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Fuzzy-Biemm: An Emotion Recognition Model Based on Bidirectional Deep Learning and Extended Fuzzy Markov Model

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Abstract

Nowadays, a huge number of messages is transmitted by users on social media such as Twitter, Amazon and Facebook. A lot of data and information are exchanged in these media. Considering the need of these social media to detect the negative or positive feelings of users in the text and news, the idea of opinion mining has been proposed. Opinion mining provides the possibility of analyzing users' opinions and discovering knowledge to detect emotions in social media. Some of the most important challenges in social media have been the lack of accuracy, transparency, and accuracy in detecting users' feelings. Various methods have been proposed to detect the sentiments of users based on opinion mining in social media, which, despite their many applications, still face challenges such as lack of accuracy in sentiment analysis. Therefore, in this paper, a sentiment recognition system called Fuzzy-BiEMM based on extended Markov model (EMM), Bi-LSTM deep neural network and fuzzy logic is proposed. Fuzzy logic approach is used to derive effective rules, Bi-LSTM deep neural network is used for sentiment recognition, EMM is used to improve deep neural network. In this paper, the customer datasets of Amazon, Twitter, Facebook, fake news of Covid-19, Amazon and fake news network are used. By simulating the proposed Fuzzy-BiEMM approach, it was observed that the average accuracy of emotion recognition was 96.75%, which is 7.62% better than the proposed Fuzzy-BiEMM method without applying the fuzzy logic approach and 5.02% better than the CSO-LSTMNN approach.

Keywords: Opinion mining, Sentiment analysis, Extended Markov Model, Deep neural network, Fuzzy logic.

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1. Introduction

Today, with the increasing spread of the Internet, the use of social media is increasing day by day. A key feature of social media is that anyone from anywhere in the world is free to express their opinions and views without revealing their true identity. These comments are extremely valuable [1-3]. Microblogs are a type of these media, the most famous of which are Amazon and Twitter, and its use among users to express opinions and feelings on various topics is increasing [4]. Despite the fact that this source contains users' opinions and feelings, extracting information from it is necessary and necessary, which can have useful applications [5]. Among the most important challenges in social media such as Amazon and Twitter are the processing and analysis of huge amounts of data, classification accuracy and information processing time. It is not possible to analyze and implement data by normal systems and there is not enough space for data processing and analysis. Therefore, data management, including processing, analysis, classification, etc., is the main topic of this paper. With the increase in the number of social media users and sending comments and tweets in these systems, the amount of data has increased. If the three components of speed, high volume of production and its variety are significant, it is referred to as data. Data is a set of data that cannot be executed and processed on a single system [6]. Therefore, in this paper, data processing and analysis is significant and the process of sentiment analysis is done on the data.

Sentiment analysis classification approaches are divided into three general categories of supervised, semi-supervised and unsupervised learning. In recent research for classification, mostly monitoring algorithms and approaches such as support vector machine [8], Bayesian [9], regression [10] and decision tree [11] have been used, each of which has disadvantages and the biggest challenge They are lack of accuracy, sufficient accuracy and high classification error in sentiment analysis. Due to the existence of such challenges in the classification algorithms for the analysis of user sentiments, in this paper, the combination of EMM and fuzzy logic approach is used to solve the existing challenges in sentiment classification.

Therefore, the categories used in the existing papers, in addition to not having high accuracy, also face major problems for working with large data sets, which, in addition to greatly prolonging the processing time, sometimes It is not even possible to build a model from the set of data for them.

In this paper, the combination of fuzzy logic and EMM approaches is used to categorize emotions. Semantic learning approach is used in the pre-processing stage of the data and causes the input sentences to be processed and a set of rules effective in determining the positive/negative are extracted. Each sentence is divided into several main words and each word is classified in a meaningful way. Then, with the help of two-way EMM, sentences and tweets are classified. One of the most important capabilities of this proposed Fuzzy-BiEMM method is the processing and analysis of users' emotions in social media. Due to the huge amount of data, the use of online resources and parallelization tools are used to analyze the sentiments in the data. The combination of the proposed Fuzzy-BiEMM method will cover the error, improve the accuracy and accuracy of the classification.

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Among the most important advantages of the fuzzy logic approach in the proposed Fuzzy-BiEMM method is the extraction of effective rules in the classification of emotions in order to improve the accuracy of the processing and analysis of users' emotions. Fuzzy logic approach is used in the pre-processing stage of the data and it causes the input sentences to be processed and effective rules are extracted in the classification of emotions. Based on the rules extracted from the words, each sentence is classified into several main words and each word is classified in a meaningful way. For example, suppose there are negative words in tweets and sentences posted by social media users. Negative words can be semantically divided into three categories: bad, very bad and extremely bad. Therefore, in this paper, by applying the fuzzy logic approach, effective rules are extracted in the classification of emotions. After extracting the rules, the extended Markov model and deep learning are applied to sentiment analysis.

Deep learning is closely related to a set of theories of brain development proposed by neuroscientists in the 1990s. These developmental models were manifested in computational models and became processes of deep learning systems. These developmental models show a common feature that the various dynamics described for learning in the brain (such as a wave of nerve growth factor) are to some extent similar to neural networks used in deep learning models and support self-organization [12-15].

Among the most important aspects of newness and innovation of this paper are as follows:

- Applying the extended Markov model in the core of the Bi-LSTM deep neural network model as a classifier of emotions, news, etc.
- Using EMM to increase the accuracy of emotion recognition.
- Combining fuzzy logic and EMM in the proposed emotion recognition system.

So far, various approaches have been proposed to improve the process of emotion recognition, which, despite the many applications it has had in the field of improving accuracy in this field, still faces problems such as lack of accuracy and accuracy of opinion classification, lack of expandability. Therefore, in this paper, an opinion analysis system based on EMM and fuzzy logic approach is presented to increase the accuracy of emotion recognition.

In the continuation of this paper, in section 2, the works done in the past are examined and in section 3, the proposed Fuzzy-BiEMM method and proposed architecture are described. In section 4, the obtained results are evaluated and in section 5, the final conclusion is presented.

2- The related works

In [16], presented a new approach for sentiment analysis of Tunisian-accented Arabic language, which uses three support vector machine tools, neobizine, and multilayer perceptron (MLP) for sentiment classification. For this purpose, they first collected a collection with more than 17 thousand comments registered on Facebook. The evaluation results show the effectiveness of the proposed Fuzzy-BiEMM method in terms of 91% accuracy and 92.36% precision.

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In [17], presented a large-scale approach for online critical user sentiment classification using Apache Spark. In fact, this sentiment analysis approach is a hybrid approach that uses three support vector machine tools, New Business and regression. Evaluations were made on Amazon's customer reviews dataset with more than 2 million reviews. The results of the evaluations show the accuracy of 85.4% of the proposed Fuzzy-BiEMM method as well as the stability of the processing time in each percentage of the investigated dataset.

In [18], presented an adaptive approach for sentiment analysis of social media metadata. In fact, this approach includes two separate parts of sentiment analysis and adaptability to big data scale. In order to analyze sentiments, first the words are valued based on the built-in dictionary and then, based on the K-Means clustering algorithm, they are assigned to positive or negative comment categories. In order to adapt to the scale of big data, they also used two powerful tools, including Apache Kafka to store and collect data and Apache Spark to perform distributed processing. In this research, evaluations were made on the 2016 US presidential election dataset and the results show that this approach provides an average accuracy of 90.21%.

In [19], using the concept of domain adaptation and neural networks, presented a new approach to sentiment classification at the landscape level, which can be adapted to other languages. Their evaluation of the proposed Fuzzy-BiEMM method was performed on the SemEval-14, SemEval-15 and SemEval-16 datasets, and the results show that the effectiveness of the proposed Fuzzy-BiEMM method in F_1 criteria and accuracy was recorded as 79.3% and 82.5%, respectively.

In [20], presented a sentiment recognition approach for new word suggestion. In this regard, based on the previous words (based on the dictionary) and using the Bayesian probability function, they find the feeling of the text being written (positive, negative or neutral) and then perform the new word suggestion procedure. Evaluation of their proposed Fuzzy-BiEMM method was done using three datasets including Twitter dataset from SemEval 2014, movie review dataset from Pang & Lee and IMDB dataset from Twitter. The effectiveness of the proposed algorithm in terms of precision and F_1 criteria was recorded as 84.1% and 76.5%, respectively.

In [21], presented two approaches based on deep learning for sentiment analysis of Arabic texts with a Saudi accent. Their first approach is based on short-term memory (LSTM) and the second approach is based on bilateral short-term memory (Bi-LSTM). The results of the evaluations, which were conducted on a set of 32063 tweets collected from Twitter, show that the first approach recorded 92% accuracy and the second approach recorded 94% accuracy.

In [22], conducted a study on how to categorize people's personality in social media. For this purpose, in this research, sentiment analysis based on Contextual Semantic was used. The authors of this paper believe that the feeling and aspect of words change in interaction with side words. According to Maslow's hierarchy, people are divided into five categories based on their needs. For this reason, in this research, an attempt has been made to categorize tweeting users into five groups based on the weight of the words in the text. In this regard, the well's word power dictionary was used to classify each tweet into three categories: positive, negative,

Power System Technology
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or neutral. In order to validate their proposed Fuzzy-BiEMM method, they asked their students to label more than 3000 tweets. The evaluations were carried out using three criteria: accuracy, sensitivity and F_{score}, and the results in each of the criteria were recorded as 75.23%, 78.22% and 76.69%, respectively.

In [23], presented an approach based on deep neural networks to predict the opinions of Amazon site users. For this purpose, they first received the data from the Amazon customer review collection and then improved the quality of the collection in the pre-processing stage, which includes categorization, removing irrelevant comments, and removing stop words and URLs. Then, using the previous approaches based on fuzzy C-Means, they extract the keywords of each tweet. In the final stage, using deep neural networks, they categorize the extracted general words into three categories: positive, negative and neutral as the final class of that tweet. The simulation results show that the proposed Fuzzy-BiEMM method of this research provides 6% to 20% higher accuracy than similar tasks.

In [24], presented a new hybrid approach focusing on deep learning to analyze the sentiments of Farsi-speaking users' comments. For this purpose, first extracting the features of comments, at two general levels and words (each with an independent CNN model) and then, the extracted features are fed to a Bi-LSTM (Bi-LSTM) network to class the comments (positive) or negative) to be determined. The tests performed on the Digikala Persian dataset show the accuracy of 95% of the proposed Fuzzy-BiEMM method.

In [25], presented a new approach for sentiment classification of political tweets. In their proposed Fuzzy-BiEMM method, first each tweet is converted into combined N-grams (single and multiple) and then the extracted combined N-grams are categorized using Newbizin tool. Their proposed Fuzzy-BiEMM method was implemented on the Obama-McCain election Twitter dataset and the evaluation results show that this approach provides 76.05% accuracy in F_{score}. Among the disadvantages of this approach, the lack of real-time performance and the lack of analysis of multilingual datasets have been mentioned.

In [26], presented a new approach based on symbology for multidimensional sentiment analysis on Twitter. For this purpose, they stated that examining emoticons and symbols in the text can have a useful effect on sentiment analysis. In this way, a reference table was created to score emoticons, and for each tweet, the polarity of the textual part was determined using previous approaches based on regression, and the reference table is also used for the symbols in the text, and the result of these two The section will determine the overall feel of the text. The evaluations were done on a dataset collected from about 2000 tweets and the results show that the efficiency of the proposed algorithm in terms of F_{score}, accuracy and precision is 89.61%, 86.55% and 92.89% respectively.

In [27], presented a new approach to sentiment analysis of the comments of users of the Spanish Catalan domain website. In their proposed Fuzzy-BiEMM method, first, in a pre-processing step, stop words are removed from the text and their roots are determined for other words, and then in the main phase, the recorded comment is categorized into one of two categories, positive or negative. The classification of opinions is also done using five tools of New Business, maximum disorder, support vector machine, decision tree and artificial neural

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networks, and then voting is done based on their output. Considering that there was no dataset for this language before, the authors of the paper first created a dataset for this purpose. The evaluation results show that the effectiveness of their proposed Fuzzy-BiEMM method in terms of accuracy, precision and F_{score} is 81%, 82% and 81%, respectively.

In [28], presented a new model based on artificial neural networks in order to categorize the sentiment of the text so that it can extract the content information of the text. For this purpose, they proposed to extract the content of the text from the CNN and to extract the global feeling of the text from the short-term memory network. Their evaluation was done using IMDB, Yelp 2013 and Yelp 2014 datasets. They recorded the accuracy of their proposed Fuzzy-BiEMM method in terms of accuracy and RMSE of 53.3% and 68.2%, respectively.

In [29], presented a new approach to detect more important comments and link comments based on their importance for video sharing social network comments (such as YouTube). In this approach, comments are ranked based on the user's history and the amount of useful (or not useful) information in them and using a support vector machine, and then, the comments are sorted based on the grade obtained. The evaluation performed on this approach using the database of TED video comments shows a maximum accuracy of 92.3%.

In [30], presented a new approach of sentiment analysis in comments recorded in social networks by dual use of deep learning. In this approach, instead of using the existing emotional dictionary, they first created a new emotional dictionary using a deep learning network and then, using a two-layer bilateral short-term memory (Bi-LSTM) network. They analyzed the opinion. To evaluate the proposed Fuzzy-BiEMM method, they used the comments in Taiwan's largest social network called PTT Bulletin Board System with 150,000 active users and more than 500,000 daily posts and comments. The evaluation results showed that the efficiency of this approach in terms of F_{score} and accuracy is 84.43% and 92.68% respectively.

In [31], proposed an approach to improve the performance of sentiment analysis in tweets containing fuzzy sentiments based on feature sets and CNN models. The feature set model was built by combining the information of five feature vectors extracted from vocabulary, word type, semantic, position and emotional pole of words, in tweets containing fuzzy emotional expressions. In this paper, the criteria of accuracy, sensitivity and F_{score} were investigated. The test analysis showed that the proposed Fuzzy-BiEMM method significantly improves the sentiment analysis performance of tweets containing fuzzy sentiments. The effectiveness of their proposed Fuzzy-BiEMM method is 81% accuracy, 82% sensitivity and 81% F_1 criterion.

In [32], in a research on sentiment analysis using deep learning models and RNN and CNN models. In this study, a two-way deep attention-based CNN-RNN model (ABCDM) is proposed for sentiment analysis. Many experiments were conducted on five browsing and three Twitter datasets to evaluate the performance of the developed model. Six published deep neural models for sentiment analysis are used for comparison. Testing results on these datasets show that ABCDM achieves advanced results in long review and short tweet classification and has acceptable accuracy. However, comparing the results obtained for the review and tweet datasets shows that the progress in the short tweet datasets is lower than the same case for the long review datasets.

Power System Technology
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In Table (1), the studies mentioned in the background of the research are summarized based on the performance of the proposed Fuzzy-BiEMM method, the tools used, the advantages and disadvantages of the proposed Fuzzy-BiEMM method, the tested datasets, and the evaluated criteria.

Table 1: Comparison of previous records

Authors/ year	**Approach**	**Tools used**	**Advantages of proposed approach**	**Disadvantages of proposed approach**	**Tested datasets**	**The results of the evaluated criteria**
Madhafar et al 2017	Sentiment analysis of Arabic language with Tunisian accent using support vector machine tools, Newbizin and Multilayer Perceptron.	MATLAB	Optimal accuracy and precision	Processing time, lack of scalability	Twitter dataset	Accuracy 91% Precision 92.36%
Sakar et al 2018	A large-scale approach to categorize the sentiment of online critical users	MATLAB	Fast processing time	Lack of scalability	Amazon dataset	Accuracy 85.6%
Alaoui et al. 2018	Sentiment analysis and adaptability to big data scale	MATLAB	Fast processing time	Poor accuracy and accuracy of sentiment analysis	Dataset of the 2016 US	Average Accuracy 90.21%
Yang et al. 2019	Sentiment analysis of comments using the concept of domain adaptation and neural networks	Radius map framework	Fast processing time and high scalability	Poor accuracy and accuracy of sentiment analysis	Dataset SemEval-14, SemEval-15	F_1 79.3% Accuracy 82.5%
Fu et al. 2019	An integrated word-based dual-task learning approach for sentiment analysis	MATLAB	Fast processing time and high scalability	Poor accuracy and accuracy of sentiment analysis	Twitter dataset	Precision 84.1% F_1 76.5%

Power System Technology
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Alhamari et al. 2019	Sentiment analysis of Arabic texts with Saudi accent based on deep learning	MATLAB	Optimal accuracy and precision	Processing time, lack of scalability	Twitter dataset	Accuracy of first approach 92% Accuracy of second approach 94%
Miyapan et al. 2019	Sentiment analysis based on Contextual Semantic	Apache Spark	Fast processing time and high scalability	Poor accuracy and accuracy of sentiment analysis	Tweet dataset	Accuracy 75.23% Recalling 78.22% F_{score} 76.69%
Mandhula et al. 2019	An approach based on deep neural networks to predict the opinions of Amazon users	MATLAB	Fast processing time	Poor accuracy and accuracy of sentiment analysis	Amazon dataset	6% to 20% increase in Accuracy
Zubidi et al. 2019	Sentiment analysis of Farsi language users' comments using deep learning	MATLAB	Optimal accuracy and precision	Processing time, lack of scalability	Digital Persian dataset	Accuracy 95%
Avalowo et al. 2019	An N-gram based approach for sentiment classification of political tweets	MATLAB	Optimal accuracy	Inability to perform real-time and analysis of multilingual datasets	Twitter dataset of Obama-McCain	Accuracy 76.05%
Sutaria 2019	A new semiology-based approach for multidimensional sentiment analysis on Twitter	MATLAB	Fast processing time	Lack of scalability	Tweet dataset	Accuracy 86.55% Precision 92.89% F_{score} 89.61%

Power System Technology
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Balaguer et al. 2019	An approach based on artificial neural networks to analyze the sentiments of users' opinions of the Spanish Catalan domain website	Apache Spark	Fast processing time and high scalability	Poor accuracy and accuracy of sentiment analysis	Twitter dataset	Accuracy 81% Precision 82% F_{score} 81%
Hahn et al. 2019	A new model based on artificial neural networks for text sentiment classification	MATLAB	Optimal accuracy	Time-consuming processing	IMDB, Yelp 2013 and Yelp 2014	Accuracy 53.3% RSME 68.2%
Seju 2020	A support vector machine-based approach to detect more important comments and link comments based on their importance for video sharing social network comments.	Radius map tool	Optimal accuracy and precision	Time-consuming processing, lack of scalability	TED dataset	Accuracy 92.3%
Chen et al. 2020	A new approach of sentiment analysis in comments recorded in social networks using dual deep learning	MATLAB	Fast processing time and high scalability	Poor accuracy and accuracy of sentiment analysis	Taiwan dataset called PTT Bulletin Board	Accuracy 92.68% F_{score} 84.43%
Fan et al. 2020	An approach to improve the performance of sentiment analysis in tweets containing fuzzy sentiments based on feature sets and CNN models	MATLAB	Sorting data in large volumes	Failure to analyze multilingual datasets	Tweet dataset	Accuracy 81% Sensitivity 82% F_1 81%

Power System Technology
ISSN:1000-3673

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Basiri et al. 2021	Sentiment analysis using deep learning models and RNN and CNN models	MATLAB	Real-time analysis	Poor accuracy and precision of sentiment analysis	Twitter dataset	Acceptable Accuracy

By reviewing the work done, it was found that several approaches have been introduced for surveying, which include supervisory and non-supervisory approaches. Some of these approaches have used semantic relationships between words and the grammatical role of words, and others have used dictionaries for this purpose. In the analysis, several features have been focused on. Many researches have investigated the analysis of emotions using surface and deep learning models. Some of them are designed based on computational linguistics, but most of them are based on machine learning, which considers sentiment analysis among text classification problems, and hence, three supervised machine learning approaches including simple Bayes, has used neural network and support vector machine.

Despite the disadvantages such as weakness in the accuracy and accuracy of sentiment analysis, time-consuming data processing, lack of analysis of multilingual datasets and lack of scalability in previous works, in this research by applying the fuzzy logic approach and combining it with the developed Markov model and deep learning involves data analysis and sentiment analysis.

3- The Proposed Fuzzy-BiEMM method

Fig. 1, shows the core of the proposed Fuzzy-BiEMM method. At first, the textual data is entered into the core of the proposed approach. Then the textual data is blocked and preprocessed. In the preprocessing process, words and prepositions are removed. The pre-processed data is normalized to increase the accuracy of sentiment analysis in textual data. Due to the large volume of data, duplicate samples in the dataset are removed. Removing duplicate samples not only does not have a negative effect on the created model, but also reduces the learning time of the model and reduces repetitive calculations.

After applying the usual pre-processing on the data, a Cohesive dataset is created. Then the preprocessed datasets are entered into the fuzzy logic approach. The fuzzy logic approach separates the words and extracts the weight of the words from the dictionary and extracts a set of rules. The fuzzy logic approach makes the model produced in the next step to be more accurate and the analysis of emotions can be done at a higher speed.

In the next step, the data is divided into two groups, training and testing. Using the K-fold approach, the data is divided into K parts to create the training and testing data. In this approach, the data is divided into K blocks, in each iteration, one of the K blocks is considered as test data and the rest as training data. The training data is entered into the EMM and the neural model is generated. Then the test data is entered into the generated model and analyzed. The final evaluation is based on the test data.

Power System Technology
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As seen in Fig. 1, in general, the textual data classification process includes pre-processing and data separation, data preparation, metadata normalization, fuzzy logic, separation of training and test samples, application of cellular neural network algorithm. deep which includes extended Markov model and Bi-LSTM deep neural network. In the following, each of these processes will be explained.

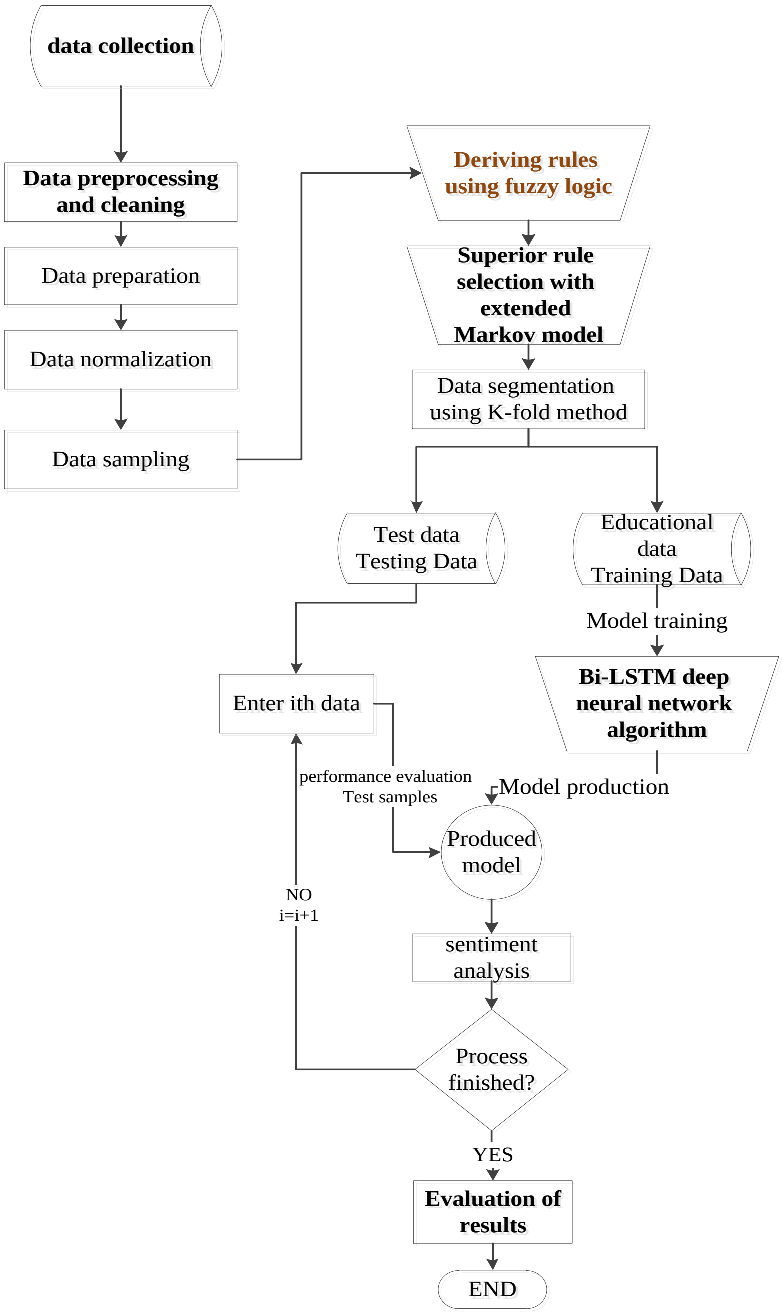

Figure 1: The proposed Fuzzy-BiEMM Architecture

Power System Technology
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3-1- Data preprocessing

The first step in the data preprocessing phase is to clean the dataset of missing-values. After the data sets are entered into the proposed system, these data are pre-processed and Missing-Value samples are removed from it. Then, the data that was converted into a coherent form after applying the pre-processing, is converted into an acceptable format for the simulation tools. Various approaches have been proposed to apply pre-processing on data, which include data cleaning, data collection, data transfer and data reduction.

In this paper, the data cleaning approach is used. The proposed method of Fuzzy-BiEMM is that the data set is checked. If a sample has a Missing-Value, it is identified and removed from the data set. Another step of the data preprocessing phase is data preparation and conversion into a standard format.

After the missing-value samples are removed from the data set, the preparation of the data set is done. The purpose of removing null data is to identify samples that have null values and modify them in the data set so that a simple model can be produced in the modeling process. The same process can increase the accuracy of detecting users' emotions. The pre-processed data is converted into a format acceptable to the simulation tools. The default data format is Excel. After the dataset has been examined superficially, it should be normalized. The last step in the preprocessing phase is the normalization of the data set.

In the pre-processing stage, in order to obtain better results, we normalize the values of each feature used in the dataset between 0 and 1, then randomly move the rows of the overall data matrix so that the order of the data is removed from the initial state of collection. In other words, all the dataset is mapped in the form of a matrix and by changing the rows of the matrix, the normalization operation takes place. Data normalization is an approach to make the range of values related to different research variables uniform and is also known as data de-scaling. If the unit of measurement of the studied variables is diverse, the data can be scaled using normalization approaches. To normalize the values of each dataset, Eq. (1) has been used [33].

$$\text{Normalize}(x) = \frac{(\mathrm{x}-\mathrm{X}_{\min})}{(\mathrm{X}_{\max}-\mathrm{X}_{\min})} \quad (1)$$

that X_{max} and X_{min} are the maximum and minimum values in the domain of the Xth feature. After data normalization, the values of all attributes are in the [0,1] range.

3-2- Rule extraction using fuzzy logic

Fuzzy logic is used in the proposed Fuzzy-BiEMM method to select features and derive effective rules for detecting users' emotions. Selecting the optimal features from the data set improves the accuracy of emotion recognition. The input of fuzzy logic is a dataset containing data from a social media. The output of the proposed fuzzy logic is a set of rules effective in detecting the emotions of users. The extraction of fuzzy rules can be described as follows [12]:

Suppose a data set is labeled as X={x_k | k=1,2, …, n} is defined to contain n number of labeled patterns $x_k \in R^p$. p is the number of (real-valued) features of f_i. If we consider x_k^m as the

Power System Technology
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value of the *mth* feature f_m of the pattern x_k, then every pattern x_k of the set X can be represented by a vector like Eq. (2).

$$x_k = [x_k^1, x_k^2, \dots, x_k^p] \tag{2}$$

Suppose all features are represented by a set F:

$$F = [f_1, f_2, \dots, f_p\ ] \tag{3}$$

We can represent the original data set into a fuzzy space using a membership set U defined as the original dataset can be defined using a membership set U into a fuzzy space according to Eq. (4).

$$U = [\mu_{11}, \mu_{12}, \dots, \mu_{1q}, \mu_{21}, \mu_{22}, \dots, \mu_{2r}, \dots, \mu_{p1}, \mu_{p2}, \dots, \mu_{ps}\ ] \tag{4}$$

where $\mu_{ij}$is the jth fuzzy set of features f_i. Indices q, r and s are positive numbers that show the cardinality of the first (f_1), second (f_2) and pth feature (f_p) fuzzy sets, respectively. Hence, the fuzzy model F_X of the original data set X as $F_X = \{(x_k, \mu(x_k)) \mid k = 1,2, \dots, n\}$ it is defined that $\mu(x_k)$is a vector which is displayed as Eq. (5):

$$\mu(x_k) = \begin{bmatrix} \mu_{11}(x_k^1), \mu_{12}(x_k^1), \dots, \mu_{1q}(x_k^1), \mu_{21}(x_k^2), \mu_{22}(x_k^2), \dots, \\ \mu_{2r}(x_k^2), \dots, \mu_{p1}(x_k^p), \mu_{p2}(x_k^p), \dots, \mu_{ps}(x_k^p) \end{bmatrix} \tag{5}$$

Assume that the number of fuzzy sets for each feature f_i as $|f_i|$ defined. In this case, fuzzy sets μ_{ij} are defined as Eq. (6).

$$\mu_{ij}: x_k^i \to [0,1];\ \forall i \in \{1,2, \dots, p\} \wedge \forall j \in \{1,2, \dots, |f_i|\} \wedge k \in \{1,2, \dots, n\} \tag{6}$$

The value of $\sum_{i=1}^{p} |f_i|$shows the amount of resolution of the set U. If the original dataset is p-dimensional, then its fuzzy projection is represented in a p-dimensional space as $\sum_{i=1}^{p} |f_i|$. Derivation of fuzzy rules determines the optimal combination of fuzzy sets μ_{ij}. If each subset of fuzzy sets can be evaluated with a criterion function J(.) and all possible combinations of fuzzy subsets are represented by the power set Θ, then the extraction of fuzzy rules into one of the subsets determining the $U_{optimal}$ fuzzy set Becomes.

$$J(U_{optimal}) = E(J(U_i)), \forall U_i \subseteq \Theta, \Theta = 2^U \tag{7}$$

where E may be the minimum or maximum operator. Therefore, based on the structure of the fuzzy logic approach, optimal rules are selected from the data received from users in social media. The output of this step is entered into Bi-LSTM deep neural network.

3-3- Separation of training and testing samples

Power System Technology
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With the help of data sampling, the training process of Bi-LSTM algorithm and the evaluation of the proposed Fuzzy-BiEMM method can be done. Data sampling is one of the most important parts of the proposed method, which separates the data set into two training and testing parts [34]. Training samples make up 80% and test samples make up 20% of the data set. The training samples are used for training the Bi-LSTM deep neural network model and the test samples are used to evaluate the proposed method based on evaluation criteria. In this paper, we have used k-fold sampling to separate the samples.

3-4- Deep cellular neural network algorithm

This phase of the proposed Fuzzy-BiEMM method has two general parts, which are the use of the extended Markov model and Bi-LSTM deep neural network, each of which is explained in the following sections.

3-4-1- Selection rules using the extended Markov model

In this paper, the extended Markov model is used to select the prominent rules. The input of the proposed Markov model is a set of rules selected by the fuzzy logic approach. The developed Markov model is a solution for identifying prominent rules that can be used to extract features that are effective in identifying users' emotions. Each rule has a set of properties. The feature in each rule determines the sentiment of the users. From the rules extracted by fuzzy logic, the developed Markov model selects the rules that have the greatest effect on the recognition of users' emotions and chooses them as the best rule. Finally, the features in the superior rule are used in Bi-LSTM deep neural network to detect users' emotions.

The superior law is the law that has the accuracy of detecting higher emotions. The first step in the extended Markov model in the proposed Fuzzy-BiEMM method is to identify the salient rules. In order to identify prominent rules, factors such as the correct detection rate of positive emotions, the correct detection rate of negative emotions and the accuracy of detection are used. Each rule has a positive emotion correct detection rate factor (K_{TP}), negative emotion correct detection rate factor (K_{FN}) and detection accuracy factor (K_{ACC}). The sum of these three factors for each law indicates the superiority of that law. The higher the rule score, the better the rule. Eq. (8) shows the total superiority of each rule (R_K).

$$R_K = K_{TP} + K_{FN} + K_{ACC} \tag{8}$$

To determine the optimal rule from three threshold limits named Th_{TP}, which indicates the threshold limit of the correct detection rate of positive emotions in rule k, and Th_{FN}, which indicates the rate of correct detection of negative emotions in rule k, the threshold limit named Th_{ACC}, which indicates the accuracy threshold limit Detection is used in k-law.

Now, this Eq. (9) is used to determine the busy node:

$$K_{Rule} = \frac{(K_{TP} - Th_{TP}) + (K_{FN} - Th_{FN}) + (K_{ACC} - Th_{ACC})}{R_K} * 100 \tag{9}$$

Power System Technology
ISSN:1000-3673
Received: 16-01-2024 Revised: 12-02-2024 Accepted: 07-03-2024

The following example shows how to calculate the percentage of superiority of K law.

$$\begin{array}{l} K_{TP} = 20 \\ Th_{TP} = 15 \\ K_{FN} = 30 \\ Th_{FN} = 20 \\ K_{ACC} = 20 \\ Th_{ACC} = 10 \end{array} \quad => \frac{(20-15)+(30-20)+(20-10)}{70} * 100 = 35.71\% \qquad (10)$$

The proposed extended Markov model calculates a probability for each rule, which is a numerical probability between the interval [0,1]. The closer the probability number is to 1, the higher the superiority of the law in question, and the features of that law can be used to detect emotions.

3-4-2- Bi-LSTM deep neural network

Bi-LSTM deep neural network or Bi-LSTM is used to detect users' emotions. Bi-directional LSTM (Bi-LSTM) is an extension of the LSTM model in which training is enhanced by traversing the input data twice, from left to right and right to left. LSTM, in turn, has been proposed to solve the Recurrent Neural Network (RNN) problem known as "vanishing gradients". LSTM models extend the memory of an RNN to allow it to retain and learn long-term dependencies of inputs. LSTM memory is used to store information over a long period of time and make decisions to keep or ignore information in memory. This allows to capture the important features of the inputs and preserve this information over a long period of time [35], [41]. In this paper, Bi-LSTM is used to generate a neural network model and finally to detect the emotions of users. Fig. 4, shows the structure of Bi-LSTM deep neural network.

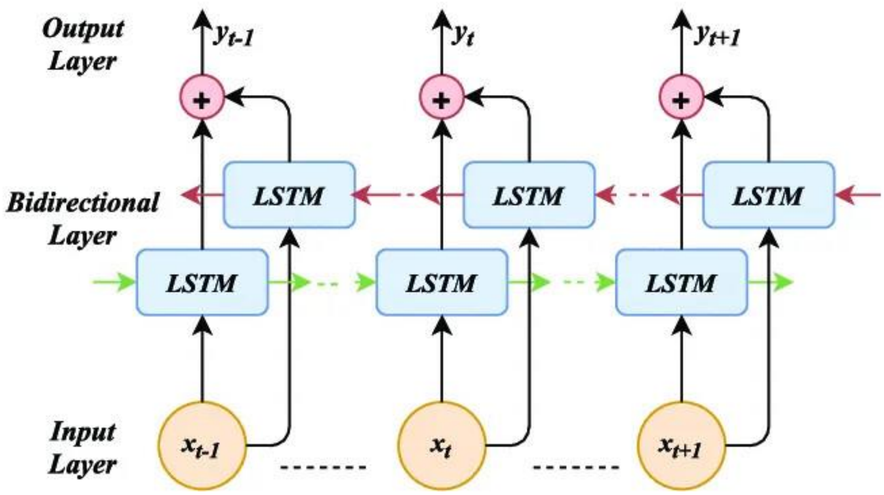

Figure 2. Bi-LSTM deep neural network structure

Power System Technology
ISSN:1000-3673
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According to Fig. 2, the general steps of the Bi-LSTM algorithm are as follows:

1. Bi-directional processing: Unlike traditional RNNs that process input sequences in only one direction (forward or backward), Bi-LSTM processes the sequence in both directions simultaneously. It consists of two LSTM layers: one processes the sequence in the forward direction and the other in the backward direction. Each layer maintains its own hidden states and memory cells.
2. Forward pass: During the forward pass, the input sequence from the first step to the last step is fed into the forward LSTM layer. At each time step, the forward LSTM computes its hidden state and updates its memory cell based on the current input and the previous hidden state and memory cell.
3. Backward pass: Simultaneously, the input sequence is also entered into the backward LSTM layer in reverse order, from the last time step to the first step. Similar to the forward pass, the backward LSTM computes its hidden state and updates its memory cell based on the current input and the previous hidden state and memory cell.
4. Combining Forward and Backward States: After completing the forward and backward passes, the hidden states from both LSTM layers are combined at each time step. This combination can be as simple as concatenating hidden states or applying some other transformation.

The advantage of Bi-LSTM is that it captures not only the context preceding a certain time step (like traditional RNNs) but also the subsequent contexts. By considering past and future information, Bi-LSTM can capture richer dependencies in the input sequence. Therefore, the data related to users' comments (training data) are entered into the Bi-LSTM model and a neural model is generated.

The algorithm strategy proposed in this paper is based on deep learning. In this way, the training datasets are entered into the core of Bi-LSTM deep neural network algorithm and the model of this algorithm is produced. Then the test data is entered into the model of this algorithm and it issues an answer for each test sample.

4- Evaluation of test results

In this section, the hardware and software specifications of the test simulation are described first. Then, the tested datasets, test evaluation criteria and finally, the analysis of test results have been reviewed.

4-1- Hardware and software specifications of simulation

The proposed Fuzzy-BiEMM method and the compared approaches in this paper have been implemented using the MATLAB-R2020b simulator. The operating system used in the test environment is Windows 7 32-bit type, RAM memory is 4 GB (3.06 GB usable), Intel Core™-i7 processor with 7 cores with specifications Q720-1.60GHz.

Power System Technology
ISSN:1000-3673
Received: 16-01-2024 Revised: 12-02-2024 Accepted: 07-03-2024

4-2- Datasets

The datasets tested in this paper are both batch and stream. In this regard, the use of available online data sets to download data from social networks is one of the basic ways for streaming datasets. Also, considering that there are feelings, opinions and opinions in every language and dialect, an efficient model should be able to extract the opinions, opinions and feelings in it regardless of the language. In addition, to examine batch datasets, Amazon's customer database has been used in the first part of the experiments [36]. In general, in this paper, the common datasets in [36] have been used and the results obtained have been compared with the results of [36].

In the second part of the experiments, in order to prove the correctness and performance of the proposed approach, its performance is investigated on other data sets. In this paper, 5 well-known and common datasets are used, which are Twitter [37], Facebook [38], Covid-19 fake news [39], Amazon [36] and Fake News Network [40]. Twitter is a sentiment140 dataset containing 1,600,000 tweets extracted using the Twitter API. Tweets are annotated with values from 0 (negative) to 4 (positive), which can be used to detect sentiment. In addition, the Twitter dataset contains 6 features as shown in Table (2) [37].

Table 2. Characteristics of the Twitter dataset

Property	Feature description
Target	Tweet polarity (0: negative, 2: neutral, 4: positive)
ID	Tweet ID (2087)
Date	Tweet date (Sat May 16 23:58:44 UTC 2009)
Flag	Query (lyx). If there is no query, this value is NO_QUERY.
user	User who tweeted (robotickilldozr)
Text	Text of the tweet (lyx is interesting)

The Facebook dataset [38] contains 10,000 newspapers and metadata is almost gone. 600 web pages from the PolitiFact website to analyze it using data science skills and get some insights on how to prevent the spread of misinformation on a wider scale and what better accuracy approach to achieve it. Gives. This data set has 6 features that are shown in table (3) and among them, the feature of the news title is the most important for classifying the news as false or true.

Table 3. Characteristics of the Facebook dataset

Property	Feature description
News title	Contains information to be analyzed.
News link	Contains the URL of the news headlines specified in the first attribute.

Power System Technology
ISSN:1000-3673
Received: 16-01-2024 Revised: 12-02-2024 Accepted: 07-03-2024

References	Names of authors who posted information on Facebook, Instagram, Twitter, or any other social media platform.
Date of announcement	Contains the date of posting of information by authors on various social media platforms.
Check date	Contains the date that this piece of information was analyzed by PolitiFact fact-checking team to label it as fake or real.
Label	5 class labels include true, mostly true, half true, hardly true, false, pants on fire.

The Covid-19 fake news dataset [39] is the result of a subtask in the CONSTRAINT-2021 joint work on hostile post detection. This subtask focuses on identifying fake news related to COVID-19 in English. Sources of data are various social media platforms such as Twitter, Facebook, Instagram, etc. Given a social media post, the goal of the collaborative work is to classify it as either fake news or real news.

Amazon dataset [36], for the paper "From group to individual labels using deep features" author Kotzias et. al, was created in 2015 and contains sentences labeled with positive or negative emotions. The score is either 1 for positive or 0 for negative. The sentences were collected from three websites including imdb.com, amazon.com and yelp.com in different contexts. For each website, there are 500 positive and 500 negative sentences randomly selected for the larger dataset of reviews. In this paper, an attempt has been made to select sentences that clearly have a positive or negative meaning, the goal was not to select any neutral sentence.

The IMDB website refers to the movie review sentiment dataset originally introduced by Maas et al. As a benchmark for sentiment analysis, this dataset contains 100,000 movie reviews, with 50,000 unlabeled reviews and the remaining 50,000 divided into a set of 25,000 for training and 25,000 for testing. Each tagged review has a binary sentiment label, positive or negative. In the experiments of this paper, only the labeled part of the training set was performed. The Amazon website contains reviews and ratings of products sold in the category of mobile phones and accessories and is part of the dataset collected by McAuley and Leskovec. Scores are on an integer scale from 1 to 5. In this paper, comments with 4 and 5 points are considered positive and 1 and 2 points are considered negative. The data is randomly divided into two 50% halves, one for training and one for testing, with 35,000 documents in each set. The Yelp website contains the dataset of restaurant reviews that is extracted in this paper. Scores are on an integer scale from 1 to 5. Similarly, comments with scores of 4 and 5 are considered positive and 1 and 2 negatives. Randomly created a 50-50 training and test split, resulting in approximately 300,000 documents for each set.

The Fake News Network dataset [41] is a repository for an ongoing data collection project for fake news research at ASU and contains all fake newspapers with the news content

Power System Technology
ISSN:1000-3673
Received: 16-01-2024 *Revised: 12-02-2024* *Accepted: 07-03-2024*

characteristics shown in Table 4. For each of the aforementioned datasets, 1000 sentences were extracted from the test set and manually labeled, 50% of which were positive emotions and 50% were negative emotions. These statements are only used to evaluate our sample-level classifier for each data set, value 3. They are not used for model training, to maintain consistency with our overall goal of ensemble-level learning and sample-level prediction [36].

Table 4. Characteristics of fake news network dataset features

Property	Feature description
Source	The author or publisher of the news.
Title	A short text whose purpose is to attract readers' attention and is completely related to the main news topic.
Text	It details the story and there is often a major claim that shapes the publisher's angle and is specifically highlighted and explained.
Image-video	An important part of the content of the news text is that it provides visual cues to frame the story.

4-3- Evaluation metrics

To evaluate the performance of the proposed Fuzzy-BiEMM method, which is based on the machine learning approach, several criteria such as accuracy (Acc), Precision (Pre), Recall (Rec) and F_{score} criteria are used, and the mathematical relationships of each of these criteria in Eq. (11) to (14) has been proposed [13]. In these relationships, TP is the number of comments that have a positive feeling and are recognized as positive by the proposed Fuzzy-BiEMM method. TN is the number of comments that have a positive sentiment and are detected as negative by the proposed Fuzzy-BiEMM method. FP criterion is the number of comments that have a negative feeling and are recognized as positive by the proposed Fuzzy-BiEMM method, and FN is the number of comments that have a negative feeling and are recognized as negative by the proposed Fuzzy-BiEMM method [33].

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (11)$$

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

In addition, one of the most important evaluation criteria in this paper is time order. The time order is calculated based on milliseconds and using Eq. (14).

$$Execuation\ Time = \sum_{i=1}^{i} t \quad (14)$$

Power System Technology
ISSN:1000-3673
Received: 16-01-2024 *Revised: 12-02-2024* *Accepted: 07-03-2024*

4-4- Analysis and evaluation of results

In Table (5), the comparison of the performance of the proposed Fuzzy-BiEMM method on the Amazon dataset and the proposed criteria without applying and with applying the fuzzy logic approach is shown.

Table 5. Comparison of the performance of the proposed Fuzzy-BiEMM method based on the criteria of accuracy, correctness, sensitivity and error of sentiment analysis without and with the application of fuzzy logic approach

		The proposed method without fuzzy logic				The proposed Fuzzy-BiEMM approach			
	number of samples	Error %	Precision %	Recall %	Accuracy %	Error %	Precision %	Recall %	Accuracy %
Amazon data	100	10.9	89.8	91.8	89.1	5.9	94.8	96.8	94.1
	500	12.5	92.3	87.7	87.5	7.5	97.3	92.7	92.5
	1000	16.75	83.82	87.68	83.25	8.75	91.82	95.68	91.25
	10.000	8.9	83.54	80.54	91.1	4.9	87.54	84.54	95.1
	100.000	5.28	7.83	72.83	94.72	1.28	74.83	73.83	98.72

From the results obtained in Table (5), it can be concluded that the proposed Fuzzy-BiEMM method performs better compared to the proposed approach without using the fuzzy logic approach. The reason for the improvement of the proposed Fuzzy-BiEMM method compared to the proposed Fuzzy-BiEMM method without applying the fuzzy logic approach is that the fuzzy logic approach has extracted effective rules in detecting user sentiments and finally features that have high disreputability in detecting user sentiments. Select the title of the outstanding features. The extraction of effective rules by the fuzzy logic approach makes a simpler model produced by the BiEMM approach and sentiment detection is done with higher accuracy. In the proposed Fuzzy-BiEMM method, the more samples are used to train the Bi-LSTM deep neural network, the more accurate the model is produced. According to the obtained results, it can be seen that the use of the proposed Fuzzy-BiEMM method can improve the accuracy of sentiment analysis compared to the normal state and other approaches based on the number of diverse data.

Power System Technology
ISSN:1000-3673

Received: 16-01-2024 Revised: 12-02-2024 Accepted: 07-03-2024

In Fig. 3, the comparison of the performance of the proposed Fuzzy-BiEMM method on the Amazon dataset based on the proposed criteria compared to other approaches is shown.

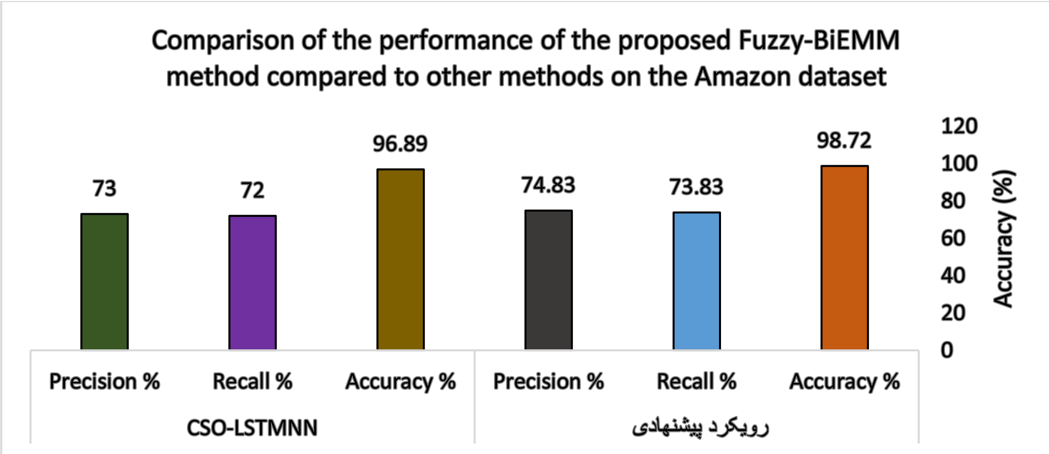

Figure 3. Performance comparison of the proposed Fuzzy-BiEMM method compared to other methods on the Amazon dataset

As can be seen from Fig. 3, the average accuracy, precision and sensitivity to detect the emotions of users in Amazon in the proposed method are equal to 98.72%, 73.83% and 74.83%, respectively, which is 1.83% better than the CSO-LSTMNN method. Is. The proposed Fuzzy-BiEMM method performs significantly better than the CSO-LSTMNN method [36] in the process of detecting users' emotions with the help of BiEMM and fuzzy logic approach. As the number and volume of samples increases, the error of the emotion recognition process decreases and reaches an acceptable and desirable value. In Fig. 4, the comparison of execution time (milliseconds) of the proposed Fuzzy-BiEMM method compared to other methods on the Amazon dataset is shown.

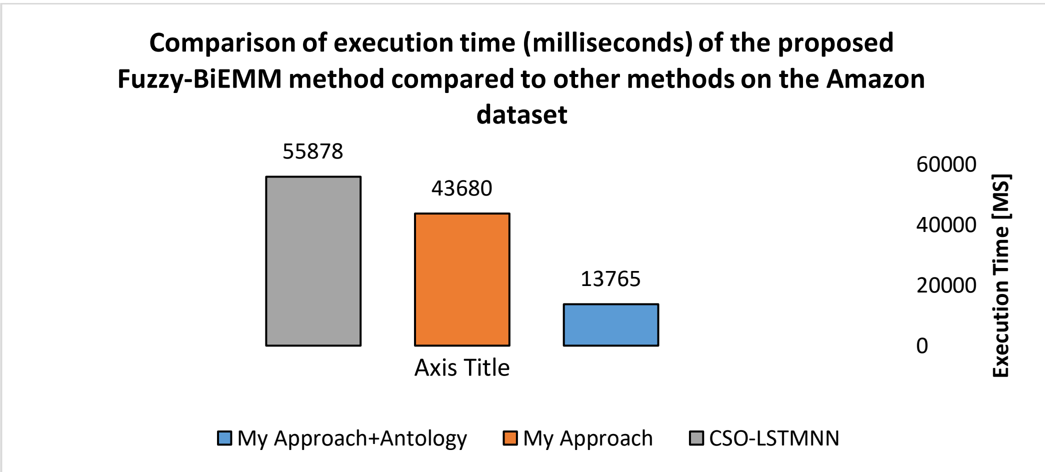

Figure 4. Comparison of execution time [MS] of the proposed Fuzzy-BiEMM method compared to other approaches

Power System Technology
ISSN:1000-3673

Received: 16-01-2024 Revised: 12-02-2024 Accepted: 07-03-2024

The average execution time of the proposed Fuzzy-BiEMM method for the number of 100-100,000 samples by applying the fuzzy logic approach is equal to 13765 milliseconds, the proposed Fuzzy-BiEMM method without applying the fuzzy logic approach is equal to 43680 milliseconds and the CSO-LSTMNN approach is equal to 55887 milliseconds It is seconds. The improvement rate of the proposed Fuzzy-BiEMM method compared to the proposed Fuzzy-BiEMM method without semantics and the CSO-LSTMNN method has improved by 29915 milliseconds and 42122 milliseconds, respectively. Therefore, the proposed Fuzzy-BiEMM method with the help of Bi-LSTM deep neural network and the extended Markov model and fuzzy logic approach based on diverse data volumes can produce better results than the most recent approaches such as the CSO-LSTMNN approach.

Also, according to the results obtained from Fig. 4, it can be seen that in all approaches, the execution time increases with the increase in the amount of data; But the best time performance (112 milliseconds to 61000 milliseconds) is the proposed Fuzzy-BiEMM method by applying the fuzzy logic approach. The reason for the temporal superiority of the fuzzy logic approach is that it extracts effective rules in the detection of emotions by the fuzzy logic approach and creates a simpler model. By creating a simple model and not processing all available features, the execution time of user emotion recognition is reduced.

In Fig. 5, the comparison of the average accuracy of the proposed Fuzzy-BiEMM method with other methods such as deep neural network of Long-Short Term Memory (LSTM), Recursive Deep Neural Network (RDNN), Multi-Perceptron Neural Network (MLP), decision tree C4.5, K-Nearest Neighbor (KNN) and support vector machine (SVM) are shown.

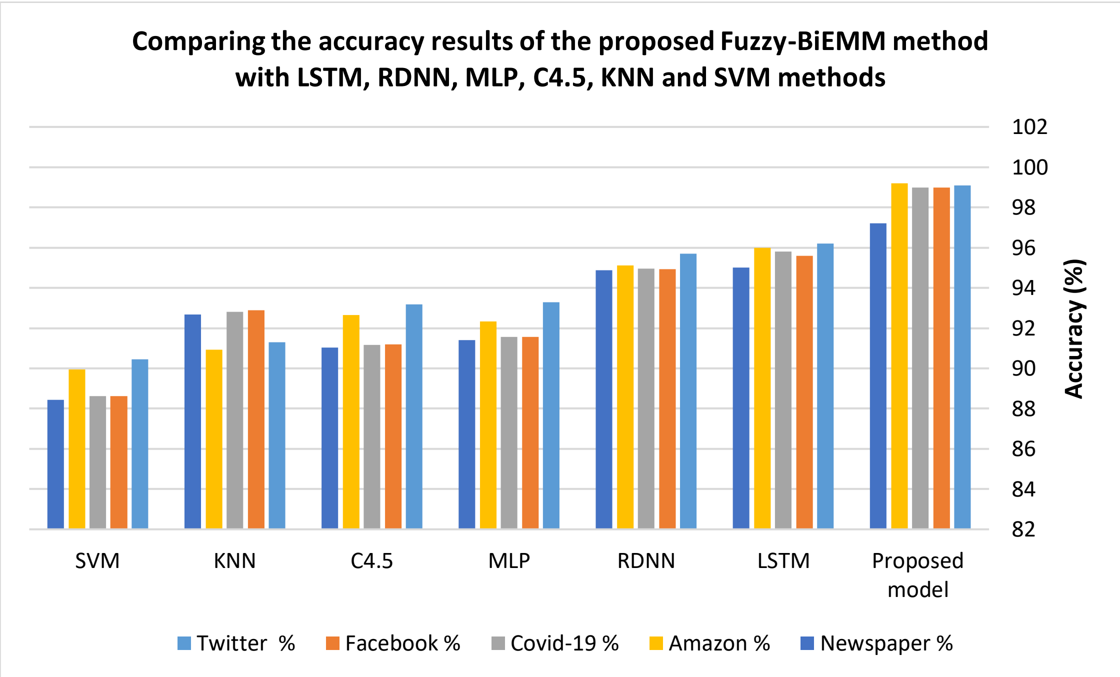

Figure 5. Comparison of the accuracy of user sentiment detection using the proposed Fuzzy-BiEMM method with LSTM, RDNN, MLP, C4.5, KNN and SVM methods.

Power System Technology
ISSN:1000-3673

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As can be seen from Fig. 5, the accuracy improvement rate of the proposed Fuzzy-BiEMM method on the Twitter dataset, compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN, and SVM, respectively, is equal to 2.9%, 3.4%, 5.82%, 5.91%, 7.81% and 8.64%. Also, the accuracy improvement rate of the proposed Fuzzy-BiEMM method on the Facebook dataset, compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN and SVM, is 3.4%, 4.06%, 7.44%, respectively. 7.82%, 6.11% and 10.39%. In addition, the accuracy improvement of the proposed Fuzzy-BiEMM method on the fake news dataset of Covid-19 compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN and SVM is 3.2%, respectively. 4.05%, 7.43%, 7.84%, 6.19% and 10.39%. Similarly, the accuracy improvement of the proposed Fuzzy-BiEMM method on the Amazon dataset compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN and SVM is 3.2%, 4.08%, 6.86%, respectively., 6.56%, 6.86% and 9.26%. Finally, the accuracy improvement rate of the proposed Fuzzy-BiEMM method on the fake news network dataset, compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN and SVM, is 2.2%, 2.33%, 5.79%, respectively 6.17%, 4.51% and 8.76%.

According to the results obtained in Fig. 5, it was observed that the proposed Fuzzy-BiEMM method has a better performance, because the application of the proposed Fuzzy-BiEMM method by extracting effective rules in emotion recognition and also, the deep neural network model of cellular Bi-LSTM to the extent Significantly, it has been able to perform better and have an acceptable accuracy compared to other approaches. In Fig. 7, the comparison of the accuracy criteria results of the proposed Fuzzy-BiEMM method compared to LSTM, RDNN, MLP, C4.5, KNN and SVM approaches is shown.

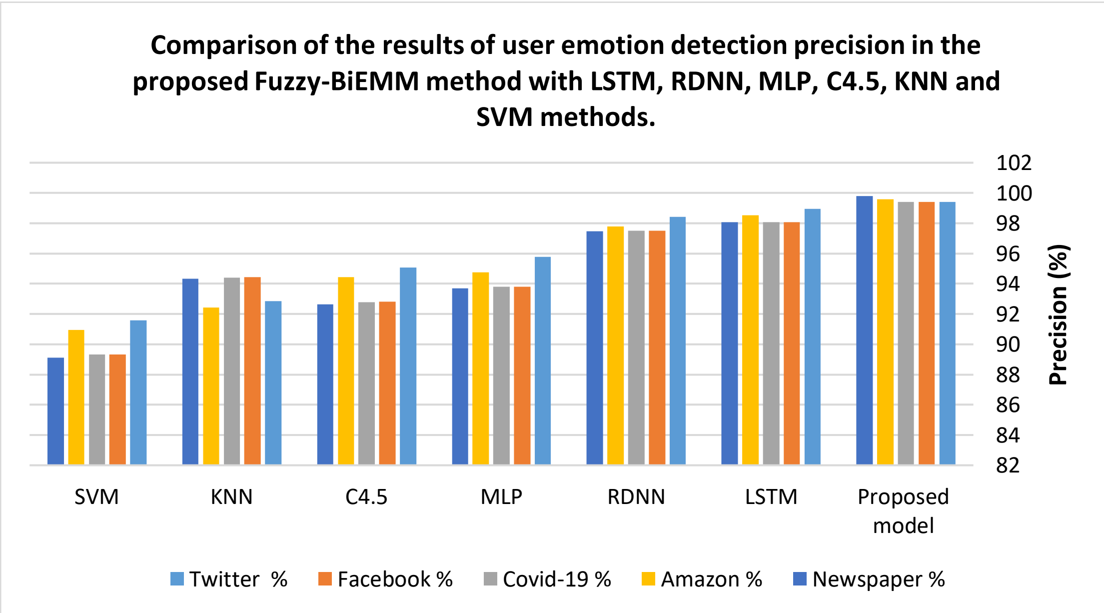

Figure 6. Comparison of the results of user sentiment detection precision in the proposed Fuzzy-BiEMM method with LSTM, RDNN, MLP, C4.5, KNN and SVM methods.

Power System Technology
ISSN:1000-3673
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As can be seen, the improvement of the precision of opinion mining on the Twitter dataset in the proposed Fuzzy-BiEMM method, compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN and SVM, is equal to 0.44%, 0.97, respectively. % is 3.61%, 4.34%, 6.54% and 7.81%. Also, the improvement of the precision of opinion mining on the Facebook dataset in the proposed Fuzzy-BiEMM method, compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN and SVM, is equal to 1.32%, 1.89%, 5.58% respectively. % is 6.59%, 4.96% and 10.06%. In addition, the improvement of the precision of opinion mining on the fake news dataset of Covid-19 in the proposed Fuzzy-BiEMM method, compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN, and SVM, is equal to 1.32%, respectively. 1.9%, 5.6%, 6.63%, 4.99% and 10.09%. Similarly, the precision improvement rate on the Amazon dataset in the proposed Fuzzy-BiEMM method compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN and SVM is 1.06%, 1.8%, respectively. 4.84%, 5.16%, 7.16% and 8.64%. Finally, the improvement of the precision of opinion mining on the fake news network dataset in the proposed Fuzzy-BiEMM method, compared to other approaches including LSTM, RDNN, MLP, C4.5, KNN and SVM, is equal to 1.74%, 2.34%, respectively. 6.12%, 7.15%, 5.48% and 10.67%. It was found that the proposed Fuzzy-BiEMM method performed better than other approaches.

According to the results obtained from the proposed Fuzzy-BiEMM method in Fig. 6, it was observed that the generated model based on the fuzzy logic approach is simple and works with high accuracy. Therefore, the simplicity of the model with a high number of hidden layers has increased the accuracy of user emotion recognition. In Fig. 7, the comparison of the sensitivity results of user sentiment detection in the proposed Fuzzy-BiEMM method with LSTM, RDNN, MLP, C4.5, KNN and SVM methods is shown.

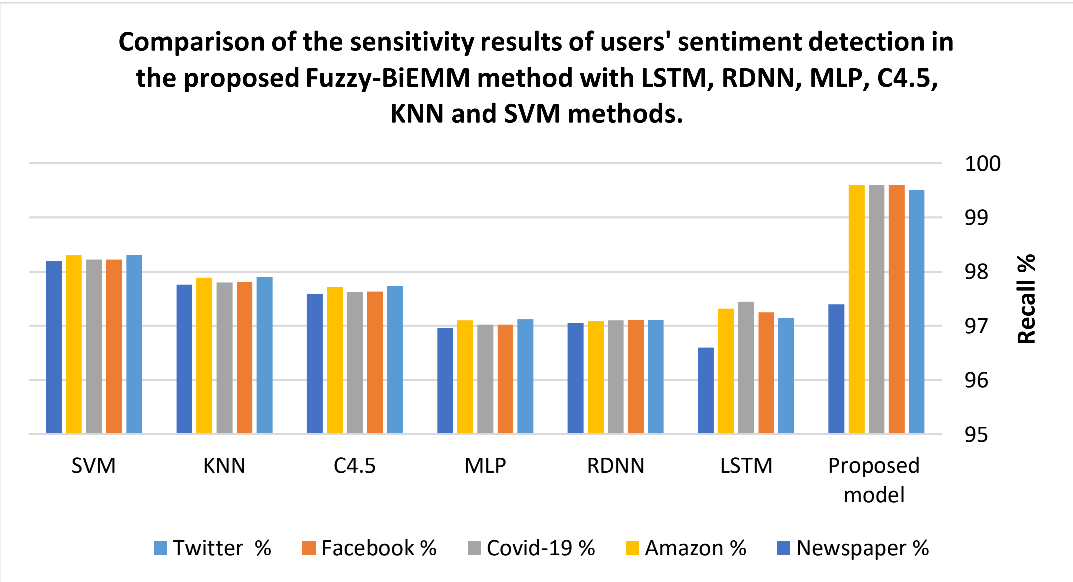

Figure 7. Comparison of the sensitivity results of user sentiment detection in the proposed Fuzzy-BiEMM method with LSTM, RDNN, MLP, C4.5, KNN and SVM methods.

Power System Technology
ISSN:1000-3673
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According to the results of Fig. 7, it can be seen that the proposed Fuzzy-BiEMM method has a better performance; Because the application of the proposed Fuzzy-BiEMM method by extracting the features that are effective in detecting users' emotions as well as the cellular Bi-LSTM deep neural network model has been able to perform significantly better and has an acceptable accuracy compared to other approaches.

5- Conclusion and future work

One of the main goals of this paper is to present a survey model based on two-way LSTM deep neural network, EMM approach and fuzzy logic approach. Fuzzy logic approach has been used to extract effective rules, Bi-LSTM deep neural network has been used to classify emotions, and EMM has been used to improve user emotion recognition model. By observing the obtained results, it was proved that the use of fuzzy logic approach in the process of detecting emotions and identifying positive and negative tweets, classifying the news of the COVID19 virus, user comments, etc. has improved the accuracy. The use of EMM with the ability to learn from tweets, comments, news, etc. made new tweets to be predicted based on the weighting of meaningful words. The process of improving the final Bi-LSTM deep neural network model has improved the accuracy of emotion recognition. By simulating the proposed Fuzzy-BiEMM method on the datasets of Twitter, Facebook, fake news of Covid-19, Amazon and the fake news network and presenting the proposed Fuzzy-BiEMM method for sentiment detection, we were able to advance to an average accuracy of 94.33%. Therefore, the application of fuzzy logic approach can significantly improve the execution speed and recognition accuracy by deep neural network approach of cellular Bi-LSTM.

The use of deep neural network algorithms such as GMDH, CNN and a combination of machine learning approaches with optimization algorithms such as gray wolf, advanced cats, dragonfly, etc. instead of fuzzy logic approach and deep neural network Bi-LSTM are some of the most important suggestions. that can be presented to develop and improve the results of this research.

References

[1] Li, Z., Fan, Y., Jiang, B., Lei, T., & Liu, W. (2019). A survey on sentiment analysis and opinion mining for social multimedia. *Multimedia Tools and Applications*, *78*(6), 6939-6967.
[2] Wang, R., Zhou, D., Jiang, M., Si, J., & Yang, Y. (2019). A survey on opinion mining: From stance to product aspect. *IEEE Access*, *7*, 41101-41124.
[3] Mäntylä, M. V., Graziotin, D., & Kuutila, M. (2018). The evolution of sentiment analysis—A review of research topics, venues, and top cited papers. *Computer Science Review*, *27*, 16-32.
[4] Balazs, J. A., & Velásquez, J. D. (2016). Opinion mining and information fusion: a survey. *Information Fusion*, *27*, 95-110.
[5] Barnaghi, P., Ghaffari, P., & Breslin, J. G. (2016, March). Opinion mining and sentiment polarity on twitter and correlation between events and sentiment. In *2016 IEEE second*

Power System Technology
ISSN:1000-3673
Received: 16-01-2024 Revised: 12-02-2024 Accepted: 07-03-2024

international conference on big data computing service and applications (BigDataService) (pp. 52-57). IEEE.
[6] Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile networks and applications*, *19*(2), 171-209.
[7] Injadat, M., Salo, F., & Nassif, A. B. (2016). Data mining techniques in social media: A survey. *Neurocomputing*, *214*, 654-670.
[8] Mohammad, S. M., Kiritchenko, S., & Zhu, X. (2013). NRC-Canada: Building the state-of-the-art in sentiment analysis of tweets. *arXiv preprint arXiv:1308.6242*.
[9] Narayanan, V., Arora, I., & Bhatia, A. (2013, October). Fast and accurate sentiment classification using an enhanced Naive Bayes model. In *International Conference on Intelligent Data Engineering and Automated Learning* (pp. 194-201). Springer, Berlin, Heidelberg.
[10] Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: tasks, approaches and applications. *Knowledge-based systems*, *89*, 14-46.
[11] Prasad, S. S., Kumar, J., Prabhakar, D. K., & Pal, S. (2015, December). Sentiment classification: an approach for Indian language tweets using decision tree. In *International conference on mining intelligence and knowledge exploration* (pp. 656-663). Springer, Cham.
[12] Rezaee, M. R., Goedhart, B., Lelieveldt, B. P., & Reiber, J. H. (1999). Fuzzy feature selection. *Pattern Recognition*, *32*(12), 2011-2019.
[13] Guo, H., Li, S., Qi, K., Guo, Y., & Xu, Z. (2018). Learning automata-based competition scheme to train deep neural networks. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *4*(2), 151-158.
[14] Mohbey, K. K. (2020). Multi-class approach for user behavior prediction using deep learning framework on twitter election dataset. *Journal of Data, Information and Management*, *2*(1), 1-14.
[15] Liu, W., Wang, Z., Liu, X., Zeng, N., Liu, Y., & Alsaadi, F. E. (2017). A survey of deep neural network architectures and their applications. *Neurocomputing*, *234*, 11-26.
[16] Mdhaffar, S., Bougares, F., Esteve, Y., & Hadrich-Belguith, L. (2017, April). Sentiment analysis of tunisian dialects: Linguistic ressources and experiments. In *Third Arabic Natural Language Processing Workshop (WANLP)* (pp. 55-61).
[17] Al-Saqqa, S., Al-Naymat, G., & Awajan, A. (2018). A large-scale sentiment data classification for online reviews under apache spark. *Procedia Computer Science*, *141*, 183-189.
[18] El Alaoui, I., Gahi, Y., Messoussi, R., Chaabi, Y., Todoskoff, A., & Kobi, A. (2018). A novel adaptable approach for sentiment analysis on big social data. *Journal of Big Data*, *5*(1), 1-18.
[19] Yang, M., Yin, W., Qu, Q., Tu, W., Shen, Y., & Chen, X. (2019). Neural attentive network for cross-domain aspect-level sentiment classification. *IEEE Transactions on Affective Computing*, *12*(3), 761-775.
[20] Fu, Y., Liu, Y., & Peng, S. L. (2020). An integrated word embedding-based dual-task learning method for sentiment analysis. *Arabian Journal for Science and Engineering*, *45*(4), 2571-2586.

Power System Technology
ISSN:1000-3673
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[21] Alahmary, R. M., Al-Dossari, H. Z., & Emam, A. Z. (2019, January). Sentiment analysis of Saudi dialect using deep learning techniques. In *2019 International Conference on Electronics, Information, and Communication (ICEIC)* (pp. 1-6). IEEE.
[22] Ramanathan, V. (2019). Prediction of Individual's Character in Social Media Using Contextual Semantic Sentiment Analysis. *Mobile Networks and Applications*, *24*(6), 1763-1777.
[23] Mandhula, T., Pabboju, S., & Gugulotu, N. (2020). Predicting the customer's opinion on amazon products using selective memory architecture-based convolutional neural network. *The Journal of Supercomputing*, *76*(8), 5923-5947.
[24] Zobeidi, S., Naderan, M., & Alavi, S. E. (2019). Opinion mining in Persian language using a hybrid feature extraction approach based on convolutional neural network. *Multimedia Tools and Applications*, *78*(22), 32357-32378.
[25] Awwalu, J., Bakar, A. A., & Yaakub, M. R. (2019). Hybrid N-gram model using Naïve Bayes for classification of political sentiments on Twitter. *Neural Computing and Applications*, *31*(12), 9207-9220.
[26] Chauhan, D., & Sutaria, K. (2019). Multidimensional sentiment analysis on twitter with semiotics. *International Journal of Information Technology*, *11*(4), 677-682.
[27] Balaguer, P., Teixidó, I., Vilaplana, J., Mateo, J., Rius, J., & Solsona, F. (2019). CatSent: a Catalan sentiment analysis website. *Multimedia Tools and Applications*, *78*(19), 28137-28155.
[28] Han, H., Bai, X., & Li, P. (2019). Augmented sentiment representation by learning context information. *Neural Computing and Applications*, *31*(12), 8475-8482.
[29] Choi, S., & Segev, A. (2020). Finding informative comments for video viewing. *SN Computer Science*, *1*(1), 1-14.
[30] Chen, L. C., Lee, C. M., & Chen, M. Y. (2020). Exploration of social media for sentiment analysis using deep learning. *Soft Computing*, *24*(11), 8187-8197.
[31] Phan, H. T., Tran, V. C., Nguyen, N. T., & Hwang, D. (2020). Improving the performance of sentiment analysis of tweets containing fuzzy sentiment using the feature ensemble model. *IEEE Access*, *8*, 14630-14641.
[32] Basiri, M. E., Nemati, S., Abdar, M., Cambria, E., & Acharya, U. R. (2021). ABCDM: An attention-based bidirectional CNN-RNN deep model for sentiment analysis. *Future Generation Computer Systems*, *115*, 279-294.
[33] Hossin, M., & Sulaiman, M. N. (2015). A review on evaluation metrics for data classification evaluations. *International journal of data mining & knowledge management process*, *5*(2), 1.
[34] Malik, J. S., Goyal, P., & Sharma, A. K. (2010). A comprehensive approach towards data preprocessing techniques & association rules. In *Proceedings of the 4th National Conference* (Vol. 132).
[35] Siami-Namini, S., Tavakoli, N., & Namin, A. S. (2019, December). The performance of LSTM and Bi-LSTM in forecasting time series. In *2019 IEEE International conference on big data (Big Data)* (pp. 3285-3292). IEEE.
[36] Alarifi, A., Tolba, A., Al-Makhadmeh, Z., & Said, W. (2020). A big data approach to sentiment analysis using greedy feature selection with cat swarm optimization-based long short-term memory neural networks. *The Journal of Supercomputing*, *76*(6), 4414-4429.

Power System Technology
ISSN:1000-3673
Received: 16-01-2024 Revised: 12-02-2024 Accepted: 07-03-2024

[37] https://www.kaggle.com/datasets/kazanova/sentiment140.
[38] https://www.kaggle.com/datasets/techykajal/fakereal-news.
[39] https://www.kaggle.com/datasets/elvinagammed/covid19-fake-news-dataset-nlp.
[40] https://www.kaggle.com/datasets/marklvl/sentiment-labelled-sentences-data-set.
[41] Zhou, C., Sun, C., Liu, Z., & Lau, F. (2015). A C-LSTM neural network for text classification. *arXiv preprint arXiv:1511.08630*.