for classification since it converts the nonlinear problem to quadratic programming. Also, Svm gives out a unique and globally optimal outcome [65].

Naive Bayesian [81], a Bayesian theorem based classification method [13] is supervised learning algorithm. It is a probabilistic model which makes assumption that each and every feature makes equal and independent contribution to outcome. This would ensure conditional independence in between each pair of features which are given the value of the class variables. Different Naïve Bayes classifiers are used namely, Gaussian Naïve Bayes, Multinomial Naïve Bayes (for document classification), Bernoulli Naïve Bayes. Of these Multinomial Naive Bayes (for document classification) has feature vectors showcasing frequencies with which events are generated by multinomial distribution. Bernoulli NB has features which are independent Boolean. Gaussian NB has continuous valued features which are distributed as per Gaussian distribution.

Bayesian networks [35] model conditional independence relations among variables which learn the directed acyclic graphs and represent factors of the joint probability distribution over the relevant variables [1]. So it is basically, a probabilistic graph-based model which has each edge as conditional dependency and each node as a unique random variable. The BN uses Bayesian inference for probability.

Convolutional Neural Network (CNN) works on 2D data; however, it is also suited to work with 1D and 3D data. The method gets its name from an operation called convolution which is performed in the layers of the neural network. The basic CNN model is build using convolutional, pooling and fully connected layer [92]. The convolution, a linear operation involving element-wise multiplication of array of weights (filter) with filter-sized patch from the array of input, which is then summed up to obtain a single value. Convolutional Neural

Networks (CNNs) are vividly employed for text classification and tasks which learn extracting hierarchy of crucial text elements [89].

Bi-GRU is Bidirectional Gated Recurrent Unit is two way GRU wherein output depends on the forward and backward states. It solves the problem of unidirectional GRU thus, the final output more accurate [92]. It consists of two GRU. One of the two takes input in forward direction and other in backward direction. It has input and forget gates and hence can be seen as a bidirectional Recurrent NN.

LSTM is a better recurrent neural network which overcomes the long-distance dependence problem [76]. For this reason, they are preferred for applications that require sequence prediction. LSTM reduces the effect of vanishing gradients and exploding gradients on a large scale. LSTM successfully predicts the next outcome as per information of the previous time [76]. But there are times when the current outcome relies on the past and future states.

In such times we need Bi-LSTM. Bi-directional Long Short-Term Memory is a 2-way LSTMs, that identifies and holds bidirectional semantic dependency in order to better memory [88]. Of the two, one takes input in forward direction while the other takes input from the back. This increases the total amount of data which is being made available for the network. Thereby causing improvement in context available to algorithm.

Recurrent Neural Network (RNN) has an internal memory and is recurrent over time. CNN does not have the memory to capture long-distance dependencies which exist in the texts which RNN has[92]. It does the same function for each input data while the output depends on current input and the previous computation. On generating output, it copies it and sends it back to recurrent network. RNN, a generalised feedforward NN uses its memory to process input sequences which are related to one another. Recursive NN (RNN), on the other hand are created on applying same set of weights recursively on structured inputs, particularly directed acyclic graphs in order to obtain structured prediction. This model are both non-linear and adaptive.

Random Forest (RF) is a forest of many decision trees. The dependance is diversified ato various decision trees and thereby onsub-samples of the document [78]. RF creates decision trees of data samples. These trees operate as ensemble and each of them work on input and give out result. The class which is highly voted is chosen as the outcome for the forest. This supervised learning algorithm does classification as well as regression. It reduces overfitting by averaging the result and not concentrating on the outcome obtained from a single decision tree.

Logistic Regression (LR) [83] is a Supervised Classification Algorithm which builds regression model and forecasts if the data point would belong to a category. The output is modelled using a sigmoid function and takes discrete values for input which is fed to the model.

Bidirectional Encoder Representations from Transformers (BERT) [91] has encoders and decoders superimposed with layers of transformers. It is a costly in terms of expense and has a high configuration with complex training procedure and large training time [93]. It makes use of transformers, attention mechanism to learn contextual relation between words. It is used for NLP trainings as it is based on network.

Boosting aims at transforming a weak learner into a strong one [94]. This is put in practice by making a model work on correcting the errors made by the actual model and perfecting predicting the training data. Adaboost and gradient boosting are popular boosting algorithms. Adaboost is used for boosting performance machine learning algorithms like decision trees [82] and works well for binary classification. Gradient boosting has 3 parts viz., a weak learner for predicting, a loss function which is to be optimised. and an additive model. The additive model adds weak learners thereby, reducing the loss function. It is a greedy algorithm which benefits from regularisation method by penalizing parts of algorithm to enhance the performance by reducing overfitting.

Multi-layer perceptron, a supervised algorithm trains on a function using the training dataset. It is formed of input, output layers and one or one plus hidden layers. It has the ability to learn non-linear models and real time models.

4.5 Metrics for validation and testing

For validating and testing the performance, practicality and robustness of the models put forward in these study different standard parameters were chosen namely, visualization techniques, validation by a group of experts and users, effect of different model parameters like epochs, dropout, embedding size etc. The most popular ones being accuracy, F1-value, precision, recall, MSE (mean square error) as well as MAE (mean absolute error).

The parameters required to define the metrices above are true positive (positive entity correctly labelled), true negative (negative entity correctly labelled), false positive (negative entity incorrectly labelled), false negative (positive entity incorrectly labelled).

Of the metrices mentioned, the accuracy is the number of correct predictions upon the all the predictions whether correct or incorrect. It is given by the first (1) equation; signifying t as true, f as false, p as positive and n as negative.

$$\boldsymbol{accuracy = \frac{(tp+tn)}{tp+tn+fp+fn}} \qquad (1)$$

To understand how much of true positive values were correct from all the predicted positive values we make use of precision. It is given by (2) and shows the ability of the model's classifier to not incorrectly label a sample as positive if it is not positive.

$$\boldsymbol{precision = \frac{tp}{tp+fp}} \qquad (2)$$

Recall is used to know the actual number of true positives which were recognized correct asnd is given by equation (3).

$$\boldsymbol{recall = \frac{tp}{tp+fn}} \qquad (3)$$

F1-score which is calculated using precision and recall, as it is the weighted average of the two. It could be used if we need to strike balance among Precision and Recall or if the class distribution is uneven.

$$\boldsymbol{f1 = \frac{2*precision*recall}{precision+recall}} \qquad (4)$$

(MAE) Mean absolute error, that is, mean of absolute error measures the absolute average distance between the real and the predicted data it could at times fail to penalize large errors while predicting. The MSE gives a measure of the real and the predicted data in terms of squared average distance between them.

Apart from these measures undertaken to test the proposed model's effectiveness most papers also made comparative study of their model / dictionary or lexicon with the standard models.

CHAPTER 5

SUMARIZING THE STUDY

The summarization of the study of the papers performed is put forward in the table 1 and 2. One may take a look at the tables to understand the key details which were the focus of performing this collective study. Consideration of the driving cause for performing a study (Area of focus / Application) along with this the train / test dataset using which the models had been trained, tested or a corpus / dictionary was built is considered. The built of the model as per our understanding is briefed as well. The parameters which were used to judge the performance, robustness and effectiveness of the model by the authors is also jot down. Table 1: summary of different aspects of literature studied, contains 5 columns namely, paper number (paper no.), year of publication (year), area of focus / application, dataset, parameters used for testing (in order of appearance). Table 2: List of accuracies of papers which worked on SemEval-2014 Restaurant dataset is jot down.

In paper [1], the authors have developed a Dynamic Bayesian network using a Gaussian Process. Along with this a sequential Monte Carlo sampler is also designed for performing Bayesian Interface. Study [5] proposes a Naïve Bayes classifier in order to predict posterior probability for a Danmaku sample. This would categorize the sample as per he prior probability distribution and the group with maximum probability is put out as forecasted sentiment.

Utilizing a lexicon for feature enhancement, CNN and GRU for extracting major features and context features along with the attention mechanism sentiment classification is performed in [2]. From the context of the study performed in [8], the best possible accuracy of 92.4% is obtained by the features of embedding vectors which are fed to attention layers which are connected to one another in a hierarchical format. The one of the two does feature extraction using attention layer and makes utility of features to get aspect data for the sentiment using second attention layer. The second one extracts aspect features with the help of attention layer and makes use of features to get aspect data using the earlier attention layer.

This work [38] aims for sarcasm detection by proposing a multi-dimension question answer network using attention with Bi-LSTM. MQA introduces abundant semantic information and builds conversation context information using Bi-LSTM and attention mechanism. Model is based on 2 components. The study [24] works on building a Soft attention based Bi-LSTM and CNN hybrid model to detect sarcasm in short tweets. The model built consists of the layers mentioned the embedding and input, attention with Bi-LSTM followed by convolution layer. After which is an activation ReLU layer with max pooling. The last layer is the representation one.

Paper [39] puts attention on enhancing the performance of sarcasm detection by identifying key parts of the sentence. A Bi-LSTM with multiple-head self-attention is worked on for this purpose. The NN consisting of 2 layers is built viz., multiheaded attention sentence level (understands the aspect) and word encoder (summarizes contextual information). While the word encoder represents each word by summarizing its contextual information from both directions in the comment, the sentence level multiheaded attention layer looks into different part of comment to understand the aspects of the text semantics.

In [32], there are 2 parallel paths with each path having CNN, Bi-LSTM modules combined with attention mechanism. While these are used to extract feature aspect in both local- and global domain, their fusion helps detect relevant semantic information. They are then united with semantic information received from another path through mutual operation. Thus, generalization of the model is enhanced. For text classification, in order to filter out semantic features [45] proposes a cross layer attention model base stacked residual RNN. Various kinds of linguistic features are used to construct a stacked network. The cross layer attention mechanism refines the filtering process. It makes use of the features from high-level to supervise the low-level features. This can be utilized to select more sematic features which could be used for text classification.

The authors of [52] focuses on aspect level sentiment analysis by constructing an attention network based on interactive rules by designing a grammar-based encoder to simulate grammar functions. It does this by standardizing the output of adjacent positions and constructing an interaction attention network and learns attention information using the target and context. By implementing this model the best accuracy obtained is 81.96%.

Study [3] focuses on calculating reputation of an entity viz. movie, product, hotel, restaurant, service etc. For this review helpfulness and time scores are computed. Then BERT model is tuned to predict probability of sentiment orientation. For each review, a numerical score, reputation value is calculated by making use of the proposed formulas. The paper also proposes a way to visualize reputation.

In [22], using 3 domain related corpora authors have finely tuned the BERT model for context embedding and opinion mining at aspect level. BERT as an embedding extracts local and global context features concurrently . And for merging local and global features concurrently Multi-head attention mechanisms and convolution operations is developed. This helps in understanding the polarity of targeted aspect. To fuse the semantic text representation Multi-head Self-Attention is used whereas to model the interaction of aspect term convolutional layers are used. This model gives out the best accuracy of nearly 91.6%.

A statement could refer many targets and each of which could have its own context. A BERT model that is target dependent is discussed in [46] with three variations is proposed in this paper. The output is positioned at the target terms. A framework for domain adaptive text classification for leveraging domain knowledge during training stage an adversarial-powered multi-domain learning-based method is put forward in [17]. It reduces the necessity for training data for each source domain. It ensures a split in between private and shared features by using orthogonality constraints and adversarial training. This ensures that shared realm does not get adulterated domain private features.

The domain specific approach of [43] focuses on at first building a manually labelled (positive, negative, neutral) football sentiment dataset which is then used to automatically build a lexicon which is football specific. A classifier then identifies the sentiment of the conversation. The algorithm performance and features for sentiment recognition on the created dataset is tested. The study [6] at first extracts the features then tweet embeddings are created using a feature ensemble model and feature vectors. CNN model then classifies the tweets into 5 sets negative, positive, neutral, strong positive and strong negative sets. The [11] study gets sentiment embeddings of words in and not in lexicon by utilizing a pretraining word classifier. Accuracy of the word representation increases by combining sentiment embedding and word embedding. A proposed method based on LSTM and attention suggests finding attention vector without target to improve LSTM's ability in capturing global sentiment and semantic composition.

To perform Aspect based analysis in [7] a hierarchical model built up of recurrent NN cascaded to the recursive NN. The model consists of constituency parser and dependency parser responsible for converting text to phrases, building trees of phrases and connecting words if they have binary relation respectively. Using these parsers reviews are cut into pieces including sentiment information relevant to aspect terms. This model was able to achieve the best accuracy of 79.5% and 81.38% for single and multiple aspect scenario on the restaurant dataset of SemEval-2014 task 4 as shown in the Table 2.

For the improvement of Accuracy, overcoming shortcomings like overfitting, vanishing gradient in sentiment analysis; the study [15] puts forward a multichannel paradigm is exploited for extracting multi-grain features. Every channel extracts context information and local features using Bi-GRU and CNN respectively. VIB (Variational Information Bottleneck) for compressing extracted sentiment features. To make this work sections of model are formed for extracting context information and local features, compressing features and calculating entiment polarity.
In [25], Backdoor attack is injected into the model this makes the model misbehave through inputs. The adversary with knowledge only regarding the few training datas' but not the structure or training algorithm is considered. On the backdoor injection, the model begins misclassifying text samples with trigger sentences into the target group specified by adversary. This doesn't affect the model's performance as such.

A text mining technique, NN based iterative opinion mining is used in [26].It analyzes posts from users of social media. It makes use of automatic incremental procedure based on Feedforward NN. By exploiting a small amount of classification rules from some hashtags which are biased to specific factions, new classification rules are generated iteratively. Generated rules help determine polarization of people.

The paper [28] looks into classification of app reviews. At first textual and non-textual information is extracted, then the textual information is processed to create a digital vector. History of the reviewer is also looked into. Then, it trains CNN classifier to classify multi-class reviews. Paper [33] deals with incorporating prior information in RNN models for classification and recognition of named entity task. Firstly, prior knowledge could be put up by extracting a group of rules consisting of syntactic dependence, knowledge and social graph and. Then a way for embedding these rules into RNN is suggested.

A sales factor neural network model that is based on multilayer back propagation perceptron is proposed [34]. It makes use of the weight matrix operation to get the relative strength which denotes the strength between ith input and jth output. In [41], four different kinds of memory networks are curated for different tasks. One uses CNN for capturing local information while other uses Bi-LSTM to capture sequence information in documents. The other two are also based upon CNN, Bi-LSTM. While one of them builds hierarchical NN to combine local and sequence information together, the other captures local information and sequence information through different modules. The resultant representation is combined to classify sentiments considering the aspects and results give the best possible accuracy of 80.965% as shown in the Table 2.

Multinomial LR, SVM, DT, RF are used in the study performed in [4] for categorization puposes. Similarly, in [9] multi-strategy sentiment analysis method based on SVM and NB is used for working with Chinese characters. The goal of [42] is identification of hate text on twitter for which a twitter corpus is developed and distinctive features are created for ease of identification. This is used to evaluate ML algorithms based on ensemble, multi-meta-learning models of SVM, LR, RF, GB algorithms and on hyper-parameter optimization.

Four main parts of the model from [36]: Collecting data, Storing data, Analyzing data and data visualizing data. Needfull [36], consists of a module dedicated for data collection that crawls twitter to collect raw data. This data is then labelled before the data is put into the database. On entering the query from User interface, one gets all the necessary data of the database from the index system of where the data is stored. Analysis of these tweets is then put up using the data visualization module.

Operation of the framework in [44] carried out by 2 blocks namely, spam detection which operates in real time and the update module which operates in batches. The spam detection module has 4 lightweight detectors to label tweets coming from blacklisted URLs, tweets which are near duplicates of prelabelled tweets, tweets posted by trusted users without spammy words. Tweets apart from these categories are labelled by the multi-classifier-based detector. Tweets labelled in a time window are used to update the next time window's data in batch mode as required by the detection module.

Model of [49] is built comprises of RNN, CNN and has layers like input, convolutional, forward and backward LSTM, pooling, convolutional layer and fully connected and output layer. While CNN learns classification features RNN abstracts and memorizes sequence of semantic relations. Pre-trained word embeddings are used to reduce the representation dimension of text.
In [51], Sentiment information is integrated into TF-IDF to generate weighted word vectors. These are fed to Bi-LSTM to obtain context information and get a better representation of comment vector. Feedforward NN helps find out sentiment tendency.

The authors of [53] put forward a model (called ADeCNN) for analyzing sentiments using aspect. It uses an attention mechanism into deformable CNN, Bi-LSTM. The model built generates attention weights as per targets. This would also enhance correlation between target and parts in the statement. The best accuracy obtained on SemEval-2014 Restaurant dataset by this model is 84.03%. In [10], a word refinement model is proposed that is applicable on pretrained word vectors which makes use of real valued sentiment scores from the lexicon. The model works to get the word vector closer to similar words both semantically and as per the intensity score. This improves the word embeddings and sentiment embeddings and helps in rankingeach word's similar nearest neighbor. These ranked nearest ones direct the movement and distance of refinement procedure to better the word vector.

Using the add-on sentiment dictionary and the designed score rules in [13] the authors derive the sentiment. The NB classifier gives the field of text which comprise of the polysemic sentiment word by using the sentiment dictionary proposed. Using many sentiment dictionaries and sets of semantic rules, [14] suggests a Chinese microblog sentiment classification method is proposed. The semantic rule set consists of both inter-sentence and sentence pattern rule analysis. The flow of the method begins by preprocessing the data and using sentiment dictionary and rule analysis sets to calculate the value of sentiment which is then used for sentiment classification.

A manual corpus with annotated scheme is built in [21]. It identifies sentiment in metaphorical sentiment using 3 methods. The study conducted by the authors found the third one works better in tasks that relate to metaphor and the first one works better for classification.
For study of tweets and evolution of the behavior of users as per topics they discuss over the time, a word embedding based approach is proposed in [29]. Along with this, temporal transitions of topics are tracked using 5 topic evolution events.

To begin with the model [37] functioning at first sample users are selected by random sampling. Their tweets form the corpus. Each tweet is defined with an emotional score. The emotion dictionary has an emotion score for each word and the sum is the emotion score of the tweet. After this, an emotion score average is calculated for each user to get the emotional trend of the user. Then, 2 groups viz., positive and negative are defined and sorted in descending order as per the average emotion scores. The top one forth are positive grouped and bottom one forth are negative grouped. Applying statistical test on these groups would help investigate impact of emotional behavior on user’s relations over twitter.

The study [40] Comprised of 2 processes of which one works by cleaning data in regular dictionaries and the other is meant for extracting semantic relation. It is based on the interpretation relation between lexicon and corpus along with the rule-based method. The study [12] proposes a method for contextual analysis is built, for which, a Hierarchical Knowledge Tree (HKT) using unlabeled dataset is built. This helps understand the subject or knowledge of data and build a relation between words and sources in HKT and this paves path for comparison between training and actual dataset and thereby, figure out amount of success of any supervised ML algorithm. It also looks into detecting and understanding positive changes between both the positive words and the negative words based on the modes in the trees.

In [16], twitter hierarchical latent Dirichlet allocation, thLDA is proposed. It aims at getting the hierarchy of tweet topics which are further employed for online analytical processing on tweets. The technique begins by data collection, preprocessing. After which text modelling is done to identify relation between tweeters and tweets. Hierarchical text modelling is also done to extract twitter data's topics and build the hierarchical topic dimension based on probability distribution of parts of topics. Tweeters are analyzed from different dimensions using online analytical processing.

Model proposed by authors in [19] focuses on Arabic sentiment analysis by employing and evaluating a feature ensemble model. It comprises of surface features which are manually extracted features and the the deep features are generic word embeddings and word embeddings which are sentiment specific. By understanding these word embeddings from tweets, its performance with generic embeddings and manually extracted features is compared.

By reaping the benefits of MOOC-related aspects the framework proposed in [20] propagates the weakly supervised signal in order to identify aspect categories form the unlabeled students' reviews. The analysis of architecture is made up of 4 major components viz., information fed by the user, weak label propagation, aspect section learning and polarity. The proposed framework [23] gives attention on implementation of GAWA with modified fitness function. For this purpose, Wrapper approaches (WA) are utilized for selecting features and Genetic Algorithm (GA) is utilized for reduction of those features. The focus is to study [27] the movement of stock market. For this multiple information sources are used. Common estimated true label among hinge losses of different data is shared for modelling latent consistencies among different data sources. For the data extracted from different sources, methods involving Restricted Boltzmann Machine as well as sentence2vec to get dense vectors are used for training purposes.

In order to improve sentiment classification of product reviews cross modal hypergraph model is proposed in [30]. It captures textual information and sentiment information simultaneously. To merge multimodal feature, the hypergraph model are extended. By coupling LDA based topic model with proposed model, ambiguity of words expressing opposite polarity in different contexts is mitigated and run time is lowered. The task of rumor detection from Chinese micro-blogs [31] uses sentiment dictionary, dynamic time series algorithm and GRU model with 2 layers. The sentiment dictionary captures the fine-grained aspects. The fuzzy clustering method, Dynamic Time Series method retains data distribution of events over the time.

Paper [35] works on: Sentiment dimensions aide to map financial news articles from source to target into the feature space. Different transfer principles are developed considering the highly correlated stocks' price time series, source and target stocks in same sector, highest prediction performance in validation dataset. Voting mechanism is designed to select most proper source stock from candidate stocks which are generated from different principles just mentioned. The final prediction is based on the prediction model which are trained on selected stocks.

In [47], Multivariate regression models (The least squares support vector regression) and time series models predict monthly total vehicle sales. 3 types of data are used to forecast monthly total vehicles viz., sentiment scores of tweets, stock market values, and hybrid data (mix of both). Multivariate regression data is dealt with least squares support vector regression models, naïve model, the exponential smoothing model, the autoregressive integrated moving average model, the seasonal autoregressive integrated moving average model, and backpropagation neural networks and LSSVR with time series models are all the time series models.

The paper [48] works on ASP and Deep2S. Answer Set Programming (ASP) is used for implementing aspect extraction that is based on semantic structure by making use of Abstract Meaning Representation (AMR) graph. AMR represents semantic relations which prevail between the aspects and opinion words is worked on to get semantic data in reviews. Deep2S works for extracting aspects. It integrates AMR with syntactic structure. It obtains dependency relations using syntactical rules and semantic information using semantic rules.

In [50], Members of group are categorized as per their interest and the response they give to various posts. This filtering mechanism would cluster members based on their aspect-based characteristics. The posts are also clustered on various aspects. This using a 2-level clustering would help in recommending users the posts which would likely be of interest to them.

In [54], deep CNN were used by making use of sentiments and emotion features for detection of sarcasm. For [55], the major emphasis is on how the pattern-based features can be used to detect sarcasm. The authors detected sarcasm on the Twitter datasets using a pattern-based approach which used four sets of features that covered different types of sarcasm. The study [56] puts forward that area under the curve is a robust performance measure for data with unbalanced class distribution. It also mentioned the content-based features are majorly used for sarcasm classification.

In [110], a Bayesian Model Averaging was considered for the main ensemble during classification along with the Majority Voting. Apart from this, the paper also proved that not all features characterize sarcasm and BMA gives generalization for the sarcastic texts. The sarcasm detection for English and Czech was studied in [111], for this the authors considered scrapping twitter and cleaned the obtained tweets to form a dataset for both the languages. Support Vector Machine and Maximum Entropy Classifier were used for classification. From [112], researchers proved that sentiment and sarcasm identification tasks are correlated to each other. They prove this by putting forward a multi-task learning method that uses deep neural network.

Authors of [113], propose a automated way to get cognitive features from the movement of eyes of the readers and use it as feature. Along with this they also use text-based features to get the polarity of the text and identify sarcasm. For this they proposed a CNN based technique and proved that using both of the features obtained from the gaze as well as the text gives a better performance as compared to CNN models that rely solely on the text and the models that rely on handcrafted gaze and the text.

From [114], the authors have contributed to a way to detect and categorize hateful speech. These speeches are pulled from Twitter communities that identify hate speeches. The research concluded that Naïve Bayes classifier performs better over existing methods. The goal of [115] is to recognize hate text on twitter. For this a twitter corpus is created and is used to evaluate ML algorithms based on ensemble, multi-meta-learning models of SVM, LR, RF, GB algorithms and on hyper-parameter optimization.

In [116], different classification algorithms were applied on four datasets to detect sarcasm. They also tried different amount of ratio splits in the dataset before checking for accuracy. Of these they concluded gradient boosting performs the best across all the dataset splits. In [117], authors propose a multi-modal sarcasm detection way which employs text and visual information and makes use of RNN- recurrent neural network, deep learning techniques. With this research, this paper concludes that the role of visual modalities is extremely vital in determining the performance of the outcome.

[118] makes use of twitter for getting data in order to detect sarcasm. The authors, use extracted features as well as contextual handcrafted features and on their deep learning-based model. The focus was to get the optimal features sets so that they can detect sarcasm well. Hence, they curated some feature sets which are dependent while others are independent. The model extracts features from the CNN – Convolutional Neural Network and then it is combined with the contextual features.

Table 5.1: summary of different aspects of the literature studied

Paper No.	Year	Area of Focus / Application	Dataset	Parameters used for testing
[1]	2020	Topic level sentiment classification	Twitter data - # Brexit	Heatmaps
[2]	2020	Bipolar sentiment classification	dangdang.com, Chinese e-commerce website	Accuracy, recall, precision, F1 value, Effect of no. of iterations, epochs, length of statement, dropout, impact of the thesaurus size was also studied considering these parameters
[3]	2020	reputation generation for online entities and visualize reputation for supporting customers though the decision-making process	IMDb, TripAdvisor and Amazon websites are scrapped	Accuracy, recall, precision, F1 value for the study of model and to study the reputation systems, survey was held
[4]	2019	classifying tweets into several ordinal classes using machine learning classifiers	Twitter dataset by NLTK corpora resources	accuracy, MAE, MSE, validation scores (precision, recall, F1-score, support), 10-fold cross-validations
[5]	2020	constructing a Danmaku sentiment dictionary and using it along with Naïve Bayes.	Danmaku video platform's live commenting function	Accuracy, recall, f1, precision
[6]	2020	a feature ensemble model is built consisting of lexicons, semantics, position, and polarity	Twitter dataset	Precision, recall, f1
[7]	2020	Aspect-Based Sentiment Analysis Using Inter-Aspect Relations	SemEval-2014 Task 4	Accuracy
[8]	2019	An Aspect-Level Classification with the help of Attention in hierarchical form	SemEval-2014 -4th task, SemEval-2015-5th and 12th task	Accuracy
[9]	2018	Analysis of semantic fuzziness to get opinion on Chinese texts	Dataset from Virtual reviewers. Meant for exploring collaborative movie reviews	Accuracy and precision, MAE, RMSE
[10]	2018	paper focuses on refining the pretrained word vectors using intensity scores from lexicons.	Stanford Sentiment Treebank, SemEval dataset	Accuracy of different word embeddings, macro-averaged F1-score
[11]	2018	sentiment lexicon in introduced into LSTM. Also attention mechanism without a target is added for general sentiment analysis	IMDB, Yelp2013, MR, NB4000(Chinese), book4000(Chinese)	accuracy on different test sequence lengths
[12]	2019	Create an alarm when the performance of ML model starts deteriorating with new datasets.	Amazon datasets introduced by Ghaddar and Naoum-Sawaya [54]	the accuracy, Recall, Standard Error of Estimate
[13]	2019	an extended dictionary consisting of the basic, fields and polysemic sentiment words is built	sentiment dictionary combines National Taiwan University's Dictionary of sentiment,	precision, recall and F1 value

			Hownet's sentiment dictionary and popular sentiment words from internet, data crawled from Jingdong, Ctrip and eLong websites	
[14]	2019	constructing multiple sentiment dictionaries, sentiment classification in 3 categories	crawler software crawls the Chinese blogs with ''#Short Video Rectangle#'' and ''#'' I am not a drug god'' burst red lead social hot discussion#'' data.	comprehensive metric (F), along with precision, recall rate are used
[15]	2020	Addressing issues of over-fitting, vanishing gradient and improve accuracy and proposing BiGRU and CNN based model	Chinese product reviews of a shopping website and the Chinese hotel reviews from the travel app	Accuracy, precision, recall, f1
[16]	2019	The dimensional hierarchy of the topic of tweets is found	Twitter REST API	Pointwise Mutual Information score and perplexity
[17]	2019	multi-domain adversarial network (MDANet) is proposed to classify text	word embeddings were trained from Sina Weib, Amazon product review corpus by [56], consumption intention corpus [55] and sentiment analysis corpus [56]	classification accuracy.
[18]	2020	using context-dependent part-of-speech, sentiment lexicon is built	long text review dataset (LMRD) [57], (MRD)[58]	precision , recall , F1, accuracy and coverage
[19]	2019	Using sentiment specific word embeddings from Arabic tweets for sentiment classification using a feature ensemble model	SemEval-2017 Arabic tweet dataset, AraSenTi-Tweet dataset [59]; ASTD dataset[60]	Fscore (F1), Precision (P), and Recall (R)
[20]	2020	weakly supervised learning is used for aspect-level sentiment analysis	Coursera	Fscore (F1), Precision (P), and Recall (R)
[21]	2018	Identification of emotions in Chinese metaphorical texts is done	sentiment corpus of Dalian University of Technology	Accuracy, recall, f-value
[22]	2020	Fine grain aspects are mined using deep learning model	Laptop, Restaurant dataset from SemEval2014 and Twitter datasets	Accuracy, precision, recall, f1 value
[23]	2020	feature selection by modifying the fitness function of the Genetic algorithm and Wrapper approaches	Scrapping twitter for apparel brands names as keywords	Accuracy, precision, recall, f-measure
[24]	2019	Sarcasm detection using soft attention-based bi-LSTM and convolution neural network	SemEval 2015- 11^{th} Task, twitter's random tweets	accuracy, recall, precision, and F-measure
[25]	2019	backdoor attacks happening on text classification based on LSTM	IMDB movie reviews dataset	Attack Success rate, Test Accuracy, Poisoning rate, Trigger length
[26]	2020	figuring out polarity of social media during elections using neural networks	Scrapping twitter data using relevant hashtags 2016-US elections, 2018-Italy elections	mean percentage and absolute errors, log accuracy ratio (LogAcc), MAPE
[27]	2018	prediction for stock market composite index movements	stock market-data for 1.1.2015 to 31.12.2016, from Wind, financial information service provider in China. Xueqiu	F1-score and accuracy
[28]	2020	Classification of App Reviews using Convolutional Neural Network	reviews dataset from Google store and Apple store of different categories	f1, recall, precision,

[29]	2018	Observing evolution of behaviour based on topics discussed	Twitter datasets	proximity threshold as well as word embedding dimension are evaluated
[30]	2018	Sentiment classification of reviews and dealing with ambiguity of words with different polarity in different context	Amazon reviews from categories like kitchen product, DVD, book, electronics	Accuracy
[31]	2019	rumor detection in Chinese	Sina Weibo datasets,	Accuracy, precision, recall, f-value
[32]	2020	Aspect based fashion recommendation	the Clothing, Shoes & Jewellery data of Amazon 5-core and the reviews from US online retailer	MAE, MSE
[33]	2019	method to add prior information in the RNN models	datasets Yelp 2013 and Dangdang	Accuracy MSE (mean squared error)
[34]	2019	Identifying factors influencing online product sales on online platform	Taobao.com	prediction goodness of fit (R2), RMSE, MSE
[35]	2018	sentimental transfer learning for stock prediction model	Hong Kong Stock Exchange data(2003-08), news archive from FINET5 from Jan. 2003 to Mar. 2008.	the classification performance is evaluated using Accuracy
[36]	2020	tweet analysis platform to study psychological needs (during covid-19)	tweets scrapped from Twitter	Accuracy, f-score, Recall, Precision
[37]	2020	keyword matching for studying the impact of emotional behaviors to user Emotion scores	Twitter scraping (Japanese)	Brunner–Munzel test, coverage rate, mean, median, standard deviation
[38]	2020	Sarcasm detection using multi-dimension question answering (MQA) network and building the conversation context information using attention and BiLSTM	Internet Argument Corpus (IACv2)	Precision, Recall and F1-measure
[39]	2018	Sarcasm detection using multi-head attention network based on Bi-LSTM	self-annotated corpus SARC 1 dataset	Precision, recall and F-score
[40]	2019	extract rule-based semantic relation using Chinese sentiment lexicon.	Baidu interpretation, modern Chinese dictionary	Precision, accuracy
[41]	2018	Aspect level sentiment classification using CNN + Bi-LSTM	SemEval 2014, one is from Laptop domain and another is from Restaurant domain	Accuracy, classification accuracy. Effect of width of convolution filter, attention layer were also studied
[42]	2020	Detecting hate speech using ML algorithms and developing English corpus from South African tweets	twitter data from 5.5.2019 and 13.5.2019 using Twitter Archiver.8 (plugin for Google Sheets)	Accuracy, true positive rate, F1-score, recall, precision
[43]	2018	Football-Specific Tweets for sentiment classification	UEFA Champions League 2016/2017 , FIFA World Cup 2014	Accuracy and f-score
[44]	2018	spam detection at tweet-level	HSpam14 data set (15 days data collected)	Precision, Recall, and F1 scores
[45]	2020	Paper focuses on selecting semantic features to perform text classification.	Stanford Sentiment Treebank (SST1, SST2), MPQA dataset, IMDB, Movie Review, TREC datasets, Subjectivity dataset, customer reviews for products	the effect of integrating external knowledge, the model layer, the cross-layer attention, is studied
[46]	2019	using target information with BERT for sentiment classification	SemEval-2014 task 4 restaurant and laptop data, twitter dataset	classification accuracy and F1 value

[47]	2018	Predicting Vehicle Sales	Bureau of Economic Analysis, U.S. Commerce Department, Yahoo Finance, monthly Tweets using API	MAPE, WAPE [61] and NMAE [62]
[48]	2020	exploring the feasibility of deep semantic representation, improve the performance of aspect extraction.	SemEval-2014 and SemEval-2015 datasets and also datasets relating to digital cameras, cell phone, MP3 player, and DVD player. Computer wireless router, and speaker	precision, recall, and F1-score
[49]	2018	subjectivity classification using recurrent CNN with the multi-features combination.	STS-Test dataset, SemEval2014, 2015,2016 dataset, SE-Twitter dataset, SS-Twitter,	F1-Measure, precision, accuracy, recall
[50]	2018	Filtering Mechanism for Recommending Posts in a Social Networks using Linguistic Features	3 open Facebook groups	Accuracy, precision, recall, MAE, MAUE
[51]	2019	Aims to classify text using Bi-LSTM	crawled from Ctrip (https://www.ctrip.com/)	precision, recall, and F1 score.
[52]	2020	Aspect based sentiment analysis	SemEval and ACL Twitter Dataset (2014)	F1-Measure and Accuracy
[53]	2020	Aspect based sentiment analysis	Task 4 of SemEval 2014, 2017 datasets	Accuracy

Table 5.2: List of accuracies of papers which worked on SemEval-2014 Restaurant dataset

Paper	Best accuracy
[7]	81.38%
[8]	92.40%
[22]	91.60%
[41]	80.965
[52]	81.96%
[53]	84.03%

CHAPTER 6

DATASET FOR THE PROPOSED MODEL FOR SARCASM DETECTION

The model was tested on two different datasets News headlines Dataset[127] for sarcasm detection and SARC dataset viz., A large Self Annotated Reddit Corpus[126] for sarcastic comments.

The News Headlines Sarcasm dataset[127] has collection of headlines form two news websites which are TheOnion and HuffPost. From TheOnion sarcastic headlines from the News in Brief and Photos section were collected. And from HuffPost both sarcastic and non-sarcastic headlines were collected. The major motive of creating this dataset was to overcome the disadvantages like improper labelling, absence of proper contexts, language in the existing datasets collected by using hashtags on social media.

This dataset overcomes these challenges since the headlines are spelled correctly and are not informal. So, we easily get pre-trained embeddings for this dataset. Since, TheOnion publishes sarcastic news itself the dataset is accurately annotated, contains appropriate context and contain very less noise.

The dataset consists three items viz., the headline, the link for the article and the label that tells if the headline is sarcastic or not. Considering both the versions of the dataset, in all we have a total of 55328 samples. The sarcastic samples amount to 25358 while the non-sarcastic samples amount to 29970 as shown in the figure 6.1. The figure 6.2 and figure 6.3 show the words which widely occur in the sarcastic and non-sarcastic category respectively from the news headlines sarcasm detection dataset.

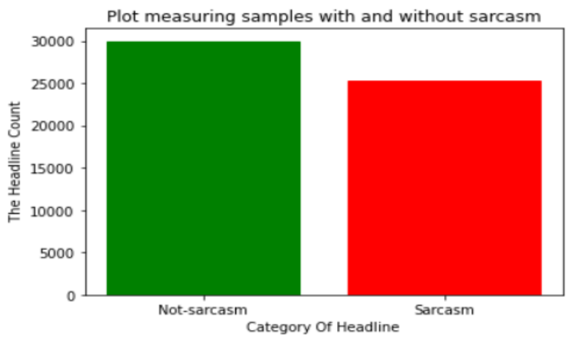

Figure 6.1: Division of samples as per the categories for News Headlines Sarcasm Dataset

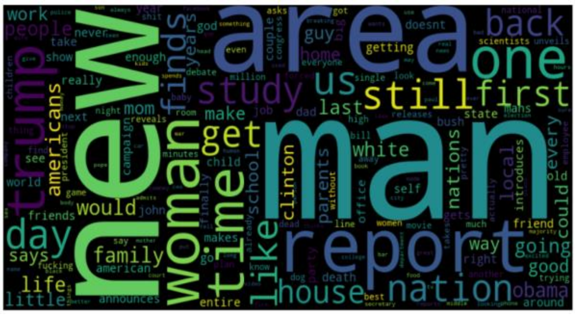

Figure6. 2: Widely used words under samples for sarcasm for the News Headlines Sarcasm Dataset

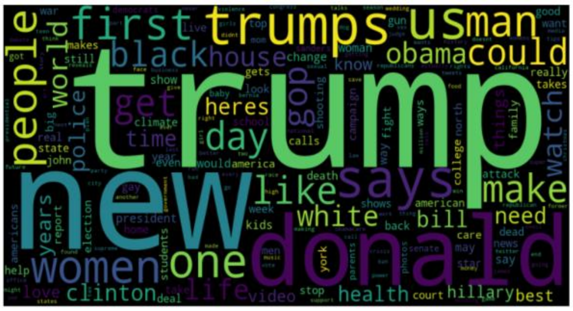

Figure 6.3: Widely used words under the samples for not sarcastic for the News Headlines Sarcasm Dataset

We have also made use of the SARC – Self Annotated Reddit Corpus dataset[126] it, which comprises of 1.3 million samples which are scrapped from Reddit which is commentary website. This dataset can be used to detect sarcasm since it contains a tag '\s' which the users of Reddit use to indicate of their comment to not be taken seriously since it is put in a sarcastic manner.

In all the dataset considered for this paper comprises of 1010826 samples of which half are sarcastic and half are not sarcastic as shown in the figure6. 4. In figure6.5 and figure 6.6

we see the most frequently occurred words in the SARC dataset [127] for sarcastic and non-sarcastic samples kinds.

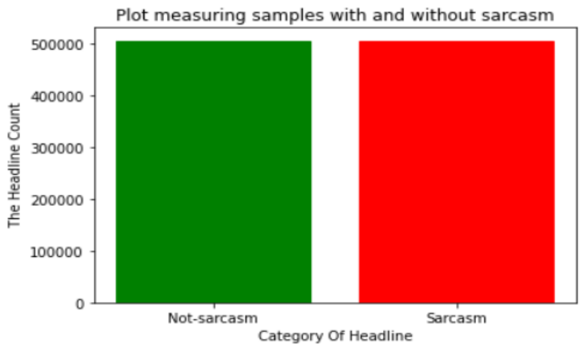

Figure 6.4: Division of samples as per the categories for the SARC dataset

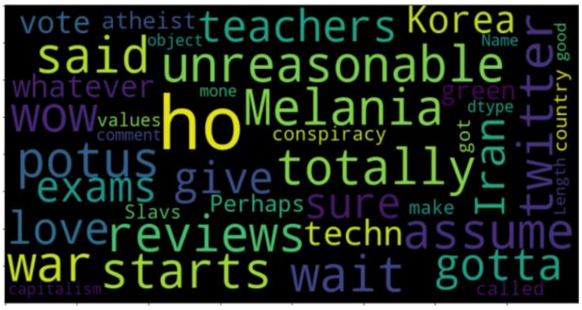

Figure 6.5: Widely used words under the sample for sarcasm of SARC Dataset

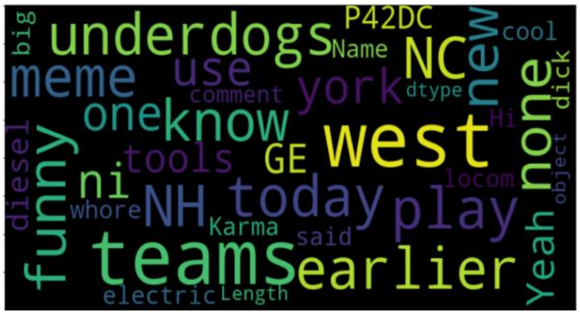

Figure 6.6: Widely used words under the samples for not sarcastic for the SARC Dataset

CHAPTER 7

PROPOSED MODEL

The process for sentiment analysis begins by collecting the dataset and preprocessing it. The preprocessed data is then divided so that part of it goes for training the model and the other part is used for testing the model. Then the model is built. To train the model we compile the model and fit it as per the training dataset. Then the trained model can be used for prediction of data, plotting graphs etc. This is the bird view of the functioning of the model.

The model is built using several layers which are the input layer, embedding layers, spatial dropout layer, dropout layer, Bi-LSTM layer, Attention layer, Dense layer and the concatenation layer. Now, we discuss the usage of these layers in the model in details.

The Input Layer: It is generally at the beginning of the model and is responsible to get the initial data into the model, hence, the neurons from the input layers do not take in the work of the previous layer.

The Embedding Layer: Embeddings improve computational efficiency by mapping discrete words to a vector space with lower dimensions. The model proposed in this paper comprise of two embeddings: a coarse tuning embedding and a fine-tuning embedding. For the coarse tuning embedding we make use of the Glove Embedding where as for the fine-tuning embedding, we make use of the FastText Embeddings.

Coarse-tuning layer: Global Vectors – Glove[124] are used as word representations by making use of aggregated global word-word co-occurrence. It is based on matrix factorization and uses word -context matrix. treats every word from the dataset individually for generating a vector for each word.

Fine-tuning layer: FastText,[125] developed by Facebook, treats every word to be composed of many sub-words (grams). Hence, a word vector is prepared by taking sum of these character grams. This helps it to understand the meaning of parts of words, the prefixes, the suffixes etc. It also considers the structure and the syntax while preparing embeddings. Due to this, Fasttext can create better embeddings even for words which have few character n-grams, since they can still match up with other words. This ability of Fasttext also allows creation of appropriate vector from the available character n-grams for unknown words.

As we see from figure 4, how our embedding layer can categorize sentiments or emotions which are associated to sarcasm like cynicism, sardonic, wry etc away from the emotions like sadness, anger, fear etc. Thus, using the coarse tuning layer we make use of the global statistical information within the document and using the fine-tuning layer we consider parts of words to leverage the understanding of the syntax, structure and sub-words.

The Spatial Dropout Layer: This layer is a little similar to the dropout layer, however it allows independence between the feature maps since it drops the feature maps and not the elements individually.

The Bi-LSTM Layer: This is the Bidirectional Long Shot Term Memory layer. Basically, it is the LSTM (long short-term memory) in the forward as the backward direction. Since the LSTM which is unidirectional keeps the information of the states it has already been through by making use of the hidden state. As all of its inputs come from the past it has no information of the future, this is where the role of a reverse LSTM / backward LSTM comes into picture. The LSTMs and the Bi-LSTMs comprise of three basic gates in each cell, which are input gate, forget gate, and the output gate. The input gate regulates how much of the past information must be let into this cell, the forget gate decides how much of the information needs to be remembered, while the output gate chooses how much of the information is to be sent to the next cell in the sequence.

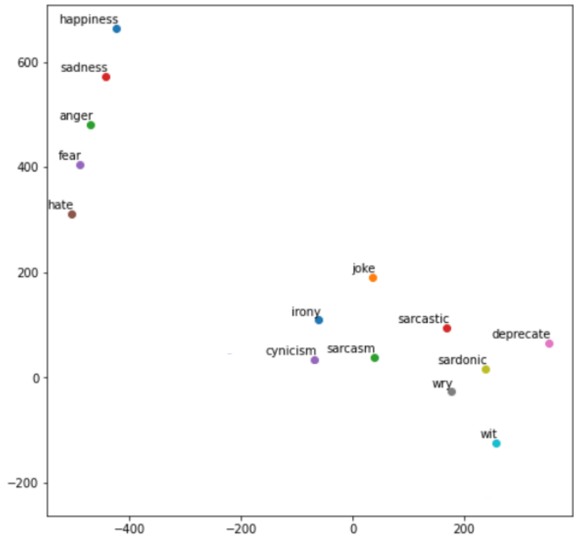

Figure 7.1: Use of coarse-tuned layer and fine-tuned layer as embeddings

The calculations for each of the gates, states and output for the cells is as shown in the equations below:

$$I_t = \delta\,(\omega_i \cdot [h_{t-1}, w_t] + z_i) \qquad (1)$$

$$F_t = \delta\,(\omega_f \cdot [h_{t-1}, w_t] + z_f\,) \qquad (2)$$

$$O_t = \delta\,(\omega_o \cdot [h_{t-1}, w_t] + z_o) \qquad (3)$$

$$S_t = tanh\,(\omega_s \cdot [h_{t-1}, w_t] + z_s) \qquad (4)$$

$$C_t = F_t \; x \; C_{t-1} + w_t \; x \; S_t \qquad (5)$$

$$h_t = tanh\,(C_t) * O_t \qquad (6)$$

here,

- w_t is the t^{th} word vector of the words in w (sentence / document being processed)
- x is the element wise product
- $\omega_i, \omega_f, \omega_o, \omega_s$ form the parameters of the model
- z_i, z_f, z_o, z_s form the bias vectors for the gates
- The δ is the sigmoid gate activation
- tan h is the hyperbolic tan operation

H = [h_i, h_j …..h_n] is the word feature from both the sides of the network, the forward direction and the reverse direction. The forward LSTM process the word from the word $w_1, w_2, \ldots\ldots w_n$ to give out word feature h_{t+} and the reverse LSTM does it beginning at w_n to give out word feature h_{t-}. In order to get any h_i, viz., output for i^{th} word we do equation (7).

$$h_i = h_{t+} \odot h_{t-} \qquad (7)$$

here, $\odot$ is a concatenation operation, for combining the two outputs. The Bi-LSTM layer gives two outcomes which is the running state h_t and the current state S_t.

The Concatenation Layer: As the name suggest, it simply concatenates the list of inputs. It takes in a list of tensors provided they are of same shape and gives out one output tensor which is a concat of all the inputs.

The Attention Layer: While comprehending a statement, certain words or group of words convey the maximum amount of information and the rest of the words are the filler words that need to be added to make it sound logically and grammatically sound. The idea of attention layer is to put ‘attention’ to specific words that could be of high importance. For this model, soft attention is used to get a weighted combination of all the incoming states instead of making use of just the previous state. It is deterministic and differentiable kind of attention that is used to get the attention score (ε) of a j^{th} word at t^{th} timestep as shown in (8).

$$\varepsilon_j = tanh\ (\omega_{attn} h_j + z_{attn}) \qquad (8)$$

here, ω_{attn}, z_{attn} is the attention layer's weight and bias. And then we allot each word feature h_i a weight ω_j using this formula

$$\omega_j = \frac{e^{\varepsilon j}}{\sum_{j=1}^{N} e^{\varepsilon j}}, \ \sum_{j=1}^{N} \omega_j = 1 \qquad (9)$$

Then, we calculate the soft attention by doing a weighted sum as shown in (10).

$$\alpha = \sum_{j=1}^{N} \omega_j h_j \qquad (10)$$

The Dropout Layer: During the training stage, this layer randomly makes input units 'zero' as per the rate at each step. To compensate the change of sum of over all inputs, it also scales the unchanged inputs by rate -1. This helps easing out the model fitting and ensures that the model is not overfit.

The Dense Layer: This layer is the regular fully connected neural network layer. It takes a dot product of the input and the mask, then performs activation on it, then, to this, it add the bias to produce the output for that neuron. This can be visualized using the formula below:

$$outcome = \ delta\ (input.mask) + b \qquad (11)$$

here, the delta, is the element-wise activation function, the 'mask' is a kernel / weight matrix, 'b' is a bias vector.

All of these layers are put together to form the final architecture of the model. The architecture of the model begins at the input layer.

The outcome of the input layer is feed at the coarse tuning layer which looks into the words. The outcome of this coarse tuning layer passed through the spatial dropout layer and then fed to a Bi-LSTM_1 layer.

The outcome of the input layer is also fed at the fine-tuning layer which looks at the sub-words to get the deeper, narrower context. This is then passed to the Bi-LSTM_2 layer through the spatial dropout layer.

The outcome of Bi-LSTM_1 and Bi-LSTM_2 is then concatenated using the concatenation layer. The concatenated outcome is fed to the soft attention layer. After passing through the soft attention layer, we have a drop out layer to minimize overfitting. Followed by this is a fully connected dense layer. This is in turn connected to a dropout layer. Lastly, we have the representation layer or the dense layer.

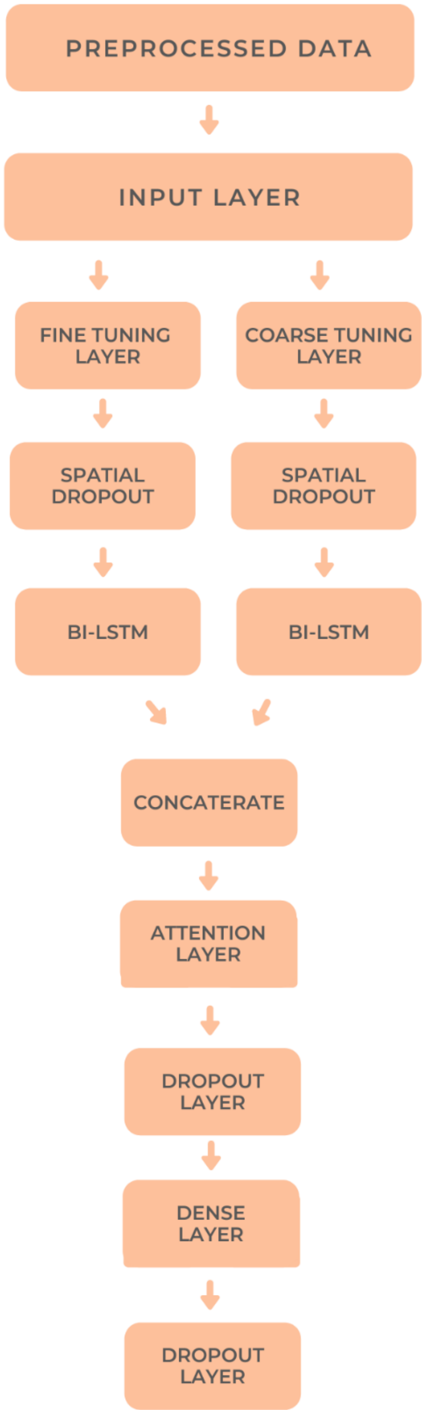

Fig 7.2: The Proposed Model

CHAPTER 8

RESULTS & DISCUSSION

Before getting into the results, let us look into the hyper parameters for the model set up. As discussed previously, the version 1 and version 2 of the dataset News headlines sarcasm detection dataset were considered for this experiment and the balanced training dataset from the SARC[126] dataset was used. The dataset was split in two, one for training purposes comprising of 80% of the data, and the remaining for the validation purpose. The maximum length chosen for the news headline dataset[127] was 25 and for the SARC[126] it was 100.

The coarse tuning layer has dimensions of 200 and the fine-tuning layer has dimension 300. The dropouts are kept at 20%. The Adam optimizer is chosen for compiling the model with loss set to binary cross entropy. The batch size was set to 32 and the model was trained for 20 epochs for news headline dataset[127] and 10 epochs for SARC[126] dataset. Referring the table 1 we get to know the performance of the model proposed on both the datasets.

Apart from testing the model on two different datasets, viz., News headline sarcasm dataset and SARC. The performance of the dataset on various baseline models were also tested to find out a comparative performance of the proposed model. For this sole purpose the dataset was tested on the Bi-LSTM, CNN + Bi-LSTM, Bi-LSTM + Attention and the proposed model.

Table 8.1: Accuracy, Precision, F1-value of the proposed model on both the datasets

Dataset	Accuracy	Precision	F1-value
News headline Sarcasm data	**94.49**	**46.48**	**63**
SARC data	**92.54**	**94.04**	**91.47**
Average	**93.49**	**70.26**	**77.23**

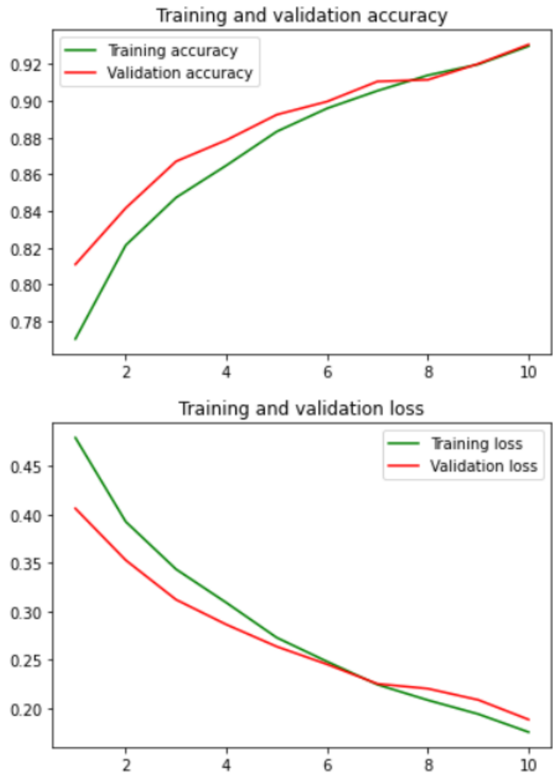

Figure 8.1: Training and validation accuracy and training and validation loss of the proposed model on the SARC dataset

From this we can the that the proposed model out performs the other models. From the figures 10 & 11 we see the rise in accuracy with the increasing epochs for each of the dataset and the deduction in loss as the epochs progresses.

Table 8.2: Comparison of Accuracy, Precision, F1-value on various models

Sr.	Model	Accuracy	Precision	F1-value
1	Bi-LSTM	57.16	54.32	84.38
2	Bi-LSTM + CNN	48.47	45.47	68
3	Bi-LSTM + soft attention	85.34	45.47	62.13
4	Proposed Model	93.49	70.26	77.23

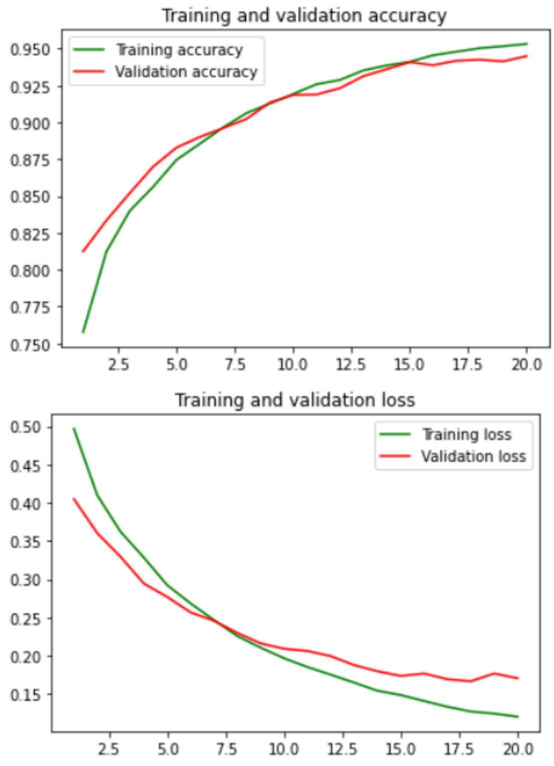

Figure 8.2: Training and validation accuracy and training and validation loss of the proposed model on the News Headlines Sarcasm dataset

CHAPTER 9

CHALLENGES & GAPS

There is a huge buzz among researchers and companies for building a model that fits well for data of different kinds and gives the perfect sentiment analysis. However, to build one such model, choosing the dataset and fixating parameters and hyperparameters to suit it to the model and get the correct response is a huge task, especially because there is lack of annotated datasets which would be compile, fit and train models for domains of all varieties. This is majorly as the samples from source realm which are to be collected and labelled are found to be difficult and costly [99]. There could be ways to deal with this, one of them could be to construct sharing networks at output for distinctive tasks. This could help the model to learn information of other tasks within the network. Other one, could be adding manually annotated data to the unlabeled data so that it could be used as well or by combining domain knowledge like the rules and the dictionaries. Also, by taking advantage of other models by using transfer learning the issue of poorly labeled data could be dealt with. Transfer learning has garnered interest as it utilizes prior experience and analogical learning [99]. But, it could still have to deal with issues like differences between the train and test dataset, ensuring stable outcome over source and target areas which could be affected due to various data distributions between the cultural factors, data sources, domains, noise in data and linguistic variations as well as differing contexts. Recent studies [35], [64], [98]-[101] , however, show good results for sentiment analysis through transfer learning.

Majority of the studies pertaining to the classification of sentiments deals with binary, ternary or 7-8 emotion classes. This does not seem fully practical as there are circumstances when the amount of tilt towards a particular sentiment might be needed to give the real sentiment. Like for the case, “The ice creams from that shop are really tasty but do not seem worth the extravagant fanfare !!”- here the ice cream is expressed to be good enough but so good to be hyped about. Another takeaway from this sentence could be the issue of feature deviation, meaning, the phase - “extravagant fanfare” shifts the focus from the ice cream to the fanfare. The target data holds more importance, as a single statement could refer to many targets, of which each has its own context [46]. It is hard to find out the sentiment for a target if no accurate aspect information is given [97].

India is a hugely populated country with approximately 1.3 billion people. Of lately, there has been a surge in the people using internet through their mobile devices. This calls for a huge potential in exploring regional languages from India, namely, Hindi- the most popular language across majority of the country, Marathi, Bengali, Gujrati, Punjabi and another regional language. These languages aren't as well-resourced as the English, especially for sentiment analysis. Recently, the studies aiming creation of publicly available dataset and sentiment analysis in Hindi, widely used language across India, are been worked upon [102]-[105]. Further development in this realm would help understanding Indian consumers and Indian Market deeply.

It so happens those different social networks cater different audiences. This has to be taken into account. To deal with this, a few steps could be taken like collecting data from different networks. Like collecting data from Twitter, Facebook, Instagram etc and then using all of this data to get more clarity rather than relying on dataset coming from one stream. Another step could be to look into the amount of likes, shares, saves, comments a particular post has received. As it is a good indicative of the amount of support a topic has garnered from a set of people. The study [106] explores the connection between liking behaviour of a user, the user's relation with the poster and sentiment of the post. A social network connects people across the globe thus one wrong message or misinformation has the potential to trigger million minds. Also, the preaching offensive and hate over social networks has increased despite the term of service which disallows such speech [42]. Keeping a study of such activities by looking into the number of likes, shares, comments etc and trying to form a pattern of such post creators and post spreaders could have a tremendous impact in curbing misinformation from ruining and corrupting people's mindset.

Recently, the introduction of bots has eased automation and changed social media. The use of bots isn't limited for the good, but also different malicious tasks. The content over social media may be full by the content coming from bots such as Influence Bots, Spam Bots [107]. They are put to work for increasing a kind of sentiment post receive, or inflating the number of followers or friends on social media etc. Thereby making it really crucial to identify the network of such malicious practices and desert it to maintain the sanity of social media. More study on this regard is expected to bloom in the upcoming years.

Online communication, which are relating to politics are many a times sarcastic and ironic [108]. Such texts are tough to recognize even by humans, however, of lately, many studies have been performed for detection of sarcasm. But study of identification of fake content which could influence, mislead masses causing ruckus needs to be given more attention to. Tracking how people's opinions / sentiments are shaped on social media and the users influencing and spreading misinformation must be tracked down and their patterns must be studied.

Online Social Networks have immense amount of network-centric data which can be utilized for getting the know-how of social and behavioral characters of individuals or groups. This has led the operators of social network to publish the data for use to researchers and advertisers etc. The data published on social media data is prone to a wide variety of reidentification and disclosure attacks [109], hence mechanisms to protect the privacy must be taken care of. In recent times, several cases of exploiting and breaching data safety practices have come forward. Utmost importance must be given to maintain the privacy and trust of social media users and other online platform users.

CHAPTER 10

CONCLUSION & FUTURE WORK

Detecting sarcasm, wry, cynicism in real-life conditions from the content put out by users of the internet is a tedious task since each one has a different style of expressing one's self and each one has different abilities to comprehend and gauge a comment, statement, post etc. This aim of this work was to put forwad a way to effectively isolate and identify sarcasm using different datasets and comparing the performance obtained with the existing models. By using the coarse tuning layer and the fine- tuning layer, the model got feature rich by understanding morphological features within the text. Thus, the model was able to improve its performance significantly.

To advance this study further it would be interesting to look at the link between the hate texts and the sarcastic texts. Often, underlying hate or disinterest is coated with sarcasm. Over the social media there seems to be some connection between the text that puts forward hatred undisguised and the sarcastic texts. In this regard, the context of the text or the chain of successive texts also needs to be looked at.

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LIST OF PUBLICATIONS

[1] The study performed in this work is submitted as "Survey of Recent Advances in the Text Based Sentiment Analysis" for possible publication in “Multimedia Tools and Applications”. The process for publication is under review.