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Evaluation of Machine and Deep Learning Approaches for Sentiment Classification in Movie Reviews as Social Media Data

Praveen Sharma[1], Divyarth Rai[2]
[1] *Research Scholar SOCST LNCT University, Bhopal,MP*
[2] *Professor Department of Computer Science and Engineering LNCT University Bhopal, India*

Abstract— **Sentiment analysis is a very important part of Natural Language Processing (NLP) that looks at text data, from short sentences to long documents, to find the polarity (positive, negative, or neutral) and the underlying intention. Humans can easily read emotions in communication, but it's still hard to teach machines how to do the same. Sentiment analysis uses text analytics and advanced natural language processing (NLP) techniques to solve this problem. Social media data, especially movie reviews, are useful for figuring out what people think because they directly affect how many people watch and engage with something. Recent studies have utilized machine learning and deep learning methodologies to tackle significant challenges, including sentiment polarity classification. Sentiment analysis alone is often insufficient in specific contexts, necessitating the incorporation of emotion detection, which concentrates on discerning an individual's emotional or psychological state. This review highlights the levels of sentiment analysis, existing emotion models, and methodologies for detecting both sentiment and emotion in text, while also discussing the persistent challenges in accurately analyzing complex human emotions.**

Keywords— Text sentiment analysis, NLP, machine learning, deep learning.

I. Introduction

In the modern digital age, social media sites create a lot of user-generated content, like comments, posts, and reviews, that give us a lot of information about what people think and how they act. Movie reviews shared on platforms like Twitter, YouTube, and IMDb serve as significant repositories of sentiment-rich data, significantly influencing audience perception and decision-making [8]. Consequently, the analysis of such data has become a crucial undertaking for opinion mining and natural language processing (NLP). Because so much information and opinions are shared and created every day on the internet and digital platforms, sentiment analysis has become an important part of opinion mining systems. Opinion mining or sentiment analysis is the use of computational linguistics, natural language processing, and text analysis to figure out what text means. In this context, Sentiment Analysis (SA) refers to methods used in natural language processing and text mining to find and measure subjective and emotional feelings. Modern studies on text sentiment analysis include many areas, like information extraction, text mining, information retrieval, and machine learning.

Aspect-Based Sentiment Analysis is a specific type of sentiment analysis that focuses on figuring out the sentiment polarity of certain aspect terms in a text [1]. ABSA can tell if people feel positively or negatively about things or services. For example, the sentence "Dinner was okay, service was mid-ranged" shows mixed polarity [2][3]. Traditional aspect-level sentiment analysis relied on sentence-level feature extraction through deep learning annotation frameworks such as "BIO" and "BIEOS." [4][5]. Previous methodologies often treated subtasks in isolation, limiting interaction despite their semantic interrelation [6][7]. Recent advancements employ deep learning and multimodal lexical extraction to enhance feature identification and efficiency, leveraging the structural adaptability of deep learning for word processing and semantic understanding.

Sentiment Analysis: The rise of social networking sites and the expanding use of virtual communication are two reasons why knowledge is developing so quickly online. The Internet helps people find knowledge in this Big Material Era, but it has also made many feel overwhelmed by too much noisy and unneeded material. It is important to find a strategy that works well and can get useful information from this huge amount of

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data right away. NLP, which is a part of AI, is a valuable and practical way to analyze the language that people use when they talk to computers and other technology, whether they are speaking or writing. For more than 30 years, the area of NLP has been looking into problems with how people and computers interact. Named entity recognition (NER), connection extraction, SA, audio recognition, information extraction, parsing, information retrieval, and machine translation are some of the most essential tasks in NLP. One of the most intriguing and difficult things for SA to do is to get views and subjective knowledge from SM posts by using sophisticated methods from NLP, machine learning (ML), and information retrieval (IR). Also called SA. The emergence and expansion of social media platforms have enabled millions to express their opinions, interests, and experiences instantaneously. As a result, a huge number of sentiment lexicons have been made that may be gathered and studied.

Initially, SA focused mostly on textual content, including product reviews and social media comments on sites like Facebook, Twitter, and Weibo. Through text analysis, they could ascertain if the lines were positive, neutral, or negative and categorize them appropriately. Some people think that machine learning methods like the Naive Bayesian approach and SVM can be used to train sentiment classifiers for text using positive and unlabeled data [8]. After that, sentiment lexicons-based algorithms for SA were created, and neural networks made it feasible to make big strides in the categorization of text sentiment. Sentiment Analysis is a new subject of natural language processing that looks at the attitudes, sentiments, and opinions of data. It has become more popular and beneficial in many industries. It is used in many different ways, from small things like making a buying decision to big things like making a marketing decision or forecasting the results of a poll [9].

Sentiment analysis is a technique employed to get a concise opinion or minimal emotional insights on any issue or context from extensive datasets. Sentiment analysis is a rapidly expanding domain within NLP that seeks to extract subjective insights from textual data. SA is a type of machine learning (ML) that is used to look over texts and figure out how positive or negative they are. Machines can learn how to analyze human emotions on their own, without the need for people to help or stop them. In today's environment, SM has become more important. People talk about a lot of things on SM, such politics, movies, and marketing. You may pick from a lot of social networking sites, such Instagram, Facebook, Twitter, and many more. They use these SM venues to offer their thoughts on a wide range of topics [10]. Because of this, SA looks at the text that someone from a foreign country types in. It will use the training data set to figure out how that text makes people feel by first figuring out how that group of people feels.

A branch of SA deals with managing subjective opinions, feelings, and language. SA is the study of how customers or users feel or rate something. The purpose of this evaluation is to ascertain the sentiments of the intended consumers toward a certain thing, whether it be a service, product, article, document, or other entity. It takes into account not just the polarity of sentiments but also how strong those feelings are toward a given service or product. One of the goals of sentiment classification is to figure out if a piece of writing has a good or bad tone. Companies in several fields utilize sentiment categorization to better understand and meet the demands of their customers. This is because it helps them comprehend and respond to customer feedback. People can show a wide range of feelings, which can be grouped into the following categories [11]:

- Happy: This feeling is shown by a person when they are happy or glad.
- Sad: This sensation is shown by a person who is sad or unhappy.
- Anger: This sensation comes from being really angered about anything that is incorrect or harmful.
- Fear: People feel this way when they are scared of danger, suffering, or harm.
- Disgust: This sensation or emotion is shown by thinking about anything that went wrong.
- Shame: This sensation or emotion is felt when someone is upset because they know they did something wrong or stupid.
- Kindness: This is shown when someone is happy and cares about how other people feel.
- Love: Showed strong sentiments of love for both persons of the same gender and people of the opposite gender.
- Surprise: This feeling comes from something that happened out of the blue.
- Trust: This feeling comes from someone being honest, truthful, or having integrity.

Another advantage of doing opinion research is that it enables clients to have a more thorough understanding of the advantages and disadvantages associated with the product or service. In contemporary society, opinion-driven technologies such as evaluation websites, blogs, and analogous platforms are more accessible and widely utilized [12].

Levels of sentiment analysis: SA can be conducted at three distinct levels. Emotion analysis facilitates the categorization of sentiment patterns, the examination of opinionated and emotional online data, and the retrieval of sentiment-related information. Various specific levels of SA can be identified, including the following [13]:

Document Level: The objective of document-level sentiment analysis is to ascertain if an opinionated material conveys a mostly positive or negative perspective on a subject. To assess the overall sentiment of a customer review for a particular product, a system may do sentiment analysis (SA). At this level of sentiment analysis, it is assumed that an individual document expresses opinions on a certain subject, such as customer reviews of products or services. This is because SA outcomes can consist of only two or three outputs, with only one being neutral [14].

Sentence Level: At the phrase level, sentiment analysis involves determining if each sentence conveys an opinion, a neutral position, or a strong negative sentiment [15]. As sentences constitute concise documents, there is no distinction between document-level sentiment analysis and sentence-level sentiment analysis regarding sentiment. This assignment typically has two phases: first, determining if the statement is subjective or objective; second, if it is subjective, assessing whether it conveys a positive or negative opinion; and finally, confirming its subjective or objective nature.

Phrase Level: Furthermore, they will do a sentiment analysis, which involves the extraction of opinion words at the query level and their subsequent classification. Each phrase may possess a singular aspect or several aspects. This acknowledges that a phrase constitutes a singular element, perhaps beneficial for multi-line product reviews. Researchers have demonstrated significant interest in the area during the past several decades. Phrase-level analysis is more successful than document-level analysis for documents including both positive and negative remarks [16].

Aspect Level: Document- or sentence-level sentiment classification is helpful, but it doesn't always work because it doesn't have clear opinion targets. A favorable perspective on one facet does not ensure analogous sentiments regarding other facets of the same subject [17].

Different kinds of sentiment analysis
It is to understand the different ways that SA shows up. After that, the method that best meets these standards is chosen as the best option.

- **Nuanced sentiment:** This study is the source of the data that consumers give. The polarity of the input can produce exceedingly precise conclusions. On the other hand, understanding this issue may require more time and money than other categories [18]. • Emotion Detection: The experience of being human is deeply connected to how we feel. These kinds of feelings affect how people make decisions and make it easier to talk to other people. Emotion detection, also called emotion identification, is the process of figuring out what different feelings or emotions a person is having, like happiness, sadness, or anger. The aspect-based analysis of this influence affects the elements of a product. For instance, if a TV store uses this idea, it might send out reports on things like the TV's brightness and sound quality. • Intent analysis: The consumer's goal is given a lot of attention and thought. The company can also guess what customers want to do with the product [19]. So, it is possible to figure out what a specific customer wants and then use that information for marketing or advertising purposes.

Classification Of Text Sentiment

Sentiment Analysis (SA) is an expanding research area with diverse applications, resulting in the ongoing advancement and evaluation of novel methodologies. In general, SA techniques fall into four groups: machine learning, lexicon-based, hybrid, and deep learning models. Based on a lexicon Approaches depend on pre-established opinion lexicons that categorize words as positive or negative along with corresponding scores. Tokenization involves deconstructing a sentence into its components and aggregating the emotional values of individual words to determine the overall polarity. These methods work best for analyzing phrases and attributes. Knowledge-Based Approaches build lexicons that show how people feel about things before they are analyzed. Most of the time, lexicons are made by starting with seed words, adding linguistic heuristics, and then polishing them with tools like SentiWordNet 3.0 [20]. Dictionary-Based Methods put together lexicons by hand and then add to them with synonyms and antonyms from sources like WordNet and thesauri [21][22]. The process starts with seed words, builds up over time, and is often finished by hand to make sure it's correct.

- **Based on Lexicon:** The primary objective of this methodology is to develop word lexicons that signify positive or negative categorization. Before starting the SA work, decisions are taken on the sentiment values of the lexical words. There are several ways to make lexicons. It is feasible to make it by beginning with a few seed words and then adding more words to them by the use of linguistic heuristics. You may also build it by starting with a group of seeding words and then adding additional words to them. The order in which these words appear in the text dictates how it is formed. The third edition of SENTIWORDNET is a lexical resource that anybody can access. It was made so that programs that employ opinion mining and sentiment classification algorithms may work with it[20].

- **Based on Dictionary:** A record of predetermined set of terms is manually gathered to make up the dictionary-based method [21] [22]. The idea behind this approach is that opposites define root words and their antonyms, whereas synonyms and antonyms are the same. These antonyms and synonyms originate from the huge corpora, such thesaurus and wordnet, and they are added to the list of seed words that was already made. The first step is to make a list of words and their meanings by hand. Then, kids look through the available vocabulary resources such as antonyms and synonyms that they add to their list. Then, more words are added to the list one at a time. The last stage may involve a manual evaluation or change to make sure the system is working well.

- **Based on Hybrid Method:** The hybrid strategy uses both ML-based and lexicon-based methods. The main reason for this technique is the necessity to combine the context of emotive phrases and deal with ambiguities. This means combining the accuracy and flexibility of ML with the dependability of a lexicon-based approach. Consequently, the hybrid strategy possesses the capacity to improve sentiment classification by amalgamating the two techniques, having addressed their individual shortcomings and optimized their separate advantages [23].

Various Application of Sentiment Analysis

There are several situations and reasons why SA could be used. This section of the article will talk about some of the more common ones. The examples of the selections in this part are just that: examples. For additional possibilities, you only need to choose [24].

- **Analyzing a Business:** There are a number of benefits to using SA in the business intelligence process. In addition, businesses may use the information they get from SA to improve their products, get feedback from customers, and come up with a convincing marketing plan. When it comes to business intelligence, sentimental analysis (SA) typically means looking at how customers feel about the products or services they've used. In the world of business intelligence, SA has a number of advantages. Businesses might utilize the findings of the SA to come up with new marketing plans, get feedback from customers, and make modifications to their goods. The most common use of SA in business analytics is to find out how consumers feel about a service or product.

- **Voice of the Customer (VOC):** VOC means that customers are worried about the products or services they have bought. It needs to look at the reviews and comments that customers have already read. VOC is an important part of customer experience management, along with other parts. Because of this, having VOC will make it easier to find fresh product ideas. Another good thing about getting input from customers is that it helps figure out what the items need to do, as well as some non-functional factors like cost and performance. The VOC procedure gives product producers a lot of important results and benefits.

- **Buying things online:** Most of the time, SA is used when people do things relating to purchasing online. People who use websites can talk about their purchasing experiences and the quality of the things they find on those sites. They give a description of the product and its numerous good attributes by using ratings or scores. Customers may readily find reviews and suggestions for the complete product, as well as information about individual aspects. Users get a visual overview of the product as a whole and the features it has. Ratings and reviews from both editors and real consumers may be found on popular purchasing sites Like Amazon.com.

- **The Field of Healthcare and Medicine:** Many businesses, like this one, have depended on SA in the previous five years. There are a lot of locations where you can find data, including Twitter and surveys. [26] Blogs, news stories, reviews, and other types of articles After then, this information may be utilized for a number of things, such as checking the standards of the medical field and looking into possible new developments. [27]. The main purpose of this software is to help healthcare practitioners gather and analyze patient feelings, outbreaks, bad drug responses, and infections in order to make healthcare services better.

- **Voice of the Market (VOM):** The Voice of the Market campaign's goal is to find out what customers think about the goods or services that competitors offer. Having precise and up-to-date information from the Voice of the Market may help you get ahead of the competition and come up with innovative goods. Finding this kind of information as soon as possible is useful for making marketing plans that are both direct and focused. With SA, businesses can get feedback from their customers right away. With this real-time knowledge, they can come up with new marketing strategies, improve product features, and figure out how likely it is that a product would fail [28].

Challenges on Text in Sentiment Analysis

Users are creating a lot of knowledge by writing informally on the Internet these days. Some of these flaws are spelling errors, employing new terminology, and not following the rules of grammar. Because of these limitations, robots can't figure out how people feel. People can't always articulate how they feel right away. For example, "Y, have you been sooo late?" The words "why" and "you" are spelled correctly, and "soooo" is added to make the line sound more serious. The phrase also doesn't say if the person is angry or scared about the circumstance. Consequently, discerning mood and emotions from real-world data is challenging for several reasons [29].

One of the problems with figuring out how to detect emotions and use SA is that there aren't enough resources. For some statistical methods, you need a big dataset that has been marked up. On the other hand, acquiring data is not hard; nevertheless, marking the huge dataset by hand is a long and inconsistent process [30]. Another problem with resources is that most of them are only available in English. Research on SA and emotion identification from non-English languages, particularly regional languages, presents both obstacles and potential for the academic community. Moreover, the relevance of certain lexicons and corpora to a designated domain is constrained, inhibiting their application in alternative situations.

It's also hard to express more than one feeling in a single line. When a statement includes a lot of viewpoints, it's hard to figure out what the different parts of the sentence are and how they make you feel. The statement "view at this site is so peaceful and calm, but this place smells" shows both the bad and good sentiments of "disgust" and "soothing." Another problem that has to be solved is that it is hard to figure out polarity from comparison words.

- **The need and Purpose of Sentiment Analysis:** SA is highly essential since it gives them a better idea of how consumers really feel about their brand. By automatically sorting the sentiments that are behind interactions on social media, reviews, and other types of feedback, businesses can make better judgments. Companies may utilize SA to find out how their consumers truly feel about a product or service when they collect data on how they feel about it. To find out the Polarity: ? Tells you if a feeling is good or terrible. Please explain me what this talk is about. Who do you think has the right to say? Something or someone that can express the sentiment. The process of SA [31] includes automatically analyzing natural language utterances, finding key statements or views, and sorting such utterances by their emotional tone.
  • The use of SA to meet corporate needs has led to higher consumer satisfaction through better goods, the ability to find problems right away, and the establishment of a new market.
  • Using SA to look at customer satisfaction: The customer talks about their experience with a product and shares their thoughts and feelings about it through comments written in everyday language. With this information, businesses may learn a lot about whether or not the consumer is happy with the product and, if necessary, how they could make it better.
  • Be aware of and deal with problems as they come up: A client may quickly let the whole world know how unhappy he is through SM.

Classification of Sentiment

Sentiment classification is one of the most well-known and well-studied challenges in SA. The term "polarity determination" is often misused in conversation. Determining polarity is a smaller part of categorizing emotion. On the other hand, this is really a subtask that aims to find out how each piece of writing makes you feel. It is often believed that polarity may be classified as either positive or negative [32]. A number of studies include a third group known as neutral.

• **Classification of subjectivity:** To ascertain the presence of subjectivity inside the text, the task of subjectivity classification must be undertaken. One goal of categorizing subjectivity is to cut down on the quantity of objective data items that aren't needed for further processing. Many people think of it as the first step in sentiment analysis. Subjectivity classification entails the recognition of subjective indicators, including sentences that express emotions or subjective terms like "expensive," "easy," and "better" [33]. There are a number of signs that can help you tell if text objects are subjective or objective.

• Finding spam in opinions

Finding opinion spam has become a serious issue in the field of SA since more and more people are using websites that let them purchase and read reviews online. Fake reviews, often called "opinion spams," are comments that are carefully constructed to either favor or condemn a product. The purpose of opinion spam detection is to find three types of traits that are linked to fake reviews.Some of these traits are true product information, review content, and review metadata [34].

• Detecting language without being obvious

IRony, sarcasm, and humor are all examples of linguistic patterns that aren't directly stated. This kind of communication can be unclear and imprecise, which could make it hard for other people to understand. On the other hand, the implied meaning of a comment might radically shift its polarity. The goal of implicit language detection in many cases is to figure out what happened by looking at the data that goes with it. The word "pain" is a factual term that carries a negative polarity load. For instance, "I love pain." Some individuals might think it's funny, sarcastic, or ironic that the objective term "pain" and the subjective word "love" are precisely opposite each other. Some of the most prominent signs of implicit language include the use of emoticons, expressions that imply happiness, and too many punctuation marks [35].

• Taking Out Aspects

When talking about a document, "aspect extraction" means getting the target entity and parts of the target entity. The target entity [36] might be a person, a product, an event, an organization, or anything else. To do fine-grained SA, you need to know what people think about the different parts of a product. Aspect extraction is very important for SA of SM and blogs, which sometimes don't have fixed topics. There are several ways to do aspect extraction. The first method, which is also the most common, is termed frequency-based analysis.

Natural language processing

After that, NLP makes the machine understand human language. AI and NLP help software comprehend and respond to the opinions and feelings expressed in user-generated material like comments, social media posts, blogs, and more. Sentiment analysis, which is a branch of NLP, helps individuals make choices based on how they feel or what they think.

For accurate sentiment analysis, you need to do numerous NLP tasks, such as tokenization, stemming, lemmatization, negation detection, n-gram creation, and feature extraction. NLP-based pre-processing helps the polarity classifier work better by looking at subject-related sentiment lexicons [37]. As a result, NLP helps in understanding language, capturing text polarity, and doing better sentiment analysis [38]. Advanced NLP techniques are typically needed to deal with things like emoticons, multilingual data, idioms, sarcasm, meaning or tone, bias, negation, and so on. If this doesn't happen, things might go extremely wrong. When you remove stopwords during pre-processing, for example, words like "not," "nor," and "no" are commonly taken out if you use NLTK's general stopwords list. Still, getting rid of these words might influence the real mood of the data. So, depending on how they are employed, NLP activities can either make the outcome better or worse [39].

Machine and Deep Learning

Machine learning (ML) is an artificial intelligence technique that enhances system performance autonomously. The goal of this topic is to build computer systems that can work on their own, look at data, and change how they act based on new information without any help from people. Knowledge comes from seeing or knowing things firsthand, through examples, education, or data. Machine learning derives decisions from robust instances of patterns inside data. The goal of ML is to teach computers how to learn and change on their own. There are many ways to use machine learning. There are two main types of machine learning: supervised and unsupervised[40].

- Supervised learning methods use tagged data to make guesses about data that isn't labeled. These algorithms acquire knowledge from a training dataset and subsequently utilize that information to predict output values. Training the system prepares it for novel inputs and outputs. The learning algorithm can fix mistakes and change the model as needed.
- Unsupervised algorithms interact with their surroundings by taking actions and figuring out what is right or wrong. Reinforcement learning is defined by exploratory trial-and-error methods and the postponement of immediate rewards.

DLs have helped several industries, including image and voice recognition. CNNs enable cutting-edge photo classification results. Thus, DL has become a prominent subject of study in universities and organizations and an essential tool for solving complex problems. DL system can detect emotional facial muscles [43].

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II. LITERATURE SURVEY

This study examines methodologies and approaches for text sentiment analysis to provide a reference for future empirical research. Here are some examples of literature.

Basa and Basarslan (2023) analyze textual attitudes, viewpoints, and perspectives. SA research can utilize extensive amounts of website comment data. NLP, which includes SA, is a big area of AI research. SA used open-source data from the Internet Movie Database (IMDb), which has information about movies, such as the director, actors, and reviews. After preprocessing, we used frequency-based TF-IDF to turn words into vectors. Classification was done with ML. SVM was the most accurate, with 90% accuracy[44].

Ullah et al in 2022 evaluate the sentiment of movie reviews using a seven-layer deep neural network. The model has an embedding layer that takes numeric vectors representing the dataset and two one-dimensional CNN layers for feature extraction. The academic community uses two movie review databases. First dataset has 25,000 positive and negative movie reviews; second dataset has 50,000. In binary classification, these neural network models identify positive and negative movie reviews by tone. With 92% accuracy across both datasets, the model beats typical ML models in efficiency [45].
Sinha, Jayan, and Kumar looked analyzed the general tone of IMDB movie reviews in 2022. To find out how individuals feel about the IMDB dataset, they look at a few deep learning techniques, such as LSTM-CNN, GRU, and BERT. We look at the methods used for data cleaning and provide the results along with measures of recall, precision, and accuracy. They hope to discover the best ML model for future research[46].

Badal and Parmar in 2023 present a hybrid model employing a DNN 1D Convolutional LSTM. The datasets for movie reviews and Amazon reviews show that the network model might work well for SA classification. Preprocessing is helpful for making new words, filtering out punctuation, and mining text. The hybrid model did better than the base models SVM, KNN, and MNB[47].

In 2017, Singh, Singh, and Singh used four new machine learning classifiers—NBs, J48, BFTree, and OneR—to make statistical analysis work better. For the tests, three datasets were put together by hand: two from Amazon and one from IMDB movie reviews. They look at these four ways to classify things. NBs learned quickly, but OneR did much better, with an accuracy of 91.3%, an F-measure of 97%, and a classification rate of 92.34% [48].

Raza and his team worked with the IMDB dataset in 2019 using lexicon-based approaches and deep learning models like CNN and RNN. They were right 87.42% of the time. They emphasized the need for further examination of CNN's comparatively subpar performance [49].

Baid and his co-authors tested multiple machine learning approaches on the IMDb dataset in 2020. These methods included Naïve Bayes (NB), K-Nearest Neighbors and Random Forest. Their technique was 81.45% accurate, and they stressed that these smart systems provide people the capacity to make decisions without relying on their own judgments [50].

In 2021, Harsh and others created a machine learning framework that employed classifiers like NB, Logistic Regression (LR), and Support Vector Machines (SVM) on a dataset of movie reviews. They claimed it was right 73% of the time. The study found that these models were not effective at picking up on subtle or sarcastic sentiments or adjusting to new locations, even if they were easy to use and worked well [51].

Ali and his coworkers used a Multi-Layer Perceptron (MLP) model as the basis for their work in 2021. They also used the IMDB dataset to test both LSTM-RNN and CNN architectures. They got an accuracy of 87.7% and said that these methods can solve problems with hidden layer depth, which makes it easier to work with big datasets [52].

Surya and his co-authors used TF-IDF features and BERT-based neural networks on a dataset of movie reviews in 2022. Their accuracy was pretty good, at 90.67 percent. They noted that these algorithms might not be able to pick up on slight changes in context, but the obvious sentiment in reviews makes them quite useful [53].

In 2023, Bhimanadham and his team used Convolutional Neural Networks (CNN) on the IMDB dataset to help with deep learning. Their model had an excellent accuracy of 93%, and the study found that combining deep learning with sentiment analysis is a good way to solve many problems in the field [54].

III. RESEARCH GAP

Sentiment analysis has made a lot of progress, but there are still some problems and concerns that need to be dealt with. There is a type of model that is used to rate movies that relies heavily on certain datasets. A lot of models do this. This makes it hard to use them in other communities or in daily life. It's hard to understand how deep learning algorithms make predictions because they give correct answers but aren't very clear about how they do it.

Advanced models also need big datasets, a lot of computing power, and careful preprocessing, which can make it hard to scale and use them in real life. Different studies use different datasets, preprocessing methods, and evaluation metrics, which makes it even harder to reproduce and standardize results. Lastly, most sentiment analysis systems don't work well with new domains or changing language, which shows that we need more flexible and generalizable methods.

IV. CONCLUSION

The sentiment analysis is even a crucial instrument for determining the multidimensional character of human emotions and viewpoints, particularly in the textual data that is found in the vast ocean of the internet. The fact that it may be utilized in a wide variety of activities, such as the analysis of customer feedback, the management of business information, and the management of brand reputation, demonstrates unequivocally the significant influence that it has on the decision-making processes of the present day. Despite this, the study of sentiment faces a number of obstacles, such as the identification of concealed feelings, the comprehension of informal languages, and the absence of resources that are available in several languages. Both the uses of machine learning models and the obstacles they provide are discussed in this study of sentiment analysis. Through the application of machine learning and deep learning techniques, this study studies the classification and analysis of text-based sentiment analysis tools.

The findings of the study indicate, in general, that sentiment analysis is an important and relevant topic of research. Furthermore, the addition of a tertiary study proved the added value that each of the secondary studies was unable to deliver. It is anticipated that in the future, it may be feasible to increase the accuracy and scalability of sentiment analysis by combining machine learning and deep learning techniques with advancements in natural language processing.

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