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Issues and Future Challenges of Sentiment Analysis for Social Networks- A Survey

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***Abstract*— Sentiment Analysis is a approach that uses Natural Language Processing, Machine Learning, and Deep Learning to computationally identify, categorize, classify, and recover human emotions from unstructured text. The most efficient and popular method for learning from and training social media datasets is deep learning. In a range of applications, including audio, picture, and natural language processing, it has been demonstrated to be more successful. A text block is evaluated using the sentiment technique to determine whether it is positive, negative, or neutral. Not all members of the public express their feelings in the same way; as a result, some do so through comments and ratings while others do so through texts that don't reflect the right frame of mind. This evaluation lists the most typical and well-liked sentiment analysis algorithms for social media data. The classification of positive, negative, and neutral reviews using "LSTM, K-nearest method, Random Forest, Support Vector Machine, RNN, and MaLSTM" is explored and examined in this work. All of these classification methods were evaluated along with their drawbacks and difficulties.**

Keywords*— Big Data, Sentiment Analysis, Social Networks, Machine Learning, Deep Learning

I. INTRODUCTION

Sentiment analysis (SA) is a technique for identifying and examining user emotional states in texts through Natural Language Processing (NLP). It is effectively deployed in various applications like e-commerce [1], public poll analysis, heuristic search, information prediction , personalized recommendation, healthcare , and online instruction [3].

The fast expansion of these platforms has led to a shift in user behavior from passive social network consumers to active network content producers. China had 710 million Internet users as of June 2016, with a penetration rate of 51.7%, according to the 38th statistics report from the China Internet Information Center on the development of the Chinese Internet [5]. It included almost 100 million daily bloggers, 242 million Microblog users, and 656 million mobile Internet users. In this enormous volume of brief text messages, negative feelings are most frequently expressed.

Online sharing and idea expression have increased dramatically since the development of digitization and web technologies [1]. The most well-known and web technologies [1]. The most well-known and commonly used social media platforms among users include Twitter, Instagram, Facebook, YouTube, and social networking sites. Governments, customers, and brands all utilize these platforms to advertise goods and services, exchange ideas, run campaigns, and distribute promotional offers. Companies now have new methods for analyzing customer impressions using the data provided via networks, and they are striving to employ algorithms to analyze people's ideas and attitudes. For corporate analytics and intelligence, fraud detection, and SA of customer feedback, many methods are used to evaluate the data on social media. Sentiment analysis (SA) is a method that uses machine learning (ML) and NLP to find and extract human sentiments from unstructured text (NLP). The most popular sentiment analysis method is machine learning since it makes it simpler to train and evaluate social media datasets.

The most popular strategies are rule- and lexicon-based, in addition to machine learning algorithms. To distinguish between the various target content components that are provided and the idea that is being stated for each view, aspect-based sentiment analysis leverages accompanying errands. Social networks, microblogs, and other platforms on the World Wide Web are currently producing enormous volumes of data. The massive volume of information includes insightful details on perspectives that may be used to advance businesses and other industries in the scientific and business fields. It is nearly impossible to manually locate and extract this important information from such a large volume of data [3].

User post sensitivity analysis enhances business decision-making. It's a technique for gathering opinions or ideas about a certain topic, location, or product from online customer evaluations and categorizing them as positive, negative, or neutral according on people's sentiments toward the topic at hand. Emotions contain a variety of highlighted values, including tri-gram and bi-gram [4] due to polarity and amalgamations. By using training techniques, feelings and views are assessed by Support Vector Machines as both positive and negative aspects. After NLP used ImageNet to recognize objects with success in 2012, deep learning techniques were introduced [10]. The results of statistical learning were enhanced by DL algorithms in numerous fields. In recent times additional standards for NLP applications like "SA, machine translation, and question-answering systems have been added to a neural network-based NLP framework".

Researchers typically combine different Deep Learning techniques onto a single model to increase sentimental analysis' effectiveness. "Some of the well-known deep learning (DL) techniques include Deep Averaging Networks (DAN), Denoising Autoencoders

(DAE), Convolutional Neural Networks (CNN),

Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Bi-directional Long Short-Term Memory (Bi-LSTM) networks, Gated Recurrent Units (GRU), and Multi-Head Attention" were used.

A. Motivation

This report summarizes the significant research gaps identified following a review and analysis of all prior sentiment analysis studies. People use a variety of means to communicate their emotions, including words, comments, evaluations, and other visual indicators. The main challenge is gathering and exploring the range of feelings. The most difficult element is separating the authentic information from the unreliable information that is transmitted over social media and networks, such as spam broadcast, fraudulent reviews and opinions, viral posts, and so forth. Information these days is very active and grows swiftly in the form of big data, which has its own distinct set of characteristics. As a comprehensive information strategy, opinion mining and sentiment analysis do not find significant application work. As a result, it emphasizes the necessity for greater sentiment analysis research in order to meet present needs and provide fresh strategies. The communicative analysis of text-related data should be improved in the future to accommodate new developments and research in Internet-of-Things (IoT) applications. Because collaborative filtering only filters regularly sent messages and rejects discrete messages, it suggests that the current mining services are ineffective.

II. BACKGROUND AND LITERATURE SURVEY

This study's main objective is to use analytics to mine knowledge and insight from massive amounts of data. It focuses on developing innovative and effective techniques for managing massive amounts of unstructured text, audio, and visual data. Businesses have been mining social media networks for meaningful information since 2000 using sentiment analysis [6]. Although conventional approaches to sentiment analysis have been used to analyze unstructured text for financial gain, they might not be the ideal choice for processing enormous amounts of sentiment data. The author argues that it is critical to foresee the future growth of advanced data analytics approaches. In this essay, author [7] attempts to address the fundamental problem of identifying emotion polarity in South Africa. A thorough explanation of the procedure is given together with the conventional way for determining the polarity of sentiments. Data for the study was acquired from Amazon online product reviews.

The studies on sentence-level classification and review have become crucial tools. The suggested methodology [8] uses ML and a domain-dependent model to categorize twitter sentiments, which make use of a variety of textual elements, such as data from Twitter N-grams. Additionally, the author compared three alternative weighting techniques to investigate how weighing affects the classifier's accuracy. The SVM classifier performs better when a tweet sentiment score vector is included since it gives external comprehension.

The Tibetan SA in this work [9] recommends a deep

learning algorithm to evaluate the efficacy of several techniques for sentiment categorization using Tibetan microblogs. The most popular microblogging site used in this study for sentiment extraction is Twitter, where individuals can post their opinions. The author analysed reviews from the Twitter page cinema information set using the Hadoop framework and sentiment analysis on tweets in order to provide business intelligence projections. The results are displayed as discrete parts of information on Twitter that display positive, adverse and neutral expressions.

A hybrid Sentimental Analysis model [10] that blends fuzzy sets, semiconductor laws, unsupervised machine learning techniques, SentiWordNet-assisted enriched lexicon emotions, and fuzzy sets. The approach uses linguistic semantic categorization based on fuzzy sets polarity models after doing traditional hybrid classification in the first place.

Millions of individuals around the world use online social networks (OSNs) like Facebook and Twitter to connect with others [2]. The effectiveness of protection in OSN increases with the elimination of fraudulent accounts. The construction of the OSN model has the nodes and the links to identify fake profiles on Twitter.

SA of microblog entries and opinion mining were regarded by Kranjc et al. in 2015. blogging is gaining popularity daily. Millions of people share their ideas on public platforms like Twitter and Facebook every day, resulting in billions of messages representing people's attitudes and opinions.

Due to linguistic diversity and the constrained structure of microblogs, sentiment analysis over noisy data poses a number of difficulties. Data sparsity is one of these problems, while open-domain problems and data dynamics are other ones. Due to the data sparsity limitation, a lot of strange and poorly built phrases can be found in microblogs. The main focus of the open domain issue is the posts that users make. Users have the option to offer comments on any topic, not only the domain being investigated. Data dynamics, which result from the enormous and unchecked number of users that frequently post to microblogs, is another significant issue. Microblogging data processing and real-time analysis are challenging due to data dynamics.

On social networking sites, people from diverse socioeconomic and cultural backgrounds post their comments and opinions. Additionally, they express their thoughts in their mother tongues, which encourages the usage of technologies for mining multilingual viewpoints. Recently, certain bilingual and multilingual sentiment analysis methods have been developed. For bilingual SA, there are monolingual and multilingual sentiment classifiers available (Yan et al. 2014). There is only one reference language that has a sentiment lexicon in the monolingual sentiment classifier, thus other target languages must be translated into the reference language. According to Balahur et al. in 2015. developed a bilingual machine learning method in 2014 to analyze sentiment on tweets in both Chinese and English. better than contrasting remarks in Chinese and English individually. Tweets are treated as a continuous stream of text using both Chinese and English terms using a bilingual method. This bilingual approach analyzes the word stems in movie reviews posted on Twitter in order to generate feature vectors. Use SVM and N-Gram, two interchangeable natural language models, to categorize tweets.

By examining attitudes in tweets regarding stocks, Smailovic et al. (2014) described a stream-based efficient learning technique to forecast changes in stock price. This approach, which is based on the Granger causality test, asserts which is possible to predict changes in stock values many days in advance based on feelings stated in tweets about stocks. This method divides the posted Tweets into three categories based on their sentiment: positive, negative, and neutral. Lau et al. describe a semi-supervised fuzzy product ontology mining method based on social analytics (2014Conduct a fine-grained market knowledge extraction to enhance product design and marketing strategies. The development of a general framework for stock price prediction by Li et al. (2014) provides a lexicon-based method for examining the effect of news on sentiment dimensions. The general approach generates the sentiment dimensions using the Loughran-McDonald financial sentiment language and the Harvard psychology lexicon.

Ortigosa et al. (2014) describes a Hybrid Method for emotional state-based adaptive e-learning system for users. Obtain information from course participants that teachers can use., particularly when adaptive systems are being employed for online learning. The difficulty of anticipating the fundamentally concealed relationship among the news posted and the exchange of stocks as a main topic of Nassirtoussi etal(2015) .'s research.

Recently, a variety of machine learning techniques, such as SVM and probabilistic models, have been proposed for text polarity identification. The curse of dimension, or the high dimension character of text, has produced a research gap despite stimulating dimensionality reduction and feature extraction. Instead of dividing the massage into two phases, it makes more sense to take the key ideas from each book. The feature set must be selected initially before feature values can be extracted. Some methods to select representative word sets include chi square (Liang et al. 2014), local/global document frequency, bag-of-words (Rong et al. 2014; Balahur and Perea-Ortega 2015; Yan et al. 2014), feature hashing (de Silva et al. 2014a; Rill et al. 2014), and information gain (Habernal et al. 2014)

III.THE SENTIMENT ANALYSIS PROCESS

The time-consuming sentiment analysis procedure, which is used to examine sentiment data, consists of five different steps. They are as follows: See Fig. 1

1. *Data Collection:* User-generated content from blogs, forums, and social media platforms is the first source of information used in sentiment analysis. These facts are transmitted in an erroneous manner and with the use of several words, slang phrases, writing styles, etc. Practically speaking, manual analysis is impossible. As a result, the data used in social media is extracted and categorized using text analytics and natural language processing.
2. *Text Preparation:* The extracted data needs to be cleaned before analysis. Both non-textual content and analysis-relevant content are identified and removed.
3. *Sentiment detection:* involves looking over the extracted comments and concepts. Sentences providing objective ideas (facts, factual information) are eliminated, whereas sentences communicating subjective notions (opinions, views, and attitudes) are kept.
4. *Classification of Sentences:* At this point, subjective sentences are broken down into categories like favorites and haters, good and bad, positive and negative, and others.
5. *Output Presentation:* At its core, sentiment analysis aims to turn unstructured text into information that may be used. Pie charts, bar charts, and line graphs are used to present the text results after the analysis is complete. Additionally, by creating a sentiment time line with the chosen value, the remaining time can be calculated and graphically shown. (frequency, percentages, and averages) as it changes over time.

IV.WHAT SENTIMENT ANALYSIS METHOD IS BEST? DOCUMENT, SUBJECT OR ASPECT

It might be challenging to read people's written emotions, especially when doing so in a large group. To address this issue, a variety of sentiment analysis techniques are employed. Identification, evaluation, and classification of people's feelings as positive (1), neutral (0), or negative (-1) constitute sentiment analysis

It helps businesses understand their brand perception, where parts of their product or business require improvement, and how they may manage their resources. To gather human reviews, a variety of polling techniques are employed, including platforms for Voice of Customer Analytics, Voice of Patient Analytics, and Voice of Employee Analytics. Even without such specialized tools, a corporation can nevertheless benefit from social media sentiment analysis to learn important information.

We will use specific examples to illustrate the various approaches to sentiment analysis in this post. You can use this to decide which sentiment analysis technique is ideal for you. Additionally, we'll examine the features that make Repustate's sentiment analysis API the fastest and most precise in the sector and how it handles ambiguous responses.

(A). Which Methods Are Used In Sentiment Analysis?

Document-level, topic-level, and aspect-level are the three different types of sentiment analysis techniques [1]. Depending on the volume and complexity of the text data, these methods can be used. Let's take a closer look at them.

1. Sentiment analysis based on Document

Using the data in a document, sentiment-level document analysis attempts to categorise a sentiment or emotion. Basic text analytics allows for the extraction of a document's semantics from three different aspects: word presentation, sentence structure, and document composition. As long as the language has just one emotion, it is simple. However, when phrase structure and word representation are complicated, this strategy is not particularly helpful. In such circumstances, the subtleties of the comment can be lost, and the outcomes might be incorrect.

2. Opinion research based on a topic

Opinions on a certain issue are discovered using topic-based opinion analysis. This model identifies and extracts themes from the data using keywords and total scores. The subject's mood is also taken into consideration. All of these subjects can be used to train a machine learning model, which can then be adjusted to meet business or industry standards. For instance, healthcare themes may include first aid, dosages of prescription drugs, patient wait times, etc., whereas hospitality topics might include food, bookings, or services.

3. Sentiment analysis based on aspects

The Aspect-Based Sentiment Analysis (ABSA) approach pinpoints the key features or traits of a unit and calculates the typical sentiment expressed for each feature. A luxury watch is an example of a product with features and attributes that could include battery life, design, colours, etc. In other words, a more accurate method of reviewing reviews is aspect-based opinion analysis.

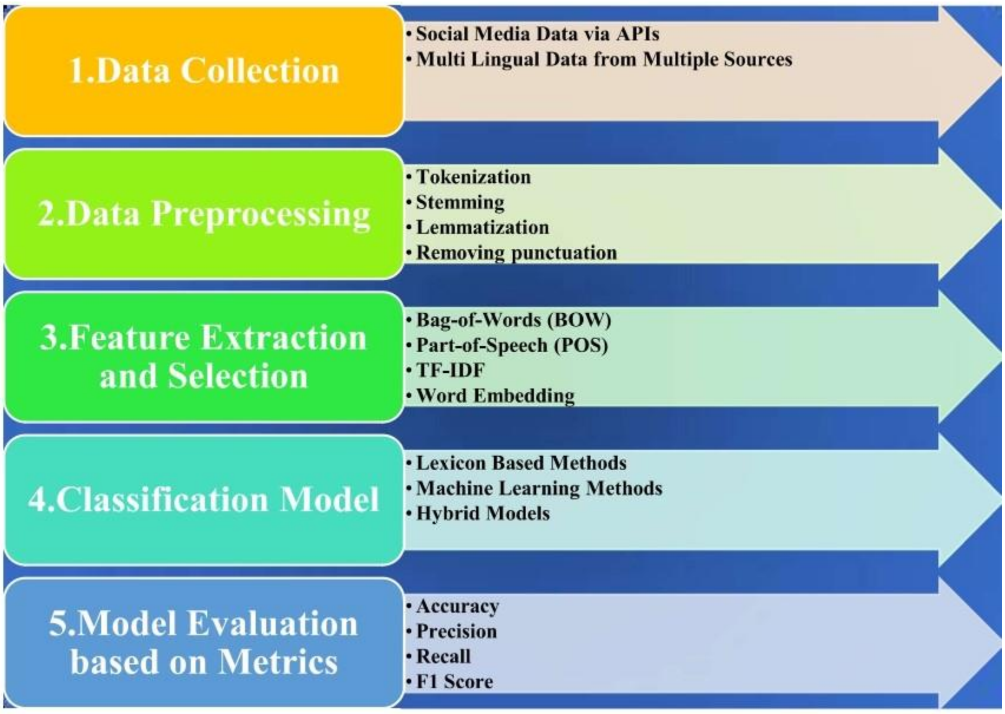

Fig 1: The Sentiment Analysis Processing Steps [1]

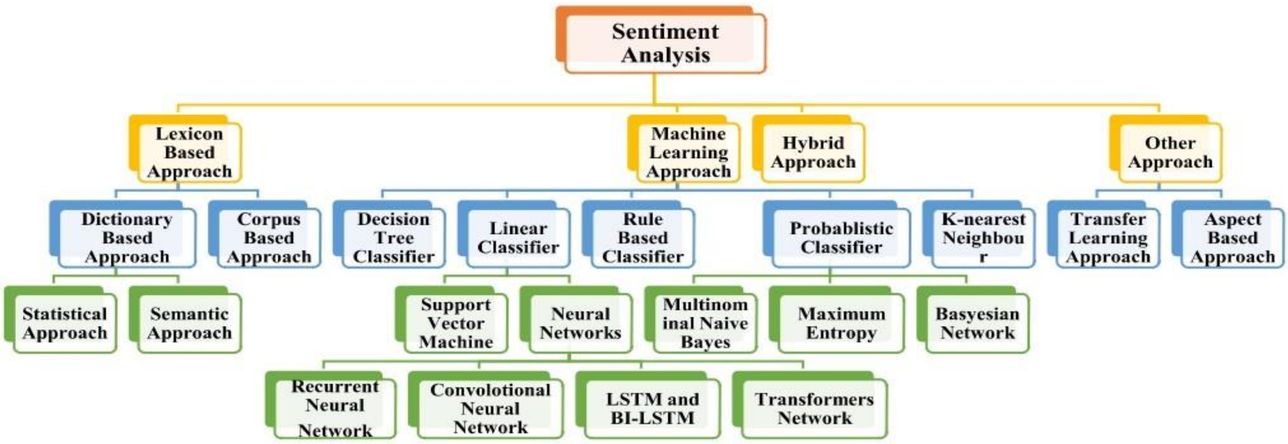

Fig 2: The Sentiment Classification Techniques [1]

V.TECHNIQUES FOR INFERRING SENTIMENTS

Sentiment classification is a method for classifying a target unit in a document as either positive (favourable) or negative (unfavorable). The three main classification subgroups are as follows:

(A). Techniques Based On Lexicon

Literally, "vocabulary" refers to a person's vocabulary. Unsupervised learning methods include word-based strategies. Documents are looked up for both positive and negative phrases under them. The classification of words as positive or negative uses a certain dictionary. The document is initialized at the top with a dot s, zero. The quantity of points grows for each word in the document that is constructive. On the other side, each negative word lowers the overall score. In order to assess if a document has a positive or negative sentiment, also known as document polarity, the evaluation compares scores with a threshold number. These methods can be broadly divided into the following categories:

1.A case-by-case technique.

The dataset gains domain specificity as a result, giving the terms in the dataset context in addition to related meanings.

2. A dictionary-based technique

Here, a group of words is initially chosen, and then its synonyms and antonyms are looked up to be added to the group. Up till a stable set is produced, this process is repeated.

(B) Techniques Based On Machine Learning

These can be categorized as classification problems and supervised learning techniques. In essence, this approach uses classification to establish if a document is constructive, destructive, or neutral. In order for the classification model to learn to distinguish between features that differentiate between documents that are positively and negatively classed, the model obviously needs a training set. The actions are as follows:

1. Text-Vector

The document vectors are computed using the document term and inverse frequency. Only words that truly offer a good or negative description words from a specified dictionary are taken into account.

2. Classification

For classification, a number of methods can be utilized, including Naive Bayes and linear regression. Classifiers can be probabilistic, linear (like SVM and neural networks), rule-based, or decision-tree based (such as Naive Bayes, Maximum Entropy, or Bayesian Network). Deep learning and neural networks can also be used to analyze emotions.

Some examples of machine learning-based techniques are

1. Sentiment analysis using neural networks.

Sentiment analysis based on neural networks Deep learning includes neural networks, which are based on the human brain. A neural network has three stages: input, hidden, and output, with a weight assigned to each node in a distinct layer. In sentiment analysis utilizing neural networks, word embedding is used.

2. Sentiment analysis based on SVM

SVM is a supervised method that may be applied to both regression and classification. SVM classification entails positioning data points in space so that a plane or line may be used to quickly divide them. To characterize the text, in other words. Text can now be represented in an n-dimensional plane thanks to feature vectors. When there are little experimental data, this is very helpful because it makes classification easier.

3. Naive Bayes classifier sentiment analysis

The Bayes theorem serves as the foundation for the probabilistic technique known as Naive Bayes classification. The chance that specific traits belong to a given class is the basis for classification. Using a Naive Bayes classifier for both positive and negative reviews in the training dataset, the number of base words is determined for each word in Sentiment Analysis. Finally, using this likelihood, predictions are formed.

4. Sentiment analysis based on maximum entropy

The maximization of entropy serves as the foundation for this method. It is a probabilistic model, and the classifier's goal is to increase the classification system's entropy. A bag of words model can be utilized in sentiment analysis utilizing the maximum entropy classifier, and it is then transformed into document vectors. The only difference between it and a naive Bayesian classifier is that the context here relates to the likelihood that each word falls into a particular category. The naïve Bayes classifier does not treat words independently as a result.

5. Using a Bayesian network for sentiment analysis

It is a probabilistic graph-based classification technique that is mostly employed to address decision-making issues. Each edge of an acyclic graph represents a connection between nodes, just as each node of a Bayesian network represents a random variable. Tween words are used to represent dependencies as a graph in sentiment research that use a Bayesian network. When the training dataset is huge, this is helpful. It offers a lot of research potential but is not frequently utilized for sentiment analysis.

(C) Techniques Based On Hybrid Model

Better results and outcomes are produced by sentiment analysis using a hybrid method. In comparison to a pure vocabulary-based strategy and a machine learning technique, the classification performance of a hybrid approach combining a vocabulary-based technique and a machine learning technique was greatly improved. Example: SAIL, pSenti

VI.APPLICATIONS OF SENTIMENT ANALYSIS

Academics and businesspeople now have a practical understanding of SA because of increased availability of sensitive data from numerous forums, blogs, and social media platforms. Sentiment analysis can help businesses understand people's attitudes and specific customers' preferences based on their past decisions. As a result, it can assist them in customizing their products and services to meet their specific needs. The following are the several SA application domains depicted in Fig 3:

1. Health Care

The most popular area in this field is healthcare. It is used to analyze the opinions made by users of various social media platforms, including Twitter, Facebook, etc., concerning their health. Health care professionals can use this sentiment dataset to understand the emotions and issues of their patients and to take appropriate action. This data can be used by hospitals to evaluate their performance in perspective of patient expectations. It is easy to identify whether a sentiment is favorable or negative by assigning each one a score. Furthermore, it can help medical facilities to determine if patients are satisfied with their care or if there is space for improvement. [17].

Fig 3: Sentiment Analysis Applications [1]

2.Government Intelligence

Government intelligence is a key field of sentiment analysis. It can be used to gauge public sentiment on impending initiatives or policies that will have an impact on laws and regulations. The results of a freshly enacted government policy can likewise be tracked and predicted using this domain [16]. Using sentiment analysis, we can determine how the general public will respond to a scandal or a topic of contention.

3.Finance Sentiment Analysis

A recent area of study in finance is sentiment analysis. Economic news can be studied using sentiment analysis in the finance industry. Additionally, it has the ability to forecast stock market behaviour and potential trends. By analysing the tweets of several important financial analysts and decision-makers, it is possible to do so. It is possible to understand how sentiment analysis is used in real-time finance by assigning words positive, negative, or neutral sentiment values. For instance, the terms "good," "profit," and "growth" all have positive values and in contrast, terms like "risk," "drop," "bankruptcy," and "loss" all have low scores. Sentiment analysis can be used to analyze client communications and identify dishonest behaviour. It can assist experts in finance and investors in taking advantage of the market and managing their market risk [18].

4. Politics

Sentiment analysis can be used to track political biases as well as general public opinions and attitudes. Political parties may benefit from having a better understanding of voter desires and issues. Political parties or leaders can therefore evaluate their situation by considering popular support or opposition and adjust as necessary. This can be done by monitoring how popular they become online throughout the course of their careers. One approach to do this is through the use of social media platforms [15]. Finding the conclusion holder, linking the hypothesis to the issues, separating the public folks, and implementation are some of the challenges in this discipline.

5. Analysis of Sports Sentiment

Nowadays, sentimental analysis can be used in many other sports. Sports fans want to communicate their feelings and opinions on social media about how their team and players are performing. It can be used with the right statistics to evaluate the opinions of fans and their level of involvement with a particular athlete or event. Examining US sports fans' tweets on the FIFA World Cup 2014 has been used in research [19] to measure their emotional responses to the game's holder, who has the power to express his ideas implicitly. Irony is most frequently found in online content [20]. For instance, "Sure, I'm glad my windows crashed right in the middle of my assignment." Despite the use of positive words like "glad," the sentence is mocking.

VII.ISSUES AND CHALLENGES IN SA

The major limitations faced in sentiment analysis are outlined and discussed below in Fig4.

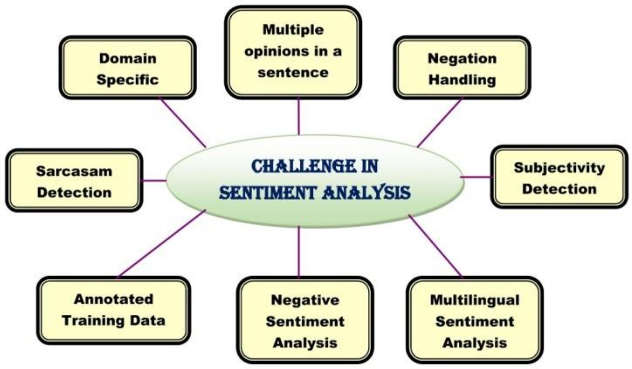

Fig 4: Challenges in Sentiment Analysis

a. Domain-Specific

The context in which a word is used has a major impact on how it is viewed. Hence it is a domain change depending on the context of their referral. For instance, the word "soft" denotes warmth in a positive way, yet applying it to athletes may be offensive. It is a particularly important factor to think about when researching about sentiments. oriented field [11]. The connotation of words can

b. Multiple Opinions in a Sentence

Multiple views can be expressed in one statement by the opinion holder, along with factual and subjective data. To determine the complete strength of opinions, a comprehensive analysis of sentiments must be conducted. "The restaurant has a beautiful ambiance, but the food is fairly expensive," as an example. The "ambience" aspect of the statement has a positive polarity, while the "food" aspect has a negative polarity.

c. Handling of Negatives

One of the biggest challenges in sentiment analysis is handling negatives because it changes the flow of the text [6]. The words "no," "not," "can't," and "shouldn't" are among them. As part of mood analysis, the degree of denial must be determined. Comparing "The movie wasn't good, but the actors did well" to "This battery will not operate for a long time," the negative in the latter statement is more general.

d. Subjectivity Detection

Identification of subjectivity is yet another important aspect of sentiment analysis. This activity is performed to keep the subjective data for later processing while removing the factual data. For instance, "The movie is releasing on Independence Day." The audience for the Fourth of July holiday will grow, and it will include both subjective and objective data. Consequently, a careful evaluation is required.

e. Sarcasm Detection

To detect sarcasm, a comprehensive sentiment analysis must be performed. A person with an opinion can communicates it implicitly via using sarcasm. Irony is most commonly found in online content [9]. For instance, "Sure, It's a good thing my computer crashed in the middle of my schoolwork. The statement is sarcastic despite the use of terms like "happy." Despite all of the research that has been done so far, the problem has still not been fully resolved.

VIII. SUGGESTION FOR FUTURE RESEARCH IN SA

Recently there have seen a significant amount of research globally in the research is sentiment analysis. Sentiment Future analysis has the potential to create systems that can be successfully used in practical applications.

a. sarcastic turns of phrase:

A lots of research need to be carried out in sentimental analysis for sarcastic statements. Consider a phrase S6 that balances good words with negative complements. S6 ought to be classified as positive, even though it is negative.

b. Slangs, symbols, misspelled words and idioms:

Some Sentiment classifiers wrongly classifies the phrases because it contains slang, symbols, a misspelt word, and idioms. Informal and symbol terms are frequently understood by people who have the same interests and can accurately interpret what another person means by utilising the most recent slang phrases.

c. Annotated training data:

Classification is a method of supervised learning. The lack of readily available benchmark training data sets for sentiment *categorization has been emphasized.*

d. Sentiment strengths:

Currently, whether a word is good or negative, it receives the same score. However, it would be feasible to give various words a varying weight based on how strongly they convey a mood. Consider the sentences S7 and S8, which both have a positive polarity, yet S7 would be more influential than S8. It is necessary to give words varied weights based on the intensity of the sentiment they convey.

e. Multiple-language sentiment processing:

Social media networks with multilingual posts challenge sentiment analysis to with levels of consistency and accuracy. Chinese, Dutch, Spanish, Aurbi, and a few more one-for-two level languages including Chinese, English, and German, English, have recently been the subject of research classification reviews. In addition, the most of them use English as a target language.

f. Additional contributions in intense thoughts:

The location of the negative can sometimes affect the text's valence. If a negative appears near to an adjective, the polarity is taken to be the opposite of the adjective's polarity. Consider the statements S9, which belongs in the positive category, and S10, which belongs in the negative category. In order to categorize anything when the adjective "not" is present, the polarity is set to the opposite of the adjective's polarity. The sentence will be classified as negative while it should be positive if sentence S11 is taken into consideration.

g. Prediction time horizon:

Researchers have recently paid a lot of attention to the study of temporal sentiment analysis and the patterns in people's sentiment through time. Using time stamps, the method extracts subject patterns. By narrowing the prediction time horizon, the connection between news impact and intra-day stock price return is investigated.

IX. NOVELTY OF THE RESEARCH AND IMPORTANT STUDY RESULTS:

These massive data sets can now be used to disclose user opinions in large part due to NLP and deep learning. The development of hybrid-based deep learning models as a feasible sentiment analysis solution has become a recent research topic. These algorithms are used to identify a text's emotional polarity and categorise it accordingly. When compared to a single model's performance across all dataset categories, hybrid deep learning models increased sentiment analysis's accuracy. When performing sentiment analysis, combining deep learning models improves using just one model. Design and construct hybrid deep learning models to enhance social network sentiment analysis performance. Deep Learning Hybrid Models Enhance emotion classification accuracy while lowering computational expense.

Multilingual, multimodal sentiment analysis needs to be studied as an additional area of study. To merge audio-visual categories, existing textual sentiment analysis methods should be taken into consideration. When performing multi-label classification tasks, ABSA (Aspect

Based Sentiment Analysis) techniques such as aspect term discrimination, aspect category detection, and its sentiment classification combine RNN and CNN. Using MaLSTM to create a real-time hybrid deep learning model for sentiment analysis that will be built on recurrent neural networks and support vector machines.

We put a lot of effort into creating new models that are better at evaluating emotional responses in people. In order to summarize to any language while performing prediction tasks, we also put a lot of effort into making these models language independent. In order to do topic recognition and sentiment classification simultaneously using a single model, the model can be created to operate in parallel mode. Expand the strategy to include other OSNs, discover new methods and techniques for analyzing non-text signals, and attempt to understand their underlying contents in order to protect the organization's reputation.

X. CONCLUSION

The analysis of sentiments, thoughts, and opinions in relation to particular topics, things, people, groups, and services is known as sentiment analysis. This paper gives a detailed survey on supervised, unsupervised, and hybrid Sentimental Analysis approaches along with a recent research review. Various feature evaluation and classification algorithms for SA are also reviewed in this research. The evaluation of features is contrasted to establish the minimal and optimal feature vector set. This paper also includes the issues identified during classification is that the simplistic usage of only positive, negative and neutral groups. A complete opinion's overall rating cannot be generated by combining ratings from different lines or paragraphs. Dealing with snarky remarks, symbols, misspell phrases, and idioms is still challenging. The existence of many languages and geographical contexts in social media posts makes it more challenging to perform sentiment analysis with adequate levels of consistency and accuracy.

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