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ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

Hierarchical Bi-LSTM based emotion analysis of textual data

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Abstract. Nowadays, Twitter is one of the most popular microblogging sites that is generating a massive amount of textual data. Such textual data is intended to incorporate human feelings and opinions with related events like tweets, posts, and status updates. It then becomes difficult to identify and classify the emotions from the tweets due to their restricted word length and data diversity. In contrast, emotion analysis identifies and classifies different emotions based on the text data generated from social media platforms. The underlying work anticipates an efficient category and prediction technique for analyzing different emotions from textual data collected from Twitter. The proposed research work deliberates an enhanced deep neural network (EDNN) based hierarchical Bi-LSTM model for emotion analysis from textual data; that classifies the six emotions mainly sadness, love, joy, surprise, fear, and anger. Furthermore, the emotion analysis result obtained by the proposed hierarchical Bi-LSTM model is being compared and validated with the traditional hybrid CNN-LSTM approach regarding the accuracy, recall, precision, and F_1-Score. It can be observed from the results that the proposed hierarchical Bi-LSTM achieves an average accuracy of 89% for emotion analysis, whereas the existing CNN-LSTM model achieved an overall accuracy of 75%. This result shows that the proposed hierarchical Bi-LSTM approach achieves desired performance compared to the CNN-LSTM model.

Key words: emotion analysis; machine learning; emotion detection; deep learning; hierarchical Bi-LSTM.

1. INTRODUCTION

The evolution of social media platforms has recently increased textual data generation. Social media platforms help in creating virtual bonds between multiple users by allowing them to express their opinions and share their ideas with other users instantly [1]. Twitter is one such popular social media platform that is growing at a faster pace. Twitter is a micro-blogging site where users can post using short texts called tweets. This platform has resulted in the significant transformation of conventional text-sharing media. The tweets shared by the users have been used to collect essential and valuable information that they can share with multiple users [2]. The empirical analysis of the semantic information obtained from the Twitter data is called sentiment analysis (SA) [3–7]. SA is typically a method used to identify and categorize the emotions and opinions of a given text depending on the text polarity [8]. The primary goal of the SA is to determine whether the reader has positive or negative sentiment based on the standard categorization [9]. These techniques achieve superior efficiency for segmentation, classification of opinions, emotions, and sentiments from the textual data [10]. Analysis of emotions during critical circumstances can be challenging since these situations possess high uncertainty and mixed feelings. Existing research works on the classification [11–15] of different sentiments from short texts employ two techniques mainly: opinion lexicon and natural language processing (NLP) [16]. The majority of the semantic analysis approaches use the sentiment lexicon for recognizing emotional keywords for classification. However, it is not practical to analyze the sentiment based on a few emotional keywords since these keywords do not represent the sentiment of an entire sentence. Besides, there are chances that some of the important factors, such as logical relation between words, might be neglected. Hence, in most of the existing approaches, the semantic relations and the cognitive factors used for producing the sentiments [17] are given minor prominence. The evolution of machine learning (ML) [18, 19] and deep learning (DL) techniques offer potential solutions to these problems and improve the accuracy of sentiment classification [20, 21]. The proposed research aims to effectively analyze the emotions of the users based on textual data from social media sites and to predict sentiments using machine learning algorithms [22, 23]. This research uses an ML-based hybrid CNN-LSTM as an existing approach for comparative analysis and proposes EDNN based hierarchical Bi-LSTM model for emotion analysis. The remaining article is organized as follows: Section 2 gives a concise review of related research on emotion analysis using various ML approaches. Section 3 discusses the research methodology. Section 4 explains the proposed hierarchical Bi-LSTM Model used for emotion analysis from textual data. Section 5 discusses the results of the proposed approach and the comparison with the existing hybrid CNN-LSTM model, and Section 6 concludes the paper by providing a summary of the research and prominent observations from the results.

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1.1. Problem statement

Various researchers have proposed several techniques for accurate emotion analysis and sentiment prediction.

However, emotion analysis from Twitter data has several challenges:

- The data obtained in tweets are generally in short text lengths with incomplete information, which makes it difficult for the classifier to identify different emotions based on the restricted word length.
- The Twitter data is rich in data diversity, i.e., it incorporates various emotions and sentiments hidden in a single tweet. Besides, the tweets have several implicit complex features that are difficult to analyze.
- Most of the approaches used for emotion analysis and sentiment prediction work effectively for a limited number of emotions resulting in inaccurate predictions. Unwanted features and false data deteriorate the efficiency of the classification models.

1.2. Primary objective

The primary objective of this proposed work is to develop an effective emotion classification model based on textual data to analyze different emotions. The proposed approach comprises a hierarchical Bi-LSTM model for extracting word sequence and word semantic features for emotion analysis.

The main contribution of the proposed research is summarized in the points below:

- This research proposes a hierarchical Bi-LSTM approach for analyzing different emotions from textual data. The hierarchical Bi-LSTM combines two or more Bi-LSTMs and can learn complex contextual features and semantic information from the Twitter data.
- The experimental analysis was based on the real dataset collected from Kaggle, the emotions dataset for NLP classifying six dimensions of emotions such as surprise, love, fear, anger, sadness, and joy (https://www.kaggle.com/praveengovi/emotions-dataset-for-nlp).
- The findings obtained are compared with pre-existing CNN-LSTM model with various performance metrics such as F_1 Score, Recall, Accuracy, and Support to verify the efficacy of the proposed method.

2. RELATED WORK

Emotion analysis from textual data has gained vast significance in recent years. Emotion analysis identifies an individual's emotions from the text, speech, or action using suitable approaches. The main objective of these approaches is to develop an intelligent model capable of perceiving, recognizing, and understanding human emotions. Various researchers have proposed different techniques that use classifiers for analyzing emotions from textual data. This section discusses some of the major works done in this context.

Wang *et al.* (2020) [24] suggested two different deep neural network-based models CNN-LSTM2 and second CNN-LSTM2-STACK, for predicting six different emotions such as anger, joy, surprise, love, fear, and sadness. CNN-LSTM2 model is constructed into two parts; in this model, there is a problem of vanishing gradient. That is why it is fragile in deep back-propagation. To solve this vanishing gradient problem, the authors suggested the CNN-LSTM2-STACK model. The authors use short and long text as inputs for their proposed model. This research article used three different datasets: the news articles' Title, Body, and Comments. Xu *et al.* (2020) [25] suggested a hybrid 3D Conventional LSTM (Conv LSTM) model that can categorize visual emotions, and they also suggested a hybrid CNN and recurrent neural network (RNN) model for categorization of textual emotions such as angry, happy, sad, and neutral. Chatterjee *et al.* (2019) [26] proposed a novel DL-based model for detecting different emotions from the textual dialogues such as happy, angry, and sad. The primary objective of this research was to combine both sentiment and semantic-based representations for obtaining accurate and precise emotion detection. The study combined semi-automated methods for collecting large amounts of training data with various defining emotions to train the proposed model. The proposed model was evaluated based on real-time dialogue-based datasets. The potential of the proposed approach was assessed by examining it in practical scenarios. It was observed from the results that this DL-based model showed remarkable performance compared to conventional ML algorithms and other deep learning models. Akhtar *et al.* (2019) [27] proposed a practical deep learning-based multi-task learning approach for performing emotion recognition and sentiment analysis. The study implemented a three bi-directional gated recurrent unit (biGRU) network to extract the contextual data. The multimodal inputs such as speech, optical frames, and textual data obtained from the video datasets do not contribute to the decision-making process due to uncertainties in the multimodal data. A context-level inter-modal attention approach was proposed to overcome this in the research that simultaneously predicts the sentiment and identifies the emotions precisely. Evaluated the potency of the biGRU by testing it on the CMU-MOSEI dataset. Results demonstrated that the developed biGRU technique showed significant enhancement compared to the single-task approach. Additionally, the suggested method gives an advanced state-of-the-art output for emotion analysis and sentiment prediction. Poria *et al.* (2019) [28] proposed an analysis for emotion recognition that includes analysis of main research challenges, various techniques, and recent technological advancements related to emotion recognition. This research work provides a thorough review of recent progress and how these advancements are used to overcome the limitations of conventional emotion recognition models. The study summarized the effectiveness of the emotion-shift recognition model and context encoder capable of yielding superior efficiency and enhancing the functionalities of the task-based dialogues. Lastly, the study stated that fine-grained speaker-specific continuous emotion recognition could emerge as one of the main approaches for understanding emotions during long monologues.

3. RESEARCH METHODOLOGY

This research aims to analyze the emotions from the text messages from social media sites to understand the user's feelings. This research uses an enhanced deep neural network-based hierarchical Bi-LSTM model for emotion analysis. The study also uses a hybrid convolutional neural network (CNN) and LSTM based models as an existing approach. The performance of the proposed hierarchical Bi-LSTM model will be compared with the hybrid CNN-LSTM model to validate its effectiveness. The Workflow of the proposed approach is as follows:

3.1. Data extraction

Extraction of data is the initial stage that involves selecting input data in the form of text from the Twitter database. The dataset (tweet corpus) is appropriate for emotion analysis extracted from Twitter. The emotions dataset for NLP is available at Kaggle. In this dataset, 20 000 rows and two columns with six labels, including 719 rows for surprise, 1641 rows for love, 2373 rows for fear, 2709 rows for anger, 5797 rows for sadness, and 6761 rows for joy. This paper uses an 80:20 ratio for the training and testing dataset, 16 000 rows for training data, and 4000 rows for testing data.

3.2. Data preprocessing

The data is obtained from a microblogging site (Twitter). Data pre-processing is the basic step of feature extraction [29], emotion classification. The main operation of the preprocessing stage is to remove unwanted noise, inconsistency, and redundancy from the textual data. Generally, the obtained data will be raw and contain noise, incompleteness, and inconsistencies. Hence it is essential to perform data preprocessing to process the data and make it suitable for further processing. Various activities such as stemming, lemmatization, stop words removal, etc., are performed in this stage. Preprocessing of tweets is performed using the following steps:

- Removal of all URLs, hash-tags (#content) and targets (@username).
- Removal of unnecessary numbers, symbols, and punctuations.
- Common stop words are eliminated.
- Converting all the tweets into the lower case makes the dataset uniform.
- Removal of all redundant characters and words from the tweets.

3.3. Feature extraction and selection

During this phase, all the necessary features are extracted, which is helpful for formulating the main characteristics of the text. This is advantageous in identifying valuable words from the text which express an opinion or a sentiment. In this stage, new feature subsets are obtained to select relevant and appropriate features from the text. The study uses a Bi-LSTM to extract relevant features from the textual data and chooses the right features for recognizing the emotion.

3.4. Emotion recognition

This study proposes an EDNN-based hierarchical Bi-LSTM model for emotion recognition. The model will map the input text to the corresponding class of emotion based on the data set samples in the training phase. The feature vectors and related class labels will be supplied to the deep learning model. The feature extractor is employed to obtain feature vectors from a new and unseen text in the prediction process. The model will use these feature vectors to generate prediction results.

4. PROPOSED HIERARCHICAL BI-LSTM FOR EMOTION ANALYSIS

The process flow of the proposed approach for emotion analysis is illustrated in Fig. 1. This architecture consists of two modules: the data preparation and the emotion extraction module. Initially, the obtained dataset is made suitable for testing by processing them. The obtained dataset is classified into subjective and neutral data. Personal textual information reflects positive and/or negative sentiment, while neutral textual information does not incorporate any feeling. Data preparation is performed in the data preparation module of the proposed approach, whereas the emotion extraction module in the model will extract the emotion from the processed data.

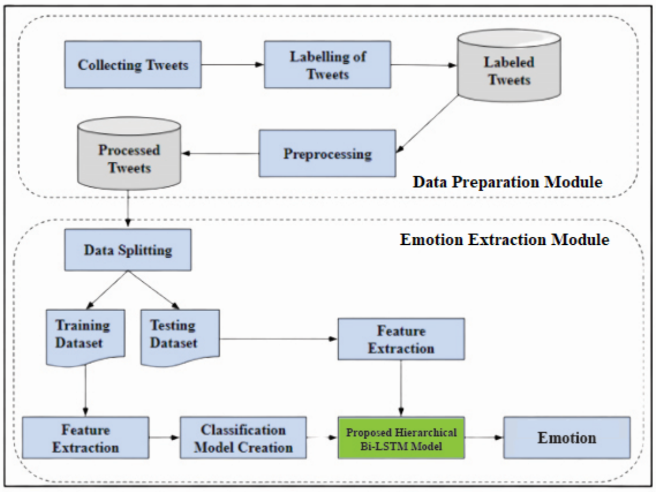

Fig. 1. Workflow of the proposed approach for emotion analysis

- **Data preparation module:** In this module, the obtained data is processed before feeding it to the classifier. On Twitter, users express their opinions and emotions in short texts. The collected tweets are subjected to cleaning wherein the tweets containing links to other multimedia systems and re-tweets are eliminated. Further, the tweets are labeled manually based on emotions. In this research, the tweets are labeled based on six emotions: sadness, love, joy, surprise, fear, and anger. Tweets containing no emotions are labeled as neutral tweets. As discussed in the previous section, preprocessing eliminates irrelevant parts from the collected tweets. Pre-processing is important since it influences the accuracy of the classifier. Tokenization preprocessing of tweets is performed, wherein the text is segmented into a sequence of words, phrases, symbols, and other relevant units called tokens. Tokenization also eliminates certain symbols such as punctuations.
- **Emotion extraction module:** This is a crucial module wherein the emotions from the text data are extracted and

classified using the six emotional classes. In this approach the tweets are represented via feature vectors because the classifier predicts the different emotions. The emotion extraction module is constructed using Bi-LSTM. The LSTM technique in hierarchical Bi-LSTM enhances the caliber of learning for long-time sequential data and is more appropriate for evaluating the time-dependent word sequence. The detailed architecture of the hierarchical Bi-LSTM for emotion analysis is discussed below.

4.1. Structure of hierarchical Bi-LSTM for emotion analysis

In the proposed approach, the hierarchical BiLSTM will be used for classifying the emotions from the obtained textual data. The proposed hierarchical Bi-LSTM model architecture is illustrated in Fig. 2. The architecture of hierarchical Bi-LSTM consists of two or more Bi-LSTMs connected. In the proposed approach, two Bi-LSTMs are connected in forward and backward directions to constitute hierarchical Bi-LSTM. This arrangement strengthens the efficiency of the system architecture for emotion analysis, where different emotions are classified accurately. The four layers of the hierarchical Bi-LSTM obtain detailed contextual information from both past and future scenarios. Compared to conventional Bi-LSTM, hierarchical Bi-LSTM consists of more upper layers for extracting relevant features. As shown in Fig. 2, for time sequence K, the input sequence $\{z_1, z_2, \dots, z_K\}$ enters the network through hidden layers of the input in the forward direction i.e.$\{\overrightarrow{a_1}, \overrightarrow{a_2}, \dots, \overrightarrow{a_K}\}$ for acquiring detailed contextual information from all the past time sequences, and further it passes through hidden layers in the backward direction $\{\overleftarrow{a_1}, \overleftarrow{a_2}, \dots, \overleftarrow{a_K}\}$ for acquiring detailed contextual information from all the future time sequences. Step at each point, the upper hidden layers of the hierarchical BiLSTM extract the outputs from the lower hidden layers as their inputs for extracting the remaining features. Especially the upper layers of the forward hidden layers $\{\overrightarrow{b_1}, \overrightarrow{b_2}, \dots, \overrightarrow{b_K}\}$ and backward hidden layers $\{\overleftarrow{b_1}, \overleftarrow{b_2}, \dots, \overleftarrow{b_K}\}$. Finally, the output layer of the hierarchical Bi-LSTM integrates the hidden vector of the two upper layers to generate a combined output. As shown in Fig. 2 above, each LSTM cell of the hidden layer is represented in the form of a node that has a new input gate (i_k), forget gate

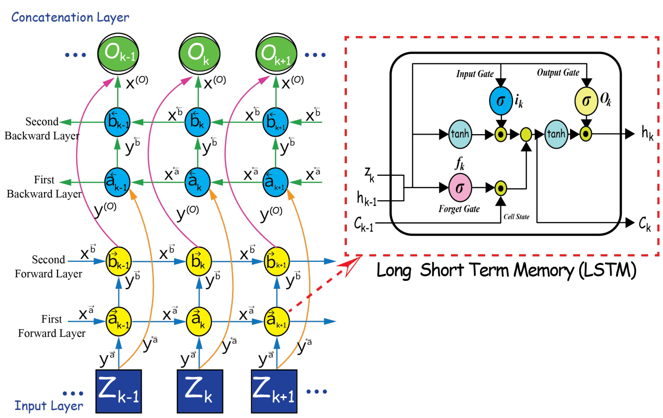

Fig. 2. Architecture of the hierarchical BiLSTM for emotion classification

(f_k), memory unit (u_k), and output gate (o_k).The new memory defines the value of the new input, and now the input gate stores the new data in its cell. Forget gate represents the data dumped from the cell state, and the output gate generates the required output. The control parameter C_k controls the mechanism of data storing and dumping. The hidden states of each layer ($\overrightarrow{a_k}, \overleftarrow{a_k}, \overrightarrow{b_k}$, and $\overleftarrow{b_k}$) of the hierarchical Bi-LSTM at each time step k is calculated as:
The hidden state $\overrightarrow{a_k}$ of the first forward layer is expressed in the equations below:

$$i_k^{\vec{a}} = \sigma\left(Y_i^{\vec{a}} z_k + X_i^{\vec{a}} \overrightarrow{a}_{k-1} + b_i^{\vec{a}}\right), \tag{1}$$

$$f_k^{\vec{a}} = \sigma\left((Y_f^{\vec{a}} z_k + X_f^{\vec{a}} \overrightarrow{a}_{k-1} + b_f^{\vec{a}}\right), \tag{2}$$

$$o_k^{\vec{a}} = \sigma\left((Y_o^{\vec{a}} z_k + X_o^{\vec{a}} \overrightarrow{a}_{k-1} + b_o^{\vec{a}}\right), \tag{3}$$

$$u_k^{\vec{a}} = \tanh\left((Y_u^{\vec{a}} z_k + X_u^{\vec{a}} \overrightarrow{a}_{k-1} + b_u^{\vec{a}}\right), \tag{4}$$

$$C_k^{\vec{a}} = i_k^{\vec{a}} \odot u_k^{\vec{a}} + f_k^{\vec{a}} \odot C_{k-1}^{\vec{a}}, \tag{5}$$

$$\overrightarrow{a_k} = o_k^{\vec{a}} \odot \tanh\left((C_k^{\vec{a}}\right), \tag{6}$$

The hidden state $\overrightarrow{b_k}$ of the second forward layer is expressed in the equations below:

$$i_k^{\vec{b}} = \sigma\left(Y_i^{\vec{b}} \overrightarrow{a_k} + X_i^{\vec{b}} \overrightarrow{b}_{k-1} + b_i^{\vec{b}}\right), \tag{7}$$

$$f_k^{\vec{b}} = \sigma\left(Y_f^{\vec{b}} \overrightarrow{a_k} + X_f^{\vec{b}} \overrightarrow{b}_{k-1} + b_f^{\vec{b}}\right), \tag{8}$$

$$o_k^{\vec{b}} = \sigma\left(Y_o^{\vec{b}} \overrightarrow{a_k} + X_o^{\vec{b}} \overrightarrow{b}_{k-1} + b_o^{\vec{b}}\right), \tag{9}$$

$$u_k^{\vec{b}} = \tanh\left(Y_u^{\vec{b}} \overrightarrow{a_k} + X_u^{\vec{b}} \overrightarrow{b}_{k-1} + b_u^{\vec{b}}\right), \tag{10}$$

$$C_k^{\vec{b}} = i_k^{\vec{b}} \odot u_k^{\vec{b}} + f_k^{\vec{b}} \odot C_{k-1}^{\vec{b}}, \tag{11}$$

$$\overrightarrow{b_k} = o_k^{\vec{b}} \odot \tanh\left(C_k^{\vec{b}}\right). \tag{12}$$

The hidden state $\overleftarrow{a_k}$ of the first backward layer is expressed in the equations below:

$$i_k^{\overleftarrow{a}} = \sigma\left(Y_i^{\overleftarrow{a}} z_k + X_i^{\overleftarrow{a}} \overleftarrow{a}_{k+1} + b_i^{\overleftarrow{a}}\right), \tag{13}$$

$$f_k^{\overleftarrow{a}} = \sigma\left(Y_f^{\overleftarrow{a}} z_k + X_f^{\overleftarrow{a}} \overleftarrow{a}_{k+1} + b_f^{\overleftarrow{a}}\right), \tag{14}$$

$$o_k^{\overleftarrow{a}} = \sigma\left(Y_o^{\overleftarrow{a}} z_k + X_o^{\overleftarrow{a}} \overleftarrow{a}_{k+1} + b_o^{\overleftarrow{a}}\right), \tag{15}$$

$$u_k^{\overleftarrow{a}} = \tanh\left(Y_u^{\overleftarrow{a}} z_k + X_u^{\overleftarrow{a}} \overleftarrow{a}_{k+1} + b_u^{\overleftarrow{a}}\right), \tag{16}$$

$$C_k^{\overleftarrow{a}} = i_k^{\overleftarrow{a}} \odot u_k^{\overleftarrow{a}} + f_k^{\overleftarrow{a}} \odot C_{k-1}^{\overleftarrow{a}}, \tag{17}$$

$$\overleftarrow{a_k} = o_k^{\overleftarrow{a}} \odot \tanh\left(C_k^{\overleftarrow{a}}\right). \tag{18}$$

The hidden state $\overleftarrow{b_k}$ of the second backward layer is expressed in the equations below:

$$\overleftarrow{i}_k^b = \sigma\left(Y_i^{\overleftarrow{b}} \overleftarrow{a_k} + X_i^{\overleftarrow{b}} \overleftarrow{b}_{k+1} + b_i^{\overleftarrow{b}}\right), \tag{19}$$

$$\overleftarrow{f}_k^b = \sigma\left(Y_f^{\overleftarrow{b}} \overleftarrow{a_k} + X_f^{\overleftarrow{b}} \overleftarrow{b}_{k+1} + b_f^{\overleftarrow{b}}\right), \tag{20}$$

$$\overleftarrow{o}_k^b = \sigma\left(Y_o^{\overleftarrow{b}} \overleftarrow{a_k} + X_o^{\overleftarrow{b}} \overleftarrow{b}_{k+1} + b_o^{\overleftarrow{b}}\right), \tag{21}$$

$$\overleftarrow{u}_k^b = \tanh\left(Y_u^{\overleftarrow{b}} \overleftarrow{a_k} + X_u^{\overleftarrow{b}} \overleftarrow{b}_{k+1} + b_u^{\overleftarrow{b}}\right), \tag{22}$$

$$\overleftarrow{C}_k^b = \overleftarrow{i}_k^b \odot \overleftarrow{u}_k^b + \overleftarrow{f}_k^b \odot \overleftarrow{C}_{k-1}^b, \tag{23}$$

$$\overleftarrow{b_k} = \overleftarrow{o}_k^b \odot \tanh\left(\overleftarrow{C}_k^b\right). \tag{24}$$

The output O_k is represented as the integrated hidden vector form of the second forward layer $\overrightarrow{b_k}$ and the second backward layer $\overleftarrow{b_k}$ at each stage k, represented as the hidden vector form of the second forward layer $\overrightarrow{b_k}$ and the second backward layer $\overleftarrow{b_k}$ [30]:

$$O_k = Y^{(O)} \overrightarrow{b_k} + X^{(O)} \overleftarrow{b_k} + b^{(O)}. \tag{25}$$

In the proposed model, the hierarchical Bi-LSTM defines the contextual features from past and future time steps and integrates the features of both past and future time steps as the output of the proposed hierarchical Bi-LSTM.

The algorithm of hierarchical Bi-LSTM for emotion Analysis is illustrated in Algorithm 1.

Algorithm 1 Hierarchical BiLSTM model

Input: Labelled Tweet Dataset
Preprocessing:
Removal of redundant words
Trimming the dataset
Stemming the dataset
Extraction of textual data from a tweet:
Extraction of adjectives from extracted tweets:
Combine step 1 and 2:
Preprocessed file =file path name
Stop word file list=path name of file
Extracted tweets=file path of extracted tweets list
Control the data flow through BiLSTM gates
if
the value of sigmoid function = 1
the data is passed through the gates
else
no data flow through the gates
Control the output of the sigmoid function
Emotion Classification
Obtain the textual feature
Provide the textual feature as input to BiLSTM
Obtain the textual feature representation
Determine the output of Bi-LSTM emotion (O_t) **for the input sequence** z_t
Classify the emotions (O_t) = {Sadness, Love, Joy, Fear, Anger}
end

5. RESULT AND DISCUSSION

Performance of the proposed hierarchical Bi-LSTM model was evaluated based on various performance metrics such as F_1 Score, Recall, Accuracy, and Support. The experimental results for emotion recognition are illustrated in the below sections, and the effectiveness of the proposed approach was measured using the confusion matrix.

5.1. Activation functions

The activation function [31] is considered the building block of the neural network [32]. This research uses a sigmoid function as an activation function for the proposed hierarchical Bi-LSTM. In this research, the sigmoid function S is used as an activation function that is denoted as (26):

$$S = \frac{1}{\left(1+e^{(-x)}\right)}. \tag{26}$$

5.2. Confusion matrix

The confusion matrix is mainly used for solving the problems related to classification accuracy where the output can be two or more classes. Confusion matrix is a table with four different combinations of predicted and actual values as shown in Fig. 3: The terms TP represents true positive, FP is false positive, FN is false negative, and TN is true negative. The confusion matrix in this research is used for measuring Recall, Precision, Specificity, Accuracy, and the Receiver operating characteristics (ROC) curve [33]. The performance metrics are evaluated as:

- **Accuracy:**

$$\text{Accuracy} = \frac{(\text{(No. of Correctly Labeled Tweets)})}{(\text{(Total Number of Tweets in the Test Set)})}. \tag{27}$$

- **Precision:**

$$\text{Precision} = \frac{TP}{(TP+FP)}. \tag{28}$$

- **Recall:**

$$\text{Recall} = \frac{TP}{(TP+FN)}. \tag{29}$$

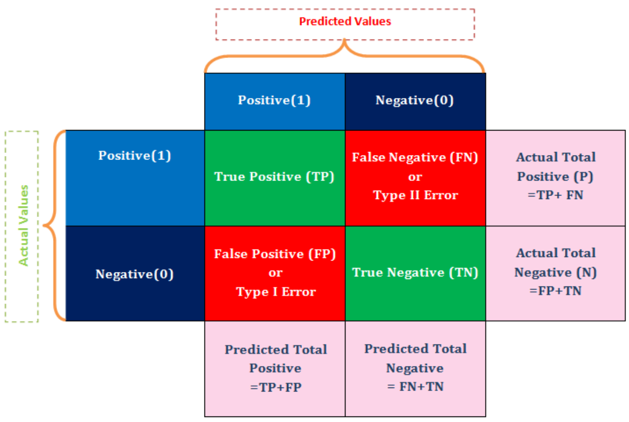

Fig. 3. Confusion matrix

• F_1 **Score:**

$$F_1 \text{ Score} = \frac{(2 * \text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}. \tag{30}$$

The ROC curve in this research is used to visualize the performance of the multi-class classification problem during emotion analysis. ROC curve is a probability curve that defines the capability of the proposed classifier in distinguishing between multiple classes. The ROC curve is defined by the terms True positive rate (TPR) or recall, or sensitivity as defined in equation (30). Other terms that define the ROC curve are specificity and false positive rates which are given as:

• **Specificity:**

$$\text{Specificity} = TN/(TN + FP). \tag{31}$$

• **False Positive Rate (FPR):**

$$\text{FPR} = 1 - \text{Specificity}. \tag{32}$$

5.3. Hierarchical Bi-LSTM for emotion analysis

The loss function and accuracy of the hierarchical Bi-LSTM is given in Figs. 4 and 5, respectively. It can be observed from the above figures that the loss function significantly reduces after training the hierarchical Bi-LSTM model effectively. The significant improvement in the accuracy of the model can be observed from Fig. 5 where the trained Bi-LSTM model achieved an accuracy of approximately 0.89. The classification data of hierarchical Bi-LSTM for emotion analysis is illustrated in Table 1. The confusion matrix of hierarchical Bi-LSTM for the emotion analysis is illustrated in Fig. 6. The confusion matrix was constructed for six different emotions such as sadness, surprise, love, joy, fear, and anger, and the values for the true label were plotted against the predicted label. The ROC curve is presented in Fig. 7. The ROC curve determines the true and false-positive rates. The area under curve (AUC) is approximately 0.95.

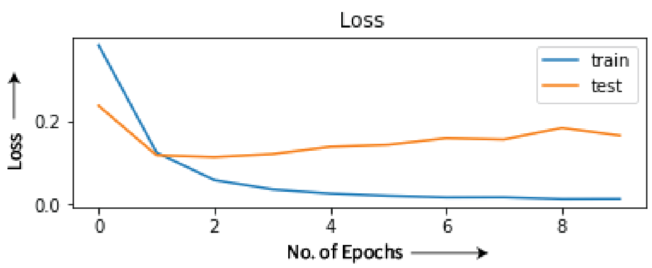

Fig. 4. Loss function of hierarchical Bi-LSTM for emotion analysis

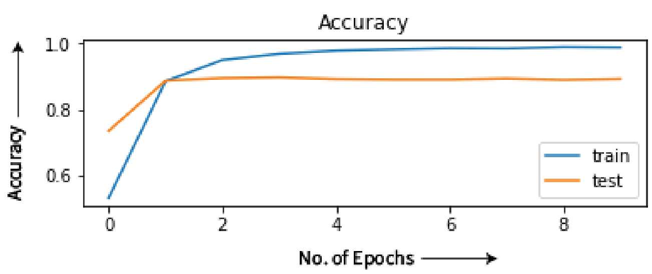

Fig. 5. Accuracy of hierarchical Bi-LSTM for emotion analysis

Table 1
Classification data of hierarchical Bi-LSTM for emotion analysis

Emotions	Precision	Recall	F_1 Score	Support
Anger	0.90	0.90	0.90	536
Fear	0.87	0.82	0.84	458
Joy	0.90	0.92	0.91	1339
Love	0.78	0.70	0.74	335
Sadness	0.95	0.92	0.93	1173
Surprise	0.80	0.73	0.76	159
micro avg	0.90	0.88	0.89	4000
macro avg	0.87	0.83	0.85	4000
weighted avg	0.90	0.88	0.89	4000
samples avg	0.88	0.88	0.88	4000

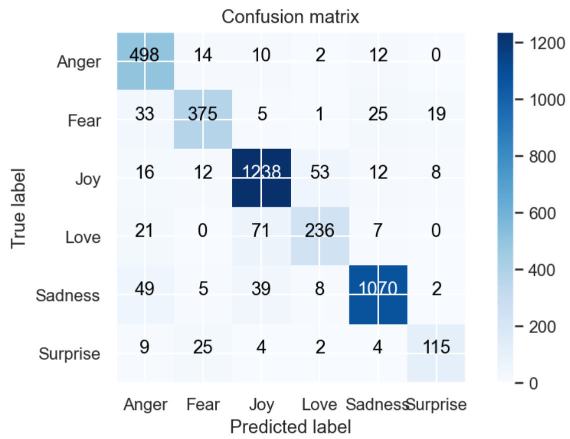

Fig. 6. Confusion matrix of proposed hierarchical Bi-LSTM

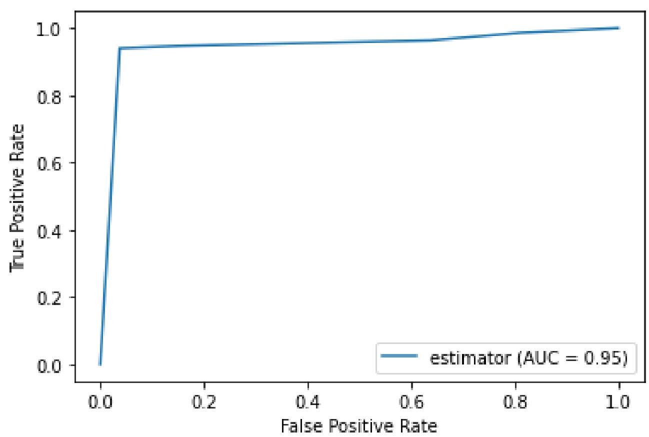

Fig. 7. Region of curve (ROC) of hierarchical Bi-LSTM

5.4. Hybrid CNN-LSTM for emotion analysis

The loss function and accuracy of the hybrid CNN-LSTM are given in Figs. 8 and 9 respectively. It can be observed from the above figures that the loss function reaches a lower value for the trained Hybrid CNN-LSTM data. The classification data of hybrid CNN-LSTM for emotion analysis is illustrated in Table 2. The ROC curve is presented in Fig. 10. The ROC curve determines the true and false positive rates. The area under curve (AUC) is approximately 0.80.

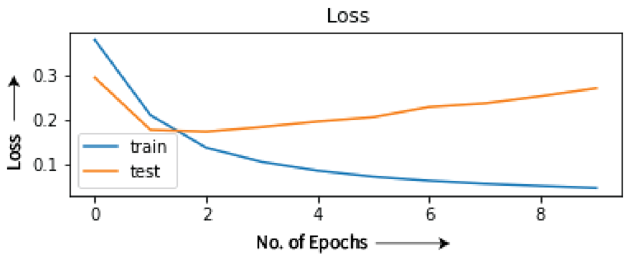

Fig. 8. Loss function of hybrid CNN-LSTM for emotion analysis

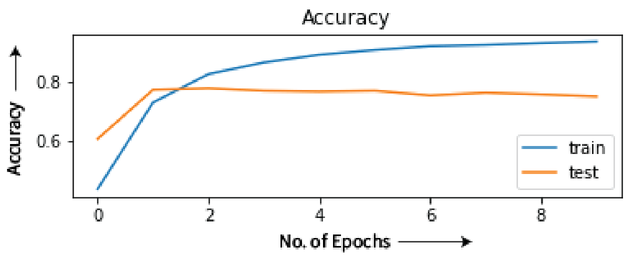

Fig. 9. Accuracy of hybrid CNN-LSTM for emotion analysis

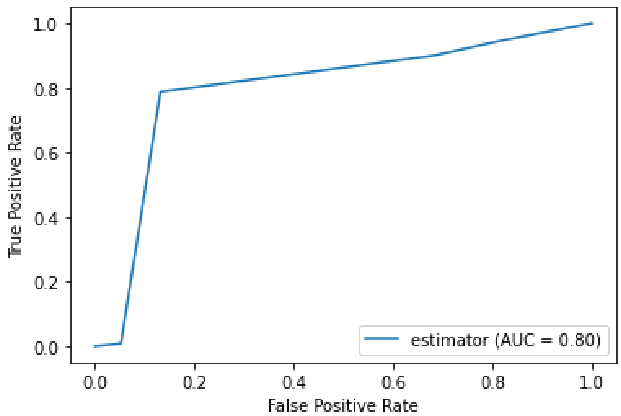

Fig. 10. ROC of Hybrid CNN-LSTM for emotion analysis

Table 2
Classification data of hybrid CNN-LSTM for emotion analysis

Emotions	Precision	Recall	F_1 Score	Support
Anger	0.74	0.55	0.63	536
Fear	0.71	0.58	0.63	458
Joy	0.80	0.63	0.70	1339
Love	0.60	0.50	0.55	335
Sadness	0.76	0.63	0.69	1173
Surprise	0.76	0.63	0.69	159
Micro Avg	0.75	0.60	0.67	4000
Macro Avg	0.72	0.58	0.64	4000
Weighted Avg	0.75	0.60	0.67	4000
Samples Avg	0.60	0.60	0.60	4000

5.5. Performance comparison

The performance of the proposed hierarchical Bi-LSTM is compared with the existing CNN-LSTM approach, and the results are tabulated above. It can be observed from the effects that the proposed Bi-LSTM achieves an average accuracy of 89% for emotion analysis. In contrast, the existing CNN-LSTM method achieved an overall accuracy of 75%. This shows that the proposed approach achieves desired performance compared to CNN-LSTM.

6. CONCLUSION

The proposed research work resulted in an efficient hierarchical Bi-LSTM model based on Enhanced Deep Neural Network for emotion analysis using textual data from social media platforms. Emotion analysis is performed on six different emotions: sadness, love, joy, surprise, fear, and anger. The model was experimentally evaluated with the data collected from Twitter. The proposed hierarchical Bi-LSTM model was assessed on performance metrics such as F_1 score, recall, precision, support, and accuracy. The performance of the proposed approach was then compared with the existing hybrid CNN-LSTM method. The proposed technique for emotion analysis is also validated with an average of 89% accuracy, which is superior in respect to the hybrid CNN-LSTM approach with 75% overall accuracy. This performance accuracy of emotion analysis can be enhanced in future work by deploying various other enhanced deep neural network techniques models.

DECLARATION OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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