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Hybrid Feature Extraction and Deep Learning Classifier Based Effective Classification for Twitter Sentiment Analysis

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Abstract: Twitter is a widely used social media platform that is regarded as a crucial information source for gathering opinions, attitudes, reactions, and emotions from individuals. Therefore, the Twitter Sentiment Analysis (TSA) is developed for deciding the whether the textual tweets express a positive or negative opinion. The abundance of slang phrases and poor spellings in short sentence formats make it challenging to analyze Twitter data, nevertheless. In this paper, Hybrid Feature Extraction (HFE) is proposed along with the deep learning classifier to improve the classification. The HFE is the combination of Bag of Word (BoW) and FastText Word Embedding (FTWE) techniques that are used to extract the syntactic information and semantic information-related features from the tweets. The deep learning classifier namely Long Short-Term Memory (LSTM) with Softmax Regression Model (SRM) is used to classify the tweets as positive and negative. The datasets used to analyze the proposed HFE-LSTM-SRM method are Twitter and Sentiment140 datasets. The HFE-LSTM-SRM is analyzed by means of accuracy, precision, recall, F1-measure, and average computational time. The HFE-LSTM-SRM is evaluated using current techniques like Robustly Optimized Bidirectional Encoder Representations from Transformers (ROBERT-LSTM) and Spider-Monkey-Optimizer with K-Means Algorithm (SMOK). HFE-LSTM-SRM is more accurate than ROBERT-LSTM for the Sentiment140 dataset at 98.87%.

Keywords**:** *Accuracy, hybrid feature extraction, long short-term memory, softmax regression model, twitter sentiment analysis*

1. Introduction

The process of recognising, extracting, and classifying particular data from unstructured text is referred to as sentiment analysis. This technique makes use of the text analysis and computational linguistic approach that is included in Natural Language Processing (NLP). With the use of this sentiment analysis, the polarity of the statement may be determined based on the word clues acquired from the context of the sentence. [1] [2] [3]. Various real-world applications make use of sentiment analysis, including play evaluations, movie recommendations, restaurant reviews, microblog posts, product reviews, predictions of stock market movements, and forecasts of election outcomes. [4] [5]. The social media based sentiment analysis is rapidly developing segment in understanding opinions of people about day-to-day events [6] [7]. Social networks such as LinkedIn, Instagram, Facebook and Twitter are comprises of billions of users whereas the twitter specifically has 319 million users. Nowadays, people depends on the social network to perform opinion mining, decision making in various scenario, hence the social networks becomes a preferred mode of communication [8] [9]. Twitter is one of the famous social network that permits the user to communicate with the short text messages of 140 characters i.e., tweets [10].

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There are hundreds of millions of tweets made every single day, and these tweets cover a wide variety of topics including politics, news, products, and celebrities. Because users provide such a rich source of feedback, it is essential for various decision-makers to maintain constant vigilance across Twitter and the other social media platforms. [11] [12]. Therefore, the TSA is considered as an effective way to identify the opinion of people from the piece of text. The TSA plays an important role in classifying people's opinions and its impact on society. Accordingly, TSA is an essential NLP task to detect and analyze opinionated text and classifying sentiments [13]. But, the continuous monitoring, identification and filtering of the information exist in the applications of social media are challenging tasks while analyzing the sentiment. Language differences, a wide range of websites and social media platforms, a variety of data about people's ideas, and unstructured data are all aspects that influence sentiment analysis [14]. In tweets, people generally use slang and creates the mistake which causes the major issues in TSA. Hence, it is mandatory to utilize the intelligent techniques for obtaining the required knowledge from twitter data [15].

The contributions of this proposed TSA are summarized below:

The hybrid feature extraction that is the combination of

BoW and FTWE is used to extracts the syntactic and semantic information from the tweets. The fusion of syntactic and semantic information is used to enhance the classification. Specifically, the BoW and FTWE extract the frequency and contextual information of words.

The typical LSTM is converted into LSTM-SRM for avoiding the issues related to the multi class classifications. The precise classification of tweets is used to analyze the individual opinion about society.

The remaining fragments of paper are arranged and organised as follows: The section 2 contains the works that are relevant to the current TSA. The HFE-LSTM-SRM model is broken down into its component parts and thoroughly explained in Section 3, while its results are presented in Section 4 of this paper. In addition, the conclusion is discussed in section 5 of the paper.

2. Related Work

In the paper of Naresh, A. and Venkata Krishna, P. [16], a technique to machine learning that is based on optimisation is proposed for the purpose of classifying tweets into various categories. In order to evaluate the proposed model, there are three processes involved. In the beginning, the data is preprocessed to get rid of any noisy data. In the second stage, the features are extracted with the use of an optimisation method. In the third stage, the updated training set is then classified into three categories: positive, negative, and neutral.

A concept-based, hierarchical clustering-based, unsupervised learning approach was proposed by Bibi, M [17] for the purpose of doing sentiment analysis on Twitter. The standard hierarchical clustering procedures of single linkage, complete linkage, and average linkage are merged one after the other to form the final cluster. The techniques of term frequency-inverse document frequency (TF-IDF) and Boolean are both under investigation as independent feature representation methods. In this study, they conducted experiments with two classifiers that have been examined in the past (Naive Bayes and Neural Network) in an ensemble setting with concept-based methodologies for doing sentiment analysis.

Naz, H., et al. [18] created a hybrid classifier for supervised classification by combining Decision Tree (DT) with Feed Forward Neural Network (FNN). After Independent Component Analysis (ICA) is applied to the pre-processed data in order to determine the components of the data, the Windowed Multivariate Autoregressive Model (WMAR) is then applied in order to extract potential features from the pre-processed data. After that, the highest scores are determined by employing the Improved Bat Algorithm (IBA) approach, and the results of the experiment are compared with those obtained from other methods, including the ID3, J48, and Random forest classifiers.

[19] presents a novel hybrid clustering approach for assessing the sentiments of distinct tweets. This method is named the spider monkey optimisation algorithm utilising k-means (SMOK), and it is referred to as a clustering method. The outcomes of the proposed technique are put to use in order to provide an intelligent starting point for the population in SMO.

A hybrid deep learning model [20] that is suggested for sentiment analysis contains components from both the RoBERTa and LSTM models. While the RoBERTa model's purpose is to serve the goal of word or subword tokenization and the creation of word embedding's, the LSTM model encodes the long-distance temporal dependencies in the word embedding. Synthesizing samples with a wide range of lexical content requires the use of a data augmentation technique that includes pre-trained word embedding. Additionally, the minority classes should be oversampled. By doing this, the problem with the imbalanced dataset is fixed, and the generalization capability of the model is improved with the addition of more training samples that are rich in lexicon.

Crossword is a novel approach that was proposed by Hao et al. [24] to address cross-domain emotion coding issues by utilising a stochastic word embedding method. In addition to the labelled reviews of the source domain and the unlabeled reviews of both domains, the proposed method provides a better way to predict the probabilistic similarities between the key words and the words in the source domain.

Zhu et al. [25] have come up with a method called SentiVec, which is a core optimisation method for embedding emotional words. In the first phase of this research project, supervised learning will be performed, and in the second phase, unsupervised updating will be carried out using models such as object-word-surround reward (O2SR) and context-object-word reward (C2OR). The results of some experiments demonstrate that optimal sentiment vectors are superior to other approaches to tasks such as word analogy, similarity, and sentiment analysis due to their superior ability to effectively extract semantics and sentiment analysis functions. In order to categorise public opinion regarding Covid-19, Singh et al. [26] use a model called the Bidirectional Encoding Representations of Transformers (BERT) model. The authors of this paper performed sentiment analysis on two different datasets: the first dataset includes tweets from people all over the world, and the second dataset includes tweets from people in India. The validation accuracy of the emotion classification system was found to be 9 percent, according to the experimental data.

Emotion-based evaluation prediction method is the name of the novel approach that Munuswamy and colleagues propose. [27] Create a recommendation system that is capable of mining useful information from user reviews that have been published on social media platforms. This will allow the system to predict the exact details that users admire based on the reviews. In this particular model, the responses of customers to a product are analysed with the assistance of an opinion dictionary. In addition, in order to accurately predict and generate product recommendations, the reputation of the product is computed using all three senses. The n-gram methodology is integrated into semantic analysis and syntax as a modern function with SVM to improve the accuracy of the results, which allows for more effective classification of reviews that have been published on social media platforms.

3. Methodology Used

In this proposed TSA, the HFE based classification is done using LSTM-SRM for improving the performances. The main phases of HFE-LSTM-SRM method are dataset acquisition, preprocessing, feature extraction using HFE, feature fusion and classification using LSTM-SRM. The combination of syntactic and semantic information from HFE is used to improve the classification. Further, the LSTM classifier with SRM is used to enhance the multiple class recognitions of tweets into positive and negative. The block diagram of the HFE-LSTM-SRM method is shown in the figure 1

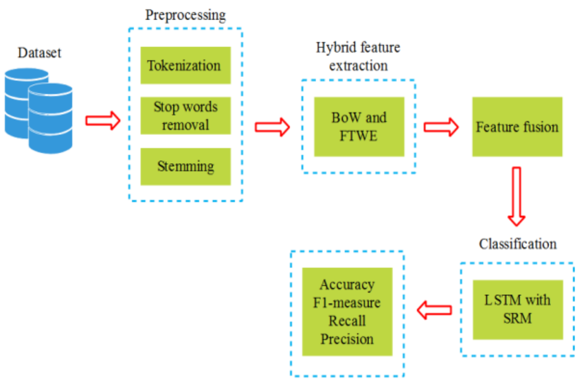

Fig. 1. Block diagram of the HFE-LSTM-SRM

3.1. Data acquisition

In this TSA research, two different datasets such as Twitter dataset [21] and Sentiment140 dataset [22] are used for analyzing the HFE-LSTM-SRM method. Twitter dataset is taken from Twitter that depends on funny images, college students, sports, saints and jokes. The twitter dataset has 2000 tweets where 1000 for positive classes and 1000 for negative classes. Sentiment140 dataset is generated from Twitter by Stanford University. This Sentiment140 dataset has 1.6 million reviews where 0.8 million for positive reviews and 0.8 million for negative reviews.

3.2. Preprocessing

In this phase, preprocessing is done for eliminating noise or unnecessary tokens from the Twitter dataset and Sentiment140 dataset. Each tweet post is preprocessed for sanitizing the tokens where the tokenization is applied for tokenizing and eliminating the alphanumeric characters. Next, the stop words are removed from the tokenized data. Because, the stop words are irrelevant words in a language which causes a noise when it is utilized in classification of text. Finally, the words are reduced to its root word using the stemming process [23].

3.3. Hybrid feature extraction

After preprocessing the input data, the HFE is used to extract the optimal syntactic and semantic information. HFE is the combination of Bag of Word (BoW) and FastText Word Embedding (FTWE) technique whereas BoW is used to extract syntactic information and FTWE is used to extract semantic information. The BoW representation is used for transforming an each tweet into the related feature vector. The BoW has three different steps such as tokenization, counting, and normalizing. Initially, the each word of tweet is tokenized followed by the weight of each tokenized word is computed using the Term Frequency-Inverse Document Frequency (TF-IDF) as shown in equation (1). The TF-IDF based features are mainly depends on the frequency of words.

$$\mathrm{TF} - IDF(e,d) = TF(e,d) \times IDF(e) \tag{1}$$

Where, the term frequency for token (e) at document (d) is denoted as $\mathrm{TF(e, d)}$ and IDF is expressed in equation (2).

$$IDF(e) = \log\frac{1+n}{1+DF(e)} + 1 \tag{2}$$

Where, an amount of tweets exist in the term e of dataset is denoted as $\mathrm{DF(e)}$. Further, the L2-norm is used for normalizing the TF-IDF vector (V) for an each tweet in document which is expressed in equation (3).

$$V = \frac{V}{\sqrt{V_1^2+V_2^2+\cdots V_n^2}} \tag{3}$$

After performing the BoW feature extraction, the FTWE based word embedding is used for preserving the contextual information of each token. Since, word embedding is an approach of denoting the word into the fixed-size vector by using the contextual information. The FTWE generates the vector of 300-D size for an each word of tweets. Accordingly, the matrix of $\mathrm{n} \times 300$ is obtained for an each tweet, where total amount of token in an each tweet is denoted as n. The word embedding matrix (W) obtained using FTWE is expressed in equation (4).

$$W = fastText(d) \tag{4}$$

The matrix of equation (4) is acquired using FastText-based embedding for the input tweet dataset (d).

3.4. Feature fusion

The features related to the syntactic and contextual information is complementary to each other for an accurate representation of tweets. Both the features from BoW and FTWE are used for better representation of an each tweet, therefore feature fusion is performed before classification. The BoW method extracts the syntactic information from tokens and FTWE extracts semantic information. Since, the extracted is already has small size (300-D) for training the classifiers, hence there is no selection of features are required in this HFE-LSTM-SRM method. equation (5) denotes the final feature matrix (X_{ij}) obtained from feature fusion

$$X_{ij} = \sum_{k=1}^{n} V_{ik} W_{kj} \quad (5)$$

Where, TF-IDF tweet matrix ($m \times n$) of BoW is denoted as V; m denotes the amount of tweets; n denotes the amount of tokens and word embedding matrix ($n \times 300$) is denoted as W

3.5. Classification using LSTM-SRM

After performing the feature fusion, the final feature matrix is given as input to the LSTM-SRM for classifying the tweets. The LSTM has the capacity of storing previous data thus capturing the important long range dependencies in the feature matrix. LSTM comprises of three essential elements such as forget gate, input gate, and output gate. The forget gate determines to forget/ discard the inappropriate data from the new input data and previous cell state. The training uses the sigmoid function for returning the values among [0,1]. If the value is nearly 0, then the information obtains less importance to remember. The determination of worth remembering of information is achieved by using the input gate, accordingly it is updated to the next state. If the value is nearly 0, then the update obtains less importance. Further, the output gate controls the information which required to be output in following cell state.

The LSTM computations at time step t in the input gate ig_t, forget gate fg_t, cell state cs_t, candidate memory cell $\tilde{c}_t$, memory cell value c_t and LSTM block output Y_t are expressed in equations (6) – (11).

$$ig_t = sigmoid(W_{ig} \times [Y_{t-1}, X_t\,] + b_{ig}) \quad (6)$$

$$fg_t = sigmoid(W_{fg} \times [Y_{t-1}, X_t\,] + b_{fg}) \quad (7)$$

$$\tilde{c}_t = tanh(W_c \times [Y_{t-1}, X_t\,] + b_c) \quad (8)$$

$$og_t = sigmoid(W_{og} \times [Y_{t-1}, X_t\,] + b_{og}) \quad (9)$$

$$c_t = c_{t-1} \odot fg_t + \tilde{c}_t \odot ig_t \quad (10)$$

$$Y_t = og_t \odot\ tanh(c_t) \quad (11)$$

Where, $W_{[ig,fg,c,og]}$ defines the weight matrices; $b_{[ig,fg,c,og]}$ defines the bias vectors and $\odot$ represents the element-wise multiplication.

Further, the SRM is used in the LSTM for avoiding the issues related to the multi class classifications. For a multi class identification issue of K classes with Q amount of training samples is represented as $\{(x^{(i)}, y^{(i)})\}_i^Q$, where $y^{(i)} \in \{1,2, \dots, K\}$, the probability value $p(y = j|x)$ computed by softmax regression for an each value of $j = 1,2, \dots, K$. equation (12) is used to compute the probability value.

$$p\left(y^{(i)} = j \middle| x^{(i)}; \theta\right) = \frac{exp(\theta_j^T x^{(i)})}{\sum_{j=1}^{K} exp(\theta_j^T x^{(i)})} \quad (12)$$

Where, the matrix of parameters is defined as θ and input sequence length is denoted as T. An appropriate values of θ is discovered by reducing the cross-entropy loss as shown in equation (13).

$$J(\theta) = -\frac{1}{Q}\left[\sum_{i=1}^{Q} \sum_{j=1}^{K} 1\{y^{(i)} = j\}\, log \frac{exp\left(\theta_j^T x^{(i)}\right)}{\sum_{j=1}^{K} exp\left(\theta_j^T x^{(i)}\right)}\right] + \frac{\lambda}{2} \sum_{i=1}^{Q} \sum_{j=0}^{K} \theta_{ij}^2 \quad (13)$$

Where, the regularization parameter is denoted as λ; the second term in equation (13) represents the purpose of regularization that used to eliminate the issue of variance. equation (14) shows the classification of softmax regression classifier.

$$y^{(i)} = arg\,max\; p\left(y^{(i)} = t \middle| x^{(i)}; \theta\right) \quad t \in \{1,2, \dots, K\} \quad (14)$$

4. Results and Discussion

The outcomes of this HFE-LSTM-SRM method is detailed in this section. The design and simulation of this HFE-LSTM-SRM method is done using the Python 3.7 software where the system is operated with 8GB RAM and i3 processor. The HFE-LSTM-SRM method is used to perform the sentiment analysis using tweets. There are two different datasets are used to evaluate the HFE-LSTM-SRM such as Twitter dataset and Sentiment140 dataset. The tweets data is separated as 80% for training and 20% for testing. The performance of the HFE-LSTM-SRM method is analyzed by means of accuracy, precision, recall and F1-measure which are expressed in equations (15)-(18). Further, the average computational time also analyzed for evaluating the classification.

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \times 100 \quad (15)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (16)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (17)$$

$$F - measure = \frac{2Precision \times Recall}{Precision+Recall} \times 100 \quad (18)$$

Where, TP is true positive; TN is true negative; FP is false positive and FN is false negative.

4.1. Performance analysis of HFE-LSTM-SRM

The performance evaluation of Twitter dataset and Sentiment140 dataset is explained in this section. The performances are analyzed in two different ways such as HFE-LSTM-SRM method for different feature extraction methods and different classifiers. The performance evaluation of HFE-LSTM-SRM (BoW-FTWE) with BoW and FTWE feature extraction methods is given in the Table 1. Figure 2 shows the graphical comparison of feature extraction methods for HFE-LSTM-SRM with Twitter dataset. The individual features of BoW and FTWE for Twitter dataset obtains the classification accuracy of 94.57% and 92.84% whereas the combination of BoW-FTWE achieves accuracy of 99.98%. Similarly, the combination of BoW-FTWE achieves higher accuracy of 98.87% for Sentiment140 dataset. The reason that BoW-FTWE achieves improved performance is the combination of syntactic and semantic information extracted from the tweets. Both the features related to frequency and contextual information of words helps to improve the classification than the individual features. Moreover, the average computational time for both the Twitter and Sentiment140 dataset are 13.81 seconds and 10.66 minutes which are less than the classification based on individual features. The classification of Sentiment140 dataset achieves average computational time as 10.66 minutes because it has to process 20% of data i.e., 0.32 million during testing process where the 20% of data from Twitter dataset is 400.

Table 1. Performance evaluation of HFE-LSTM-SRM for different feature extraction

Datasets	Feature extraction	Accuracy (%)	Precision (%)	Recall (%)	F1-measure (%)	Average computational time
Twitter dataset	BoW	94.57	93.48	94.56	95.92	20.94 seconds
	FTWE	92.84	93.11	92.09	94.94	17.67 seconds
	BoW-FTWE	99.98	98.89	99.23	98.47	13.81 seconds
Sentiment140 dataset	BoW	93.97	93.11	94.00	93.86	15.57 minutes
	FTWE	90.48	91.26	92.18	92.06	13.93 minutes
	BoW-FTWE	98.87	98.35	99.01	97.68	10.66 minutes

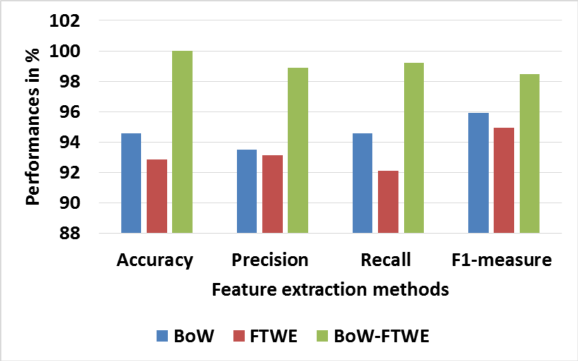

Fig. 2. Graphical comparison of the feature extraction methods for Twitter dataset

The performance evaluation of HFE-LSTM-SRM with MSVM, DNN and LSTM is shown in Table 2. Figure 3 shows the graphical comparison of different classifiers for HFE-LSTM-SRM with Twitter dataset. From the analysis, it is known that the HFE-LSTM-SRM provides better performance than the MSVM, DNN and LSTM. For example, the accuracy of HFE-LSTM-SRM method for Twitter dataset is 99.98% where the accuracy of MSVM is 88.61%, DNN is 90.11% and conventional LSTM is 93.38%. Further, the average computation time of HFE-LSTM-SRM method for both the datasets are also outperforms well than the other classifiers. The multiclass classification of the LSTM is effectively enhanced by using the SRM model while classifying the tweets into positive and negative.

Table 2. Performance evaluation of HFE-LSTM-SRM for different classifiers

Datasets	Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-measure (%)	Average computational time
Twitter dataset	MSVM	88.61	89.00	89.33	88.15	13.59 seconds
	DNN	90.11	90.64	91.48	92.31	20.16 seconds
	LSTM	93.38	94.15	94.02	93.82	15.64 seconds
	LSTM-SRM	99.98	98.89	99.23	98.47	13.81 seconds
Sentiment140 dataset	MSVM	87.25	87.09	86.93	86.99	10.09 minutes
	DNN	88.16	88.07	89.34	88.54	23.47 minutes
	LSTM	91.02	90.34	91.28	91.73	18.33 minutes
	LSTM-SRM	98.87	98.35	99.01	97.68	10.66 minutes

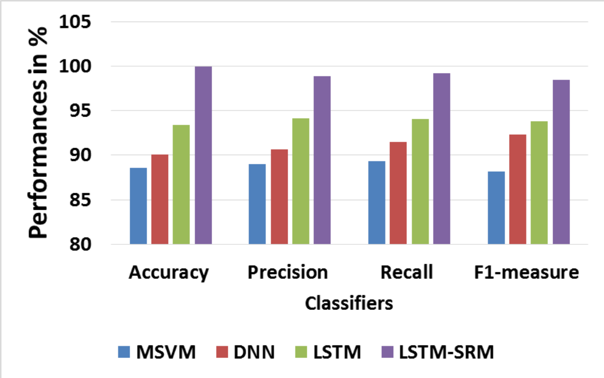

Fig. 3. Graphical comparison of the classifiers for Twitter dataset

4.2. Comparative analysis

The comparative analysis of the HFE-LSTM-SRM with existing researches is provided in this section. The existing researches such as SMOK [19] and ROBERT-LSTM [20] are used to evaluate the efficiency of the HFE-LSTM-SRM. Here, the comparison is made for two different datasets. Table 3 and 4 shows the comparative analysis for Twitter dataset and Sentiment140 dataset respectively. Moreover, the graphical comparison for accuracy is shown in Figure 4. From this analysis, it is known that the HFE-LSTM-SRM outperforms well than the SMOK [19] and ROBERT-LSTM [20] for both the Twitter and Sentiment140 datasets. The accuracy of SMOK [19] and HFE-LSTM-SRM are same, however the average computational time of the HFE-LSTM-SRM is less than the SMOK [19]. The syntactic and semantic information extracted using HFE along with the multi class classification achieved using LSTM-SRM helps to effectively improve the classification performances of the TSA.

Table 3. Comparative analysis for Twitter dataset

Performances	SMOK [19]	HFE-LSTM-SRM
Accuracy (%)	99.98	99.98
Average computational time (Seconds)	20.03	13.81

Table 4. Comparative analysis for Sentiment140 dataset

Performances	ROBERT-LSTM [20]	HFE-LSTM-SRM
Accuracy (%)	89.70	98.87
Precision (%)	90	98.35
Recall (%)	90	99.01
F1-measure (%)	90	97.68

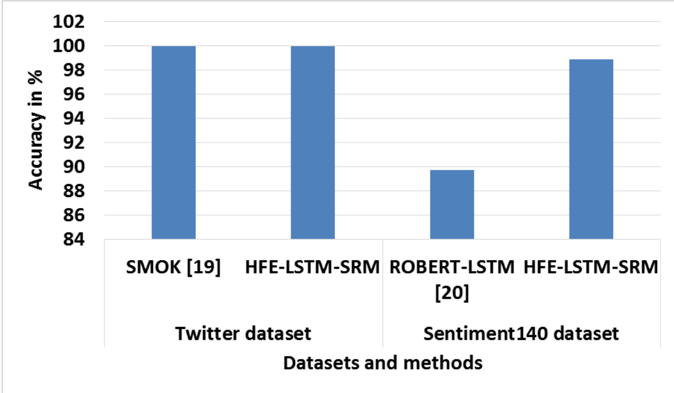

Fig. 4. Graphical comparison for accuracy

5. Conclusion

In this paper, an effective sentiment analysis of tweets is achieved by using the HFE and LSTM-SRM. The tokenization, stop word removal and stemming are accomplished in the preprocessing for avoiding the irrelevant information from the input tweets. The BoW and FWTE used in HFE are used to extract the syntactic and semantic information followed by these extracted features are fused together for obtaining an effective classification. The multi class issues of LSTM is eliminated by using the SRM during the sentiment analysis of tweets. From the experimental results, it is known that the HFE-LSTM-SRM achieves better performance than the SMOK and ROBERT-LSTM. The accuracy of HFE-LSTM-SRM for Sentiment140 dataset is 98.87% which is high than the ROBERT-LSTM.

Author contributions

Usha G R: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Software, Validation, Field study

Dr. J V Gorabal: Visualization, Investigation, Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Tam, S., Said, R.B. and Tanriöver, Ö.Ö., 2021. A ConvBiLSTM deep learning model-based approach for Twitter sentiment classification. IEEE Access, 9, pp.41283-41293.

[2] Kayıkçı, Ş., 2022. SenDemonNet: sentiment analysis for demonetization tweets using heuristic deep neural network. Multimedia Tools and Applications, 81(8), pp.11341-11378.

[3] Qiu, Y., Song, Z. and Chen, Z., 2022. Short-term stock trends prediction based on sentiment analysis and machine learning. Soft Computing, 26(5), pp.2209-

2224.

[4] Zhang, T., Gong, X. and Chen, C.P., 2021. BMT-Net: Broad multitask transformer network for sentiment analysis. IEEE Transactions on Cybernetics.

[5] Sazzed, S. and Jayarathna, S., 2021. Ssentia: a self-supervised sentiment analyzer for classification from unlabeled data. Machine Learning with Applications, 4, p.100026.

[6] Mendon, S., Dutta, P., Behl, A. and Lessmann, S., 2021. A Hybrid approach of machine learning and lexicons to sentiment analysis: enhanced insights from twitter data of natural disasters. Information Systems Frontiers, 23(5), pp.1145-1168.

[7] Basiri, M.E., Nemati, S., Abdar, M., Cambria, E. and Acharya, U.R., 2021. ABCDM: An attention-based bidirectional CNN-RNN deep model for sentiment analysis. Future Generation Computer Systems, 115, pp.279-294.

[8] Divyapushpalakshmi, M. and Ramalakshmi, R., 2021. An efficient sentimental analysis using hybrid deep learning and optimization technique for Twitter using parts of speech (POS) tagging. International Journal of Speech Technology, 24(2), pp.329-339.

[9] Jacob, S.S. and Vijayakumar, R., 2021. Sentimental analysis over twitter data using clustering based machine learning algorithm. Journal of Ambient Intelligence and Humanized Computing, pp.1-12.

[10] Rehioui, H. and Idrissi, A., 2019. New clustering algorithms for twitter sentiment analysis. IEEE Systems Journal, 14(1), pp.530-537.

[11] Alattar, F. and Shaalan, K., 2021. Using artificial intelligence to understand what causes sentiment changes on social media. IEEE Access, 9, pp.61756-61767.

[12] Swathi, T., Kasiviswanath, N. and Rao, A.A., 2022. An optimal deep learning-based LSTM for stock price prediction using twitter sentiment analysis. Applied Intelligence, pp.1-14.

[13] Gupta, I. and Joshi, N., 2021. Feature-Based Twitter Sentiment Analysis With Improved Negation Handling. IEEE Transactions on Computational Social Systems, 8(4), pp.917-927.

[14] Alsayat, A., 2022. Improving Sentiment Analysis for Social Media Applications Using an Ensemble Deep Learning Language Model. Arabian Journal for Science and Engineering, 47(2), pp.2499-2511.

[15] Bibi, M., Aziz, W., Almaraashi, M., Khan, I.H., Nadeem, M.S.A. and Habib, N., 2020. A cooperative binary-clustering framework based on majority voting for Twitter sentiment analysis. IEEE Access, 8, pp.68580-68592.

[16] Naresh, A. and Venkata Krishna, P., 2021. An efficient approach for sentiment analysis using machine learning algorithm. Evolutionary Intelligence, 14(2), pp.725-731.

[17] Bibi, M., Abbasi, W.A., Aziz, W., Khalil, S., Uddin, M., Iwendi, C. and Gadekallu, T.R., 2022. A novel unsupervised ensemble framework using concept-based linguistic methods and machine learning for twitter sentiment analysis. Pattern Recognition Letters, 158, pp.80-86.

[18] Naz, H., Ahuja, S. and Kumar, D., 2021. DT-FNN based effective hybrid classification scheme for twitter sentiment analysis. Multimedia Tools and Applications, 80(8), pp.11443-11458.

[19] Shekhawat, S.S., Shringi, S. and Sharma, H., 2021. Twitter sentiment analysis using hybrid Spider Monkey optimization method. Evolutionary Intelligence, 14(3), pp.1307-1316.

[20] Tan, K.L., Lee, C.P., Anbananthen, K.S.M. and Lim, K.M., 2022. RoBERTa-LSTM: A Hybrid Model for Sentiment Analysis With Transformer and Recurrent Neural Network. IEEE Access, 10, pp.21517-21525.

[21] Twitter dataset, (2014). https://drive.google.com/file/d/0BwPSGZHAP_yoN2pZcVl1Qmp1OEU/view?usp=sharing.

[22] Sentiment140 dataset. https://www.kaggle.com/kazanova/sentiment140

[23] Hakak, S., Alazab, M., Khan, S., Gadekallu, T.R., Maddikunta, P.K.R. and Khan, W.Z., 2021. An ensemble machine learning approach through effective feature extraction to classify fake news. Future Generation Computer Systems, 117, pp.47-58.

[24] Hao Y, Mu T, Hong R, Wang M, Liu X, Goulermas JY. Cross-domain sentiment encoding through stochastic word embedding. IEEE Trans Knowl Data Eng. 2020;32(10):1909–22. https://doi.org/10.1109/tkde.2019.2913379.

[25] Zhu L, Li W, Shi Y, Guo K. SentiVec: learning sentiment-context vector via kernel optimization function for sentiment analysis. IEEE Trans Neural Netw Learn Syst. 2021;32(6):2561–72. https://doi.org/10.1109/tnnls.2020.3006531.

[26] Bie Y, Yang Y. A multitask multiview neural network for end-to-end aspect-based sentiment analysis. Big Data Mining Analytics. 2021;4(3):195–207. https://doi.org/10.26599/bdma.2021.9020003.

[27] Munuswamy S, Saranya MS, Ganapathy S,

Muthurajkumar S, Kannan A. Sentiment analysis techniques for social media-based recommendation systems. Nat Acad Sci Lett. 2021;44(3):281–7. https://doi.org/10.1007/s40009-020-01007-w.

[28] Babu, M. C. ., & K, S. . (2023). An Intelligent Optimal Secure Framework for Malicious Events Prevention in IOT Cloud Networks. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3), 117–127. https://doi.org/10.17762/ijritcc.v11i3.6328

[29] Ali Ahmed, Machine Learning in Healthcare: Applications and Challenges , Machine Learning Applications Conference Proceedings, Vol 1 2021.