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**Research Article**

# Evaluating the Effectiveness of CNN, LSTM, and Bi-LSTM Models in Classifying Twitter Sentiments

*Naveen P[1], J.Jaganpradeep[2], R.Thalapathi Rajasekaran[3], Amirthavalli R[4], N Umasankari [5], Mohanaprakash T A [6]

[1*]*Department of Computational Intelligence, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamilnadu, India,* navee4@gmail.com

[2] *Department of ECE, SSM College of Engineering, Komarapalayam, Namakkal, Tamilnadu, India,*jgnprdp@gmail.com

[3] *Saveetha School of Engineering, SIMATS, Saveetha University, Chennai 605102. r.rajthalapathi@gmail.com*

[4]*Department of Computer Science and Engineering Velammal Engineering College, Ambattur, Surapet, Chennai, Tamilnadu, India, amirthadsk@gmail.com*

[5]*Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, TamilNadu. san_june18@yahoo.com*

[6] *Department of Information Technology, CMR University, Bangaluru, tamohanaprakash@gmial.com*

*Corresponding Author - Naveen P**, navee4@gmail.com

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**ABSTRACT**

**Introduction**: Twitter sentiment analysis is an essential tool for understanding public opinions and extracting valuable insights from social media discussions. However, the informal, concise nature of tweets, along with their context-dependent language, poses significant challenges for accurate sentiment classification. Deep learning techniques have shown promise in addressing these challenges due to their ability to learn complex patterns and contextual relationships in data. This study explores the application of Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM) models for classifying tweet sentiments into four categories: positive, negative, neutral, and irrelevant.

**Objectives:** The primary objective of this study is to evaluate the effectiveness of deep learning models, including 1D-CNN, LSTM, and Bi-LSTM, in classifying tweet sentiments into categories such as positive, negative, neutral, and irrelevant. By analyzing the performance of these models, the study aims to compare their accuracy, precision, recall, and F1-score to determine their strengths and limitations. Additionally, the research seeks to identify the most suitable model capable of effectively capturing the sequential and contextual nature of tweets, addressing the unique challenges posed by the informal and context-dependent language of social media data.

**Methods:** The study employs a publicly available Twitter sentiment dataset comprising 73,906 tweets related to general Twitter discussions. The dataset undergoes pre-processing steps, including tokenization, stopword removal, and handling emoticons and hashtags, to ensure clean input for training the models. Tweets are represented using pre-trained word embeddings, specifically GloVe and Word2Vec, which provide rich semantic information by capturing word meanings in context. Individual models—1D-CNN, LSTM, and Bi-LSTM—are trained and evaluated using this pre-processed data. Performance metrics, including accuracy, precision, recall, and F1-score, are calculated to compare the models' effectiveness.

**Results:** The experimental analysis demonstrates that each model has unique strengths in sentiment classification. However, the 1D-CNN outperforms both LSTM and Bi-LSTM models, achieving superior results in capturing both the sequential and contextual information inherent in tweet data. This highlights its efficiency and suitability for Twitter sentiment analysis.

**Conclusions:** This study underscores the potential of deep learning techniques for sentiment analysis in social media. Among the evaluated models, 1D-CNN proves to be the most effective, offering a robust approach to handling the complexities of tweet sentiment classification. Future work could explore hybrid models and further optimization techniques to enhance sentiment analysis performance.

**Keywords:** Sentiment analysis, twitter data, social media, natural language, tokenization, stop words, long term, short memory and convolutional neural networks.

## INTRODUCTION

A massive archive of real-time public opinion has been formed as a result of the fast expansion and broad acceptance of social media platforms, notably Twitter. Twitter, which receives more than 500 million tweets every single day, is an extremely useful tool for gaining knowledge of public mood and trends on a wide range of issues, including consumer preferences and political beliefs [1]. When it comes to making decisions based on data, corporations, governments, political analysts, and academics may benefit greatly from the insights that are provided by this enormous amount of data. Among the applications are market research, analysis of consumer feedback, monitoring of brands, tracking of public opinion, and sentiment analysis for political campaigns. Twitter, despite its usefulness, presents a one-of-a-kind set of hurdles for sentiment analysis due to the distinctive qualities it possesses. Because tweets on this platform are restricted to 280 characters, the network's brief nature frequently leads in shortened expressions of feeling, which makes it difficult to understand what is being said [2].

Furthermore, the casual language that is used on Twitter frequently contains slang, acronyms, misspellings, emoticons, and hashtags, all of which further complicate the process of extracting sentiment. Tweets, in contrast to traditional news stories or formal written material, frequently rely significantly on context and terminology that is particular to the individual. It is also possible for sentiment to be ambiguous or caustic, with certain tweets conveying hidden connotations that need a more in-depth comprehension of the context of the interaction [3]. Additionally, the existence of domain-specific vocabulary or jargon, such as brand names or phrases that are exclusive to an industry, might further obscure the message that is being conveyed in a tweet. On the other hand, conventional natural language processing (NLP) methods, which often rely on explicit grammatical rules and feature engineering, are frequently insufficient for capturing the complexities and subtleties of twitter data [4].

Sentiment analysis, which is often referred to as opinion mining, is the process of locating, extracting, and categorizing information that is subjective from textual data. Finding out if the feeling that was communicated is favorable, negative, neutral, or unimportant is the goal of this endeavor. This technique is especially crucial when it comes to assessing public opinion in real time because posts on social media are frequently spontaneous and represent rapid emotional reactions to events or items. An enterprise is able to swiftly analyze consumer happiness, monitor brand reputation, follow political mood, or gauge public reaction to global events by using sentiment analysis. This is made possible by the dynamic nature of Twitter [5].

Naive Bayes, Support Vector Machines (SVM), and Decision Trees are examples of machine learning models that are frequently utilized in the conventional methods of doing sentiment analysis. Despite the fact that these models have proved successful in a variety of situations, they frequently struggle with the informal and unstructured character of tweet data [6]. However, these models are unable to properly capture the semantic and contextual links that are inherent in natural language. They rely largely on manual feature extraction, such as recognizing certain words or phrases that are indicative of emotion. In addition, kids frequently struggle to deal with sarcasm, word ambiguity, and the unanticipated variety in language that is utilized on social networking platforms.

The performance of sentiment analysis has been greatly enhanced as a result of recent developments in deep learning, particularly in models that were created for sequential data. In the absence of the requirement for human feature engineering, deep learning approaches are able to automatically build hierarchical representations of data and capture complex patterns from raw inputs. It has been demonstrated that Convolutional Neural Networks (CNN) [7], Long Short-Term Memory (LSTM) networks [8], and Bidirectional LSTM (Bi-LSTM) [9] networks are particularly successful at addressing the issues that are presented by social media content. These challenges include the ambiguity, shortness, and context-dependence of tweets.

This research article is comprised of five primary sections, which are as follows: In the first section, sentiment analysis is discussed. In Section 2, a complete literature review of different sentiment analysis is presented, during which research gaps are identified, and then the purpose of the research is presented. In Section 3, we present the SA-Net sentiment analysis model is built on a different deep learning model for the categorization of twitter sentiment data. The experimental findings for the suggested SA-Net sentiment analysis models are discussed in Section 4. In Section 5, a summary of the findings is presented, and a discussion of potential directions for additional study is included.

## LITERATURE SURVEY

Numerous social networking websites, such as Facebook and Twitter, contain an enormous quantity of data. Because of this, sentiment analysis is a work that is rather difficult to complete, and throughout the processing of material from social media platforms, various problems develop. Every single day, a substantial quantity of data is produced via the use of the internet, and this data has to be processed in order to derive meaning from it. Several different methods, including machine learning and deep learning, have been utilized for SA. Researchers working in the field of natural language processing (NLP) have been creating a wide variety of strategies to address SA problems. These techniques make use of a bag of words representation [10]. As a result of the self-adaptive, self-configurative, and self-aware character of deep learning techniques, the research community is committed to discovering solutions that will allow for the extraction of important information from social networking sites by removing the material that is irrelevant and unneeded.

In this article, we examine the work that is associated with statistical analysis in two categories: machine learning and deep learning. To begin, we will discuss the conventional methods that have been utilized for SA. The primary concern in India, which is the classification of emotion polarity, was the primary focus of the study [11]. Specifically, it makes use of the Amazon product reviews dataset. The approaches of Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayesian (NB) are employed, and they have contributed to the achievement of superior outcomes. It is used in [12] that SA is used for the Thai language. In order to evaluate SA, the online community evaluations from pantip.com were utilized. These reviews were categorized into four categories: negative, favorable, neural, and need. In terms of accuracy, an unsupervised deep learning paragraph2Vec strategy for feature extraction was suggested and implemented, and it was shown to be superior than TF, TF-IDF, SVM, and NB.

Through the use of Logistic Regression, the author of [13] conducted sentiment analysis on tweets originating from Thailand. The findings of the experiment demonstrated that Logistic Regression uses Paragraph2Vec to get satisfactory results in terms of both accuracy and time. A comparison of the SVM and NB approaches for Arabic tweets and text categorization was carried out by the authors of [14] using the WEKA tool. The TF-IDF and cosine measure techniques were utilized, respectively, for the purpose of calculating the similarity of documents and the weighting scheme applied to them. NB performed well in terms of both accuracy and time, as demonstrated by the results of the experiments. A technique based on the CNN framework has been developed in [15] for the purpose of predicting the feelings associated with visual material in visual SA. Within the context of the experiment, back propagation is utilized on the dataset consisting of 1269 images that have been gathered from Twitter. The results demonstrate that the suggested system achieved great performance on the Twitter dataset in terms of recall, accuracy, and precision. Furthermore, the authors demonstrate that the proposed GoogLeNet produced results that were 9% better than those obtained by AlexNet [16].

Mohanaprakash and Nirmalrani [18] conducted an extensive study on cloud computing security threats by exploring multiple viewpoints. Their research highlights the various vulnerabilities that arise due to the dynamic nature of cloud environments, including unauthorized access, data breaches, and service disruptions. The study emphasizes the importance of robust security frameworks and policy-driven mitigation strategies to counter these threats effectively.

Dudiki et al. [19] proposed a hybrid cryptography algorithm aimed at strengthening cloud computing security. Their approach integrates multiple cryptographic techniques to enhance data encryption and decryption processes, ensuring secure data storage and transmission in cloud environments. The proposed hybrid method improves security by combining symmetric and asymmetric encryption schemes, thus addressing issues related to computational efficiency and security robustness.

Raja et al. [20] presented a systematic analysis and review of data encryption technologies and security measures in IoT, big data, and cloud computing. Their study provides a comparative assessment of various encryption mechanisms, such as AES, RSA, and ECC, evaluating their suitability in different application domains. The research underscores the necessity of selecting appropriate encryption techniques based on the computational and security requirements of specific cloud-based applications.

Mohanaprakash and Andrews [21] introduced a novel privacy-preserving system for cloud data security using a signature hashing algorithm. This approach leverages cryptographic hashing to ensure data integrity and prevent unauthorized modifications. Their findings suggest that incorporating hashing mechanisms can significantly enhance data privacy and authentication in cloud environments. [22], Varun et al. explored the integration of CNN-LSTM models with cloud-enabled IoT systems to enhance solar efficiency prediction. By combining the sequential learning capabilities of LSTMs with the spatial feature extraction of CNNs, the study achieved high prediction accuracy, underscoring the potential of hybrid models in time-series and contextual data analysis. This work highlights the versatility of deep learning techniques in addressing real-world challenges through innovative approaches.

Similarly, Mohanaprakash et al. [23] investigated the use of YOLO and CNN models for detecting abnormal human behavior in surveillance systems. By leveraging CNN's capability to extract image features and YOLO's real-time object detection efficiency, the study provided an effective framework for anomaly detection in CCTV footage. This approach demonstrates the importance of combining feature extraction and detection methods for applications requiring high accuracy and real-time performance.

## PROPOSED SYSTEM

In this section, we have to propose a different sentiment analysis model (Deep SA-Net) for analysis the sentiment of twitter data in efficient manner. There are three deep learning models can be utilized for sentiment analysis namely 1D-CNN, LSTM and Bi-LSTM model. The proposed methods consist of following stages:

**Collecting the Dataset**

- Pre-processing the Data
- Feature Extracting Process
- Building the Model (1D-CNN, LSTM and Bi-LSTM)
- Training the Model
- Test Prediction

The architecture of proposed SA-Net model is shown in Figure 1.

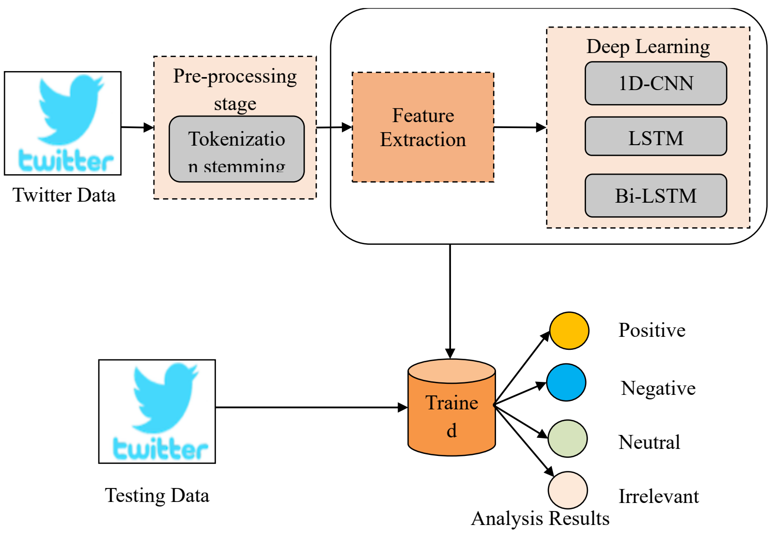


Fig. 1 Architecture of Deep-SA Net Model

**Dataset Collection**

The Twitter_training.csv dataset, which is accessible to the general public, was developed for the purpose of natural language processing and sentiment analysis, with a primary emphasis on Twitter data [17]. In most cases, it consists of a number of columns, such as Tweet ID, which is a one-of-a-kind identifier for each tweet, and Text, which is the actual text of the tweet itself. A Sentiment column is also included in the dataset. This column represents the label or sentiment that is connected with the tweet, such as Positive, Negative, Irrelevant, or Neutral.

The timestamp, which indicates the time at which the tweet was sent, the user ID, which identifies the poster, and the location, which provides geographic characteristics, are all examples of additional elements that are optional. In certain instances, the dataset could also contain a Language column that specifies the language that the tweet was written in. The dataset information of twitter data, number of classes and number of records in each class is shown in Figure 2.

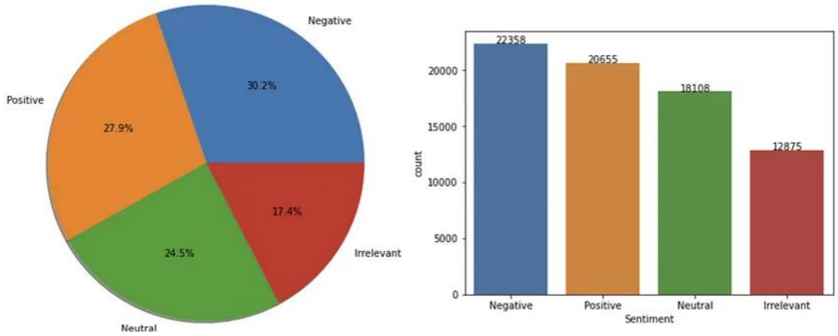


Fig. 2 Dataset information of twitter record

**Pre-processing the Dataset**

In this stage, dataset is loaded, and any duplicates or missing values are dealt with by elimination method. In further, the text will be cleaned up by eliminating noise, which includes things like URLs, hashtags, mentions, special characters, and emoticons. To text is first cleaned, then tokenized, which involves breaking it up into individual words or tokens, and finally transformed to lowercase. As a result of their lack of significance to the study, stopwords such as "the," "is," and "and" are eliminated. Lemmatization or stemming is then utilized in order to reduce words to their fundamental forms. Next, the text that has been processed is vectorized by employing techniques such as Bag-of-Words, TF-IDF, or word embeddings in order to transform it into numerical characteristics that may be used for model training. Finally, in order to assess the effectiveness of the model, the dataset is partitioned into training and testing sets.

**1D- Convolutional Neural networks**

1D-CNN architecture for sentiment analysis using the twitter_training.csv dataset involves several key layers. First, the embedding layer transforms words into dense vector representations, capturing semantic meanings. Then, 1D convolutional layers apply filters to detect local patterns or n-grams in the text, such as sentiment-specific phrases. Max-pooling layers are used to downsample the feature maps, focusing on the most important features and reducing computational complexity. Dropout layers help prevent overfitting by randomly deactivating neurons during training. The output is then passed through a flatten layer to convert the feature maps into a one-dimensional vector, followed by fully connected dense layers to classify the sentiment. The final layer uses softmax for multi-class classification or sigmoid for binary classification. The model is trained with an optimizer and a loss function suitable for the classification task, ensuring it learns to predict sentiment accurately.

**Long Short Term Memory (LSTM)**

Long Short Term Memory (LSTM), which is a subcategory of the Recurrent Neural Network (RNN), is utilized in the model that we have developed. Within a recurrent neural network, neurons are linked to one another in the form of a directed cycle. Due to the fact that it makes use of its own internal memory to handle a series of words or inputs, the RNN model processes the information in a sequential fashion. Considering that the output is reliant on the inputs of all the nodes that came before it and that it remembers information, RNN accomplishes the same task for each element. The Equation 1 represent general RNN model where ht is the new state at time t, fw is a function with w parameter, ht-1 is an old state (previous state) and xt is input vector at time t. The architecture of LSTM model is shown in Figure 3.

$$h_t = f_w(h_t - 1, x_t) \qquad (1)$$

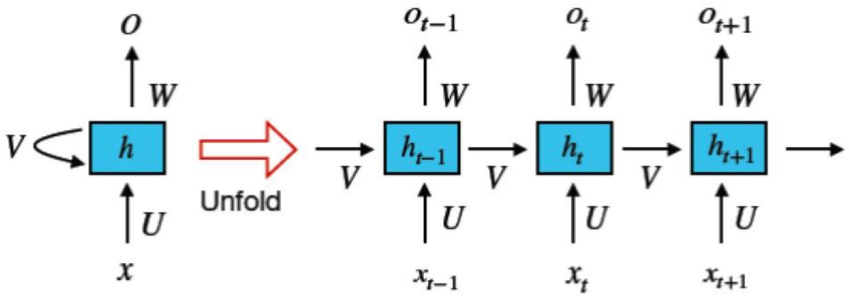


Fig. 3 Architecture of LSTM Model

**Bi-LSTM**

A model for twitter sentiment analysis is developed with the use of Bidirectional Long Short-Term Memory (Bi-LSTM), which is utilized to learn the matrix representation of texts. In order to solve the problem of vanishing gradients, the LSTM algorithm was initially created as an extension of the classic recurrent neural network. Information is stored in the LSTM architecture, which is made up of three gates and a cell memory state. The LSTM architecture processes a sequence of inputs in a directed cycle link between neurons. The sequence inputs are processed in Bi-LSTM in two different directions during the cycle: forward and backward timesteps. Basic input characteristics were used to construct the first Bi-LSTM model, which can be seen in Figure 4. In this model, each word is represented as a word vector.

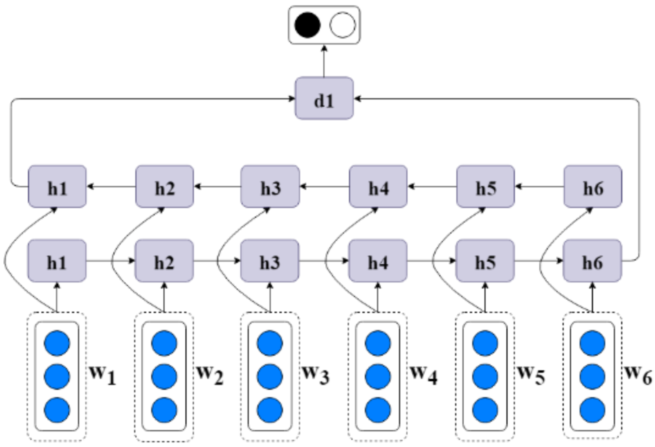


Fig. 4 Architecture of Bi-LSTM Model

**Training the Model**

In order to train the SA-Net sentiment analysis model, critical parameters such as training accuracy, validation accuracy, training loss, and validation loss after ten epochs with dropout are taken into consideration. In order to offer an estimation of the trained models, these parameters are calculated using a learning rate of 0.00001 and SGD optimization. This allows for the estimation to be provided. An assessment of the degree to which the training models have been overfit is provided by these parameters, which are calculated in order to produce this estimation.

## RESULTS AND DISCUSSION

Using standard deep learning methods, we have assessed the suggested efficient SA-Net sentiment analysis for the twitter data. A system with an i5 CPU, 8 GB of RAM, and 1 TB of hard drive was used to construct the suggested model using the Anaconda IDE tools and Python.

## Performance Metrics

Precision (Prec.): Precision is used to calculate the proportion of correctly predicted instances over all predictions. The precision can be measured as follow:

$$Prec. = \frac{tp}{tp+fp} \quad (2)$$

Recall (Rec.): Recall is the proportion of correctly predicted occurrences over all instances.

$$Rec. = \frac{tp}{tp+fn} \quad (3)$$

Accuracy (Acc.): The number of correct predictions divided by the total number of input samples generates the accuracy metric.

$$Acc. = \frac{tp+fp}{tp+fp+tn+fn} \quad (4)$$

F1-Score (F1-Sc.): To balance the precision and recall measures, the F1-measure (harmonic mean) is used. The following formula can be used to determine the F1- score:

$$F = 2 \times \frac{Prec. \times Rec.}{Prec. + Rec.} \quad (5)$$

## Result and Discussions

In this section, we conducted a detailed evaluation of different SA-Net models, namely 1D-CNN, LSTM and Bi-LSTM to assess their performance on the given twitter sentiment analysis dataset. For each model, critical performance metrics such as accuracy, precision, recall, and F1-score were computed and summarized in Table 1 for a comprehensive comparison. The 1D-CNN model emerged as the best-performing model, achieving the highest classification accuracy of 95.88%, along with commendable scores across the other metrics, highlighting its robustness in distinguishing between classes. On the other hand, the Bi-LSTM demonstrated the lowest classification accuracy of 93.88%, which suggests that it may struggle with certain patterns or complexities in the dataset.

Table 1 Performance analysis of SA-Net sentiment analysis model

| S. No. | SA-Net Model | Acc. | Prec. | Rec. | F1-Sc. |
|---|---|---|---|---|---|
| 1. | 1D-CNN | 95.88 | 95.77 | 95.72 | 95.75 |
| 2. | LSTM | 94.38 | 94.32 | 94.12 | 94.21 |
| 3. | Bi-LSTM | 93.88 | 93.82 | 93.82 | 93.82 |

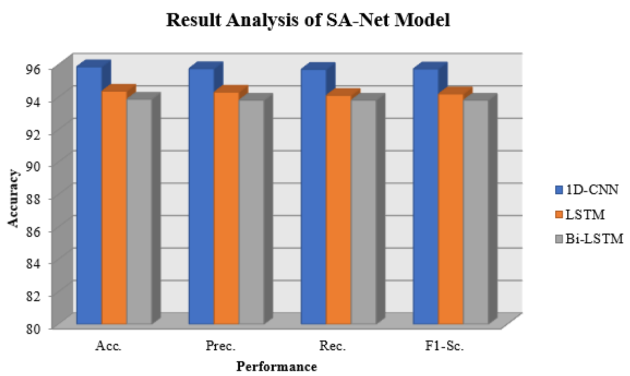


Fig. 5 Performance analysis of proposed rice leaf disease system

The comparative performance of several SA-Net sentiment analysis models, including 1D-CNN, LSTM and Bi-LSTM, is thoroughly presented in Table 1 and visually illustrated in Figure 5. Table 1 highlight that 1D-CNN consistently outperforms other deep learning models in terms of key performance metrics, such as accuracy, precision, recall, and F1-score. Furthermore, the confusion matrix of the different SA-Net sentiment analysis models, as shown in Figure 6 to Figure 8.

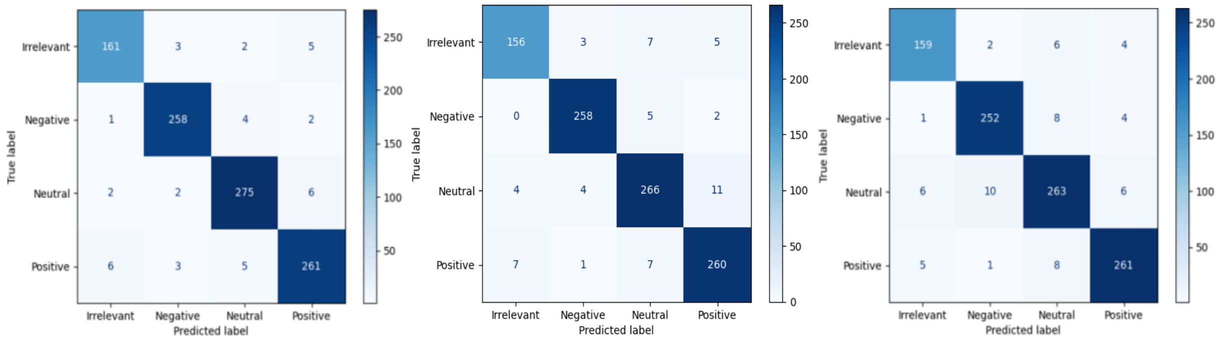


Fig. 6- Fig.8 CM of 1D-CNN, LSTM and Bi-LSTM SA-Net Model

The performance training accuracy, validation accuracy and losses of different SA-Net sentiment analysis is shown in Figure 9 to Figure 11.

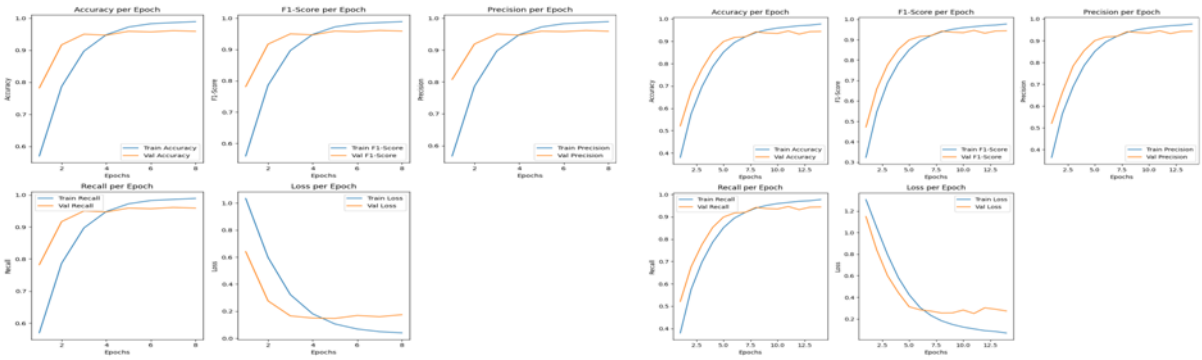


Fig. 9- Fig.10 Accuracy and Loss of 1D-CNN, LSTM SA-Net Model

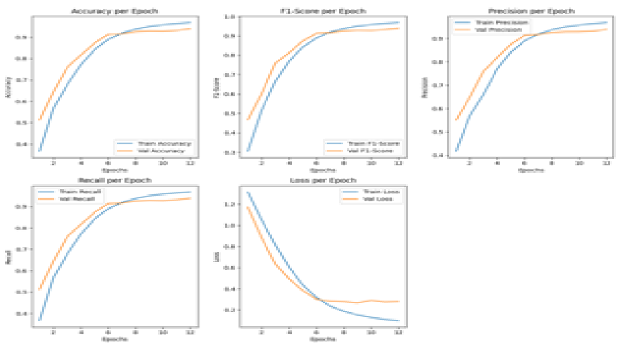


Fig.11 Accuracy and Loss of Bi-LSTM SA-Net Model

## CONCULSION

This study shows that deep learning models like 1D-CNN, LSTM, and Bi-LSTM can effectively tackle the challenges of sentiment analysis on Twitter. Tweets often contain informal language and context-dependent expressions, making it difficult to classify sentiment accurately. By using techniques like tokenization, stopword removal, and handling emoticons and hashtags, we prepared the data for the models. We also used pre-trained word embeddings like GloVe and Word2Vec to improve the models' understanding of the meaning behind words. The results showed that while all three models performed well, the 1D-CNN model was the most effective, achieving the best accuracy. This highlights CNN's ability to capture important patterns in text, even with short and noisy tweet data. Overall, this research demonstrates that deep learning models, especially CNNs, are powerful tools for analyzing sentiment in social media and can be applied in real-time monitoring systems for areas like customer feedback, market trends, and social media campaigns.

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