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A Prediction of Twitter Sentiment Class using Bi-directional Long Short Term Memory with Self-Attention Layer Mechanism

D. Ramana Kumar[1], Dr. S. Krishna Mohan Rao[2]

[1] Research Scholar, Department of Computer Science and Engineering, JNTUH, Hyderabad, Telangana State, India

e-mail: ramanad74@gmail.com

[2] Principal, GIET, Bhubaneswar, Odisha, India, e-mail: krishnamohan6@yahoo.com

Abstract: In recent decade, the sentimental analysis using twitter data gained more attention among the researchers. Due to abbreviation, unstructured nature, misspeling, slang, and limited size, it is a challenging task for the examiners for finding the sentiments utilizing twitter data. In this work, a new hybrid system was proposed to improve the performance of sentiment analysis utilizing twitter data. Initially, the input data was collected from Sanders Twitter Corpus (STC) dataset. Then, the noises such as stop words, emoji's, and URLs were eliminated from the raw tweets in the pre-processing stage. In addition, the important features were extracted from the two important feature extraction techniques and the polarities of tweet were initialized. Then, Bidirectional Long Short Term Memory (BLSTM) was used for sentiment classification, where BLSTM performance was further enhanced by predicting the learning rate using Self-Attention (SA) mechanism. The experimental results were verified on STC database, and the results showed that the BLSTM-SA achieved 91.41% of accuracy, 96% of recall, 94% of f-score and 92% of precision, which were superior related to the existing methods: Random Forest (RF) and Support Vector Machine (SVM).

Key Words: Bidirectional long short term memory, feature extraction, sentiment analysis, self-attention layer, twitter, unstructured data**.**

1. INTRODUCTION

In recent decades, the social media websites are utilized to share the people opinions like review about the films, review about the products, advertising the business, etc. [1]. In that, twitter has a separate space, because it is easy to collect the information and also easy to understand the mutual relation between the users [2-3]. In addition, the twitter posts contain only 140 characters that means it just contains a piece of information about the products, films, any social activities, etc [4, 5]. It makes the mechanism of automatically performing sentiment or opinion classification using the twitter data. Several companies and institutions uses twitter data for identifying the feeling or mentality of the user about their products that helps to enrich their business [6, 7]. The process to examine the polarity of the twitter data is named as sentiment or opinion analysis. However, it is hard to find the user sentiments in massive data [8]. Recently, the twitter sentimental analysis gained more attention among the researchers, because it gives desiring information about the products review, film review, social activities, etc [9, 10].

The difficulties faced by the researchers in developing such applications are; (i) the domain-specific words and limited lexicons of emoticons results in poor classification of user sentiments, (ii) irregular, slang, insufficient words, and abbreviations are also leads to poor classification [11]. So, it is vital to develop an automated for detecting and analyzing the sentiments of user from the twitter data [12, 13]. Several approaches are developed by the researchers in automatic classification of sentiments such as SVM, decision tree, Naive Bayes, maximum entropy, etc [14]. The major issue in the existing methodologies is the quantification of relationship between the words in a tweet. In this research, a BLSTM model based on SA process was proposed for improving the classification performance, while dealing with twitter data. The Term Frequency-Inverse Document Frequency (TF-IDF) and counter vectorization were utilized to extract the features, where text blog was used for finding the polarity of the tweets. Then, the SA layer was used to increase the learning rate of data for predicting the sentiment analysis. Lastly, the BiLSTM was employed for classifying the polarity of the tweets such as negative, neutral or positive. The sanders dataset was used to validate the performance of BLSTM-SA with the existing methods by means of recall, precision, f-measure, MAE, RMSE, MSE accuracy, sensitivity, and specificity.

The remaining article is prepared as follows, discussion of several techniques along with its advantage and limitation is stated in section II. The explanation about the proposed BLSTM-SA is detailed in section III. Experimental validation of proposed method is indicated in section IV. Finally, the conclusions of the research work with future development are detailed in section V.

1.1 RELATED WORKS

In this subsection, a recent technique on sentiment analysis is discussed for identifying the people opinions about certain topics. In addition, the benefits and limitations of existing techniques are discussed.

A.P. Rodrigues, and N. N. Chiplunkar, [15] developed Hybrid Lexicon-Naive Bayesian Classifier (HLNBC) method for opinion mining. In real time applications, the developed method was worked with the labeled dataset and then filters the irrelevant tweets using lexicon model. The developed method mainly works well on large scale dataset. Though, the sarcastic twitter data leads to misclassification and results in poor opinion mining. The developed method didn't focus on how to filter the sarcasm sentiments, which leads poor classification accuracy. The experimental simulation was conducted on twitter dataset in light of precision, accuracy, f-measure, recall and execution time, which were utilized for validating the efficiency of HLNBC with NB and lexicon approach.

S.M. Nagarajan and Usha Devi Gandhi [16] developed a hybridization technique on the basis of genetic algorithm and particle swarm optimization for opinion classification. The hybrid technique with Decision Tree (DT) attains an accuracy of 90% in classifying the tweets into three classes; negative, neutral, and positive classes. While comparing with existing methods like SVM, KNN, DT and hybrid methods of SVM and KNN, the developed method attain good performance by means of accuracy, recall, f-measure, and precision. Due to the presence of misspelling, the developed approach may leads to misclassification of twitter data.

L. Terán, and J. Mancera, [17] presented a Dynamic Voting Advice Applications (DVAA) for 2017 Ecuadorian national election. In the implementation phase, the generation of a dictionary was in Spanish language. In this literature, RMSE was used as a parameter measure to validate the efficiency of DVAA. This dictionary was manually reviewed and cannot able to recover all word combination semantics. In order to provide better recommendation, DVAA gives only minimum information, because only 118 users were able to interact.

L. Wang, et al., [18] developed a new approach named as SentiDiff for analyzing the twitter sentiments. Initially, the relationship between the sentiment diffusion patterns and the textual information about the twitter messages were analyzed. Then, the experiments were conducted on twitter dataset and the parameters like recall, and area under curve were used for analyzing the performance of SentiDiff with TBM model and Deep-CNN. While combining sentiment diffusion data with textual data, the performance of SentiDiff was degraded due to the presence of negative influence.

Z. Jianqiang, et al, [19] utilized Deep Convolution Neural Network (DCNN) for user opinion classification on the basis of twitter data. The developed approach significantly extracts the context information from the tweet data that helps in the reduction of sparseness issue. The performance of DCNN was compared with existing methods in light of accuracy, recall, precision, and accuracy. The parameter values were too high, when the features extracted from the unlabeled micro blog messages that degrade the performance of proposed method (DCNN).

M. Z. Asghar, [20] presented a system to classify the tweets by utilizing hybrid schemes such as slang, emoticon, SWN and domain specific classifiers. The hybrid methodology was also known as T-SAF that was utilized to solve the issues of incorrect classification of sentiments. The T-SAF effectively detects and classifies the emoticons in the twitter data. The performance results of the hybrid method was good compared to some baseline approaches such as RF, SVM and KNN in terms of accuracy, precision, recall, and f-measure. Without performing a lookup operation in SWN, the problem of the developed approach was the lack of automated scoring in domain-specific words.

To overcome the above concerns, BLSTM with SA mechanism is proposed for predicting the opinion of the user about certain topics. In addition, the proposed method identified the polarities of tweets before extracting the features from the tweets. The brief description about the proposed work is given below.

II. PROPOSED METHODOLOGY

Generally, the machine learning approaches are utilized in opinion mining or sentiment analysis to analyze the collected text (twitter data). Recently, the opinion mining showed great interest among the researchers and developers [21]. In this work, the source data is collected from twitter for analyzing the people sentiments. In the social networks, twitter is a key platform for celebrities, scientists, politicians, etc. to share their opinions. The opinion mining is utilized for finding the polarity of opinions and emotions stated in the sentence that helps in understanding the individual’s behavior towards a specific topic [22]. The major concern in the data mining is to process the unstructured data that significantly increases the system complexity. Since, the prior approaches are failed to achieve good performance, due to increase in the data size.

So, this research work develops a BLSTM-SA method for identifying the sentiment of the user effectively. The polarity of the tweets is identified as neutral, negative, and positive classes. In the proposed method, the important features are extracted by utilizing two feature extraction techniques and finally the initialization is done by Latent Dirichlet Allocation (LDA). Fig 1 states the working process of BLSTM-SA.

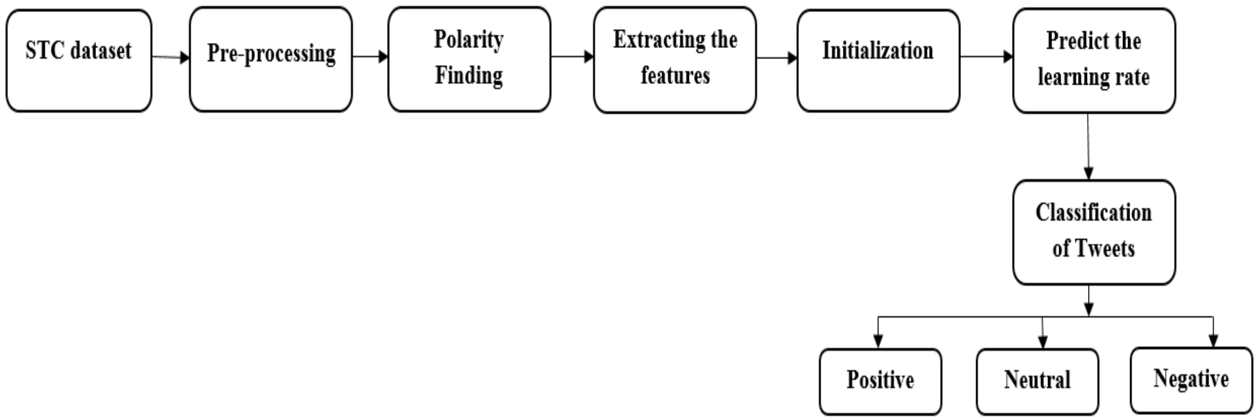

Figure 1: Working procedure of BLSTM-SA

The proposed work comprises of dissimilar phases, at first, the data is acquired from STC dataset and then tokenization is applied. Furthermore, the twitter data is pre-processed with dissimilar methods, and then the training data are generated. At last, hybrid classification methodology is employed for sentimental classification. The proposed work performance is related with the existing works by means of precision, MSE, MAE, accuracy, f-score, recall, sensitivity, and specificity.

A. Collection of tweets

In this work, the twitter data is acquired from STC dataset, which comprises of 5512 tweets on four dissimilar topics such as twitter, apple, Google, and Microsoft. In this dataset, each tweet is labelled manually as neutral, positive, negative, and irrelevant tweets on the baiss of topic. From the annotation, the tweet data comprises of 570 positive tweets, 654 negative tweets, 1786 irrelevant tweets and 2503 neutral tweets. In this work, the sentiment classification is done using BLSTM-SA methodology, which acquires only text attribute for finding the polarity.

B. Data pre processing

The social media websites comprises of several application platforms such as Facebook, WhatsApp, twitter, etc. In that, twitter is considered as a crucial platform to share the opinion of the individuals. Usually, the real time twitter data includes noise such as extra punctuations, retweets, URLs, stop words, Account Id (@), irregular words, short words, etc. The data pre-processing phase comprises of tag identification, removal of stop words, spelling correction, tokenization, abbreviation of words, and word stemming. The pre-processing steps are represented below.

- The twitter posts such as @Ram, emoticons, and the duplicate words are eliminated from the tweets for enhancing the performance of opinion mining.
- Some tweets contains casing of words (e.g., HaPPy”). So, the respective tweet is converted into lower case for providing consistency in the analysis.
- Meanwhile, the elongated words are also removed or replaced with the appropriate words (e.g., I am not happppy”). In addition, the slang words and short word messages are also replaced with suitable full form. For instance, the short word “ILY” is replaced with “I Love You”.
- The stop words (e.g., “a”, “the, “that”, “those”, etc.), and the negation short words (e.g., never, can’t, isn’t, don’t, etc.) are eliminated, because these words have less contribution in the classification of sentiments.

After preprocessing, the polarities of the tweets are identified and the final consequences are the sequence of string that is utilized for feature extraction. In this work, BLSTM-SA is applied as a text blog scheme [5] to find the text polarity that helps in improving the accuracy of classification. Usually in the existing systems, the sentences are utilized completely for determining the polarity. In this research, the twitter data is categorized into words and then the polarity is determined by utilizing text blog. This procedure helps BLSTM-SA for improving the classification of tweets.

C. Feature extraction

After identifying the polarities, generate the features from the preprocessed tweets. In this work, the feature extraction includes analyzing the frequency of negative and positive words, score of positive and negative words, overall word scoring, and tag count in the text present in the sentence. In this research, two new feature extraction methods (counter vectorization and TF-IDF) are applied to extract the features from the tweet data.

1) Counter vectorization

The counter vectorization is used to extract or represent the contextual words from the text. In this scenario, a mutual constraint is allocated to each word for finding the similarity between the words. Commonly, the counter vectorization consists of two phases; (i) computational representations and processes are applied for underlying the substantial portions of the collected twitter data and (ii) practical expedient is utilized for finding the contextual usage of the words.

2) TF-IDF

Correspondingly, TF-IDF is applied to extract the features from twitter data. The frequently appeared term in a text are identified utilizing TF-IDF, which is mathematically shown in the Eqs. (1) and (2).

$$Term\ frequency = \frac{No.of\ times\ term\,(t)\ appears\ in\ document}{Total\ no.of\ terms\ in\ a\ document} \quad (1)$$

$$Inverse\ document\ frequency = \log\frac{Total\ no.of\ documents}{No.of\ documents\ with\ term\,(t)} \quad (2)$$

The undertaken methods are used to extract the information from the tweets. In the next phase, the LDA methodology is applied for categorizing the tweets into three types such as neutral, positive, and negative classes. In this procedure, totally nineteen features are extracted from the tweets that is classified as three classes.

D. Latent dirichlet allocation

After extracting the information from collected data, LDA is used to categorize the tweets into three classes [24]. At first, the latent topic is determined by utilizing the random mixture. In this scenario, the latent topic is represented as distributed set of words. In each twitter sentence, the two phase process is carried out to select the distributed topics of each document. The parameters μ and π are observed for the three layer representation during the corpus generation. Then, the topic values are examined for every twitter sentence. In LDA, each twitter word is investigated for getting the word level values, where the joint distribution is deliberated as a generative procedure of LDA. The random value of probability density function is determined by using Eq. (3). In addition, the corpus probability and topic mixture joint distribution are evaluated by utilizing the Eqs. (4) and (5).

$$p(\aleph \mid \pi) = \frac{r\left(\Sigma_{i=1}^{k}\pi_i\right)}{\Pi_{i=1}^{k} r\left(\pi_i\right)} \aleph_1^{\pi_1 - 1}.........\aleph_k^{\pi_k - 1} \quad (3)$$

$$p(D \mid \pi, \mu) = \Pi_{d=1}^{M} \int p(\aleph_d \mid \pi) \times \left(\Pi_{n=1}^{N_d} \Sigma_{x_{dn}} p(x_{dn} \mid \aleph_d)\, p(y_{dn} \mid x_{dn}, \mu)\right) d\aleph_d \quad (4)$$

$$p(\aleph, x, y \mid \pi, \mu) = p(\aleph \mid \pi)\,\Pi_{n=1}^{N} p(x_n \mid \aleph)\, p(y_n \mid x_n, \beta) \quad (5)$$

Where, $\aleph$ is represented as document-level topic variables, π is stated as dirichlet parameter, M is stated as document, N is indicated as number of words, μ is represented as topic, x is stated as topic assignment, and y is stated as observed word. LDA is utilized for estimating the posterior distribution of the hidden values in a data that is called as intractable issue. The individual weight values of negative, neutral and positive classes are stored in the dictionary. After obtaining the weight values, the learning rate process is carried out using the SA mechanism to overcome the limitations of information loss.

E. Self-attention mechanism

LSTM is an adaptive methodology that decides the degree of prior states and also handles the features which are extracted from the input. In a few circumstances, the conventional LSTM model unclassified the sentences as input. To overcome this problem, BLSTM is used to encode the sentence and to attain the implicit vector for every time step.

Let us consider a sequence $S = \{x_1, x_2, ..., x_t\}$, where l is stated as length of the sequences, and the BLSTM methodology trains the model word by word. For each time step t, the memory cell state m_t and the hidden state h_t are updated, which is mathematically is denoted in the Eqs. (6), (7), and (8).

$$\begin{pmatrix} In_t \\ Fo_t \\ Out_t \\ \hat{c}_t \end{pmatrix} = \begin{pmatrix} S \\ S \\ S \\ T \end{pmatrix} W.\left[h_{t-1}, i_t\right] \quad (6)$$

$$m_t = Fo_t \odot m_{t-1} + In_t \odot \hat{c}_t \quad (7)$$

$$h_t = Out_t \odot T\left(m_t\right) \quad (8)$$

Where, i_t is represented as input, and $\hat{c}_t$ is indicated as current state of memory cell. The $In_t, FO_t\ and\ Out_t$ are indicated as input, forget, and output gate activate function results. Additionally, S is stated as logistic sigmoid function and T is denoted as tanh function. The BLSTM is effective for long sentences, even when the length of hidden vector is fixed. Henceforth, the output vector does not express the meaning of long sentences. To overcome this issue, a SA model is used in this work to overcome the problem of BLSTM by utilizing Veritable Length Weighted Context Structure (VLWCS). The description about SA is given as follows.

Consider a context vector $C = \{c_1, c_2, ..., c_n\}$ for BLSTM, where V is denoted as encoder output, and W is indicated as linear transformation coefficients for V, as shown in Eq. (9).

$$V' = L(V) = W \times V \quad (9)$$

Given a variable-length vector a_n as weights, and C_w as weighted context. Then, a set of location-based function is estimated by using VLWCS that is mathematically indicated in the Eqs. (10), (11), and (12).

$$a_n = soft\max\left(\left[c_1^T * V', c_2^T * V', ...c_j^T * V'\right]\right)$$
(10)
$$C_w = \left(c_1 * a_n + c_2 * a_n +, ..., + c_n * a_n\right)$$
(11)
$$\hat{C}_n = \left[C, C_w\right]$$
(12)

At last, the final probability $p(y \mid x) = soft\max\left(MLP\left(\left[\hat{C}_n, h_n\right]\right)\right)$ are obtained, where the SA process improves the performance of BLSTM for classifying the context. The working procedure of BLSTM-SA is explained as pseudo code.

Pseudo code for BLSTM Algorithm with SA layer

1. **Pseudo Code: Algorithm:** Bi-directional LSTM Algorithm with Self Attention Layer
2. **Procedure**: Bi-LSTM
3. **Class Bi-LSTM [tfidf_features, Sentiment_Analysis,Twitter_text]**
4. *Tfidf* ← tfidf_vectorizer.fit_transform*(* twitter_text *)* // **Twitter features Extracting using TFIDF**
5. *SentimentAnalysis* ← Analysis*(* twitter_text *)* // **Calculate sentiment analyze**
6. (trainX, testX, trainY, testY) ← train_test_split (features,SentimentAnalysis, test_size=0.3) // spitting the data into training data and testing data for the Bi-LSTM model
7. trainX = sequence.pad_sequences (trainX, maxlength=500)
   testX = sequence.pad_sequences (testX, maxlength=500)
8. **def** model**:**

//Bi-LSTM Model Initialization

Model ← Sequential()
Adding SelfAttention Layer ← SeqSelfAttention (attention_activation='relu')
Compile ← model.compile('Adam', 'sparse_categorical_crossentropy',
metrics=['accuracy','mae','mse','rmse'])
Model_Fit ← model.fit(trainX, trainY,batch_size=BatchSize, epochs=10,
validation_data=[testX, testY])
Model_Prediction ← model.predict_classes(testY)

9. **End function**

def Sentiment_Analysis:

Sentiment_analysis = TextBlob (twitter_text) // TextBlob utility function for sentiment polarity

If Sentiment_analysis.sentiment.polarity > 0:

return 1

elif Sentiment_analysis.sentiment.polarity == 0:

return 0

else:

return **-1**

10. **End function**
11. **End Class**

F. Bi-directional long-short term memory

Bidirectional LSTM (BLSTM) utilizes two LSTMs to process sequence in two directions such as forward and backward [25]. In this manner, the forward and backward contexts are considered simultaneously. The calculation of Bi-LSTMs is formulated as follows:

$$\overrightarrow{h_t} = lstm\left(\overrightarrow{h_{t-1}}, e(w_t)\right)$$
(13)
$$\overleftarrow{h_t} = lstm\left(\overleftarrow{h_{t-1}}, e(w_t)\right)$$
(14)

Then, the sequences of backward and forward hidden states are considered as the sign of every word w_t, and the representation is stated as $h_t = \left[\overrightarrow{h_t}; \overleftarrow{h_t}\right]$. By using the Eqs. (13) and (14), the twitter data is classified as negative, positive and neutral classes to find the sentiments of individuals. The output is utilized for finding whether the tweet is negative, neutral or positive. The validation outcome of BLSTM-SA and existing approaches are stated below.

III. Results and Discussion

In the experimental setup, the proposed methodology (BLSTM-SA) was simulated by using Python 3.7.3 with 8GB RAM. The validation of BLSTM-SA was verified by using the parameter metrics such as accuracy, precision, recall, f-score, MSE, RMSE and MAE. The below section explains parameter evaluation, quantitative and qualitative analysis of BLSTM-SA.

A. Dataset description

The STC dataset is used for the experimental analysis of BLSTM-SA, where this dataset contains total 5513 tweets for sentiment analysis [26]. In STC, there are four category such as Apple, Microsoft, Google and Twitter are presents, where these categories are downloaded from the link:

http://www.sananalytics.com/lab/twittersentiment/. Each category contains several tweets for identifying the sentiment of people opinion about the products. There are 1313 tweets for Apple, 1415 tweets for Microsoft, 1381 tweets for Google and finally 1404 tweets for Twitter categories. The proposed BLSTM-SA identifies the polarity for three classes such as negative, positive and neutral. Then, these identified polarities are assigned to positive class as 1, neutral class as 0 and negative class as -1.

B. Evaluation parameters

The BLSTM-SA is validated against existing techniques by using several parameters, which are discussed in this section. The evaluation metrics are used to check the property of the BLSTM-SA system for justifying the practical and theoretical growths of the systems. Some of the performance measures selected for evaluation purpose are recall, f-measure, accuracy, precision, sensitivity, specificity, MAE, RMSE and MSE. The equation used for calculating these metrics are given below,

$$Precision = \frac{TP}{TP + FP}$$
(15)

$$Recall = \frac{TP}{TP + FN}$$
(16)

$$F - score = \frac{2TP}{2TP + FP + FN}$$
(17)

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$
(18)

$$Specificity = \frac{TN}{TN + FP} \times 100$$
(19)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$
(20)

$$MAE = 1/N\Sigma_{j=1}^{N}\left|y_n - x_n\right|$$
(21)

$$MSE = 1/n\Sigma_{j=1}^{n}\left|\hat{y}_i - y_i\right|^2$$
(22)

Where, TP is represented as true positive, TN is specified as true negative, FP is exemplified as false positive, and FN is represented as false negative.

C. Ternary classification

The proposed algorithm is utilized for classifying the tweets polarity. In this section, the tweets are grouped into three classes; ‘‘neutral,’’ ‘‘positive,’’ and ‘‘negative’’. In this validation, the BLSTM-SA is related with existing methods such as SVM and RF [16]. Table 1 states the classification result attained by proposed and existing methods.

Table 1: Ternary classification of tweets

Methods	Precision			Recall			F-score		
	P	N	Neu	P	N	Neu	P	N	Neu
SVM [16]	0.3	0.10	0.56	0.54	0.08	0.34	0.38	0.09	0.42
RF [16]	0.54	0.39	0.67	0.41	0.05	0.85	0.47	0.09	0.75
Bi-LSTM	**0.92**	**0.46**	**0.86**	**0.74**	**0.46**	**0.95**	**0.82**	**0.46**	**0.91**
BLSTM-SA	**0.92**	**0.74**	**0.95**	**0.91**	**0.68**	**0.95**	**0.91**	**0.71**	**0.95**

From table 1, it is showed that the BLSTM-SA achieved higher precision, recall and f-score for all the three categories. When compared to SVM, the proposed scheme attained 92% precision for positive class. Due to the performance of SA mechanism in the proposed method, it achieved higher performance than other existing methods. The SA mechanism is used to predict the learning rate, where SVM and RF are failed to identify the rate. Meanwhile, table 2 shows the comparative analysis of proposed scheme with existing methodologies in light of f-measure, recall, and precision for positive tweets.

Table 2: Comparative analysis of proposed BLSTM-SA

Methodology	Precision	Recall	F-score
Binary SVM[22]	58.13	47.51	47.49
TFIDF-SVM[22]	65.82	65.24	65.17
SW-SVM [22]	81.16	80.85	80.83
PCA-RF [20]	74.74	74.20	72
Bi-LSTM	**88.12**	**92.31**	**90.17**
Proposed BLSTM-SA	**91**	**93**	**91**

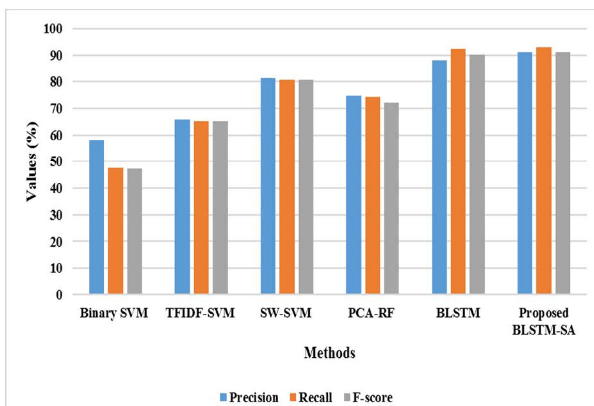

Figure 2: Comparative analysis of proposed method

From table 2 and Fig 2, the experimental consequences explain that the proposed scheme attained better performance in terms of recall, precision, and f-score for positive class. For instance, the SVM achieved only 30%, RF achieved 54%, hybrid optimization with decision tree achieved nearly 90% of precision, and the proposed BLSTM-SA achieved 92% of precision for positive tweets. Similarly, recall and f-score of proposed BLSTM-SA achieved nearly 1-3% higher than all other existing techniques. In next segment, the analysis of BLSTM-SA is carried out in light of accuracy.

D. Quantitative analysis in light of accuracy

Table 3 shows the performance of BLSTM-SA with existing sentiment analysis methods in terms of accuracy. Fig 3 shows the graphical depiction for validated outcomes.

Table 3: Performance of accuracy

Methodology	Accuracy (%)
SVM [16]	37.06
RF [16]	63.03
HL-NBC [15]	82
Hybrid optimization with Decision Tree [16]	90
T-SAF [20]	85
Bi-LSTM	**90.05**
Proposed BLSTM-SA	**91.41**

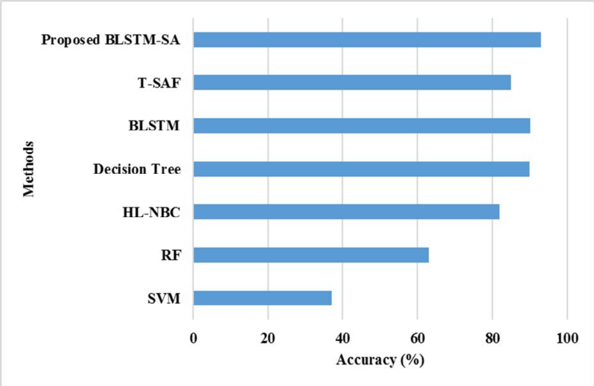

Figure 3: Performance of BLSTM-SA by means of accuracy

In this section, the validation of BLSTM-SA is verified by conducting many experiments on sanders datasets in light of accuracy. The validated outcomes showed that the BLSTM-SA performs better than the traditional techniques. For instance, the RF attained 63.03% of accuracy, decision tree achieved 90% of accuracy and T-SAF achieved 85% of accuracy, and the proposed BLSTM-SA achieved 93% of accuracy for identifying the polarity tweets. The reason behind the better performance is that the proposed methodology uses the SA mechanism for predicting the learning rate of BLSTM.

E. Quantitative analysis in light of error rate

In this section, the error analysis of BLSTM-SA is compared with existing techniques: SVM and RF in terms of RMSE, MAE and MSE. The validated results from the experiments are presented in Table 4 and figure 4.

Table 4: Performance of BLSTM-SA in terms of error rate analysis

Methods	RMSE	MSE	MAE
SVM [16]	0.92	0.85	0.70
RF [16]	0.76	0.58	0.44
Bi-LSTM	0.60	0.36	0.23
BLSTM-SA	**0.43**	**0.19**	**0.12**

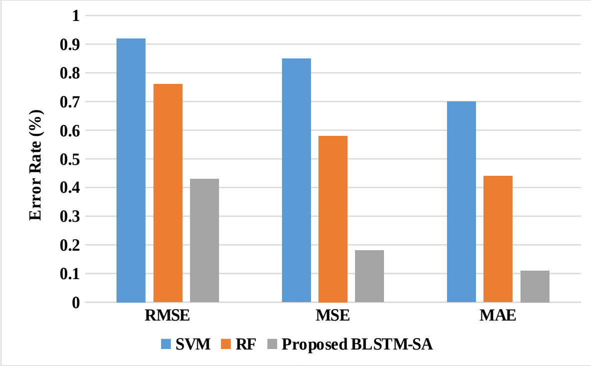

Figure 4: Error rate analysis

From the error rate analysis, the validated results state that the performance of BLSTM-SA provides less error in light of RMSE, MAE and MSE. The BLSTM-SA attained very less RMSE i.e. 0.43%, when compared to SVM (i.e. 0.92% RMSE). Similarly, the proposed BLSTM-SA achieved only 0.11% MAE, while existing techniques: SVM achieved 0.70% MAE and RF achieved 0.44% MAE. The tweet classification is enhanced by the capability of BLSTM-SA, which is proved by the experimental results. The Bi-LSTM is used to reduce the challenges in classification task, spam messages and dimensionality of tweets. However, a few limitations in BLSTM-SA method are needed to be overcome. The proposed technique is unable to correctly classify the tweets in which a user expresses conflicting sentiments. For example, the tweet “the weather is rainy :(I want clear sunshine:)” is classified as neutral by utilizing BLSTM-SA, where positive and negative class are not considered by proposed method in this particular tweet.

IV. CONCLUSION

In recent decades, the sentiment analysis using social data gained considerable attention among the researchers. Due to abundant amount of data present in twitter, it is difficult to process and analyze the data. In this paper, a new hybrid method is proposed for the classification of sentiments using twitter dataset. The collected twitter data is pre-processed by eliminating the unnecessary emoji’s, and the execution of missing value treatment. The polarity of the tweet is identified by text blogs and then the tweet is initialized by LDA approach. The classification of initialized tweet is carried out by BLSTM method, where the network performance is increased by including SA process. In this work, STC dataset is used for comparing the performance of BLSTM-SA with existing techniques. The proposed method achieved higher accuracy with less error rate compared to

SVM and RF. The proposed method improved the precision and recall around 3-15% compared to the existing methods. The proposed method (BLSTM-SA) works effectively on twitter datasets, but failed to concentrate on sarcastic, compound, and complex tweets. In the future work, a new method is developed to analyze the sentiment of the people opinion for dynamic dataset.

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