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A Review on Sentiment Analysis using Machine Learning

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Abstract— **Sentiment Analysis [SA] is a method that is used to detect the state of some information or text. It can be applied to tasks such as text classification and summarization, and various methods can be used to extract sentiment from text, including machine learning algorithms and rule-based systems. Sentiment analysis is an important tool for businesses to understand customer feedback and measure customer satisfaction and loyalty. It classifies the given text into three categories: positive, negative, or neutral. The statement "the picture quality of TV is good" expresses a positive opinion about a particular TV, while "the sound is not adequate" expresses a negative opinion. Recent challenges with sentiment analysis include capturing sarcasm, emotion in text and dealing with long texts. The paper presents a literature survey of many machine learning techniques as well as deep learning models such as CNN, LSTM, etc.**

Keywords—Machine Learning, Deep Learning, Sentiment Analysis, Natural Language Processing, Artificial Intelligence

I. INTRODUCTION

Sentiment analysis (SA) is a widely used technique in natural language processing (NLP). It enables machines to analyse human emotions and opinions by analysing text data. Sentiment analysis can be used to determine the overall sentiment expressed in a document as well as identify specific topics or aspects that are being discussed. It has become an important tool for businesses to understand customer feedback to make better decisions. Sentiment analysis helps organisations measure customer satisfaction and loyalty by analysing the sentiment expressed in online reviews and social media posts [1].

Natural language processing and sentiment analysis are two related topics that have grown in popularity recently. The study of how computers read and process human language is known as "natural language processing," or NLP. Sentiment analysis, on the other hand, is more narrowly focused on comprehending the emotions portrayed in text. Since the 1950s, when Alan Turing first outlined his concept of artificial intelligence (AI), NLP has existed. Since then, scientists have utilised AI to create algorithms that can comprehend and translate written or spoken speech [2]. With the introduction of machine learning (ML) models like deep learning (DL) networks, which enable machines to learn from data without being explicitly programmed, this technology has evolved dramatically over time.

In the late 1990s, sentiment analysis first appeared as an NLP application. It uses methods like NLP and machine learning to identify whether text-based discussions like tweets, reviews, and comments are positive or negative. Sentiment analysis can be applied to a variety of tasks, such as market research surveys or automated customer service. Today, NLP and sentiment analysis are both widely employed in a variety of sectors, from banking to healthcare. By assisting businesses in better comprehending the wants and interests of their clients, they offer insightful data into user behaviour [3]. They are also being used to automate customer care responsibilities like promptly responding to consumer inquiries or spotting possible issues before they arise.

Social media has become an invaluable source for sentiment analysis due to a large amount of user-generated content available in a variety of formats. Social media posts can include life perspectives, thoughts on many topics, current news, and internet issues. Due to a large number of opinions, sentiment analysis is used. Organizations can use the information provided by social networks to improve the effectiveness of their products and services [4]. It may not be necessary to conduct surveys, opinion polls, etc. to obtain information from user reviews. The quickest and easiest approach for a business to learn what its customers think of its goods or services is to ask them on social networks and then evaluate the results to discover what they liked, what they did not like, and how it may be improved. Political parties now employ sentiment analysis to boost their appeal. A popular example of the use of sentiment analysis in this scenario is Narendra Modi's victory in the prime ministerial election. It is possible to determine how many voters are positive, negative, or neutral towards Narendra Modi by looking at the tweets about him. Therefore, sentiment analysis can benefit analysts. Sentiment analysis is generally performed using a combination of NLP and ML techniques. In today's world, sentiment analysis is proving a boon for companies, manufacturers, politicians, etc. The value of sentiment analysis may be demonstrated by our need to know how others react to situations and what they think. Using neural networks makes this analysis more interesting. The things that matter are complexity and performance, which differ from approach to approach. So the best algorithms are needed that can do this task more efficiently while imparting high performance.

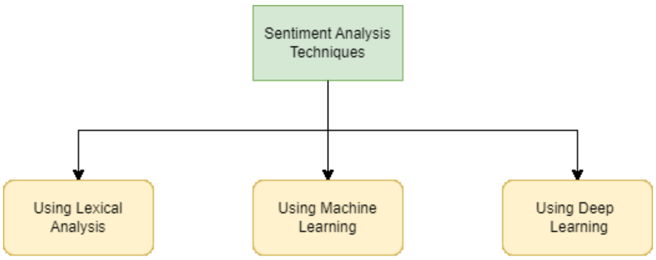
SA is performed on three levels [5], which are sentence level, document level, and aspect level. At the sentence level, the polarity of each sentence is obtained. Sentence-level classification is useful only when the sentence has sentiments related to a single object. At the document level, the main focus is to obtain the sentiment of the entire document. It is generally used when the document has sentiments related to a single object. Both sentence- and document-level classification work well when the whole sentence or document focuses on a single type of sentiment. At aspect level, fine-grained analysis is performed, i.e., first, the sentiments of an entity are calculated, then the sentiment of the object is obtained. For applications ranging from customer service to marketing and medical, sentiment analysis is commonly used in voice of the customer materials, including reviews of products and services, surveys, the Web and social networks, and healthcare resources.

Sentiment analysis uses a technique called "sentiment scoring" to measure the sentiment of a given text. Based on the emotion a sentence conveys, it is given a numerical score. A score of 0 indicates a neutral feeling, and the scale can go from negative to positive. Many methods, including rule-based algorithms, machine learning, and natural language processing, can be used to implement sentiment scoring.

A text sample is classified and assigned a sentiment label (positive, negative, or neutral) as part of sentiment analysis. A classifier is trained for classification using a labelled collection of documents. The sentiment of texts that haven't been seen is then predicted using the classifier. Word counts, n-grams, part-of-speech tags, and other linguistic variables are frequently used by the classifier to produce its predictions.

Studies generally consider positive and negative labels for the classification of tweets, ignoring the neutral label, citing the reason that neutral is less likely to learn sentiment polarity from neutral texts compared to positive or negative texts. However, it is also necessary to consider the "neutral" label, as some tweets or texts may not convey a positive or negative sentiment [6]. Additionally, considering only positive and negative tweets will not provide an accurate classification of neutral tweets. For example, the text "This TV show is unpredictable" shows no emotion. It cannot be said without context that the show is good or bad. Depending on the label, future predictions will not be accurate when this text is classified into two classes only. The neutral class, which represents the absence of emotion, should not be regarded as a state that exists between positive and negative. Instead, it should be seen as a separate class.

II. SENTIMENT ANALYSIS TECHNIQUES



A. *Sentiment Analysis using Lexical Analysis*

Lexical analysis is a technique that includes dissecting natural language texts into their individual words and phrases to identify the meaning. Lexical analysis divides lengthy texts into manageable segments that are more easily understood by both computers and people [7]. Lexical analysis looks for linguistic patterns that can be used to categorise materials based on their sentiment or emotional content. This enables us to comprehend how people feel about various subjects based on what they write or say in speeches.

The ability of lexical analysis to accurately extract significant insights from textual data sources without requiring any additional external resources beyond those already present within existing datasets themselves has allowed it to establish itself over time as an effective method for performing sentiment classification tasks. This makes it a highly cost-effective alternative to other traditional methods currently on the market [8].

B. *Sentiment Analysis using Machine Learning*

Arthur Samuel introduced machine learning in 1959. Machine learning is a statistical algorithm that can learn automatically without any help from a human. With every experience, the system becomes smarter and smarter without the interference of humans. It is a self-learning algorithm that learns from experience [9]. The model is supplied with the data, and the model learns the pattern and structure of the data and provides the output from its learning-based experience.

Machine learning has completely changed the field of natural language processing, especially when it comes to issues with sentiment analysis. Recent developments have made it possible to use computer vision and deep neural network-based solutions that were previously too challenging to address using traditional programming paradigms alone.

C. *Sentiment Analysis using Deep Learning*

Deep learning is a sub-section of machine learning with an algorithm that tries to imitate the human brain's structure and function. DL learns from experience but requires a large information base as input. A network model with neurons includes several hidden layers between the model's input and output. The beauty of DL is that it automatically learns about features and feature representation. DL is best suited for very large and complex data.

Certain neural network algorithms based on the notion of dense vector representations have previously demonstrated state-of-the-art performances in a variety of NLP-related applications. Deep learning NNs originally showed superior performance in the computer vision and pattern recognition subfields. As a result of this shift, several deep learning algorithms are being used to manage complicated NLP assertions such as sentiment analysis [10].

III. LITERATURE REVIEW

Lal Khan et al. [11] proposed a SA model for classifying Roman-Urdu and English texts. The paper proposed a framework by applying a hybrid approach using convolutional neural networks (CNN) and Long short-term memory (LSTM). For feature extraction, the CNN model was used, and the LSTM model was used for long-term dependency preservation. The output provided by LSTM is fed to ML classifiers. By combining CNN and LSTM, the accuracy and efficiency of sentiment analysis are increased.

Gen Li et al. [12] proposed a model to learn the knowledge of sentiment in Chinese text. A hybrid task learning method is designed so that valuable emotional sentiments are learned and, hence, sentiment tendencies are predicted. Experiments showed that the model performs better compared to other models and has better generalisation ability than other methods.

Naqvi et al. [13] proposed a framework by discovering deep learning techniques in addition to different representations of word vectors. For SA, the performance of some popularly known DL methods is calculated. An application of stacked layers is performed with a single layer of convolution; different filters are used in CNN. To more accurately identify sentiment in longer texts, CNNs can be used to capture long-term dependencies in text. The roles performed by pre-trained models and unsupervised self-trained models were also examined. Other deep learning models were outperformed by one with an accuracy of 77.9%.

Wang et al. [14] proposed a model in which a differentiation in the sentiment information of various words was only achieved by using sentiment representation methods. The paper uses the concept of sentiment notions for solving problems. After comparing the word embedding technique based on the sentiment idea with multiple embeddings, the word embedding method's validity based on the sentiment concept is confirmed.

Meylan Wongkar et al. [15] proposed a Naive Bayes (NB)-based SA model. The NB algorithm is used to classify social groups or levels of emotion. A comparison was tested between NB, support vector machines (SVM), and K-Nearest Neighbors (KNN) that produced an accuracy value of 75% for NB, 64% for SVM, and 73% for KNN. NB algorithm is used to classify social groups or levels of emotion.

U. Sehar et al. [16] proposed a framework that integrates elements such as graphic, acoustic, and text responses so that context-conscious sentiments are detected. To uncover useful patterns, a unique dataset that contains 1372 expressions is used. Both decision and feature dash level fusion methods are used to improve the sentiment clarity prediction. The polarity detection ability was improved from 84% to 95%.

Tam et al. [17] proposed an integrating structure of bi-LSTM and CNN with word embeddings. Compared to conventional approaches, BiLSTM is more reliable at predicting sentiment. This is due to its improved ability to grasp linguistic subtleties and comprehend sentence context. In this model, GloVe and Word2Vec word embeddings were used. The model outperformed other models with 91.13% accuracy.

Al Amin et al. [18] proposed a model for Bengali NLP. The author modified the VADER model to support the identification of Bengali sentiment polarity. English lexicon polarity is included to improve the polarity of the Bengali lexicon. They used stemming, a list of Bengali boosting words, to achieve a superior outcome.

Davcheva E et al. [19]: The author's research goal was to understand better situations and changes in mental state. The outcomes of the research showed that sentiment scoring can be implemented positively or negatively based on the situation.

Gaye, B. et al. [20] proposed a stacked ensemble model. The model used three LSTMs stacked one after another. The output of the stacked model is fed to an LR classifier. The authors reannotated the default sentiments by using TextBlob for two classes. The reannotated tweets provided better results than the default sentiments, with an accuracy of 99%.

H. Sadr et al. [21] proposed a model that finalised mixing up the features derived from heterogeneous Artificial neural network (ANN) by using multiple view classifiers to improve the combined performance of SA at the document level while also taking into account their co-relationship. The proposed network uses intermediate features derived from CNN and RNN so that classification can be performed.

A. El-Affendi et al. [22] proposed a deep learning dash-based multilevel parallel attention neural model (MPAN). It uses the concept of a simple positioning binary embedding scheme, known as PBES. Therefore, the contextualized embedding of character, word, and sentence levels is computed simultaneously. Using the public Internet movie database, the movie dataset model achieved an accuracy of 96.13%.

Hasan M. et al. [23] proposed research on the normal classification method for the measurement of the possibility of allocating the data for every sentiment class. They developed and computed the supervised learning method for the automatic classification of sentiments in textual stream data. Additionally, they planned an online technique to measure public sentiment and identify sentiment rupture emotions in lively streams.

Kotsilieris, T. et al. [24] developed a comparative survey on research for the calculation of a specific kind of nervousness disorder and research for the calculation of suicide ability using ML methods. In addition, they examined and compared the ML methods of treating anxiety disorder.

Yang et al. [25] proposed a new sentiment analysis model, SLCABG, based on a sentiment lexicon and a combination of a convolutional neural network with a bi-directional gated recurrent unit based on attention (BiGRU). The SLCABG model has the disadvantages of sentiment lexicons, but it aids in overcoming the drawbacks of the existing sentiment analysis model of product evaluations.

Anu J. Nair et al. [26] proposed a sentiment analysis model by using the Twitter dataset for COVID-19. Sentiment analysis classifies tweets as positive, negative, or neutral. The author used logistic regression (LR), Vadar sentiment analysis, and BERT sentiment analysis to perform sentiment analysis. These techniques are more sensitive to social media situations.

Tripathy et al. [27] classified a social media dataset with the help of supervised machine learning methods into sentiment categories. This paper classified film reviews by using a supervised machine learning algorithm and later, by using an n-gram approach, applied these to the IMDB dataset. Authors concluded that as the value of n increases classification accuracy decreases and combination of TF-IDE & count vectorizer technique helps in improving accuracy.

TABLE I. ANALYSIS OF VARIOUS SENTIMENT ANALYSIS TECHNIQUES

S. No	*Author*	*Classifier With Highest Accuracy*	*Conclusion*
1	Lal Khan et. al.	CNN-LSTM	Combined CNN and LSTM and Achieved 84% accuracy
2	Gen Li et. al	SINM	Chinese language classification and Achieved 89% accuracy
3	U. Naqvi et. al.	Bi-LSTM-ATT	Worked with different number of filters in CNN. Achieved 77% accuracy
4	Y. Wang et. al.	Bi-GRU	Uses sentiment notion and word embedding. Achieved 91.3% accuracy
5	Meylan Wongkar et. al.	Naïve Bayes	Used Naïve bayes algorithm to achieve 75.58% accuracy
6	U. Sehar et. al.	MultiModal	Integrated multiple elements to detect content conscious emotions. Achieved 95.35% accuracy
7	S. Tam et. al.	CNN-BiLSTM	Used multiple word embedding techniques. Achieved 91.13% accuracy
8	Al Amin et. al.	B-VADER	Using vader on Bengali language, achieved 70% accuracy
9	Davcheva E et. al.	Linear Regression	Sentiment scoring of mental situations and for better understating of situations
10	Gaye,B. et. al.	Three Stacked LSTM	Achieved 99% accuracy using stacked LSTM technique
11	H. Sadr et. al.	Multi View Deep Network	multi-view deep network outperforms single-view deep neural networks
12	M. A. El-Affendi et. al	Attention Based Neural Network	Using a custom deep learning model, produces an accuracy of 96.13%
13	Hasan M. et. al.	Supervised Learning	Detecting emotions in live text streams
14	Kotsilieris, T. et. al.	Multiple Machine learning techniques	Hybrid machine learning and SVM produces best results
15	L. Yang et. al.	SLCABG	Combining lexical analysis and deep learning produces better results
16	Anu J Nair et. al.	BERT and Vader AND Logistic Regression	Useful for government and Health Officials
17	Tripathy et. al.	n-gram based machine learning	value of ‘n’ in n-gram increases the classification accuracy

IV. CONCLUSION

Multiple machine learning and deep learning techniques were evaluated in this paper for their performance on sentiment analysis. Mostly, data is gathered from social media sites such as Twitter, as nowadays most people voice their opinions on social media. Deep learning has become an increasingly popular choice for sentiment analysis due to the advancements in hardware that have made it more accessible. Deep learning algorithms are useful for sentiment analysis tasks because they can learn from large datasets and automatically identify complicated correlations between data points. As a result, deep learning models may recognise textual patterns with greater accuracy than is practicable or even viable using more conventional machine learning techniques.

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