RESEARCH ARTICLE

Bidirectional Deep Learning and Extended Fuzzy Markov Model for Sentiments Recognition

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Abstract

Currently, a considerable amount of people are sending messages on social networks such as Twitter, Amazon and Facebook. These media is colossal with data and information. Bearing in mind the need for these social media platforms to extract the appropriate negative or positive emotions from users and even news articles, opinion mining is required. Opinion mining provides the ability to assess social media users' opinions as well as the provided knowledge that assists in emotion detection. Some issues that have been more prevalent, in social media, include the lack of sentiment accuracy, transparency, and accuracy in measuring the users' sentiments. In social media, a variety of solutions based on different methods have been suggested in an attempt to capture the red flag on user's sentiments. For that reason, in this paper a system designed for the comment sentiment recognition problem is proposed and named Fuzzy-BIEM. This is based on extended Markov model (EM) with Bi-LSTM neural network and fuzzy logic. Rules were constructed with the fuzzy approach, and the Bi-LSTM deep neural network performed the sentiment recognition. EMM was employed to enhance the performance of the deep neural network. In this case, the input data were customer data from Amazon, Twitter, Facebook, Covid-19 fake news, and the Amazon fake news network. The application of fuzzy logic to the Fuzzy-BIEM approach did result in an increase of average emotion recognition accuracy. When fuzzy logic was used, the accuracy attained was 96.75%. Compared to the Fuzzy-BIEM approach without fuzzy logic, this is an increase of 7.62%. This was also an increase of 5.02% to the CSO-LSTMNN method.

Keywords: opinion mining, sentiment analysis, extended markov model, deep neural network, fuzzy logic.

1 Introduction

Even today, the Internet continues to gain traction and more and more people are using social networking sites. A key characteristic of social networks is that users, regardless of nationality or location, can

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share comments or feedback anonymously. These comments are of immense importance [1–3]. Micro blogging is one of the "media" types we mention where Amazon and Twitter stand out for their particular popularity and the frequency in which users express their thoughts and emotions on certain topics is on the rise [4]. Regardless of the fact that this resource contains plethora of users feelings and thoughts, it is a legitimate and necessary source that exists and can be extracted for the useful purposes [5]. One of the most remarkable problems in social media of the nature of Amazon or Twitter is the collection of enormous volumes of data, the accuracy of classification and the speed of information processing. There is no possibility to normal systems to data analyze and implement, there is also insufficient space for data processing and analysis. For that reason, data management comprising processing, analysis, classification, etc. is the focus of this paper.

In today's world, both the number of social media users and the number of comments and tweets sent has skyrocketed. This has led to an increase in data. Data is defined to be from a system that has speed, high volume production, and a variety of processes. Data refers to any set that is unable to be processed or executed in a central system [6, 7]. Because of this, it is crucial to analyze the data in question, perform sentiment analysis, and extract meaning, or else one runs the risk of lacking or misinterpreting essential information.

Sentiment analysis is divided into three main categories: supervised, semi-supervised and unsupervised. Recently there have been lots of changes when it comes to the classification of data. The changes comprise the use of monitoring systems AI algorithms, and support vector machine [8], Bayesian networks [9], linear regression [10], decision tree [11] classifiers, etc. All these algorithms suffer from one or several problems, which range from an overall lack of precision, sufficient precision accompanied by high misclassification rates in sentiment Analysis, to worse: low precision and high classification error in the target. Due to these problems in the algorithms related to classifying user sentiment, this paper attempts to resolve classifiers EMM and fuzzy logic approach to solve existing sentiment classification problems.

Consequently, the existing categorization found in earlier papers, is not only inaccurate, but also proves to be extremely ineffective when it comes to managing massive volumes of data. In addition, it can greatly increase the amount of time needed to process the data, and in some cases, even make it impossible to build a model using the available data set.

The approach employed in this paper uses two previously mentioned concepts, fuzzy logic and EMM, to categorize feelings. A semantic learning approach is applied at the data preprocessing step where the input sentences are restructured and a set of rules essential for the identification of the positive and negative sentiments is created. A sentence is first segmented into its constituent words, and each word is tagged with a meaning. Then, tweets or sentences are classified by BIEM. One of the important features of the proposed extended Markov model (EM) with Bi-LSTM neural network and fuzzy logic (Fuzzy-BIEM) method is its ability to process and analyze social media users' emotional reactions. The analysis of users' sentiments makes it essential for social media experts to consider the vast amount of data generated. In order to analyze the sentiments in the data, online resources and parallel processing tools are used. The integration of the new Fuzzy-BIEM method is expected to eliminate the misclassification, and improve the classification's accuracy, quality, and efficiency.

One of the greatest strengths of the fuzzy logic approach in the proposed Fuzzy-BIEM method is the improvement of emotion processing and users' emotion analysis accuracy using effective rules during the classification of emotions. The fuzzy logic approach is applied in the preprocessing step of the data and it allows the input sentences to be processed and effective rules to be extracted in the classification of emotions. According to the classification rules derived from the words, every sentence is organized into several key words and each keyword is defined meaningfully. For instance, let us consider some tweets and sentences posted by social media that contain negative words. Such negative words can be subdivided into three categories: bad, very bad, and extremely bad. In this paper, we focus on deriving rules that are effective in emotion classification by means of fuzzy logic. These rules are then used to perform sentiment analysis with an extended Markov model and deep learning.

Sentiment analysis processes involving Support Vector Machines (SVM), Naive Bayes, and Decision Trees traditionally, very rarely tend to accomplish the properly managing the granular and very sensitive noisy data available over Social media platforms such as Twitter and Facebook. These techniques grapple with data fragmentation, high rates of misclassification, and failure to proficiently deal with multifaceted linguistic features. Even some of the modern approaches, such as Long Short Term Memory (LSTM) networks, and Transformers, have enabled improved outcomes for most tasks, however, they still have problems scaling for big datasets, as well as domain specific language issues. In this paper, we introduce the Fuzzy-BIEM approach which captures the gaps in the existing literature by merging fuzzy logic with Extended Markov Model (EMM) and Bi-LSTM. By integrating fuzzy logic utilizing the Extended Markov model with Bi-LSTM, said approaches fundamentally improve completion and deployment of complex and large scale sentiment analysis which is the key gap in the existing literature.

Deep learning has roots in a class of theories in brain development made by neuroscientists during the 1990s. These models of development manifested in computational models which served as the workings of deep learning systems. These models of development exhibit a common feature that the various dynamics explained for learning in the brain like a wave of nerve growth factor is to some degree similar to the deep learning models and enables self-organization [12–15].

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

- Incorporation of Markov model to the rest of the Bi-LSTM deep neural network model which acts as the classifier of emotions, news, etc.
- Application of EMM for increased accuracy in emotions recognition.
- The new system of emotion recognition which employs fuzzy logic and EMM simultaneously.

Up to the date of this research, more strides have been made towards enhancing emotion recognition, which, despite it having a multitude of different uses, still suffers from many issues like classification and expandability accuracy, amongst many others. Hence, in this document, an emotion recognition approach system utilizing EMM and fuzzy logic is proposed to rectify the issues of accuracy in emotion recognition systems.

The remainder of this paper is structured as follows: past work is investigated in Section 2 and in Section 3, the Fuzzy-BIEM method and the proposed system architecture is elaborated on. Section 4 discusses the results that were obtained and Section 5 makes some concluding remarks.

2 Literature Review

The related works in [16] a new method of sentiment analysis for the Tunisian-accented Arabic language is introduced. This method uses a collection of comments on Facebook in which support vector machine, neobizine and MLP are used for sentiment classification. Using this approach, they managed to obtain more than 17 thousand comments. Evaluation results demonstrate the proposed Fuzzy-BIEM method to be effective with 91% accuracy and 92.36% precision.

The classification of user sentiments critically in real-time is automated using an online method that utilizes Apache Spark in [17]. Moreover, this sentiment analysis is performed through a hybrid method that incorporates three machine methods: support vector machines, New Business, and regression models. More than two million reviews and other datasets available on Amazon were utilized to evaluate customer reviews. The results from these evaluations indicate the accuracy of the proposed Fuzzy-BIEM method is 85.4% along with the stable processing time for each percentage examined within the dataset.

An adaptive method for social media sentiment analysis was presented in [18]. As stated above, this method consists of two independent components of analysis: sentiment analysis and big data adaptability. In the Kmeans algorithm, words are first clustered into two main groups: positive or negative. These groups are then utilized for sentiment analysis, which is done through a cluster of APIs. Also, in order to make their approach adaptive to big data, they employed two other tools: Apache Kafka for data storage and Apache Spark for data processing. The analysis of the 2016 US presidential elections data showed that this approach guarantees an average accuracy of 90.21%.

In the work of [19], a new method for sentiment analysis at the landscape level along with its potential for cross language applicability was defined using domain adaptation and neural networks. In their assessment of the Fuzzy-BIEM method, they evaluated SemEval-14, SemEval-15 and SemEval-16 datasets, and found that Fuzzy-BIEM performed well with the F1 criteria and accuracy scoring 79.3 and 82.5 respectively.

In [20] the issue of sentiment recognition when suggesting new words to be added to the dictionary is addressed. In this method the previous words in the dictionary are used tiered with the Bayesian probability function to ascertain the sentiment of the text being composed positive, negative, or neutral and then the new word suggestion is executed. They evaluated their new fuzzy bimodal emotion estimation method using 3 datasets, the Twitter dataset from SemEval 2014, the movie review dataset from Pang & Lee, and the IMDB dataset from Twitter. The effectiveness of the proposed algorithm was achieved in terms of precision and F1 and was 84.1% and 76.5%, correspondingly.

In [21], two approaches adopting deep learning for sentiment analysis of Arabic texts in Saudi dialect were presented. The first approach is built on the short term memory (LSTM) neural network model, while the second approach uses bilateral short term memory (Bi-LSTM) neural network. The results of the evaluations conducted on a sample of 32063 tweets collected from Twitter show that the accuracy rates for the first approach was 92% while it was 94% for the second approach.

Over the course of years, a number of methods have been developed and implemented in relation to the field of Analysis of sentiments. Nevertheless, older methods such as SVM, or even Naive Bayes, in spite of being time saving on computations, tend to overlook or not provide the depth of detail in the sentiment expressed within informal social media data. Moreover, like many other powerful deep learning models, LSTM and CNNs suffer from the issues of poor handling of imbalanced data, long training times, and lack of interpretability. In comparison, the Fuzzy-BIEM method that we developed blends fuzzy logic for uncertain linguistics and employs EMM for rules optimisation which registers better performance in sentiment classification tasks.

In [22], a study was performed that sought to classify an individual's personality based on social media usage. For this particular, Contextual Semantic Sentiment Analysis method was applied. The authors of this paper assume that words have contextually defined feeling that changes with adjacent words. According to the concept developed by Maslow, it is possible to separate people for the purposes of social research into five categories according to his levels of need. This is why in this research, an attempt was made to classify tweeting users into five clusters of words that range based on the weight of the words in the text. In this matter the classification of synonyms to each tweet into one of three categories Moderately Positive, Moderately Negative or Neutral was done by means of well's word power dictionary. To test the effectiveness of their Fuzzy-BIEM method, its originators instructed their students to label over 3000 tweets. Evaluations were made with the use of three performance measurements: accuracy, sensitivity, and Fscore. The results recorded for each of the metrics was 75.23 percent, 78.22 percent, and 76.69 percent.

In [23], an attempt was made by the authors to develop a system that predicted online users opinions about Amazon site, by implementing deep neural networks. To achieve this, they first extracted data from the Amazon customer review collection and then, in the preprocessing stage, enhanced the quality of the collection by categorization, comment filtering, and stop words and URL removal. Then, they applied the previously existing fuzzy C-Means based approaches to keyword extraction for each tweet. In the last step, deep neural networks were employed to classify the general words extracted from tweets into three groups as final class of that specific tweet, positive, negative and neutral. In this research, Fuzzy-BIEM is proposed for that methodology and its effectiveness is compared to other techniques of similar tasks. The simulation results reveal that Fuzzy-BIEM do outperform the existing techniques with an improvement of 6% to 20% in accuracy.

In [24], a new hybrid method that applies deep learning for the sentiment analysis of comments made by farsi-speaking users was described. For this purpose, the features of the comments are extracted at two general levels and words (each of which has its own independent CNN model). Then these features are fed to a Bi-LSTM network to classify the comments as either positive or negative. Tests that were performed on the Digikala Persian dataset showed that the Fuzzy-BIEM method achieved an accuracy of 95%.

In [25], proposed a new methodology for the sentiment classification of political tweets. In their method, Fuzzy-BIEM, each tweet is first transformed to combined N-grams (single and multiple). The combined N-grams are then classified using the Newbizin tool. Their Fuzzy-BIEM method was implemented on the Obama-McCain election Twitter dataset and the evaluation results of this dataset indicate that this method has 76.05% accuracy in Fscore. Some of the shortcomings of this method are the absence of real time performance and the lack of analysis of multilingual corpus.

In [26], a novel approach for performing multidimensional sentiment analysis on Twitter using symbology was presented. For this, it was claimed that the presence of emoticons and symbols in the text can positively contribute to sentiment analysis. A scoring system was developed to evaluate emoticons, and for each tweet, using previously defined approaches, the text part was scored using regression, and the scoring system was also applied to the symbols within the text. The result of these two processes would determine the general emotion of the text. The analysis was conducted on a sample of approximately 2000 tweets and the results suggest that the proposed algorithm has an impressive Fscore, accuracy and precision of 89.61%, 86.55%, and 92.89% respectively.

In [29], proposed a new methodology of analyzing sentiment of Spanish Catalan domain users comments on website. In the Fuzzy-BIEM method, the user comment undergoes classification into a positive and negative category after the pre-processing phase where stop words are eliminated from the text and other words lemmatized. The classification of opinions is also done using five tools of New Business, maximum disorder, support vector machine, decision tree artificial neural networks and then, voting is done based on their output. Considering the fact that there was no dataset for this language, the authors of the paper constructed a dataset first. The evaluation results show that the effectiveness of their proposed Fuzzy-BIEM method in terms of accuracy, precision and Fscore is 81%, 82%, and 81%, respectively.

In developed hybrid model based on artificial neural networks whose main feature is categorizing the sentiment of the text so that it can infer the content information of the text. For this purpose, they proposed to extract the content from the CNN and the global feeling from the text using the short-term memory network. Their evaluation was done using IMDB, Yelp 2013, and Yelp 2014 databases. The accuracy of their proposed Fuzzy-BIEM method in terms of accuracy and RMSE was achieved 53.3% and 68.2%, respectively.

In this paper we describe a new approach to detect important comments and link comments for video sharing social networks (like Youtube) which is more sophisticated than previous approaches. In this approach, comments are graded according to the user's history and the comments are ranked by the amount of information they contain, and then, using a support vector machine, the comments are finally sorted. The efficacy of this approach using the TED video comments database shows a maximum accuracy of 92.3%.

In [30], a new method for performing sentiment analysis on comments in social networks was provided through the combined use of deep learning. In this case, instead of using the existing emotional dictionary, they built an emotional dictionary first, which was done via a deep learning network, and later employed a two layer bilateral Bi-LSTM network to analyze the opinion. For evaluating the method Fuzzy-BIEM, they selected comments from PTT Bulletin Board System, the largest social network in Taiwan, which has 150,000 active users and more than 500,000 posts and comments a day. The evaluation results showed that the efficiency of this approach in terms of Fscore and accuracy is 84.43% and 92.68% respectively.

Preceding [31], the authors described improving fuzzy-sentiment analysis performance using feature set modelling and CNN approaches. To account for tweets with fuzzy emotional expressions, five feature vectors were extracted from vocabulary, word type, semantic, position, along with the emotional pole (fuzzy feature set model). This study analyzed accuracy, sensitivity, and F score. Their test analysis results proved that the Fuzzy-BIEM method does have a good degree of accuracy for the problem of fuzzy-sentiment analysis in tweets. The effectiveness of their proposed method is 81% accuracy, 82% sensitivity and 81% F1 criterion.

In [32], a study was done regarding the implementation of RNN and CNN models for sentiment analysis using deep learning. This particular research has proposed a two-way deep attention based CNN-RNN model (ABCDM) for sentiment analysis. The effectiveness of the model was tested in multiple experiments conducted on five browsing and three Twitter datasets. Comparing with other models, the effectiveness of six published deep neural models specifically designed for sentiment analysis was also determined. Testing results on these datasets demonstrate that ABCDM outperforms the other models in tagging long reviews and short tweets while maintaining acceptable accuracy levels. However, the results from review and tweet datasets indicate that performance for short tweet datasets is, however, less than that of long review datasets.

In Table 1, the background of the research is

Table 1. Comparative study general sentiment analysis approaches.

Authors/year	Approach	Tools used	Advantages of proposed approach	Disadvantages of proposed approach	Tested datasets	The results of the evaluated criteria
Madhafar et al. [15]	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%
Al-Saqqa et al. [16]	A large-scale approach to categorize the sentiment of online critical users	MATLAB	Fast processing time	Lack of scalability	Amazon dataset	Accuracy 85.6%
El Alaoui et al. [17]	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. [18]	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%
Mandhula et al. [22]	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

Table 2. Comparative study sentiment analysis with specific models.

Authors/year	Approach	Tools used	Advantages of proposed approach	Disadvantages of proposed approach	Tested datasets	The results of the evaluated criteria
Zobeidi et al. [23]	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%
Chauhan et al. [25]	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%, Fscore 89.61%
Balaguer et al. [26]	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%, Fscore 81%
Choi et al. [28]	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. [29]	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%, Fscore 84.43%

supported by these studies highlighting the preferred Fuzzy-BIEM method along with the associated tools, benefits, and limitations of the proposed method, datasets used, and the criteria evaluated. Table 1 provides information on several techniques of sentiment analysis from various languages and datasets. As first shown in 2017 by Madhafar et al. [15], using Support Vector Machines (SVM) and Multilayer Perceptron on Twitter had an accuracy of 91% and a precision score of 92.36%, but challenges like time consumption and lack of scalability arose. Al-Saqqa et al. [16] in 2018 attempted a more focused large-scale approach with MATLAB, which produced significantly accurate results at 85.6% on the Amazon dataset but had slow processing speeds. Similarly, El Alaoui et al. [17] developed a big data approach in 2018, and Although they maintained fast processing speeds, their accuracy suffered when compared with Alhamri's average score of 90.21% on a US dataset from 2016. On the contrary, Yang et al. [18] in 2019 had almost perfect accuracy of 92-94% when utilizing deep learning for Arabic text analysis, although having to confront issues of scalability. Mandula et al. [22] in 2019 worked with deep neural networks to predict sentiments of Amazon users, resulting in a 6-20% increase in accuracy, but concurrently faced the same challenge of low accuracy in sentiment analysis.

As can be in Table 2, comparative Study of Sentiment Analysis with Specific Models demonstrates a focus on particular model uses for sentiment analysis. Zobeidi et al. [23] focused on Farsi language comments and

Table 3. Comparative study for advanced deep learning approaches.

Authors/year	Approach	Tools used	Advantages of proposed approach	Disadvantages of proposed approach	Tested datasets	The results of the evaluated criteria
Basiri et al. [31]	Sentiment analysis using deep learning models and RNN and CNN models	Not specified	Real-time analysis	Poor accuracy and precision of sentiment analysis	Twitter dataset	Acceptable Accuracy
Yang et al. [18]	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%
Fu et al. [19]	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%, F1 76.5%

deep learning and achieved optimal accuracy of 95%, but had issues with scalability and processing time. Chauhan et al. [25] created a semiology approach when doing sentiment analysis on Twitter and had an overall accuracy of 86.55%, precision of 92.89% , and F-score of 89.61%, but suffered from scalability issues as well. Balaguer et al. [26] used artificial neural networks to perform sentiment analysis on a Spanish Catalan website and obtained 81% accuracy and 82% precision, but poor accuracy in sentiment analysis. Choi et al. [28] applied a support vector machine approach in comment importance detection and obtained 92.3% accuracy, but was very slow to process. Chen et al. [29] performed sentiment analysis on Taiwan's PTT Bulletin Board using dual deep learning and obtained an accuracy of 92.68%, F-score of 84.43%, but faced issues with their approach's accuracy.

Table 3 shows a comparative study for Advanced Deep Learning Approaches that portrays sentiment analysis uses of these advanced deep learning models. Basiri et al. [31] Deep Learning Models Implemented RNN and CNN Focused In Real Time Analysis With Accuracy And Precision Issues. Yang et al. [18] also used deep Learning for the Arabic Sentiment Analysis and was able to achieve high accuracy but high processing time and low scalability (92%-94%). Fu et al. [19] integrated word based dual task learning and achieved 84.1% precision and 76.5% f1 score but had poor accuracy in sentiment analysis.

It was discovered that a number of methodologies have been developed for the analysis of survey data, which include both supervisory and non-supervisory methods. These approaches have been covered earlier with some using semantic relations between words and their grammatical functions, while others have branches that employ the use of dictionaries. In this analysis, a number of them have been emphasized. Many studies have been conducted regarding the problem of emotion analysis by using surface and deep learning models. Some of them are built using computational linguistics, but the greater majority are built using machine learning that assumes the sentiment analysis is one of the problems of text classification and thus implements three supervised machine learning techniques called simple Bayes, neural network, and support vector machine. In recent studies, machine learning and rule induction [27] have been applied across various sectors to enhance decision-making and optimize processes.

While there are drawbacks such as the inadequacy of the precision to sentiment analysis, the tedious and time-consuming data processing, no analysis of multilingual corpus, and lack of proper scalability in the previous works, in this work, the combination of fuzzy logic and the modified Markov model together with deep learning approach involving sentiment and data analysis is proposed.

3 Methodology

The proposed model for the Fuzzy-BIEM Architecture, as shown in the Figure 1, begins with Data Collection, which serves as the foundation for the subsequent steps. The collected data undergoes Data Preprocessing and Cleaning, a crucial phase where the data is refined and prepared for further analysis. This phase includes Data Preparation, which ensures the data is in a usable format, Data Normalization to standardize the data within a specific range, and Data Sampling that selects representative subsets of data to make the process more efficient and manageable. Following this, Deriving Rules Using Fuzzy Logic applies fuzzy logic techniques to model uncertainty and imprecision within the data, creating rules that guide the architecture's decision-making process.

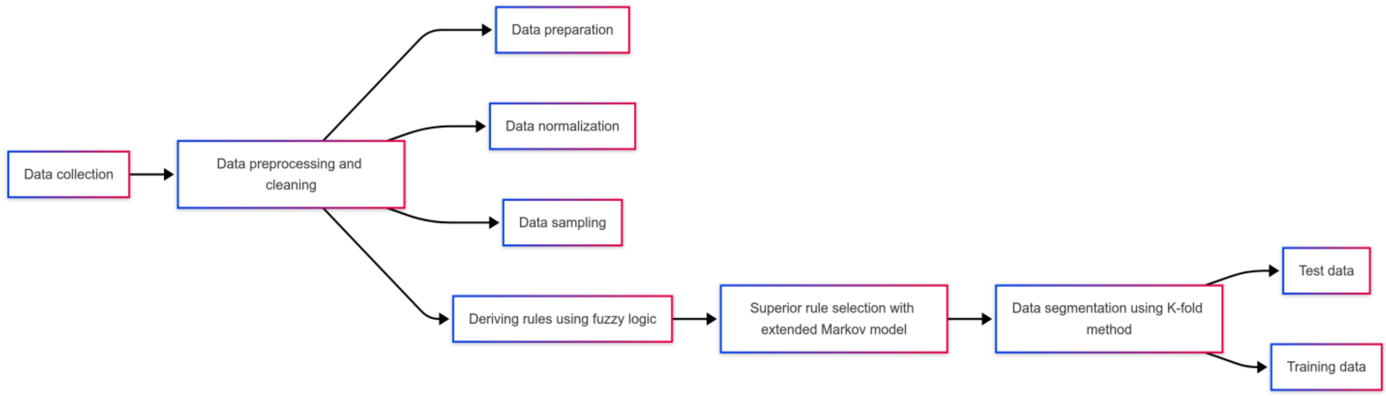

Figure 1. Proposed model for the Fuzzy-BIEM data handling architecture.

Once these rules are derived, the model proceed with Superior Rule Selection Using an Extended Markov Model. This step optimizes and selects the best-performing rules based on the probabilities and state transitions captured by the Extended Markov Model, adding adaptability and robustness to the system. The architecture then applies Data Segmentation Using the K-Fold Method, dividing the dataset into multiple subsets for cross-validation, which ensures that the model is both reliable and generalized. Finally, the processed data is split into Test Data for model validation and Educational Data for training purposes. This organized flow helps ensure that the Fuzzy-BIEM Architecture is efficient, effective, and capable of making informed predictions and decisions based on the data it processes.

The proposed model for the formulation of the fuzzy-BIEM rule selection architecture in Figure 2 focuses on optimizing the performance of the fuzzy inference engine. The model is driven by a set of steps that include deriving the rules using fuzzy logic and superior rule selection through the extended Markov model. In the beginning of the process, logic which captures the uncertainty of the data is employed and accurate decisions are crafted. The most critical part of the decision making process is performed in what is termed as Superior Rule Selection with the Extended Markov Model. This process is meant to eliminate a number of rules by taking into account the transition probabilities and state dependencies so that only the most suitable rules are passed on for consideration in the Markov process. Finally the proceedings are passed on to Segmentation of Data Incorporating K-Fold Cross Validation in Which the Set of Data is Split into Several Subsets. The model is validated through cross validation using different portions of the data to make sure the performance is not overfitted and the model is accurately generalizable. The end result is a tried model which is built around fuzziness and has a high level of accuracy. The streamlined filter enables the selection of rules that yield instant outcomes while further defining and setting boundaries where rules are effective.

The Fuzzy-BIEM method uses three components: fuzzy logic, the Extended Markov Model (EMM), and Bi-LSTM. The preprocessing step utilises fuzzy logic by extracting fuzzy rules with sentiment words in the sentences employed to the fuzzy logic system. EMM then removes the irrelevant fuzzy rules with its superior rule selection using transition probabilities and sentiment classification accuracy towards the remaining rules. Sentiment classification is performed on chronologically ordered data and is done by the Bi-LSTM model after the refined rules are applied. This method allows Fuzzy-BIEM to efficiently and accurately use large noisy datasets while maintaining an interpretable classification model. Emphasis on Bi-Level Integrated Evidential Modelling: EMM, Fuzzy Logic, and Bi-Long Short Term Memory. Figure 2 focuses on Fuzzy-BIEM Integration Flow, wherein the fuzzy rules are first extracted and refined in the body of Empirical Mode Models before being sent to Bi-LSTM for sentiment classification.

The Proposed Model Architecture for the Fuzzy-BIEM Core, which is outlined in Figure 2, depicts sequential steps in the process of training and evaluating a sentiment analysis model using a BI-LSTM DNN algorithm. The first step is the Training Data, which is relevant to the model training phase in which the collected data is processed and the model is taught how to predict using the data. The subsequent step is the BI-LSTM Deep Neural Network Algorithm, where the model is first trained and is now at the heart of the system, which understands and classifies the sentiments within the given sequential text data.

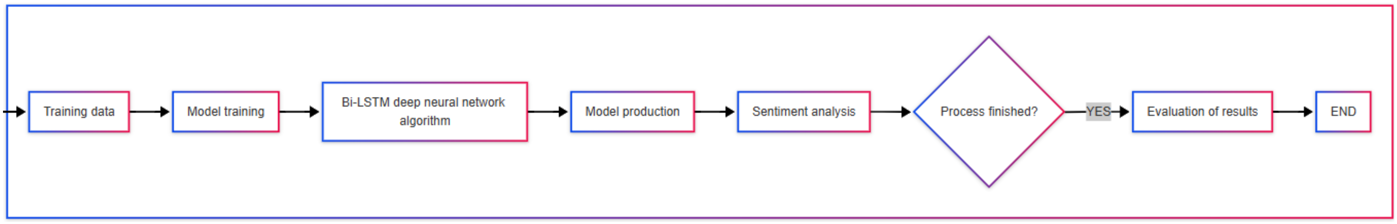

Figure 2. Proposed model for the Fuzzy-BIEM core architecture.

Once the algorithm is executed, the model proceeds to the Model Production phase, where the trained model is completed and readied for deployment. After model production, the system automatically does Sentiment Analysis, wherein the model interprets the sentiment contained in the data and categorizes it as positive, negative, or neutral. The next step checks if the procedure is completed. If the process is not complete, further changes and retraining are performed until the model is refined enough. If completed, the system conducts Evaluation of Results, where the model performance is evaluated. The process finishes once the evaluation is done.

This particular architecture focuses on the design and implementation requirements of sentiment analysis models, and like any other work, guarantees that the models are accurate and effective.

3.1 Data Preprocessing

The first step of the presented work is to account for missing values. As soon as the datasets are uploaded on the proposed system, a pre-processing procedure is carried out and Missing-Value samples are purged from the dataset. Thereafter, the processed data that has undergone pre-processing is put forth in a form that is suitable for the simulation tools. There is, however, a large number of methods to conduct the pre-processing of data like sample deletion, data extraction, data allocation, and even data squeezing.

Our pre-processing pipeline has the following stages (1) Removing incomplete records to address missing values and (2) normalising feature values through Min-Max representation which captures the varying features in to a fixed range from 0 to 1 and (3) random shuffling of the dataset to counter order bias. In order to address the skewed distribution of sentiment classes, the SMOTE algorithm was used for oversampling the minority class. Furthermore, during model training, the class weights were modified to boost the performance of the model on the dominant negative sentiment class.

Out of all the different strategies, this thesis implements the one that deals with sample deletion. The method of Fuzzy-BIEM Algorithm suggests that Before the set is applied, it is checked for Missing-Values. If found, the "s" identified is deleted from the set. The next phase of the data pre-processing step is data transformation and structure standardization.

The data set is now ready after the removal of samples with missing values. This step is very critical in modifying the samples within the data set, so that basic models can be constructed during the modeling phase. This method, in conjunction with other methods, can improve the accuracy of classifying users' emotions. The prepared data needs to be changed to the format required by the simulation tools first. The default format of data is Excel. After a cursory examination of the dataset, normalization should be done. The last step in the preprocessing phase is normalization of the data set.

In the pre-processing stage, we achieve normalization by ensuring each feature is in the 0 - 1 range, followed by random shuffling of the overall data matrix. By default, rows change place, which eliminates the order in which data was collected. More specifically, datasets are structured in a matrix form, and as the rows of the matrix change places, normalization occurs. Data normalization aims to make differing variable measurements more uniform and is also referred to as data de-scaling. If the unit of measure for the variables under study differs, it is possible to scale down the data by applying normalization methods. Equation 1 is used for normalizing the values of every dataset [34].

$$\text{Normalize}(x) = \frac{(x - X_{\min})}{(X_{\max} - X_{\min})} \tag{1}$$

where $X_{\max}$ 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

The selection of features and the formation of rules for emotion detection uses fuzzy logic in the designed Fuzzy-BIEM method. Features chosen from the data set contributes to the recognition of emotions. The dataset source is a social media platform and its corresponding fuzzy logic output is a collection of rules for automated emotion detection among users. The extraction of fuzzy rules can be described as follows:

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

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

Suppose all features are represented by a set F:

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

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 Equation 4.

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

where μ_{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 $F_X = \{(x_k, \mu(x_k)) \| k = 1, 2, ..., n\}$ it is defined that $\mu(x_k)$ is a vector which is displayed as Equation 5:

$$\mu(x_k) = [\mu_{11}(x_k^1), \mu_{12}(x_k^1), ..., \mu_{1q}(x_k^1), \mu_{21}(x_k^2), \mu_{22}(x_k^2), ..., \mu_{2r}(x_k^2), ..., \mu_{p1}(x_k^p), \mu_{p2}(x_k^p), ..., \mu_{ps}(x_k^p)] \tag{5}$$

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

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 Equation 6.

The value of $\sum^p |f_i|$ 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 as $\sum^p |f_i|$.

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.

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

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.

Fuzzy logic contributes to improving interpretability in our sentiment analysis model's comprehension of sentiment words by converting them to fuzzy sets that cover a multitude of possible sentiment ranges. For instance, this logic assumes 'very good' and 'excellent' are mapped to fuzzy sets with varying levels of positivity, thus enabling better analysis of sentiment. The reasoning behind sentiment allocation on a certain text can be linearly structured thanks to fuzzy logic that has human comprehensible representation.

3.3 Separation of Training and Testing Samples

Using data partitioning, it is possible to train the Bi-LSTM model and measure the performance of the proposed Fuzzy-BIEM method. Data partitioning is the basis of the proposed method, in which the complete dataset is divided into two sets—a training set and a testing set. The training set is 80% of the data while test set is 20%. The Bi-LSTM deep neural network model is trained using the training samples and the evaluation of the approach is done using the test samples. In this paper, we have used k-fold sampling to separate the samples.

3.4 Deep Cellular Neural Network Algorithm

This segment of the Fuzzy-BIEM method is divided into two broad categories – application of the extended Markov model and application of Bi-LSTM deep neural network which will be discussed in detail in the subsequent sections.

3.4.1 Selection Rules Using the Extended Markov Model

This paper attempts to use an extended Markov model for selection of most relevant rules. The model proposes logic-driven selection modification method where the input is a set of rules chosen by fuzzy logic. The proposed Markov model is a solution for feature extraction based on user emotions and sentiments. Each rule is composed of a general set of attributes. The developed Markov model does the selection from obscure rules selected by fuzzy logic which are more prominent than the rest for the user's emotions recognition. Ultimately, the superior defined rule's features are used in Bi-LSTM deep neural network to recognize 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-BIEM 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. Equation 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 Equation 9 is used to determine the busy node:

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

$$\begin{gathered} K_{TP} = 20, Th_{TP} = 15, K_{FN} = 30, Th_{FN} = 20, \\ K_{ACC} = 20, Th_{ACC} = 10 \\ \Rightarrow \frac{(20-15)+(30-20)+(20-10)}{70} \times 100 = 35.71 \end{gathered} \tag{10}$$

In the newly formulated extended Markov model, it associates a probability value for each rule, which stands for a numerical value within the range of [0,1]. The higher the value is, the greater the estimate of the features possessed by the law, and emotions can more effectively be detected.

3.4.2 Bi-LSTM Deep Neural Network

The framework referred to as the Bi-LSTM deep neural network or, more succinctly, Bi-LSTM is applied for emotion detection purposes. A bi-directional LSTM (Bi-LSTM) is a modification of the LSTM model that enhances the training phase by reading the input data two times: first from left to right and then from right to left. On the other hand, an LSTM architecture was designed to address the "vanishing gradients" problem of a Recurrent Neural Network (RNN). LSTM models increase the memory capacity of an RNN so that it can learn long-term dependencies. A LSTM memory allocates a space where information can be preserved for longer periods and has the ability to make decisions of whether to store new information or to discard it. This serves to filter the signals, retrieve the relevant ones, and maintain them over extended periods of time [35]. In this case, Bi-LSTM is used to design a neural network model in order to classify user emotions, as illustrated in Figure 3. Bi-LSTM shows the structure of Bi-LSTM deep neural network.

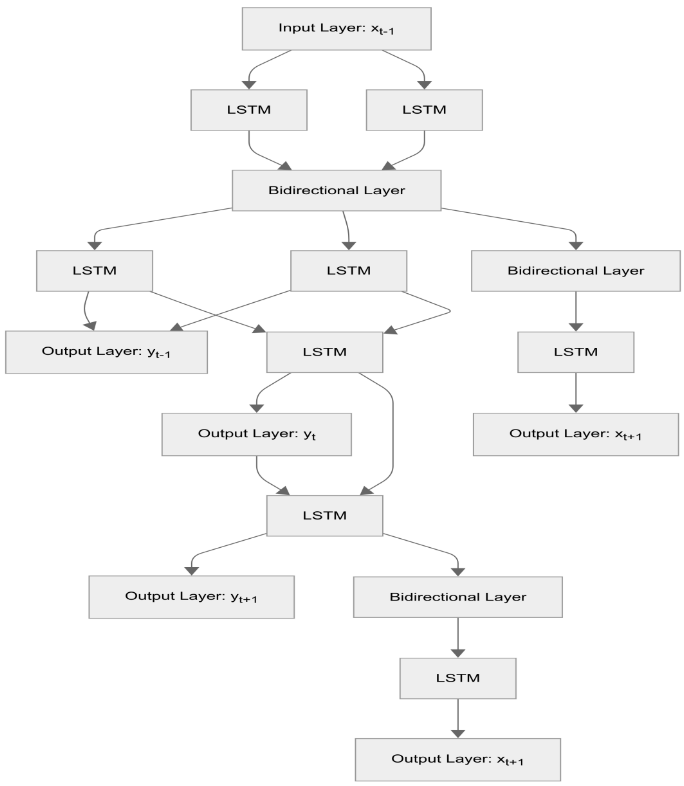

Figure 3. Bi-LSTM deep neural network structure.

As shown in Figure 3, the key parts of the Bi-LSTM algorithm are: Bi-Directional Processing: Unlike segmenting and processing an input sequence in only one direction, as single RNNs do, Bi-LSTM processes the sequential data in both directions at once. This is done by having two LSTM layers, one operating in a forward manner and the other working in a backward manner. Each layer has its own hidden states and memory cells.

Forward Pass: The forward pass processes the LSTM layer by providing it with information sequentially starting from the first step to the last. So at every time step of the forward pass, the LSTM is fed its preceding hidden state and memory cell along with the current input, which at every time step allows it to compute its hidden state and update its memory cell.

Backward Pass: The input sequence is now provided to the LSTM layer in an inverted order, starting from the last time step and passed through to the first time step. Forward pass and backward pass work similarly by having the LSTM update its hidden state and memory cell during each time step based on the last hidden state and their current input.

Merging Forward and Backward States: The combination of the two LSTM layers is performed by merging the hidden states at each time step in two steps: forward and backward passes. This combination can be accomplished, for instance, by transforming hidden states or concatenating them.

An advantage of using a Bi-LSTM is that, unlike traditional RNNs, which only consider the context before a given time step, it can also capture the context that comes after a particular time step. This allows Bi-LSTM to look at both past and future information, which in turn allows it to model richer dependencies in the input sequence. For that reason, the part of the data which contains users' comments is fed into the Bi-LSTM model and a neural model is built.

The approach advocated in this paper is that of deep learning. The reasoning is that the training datasets are input into the core of the algorithm's Bi-LSTM deep neural network and the model of this algorithm is created. Following that, the model of the trained algorithm is supplied with the test data, and produces an answer for every test sample.

4 Evaluation of Test Results

This section begins with the description of the specific hardware and software of the test simulation, followed by the details of the datasets used for testing, test evaluation criteria, and finally, interpretation of the test results.

4.1 Hardware and Software Specifications of Simulation

The proposed Fuzzy-BIEM method and the approached compared in this paper were all executed in 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.

4.2 Datasets

The datasets which were the subject of the study in this paper are of two types. In this regard, the use of social network sites for data sets streaming and downloads is one of the fundamental of streaming data set. Moreover, as there exist sentiments, opinions and thoughts in almost all languages and dialects, in order for an efficient model to be constructed, it needs to be able to identify and extract opinions and feelings without being hindered by languages. To analyze batch datasets, the customer database of Amazon in the first part of the experiments as stated in [36]. In general, in this paper, the common datasets in [38] were utilized and the outcome was compared with the results of [39].

In the second part of the studies, to validate the correctness and efficiency of the approach, its performance is examined on different data sets. In this work, 5 datasets which are very popular and widely used are chosen which are Twitter, Facebook, Covid-19 fake news, Amazon and Fake News Network. Twitter is a sentiment140 dataset of 1,600,000 tweets collected through the Twitter API. Each tweet is rated between 0 (negative) and 4 (positive) indicating sentiment. The Twitter dataset also has 6 other attributes which are shown in Table 4 [37].

Table 4. 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 previously described Facebook dataset [40] has 10,000 newspaper records and virtually no metadata.

600 web pages from the PolitiFact website for analyzing them with data science skills to derive some insights on how to mitigate the wider spread of misinformation and what the most effective accuracies for approaches to achieve it. Provides. This data set has six features which are shown in Table 5 and among them, the feature of the news title is the most important for classifying the news as fabricated and authentic.

Table 5. 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.
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 dataset on Covid-19 false information was developed as part of work package for CONSTRAINT-2021, which focused on hostile post detection. This specific task consists of finding fake news articles published in english that relate to COVID-19. The data collection is based on several social media platforms including Twitter, Facebook, Instagram, etc. The collaborative work aims to classify social media posts as news with the goal of determining if the posts contained fake news or true information.

Sentence corpus containing positive and negative things from Amazon reviews titled from group to individual labels using deep features. This was compiled back in 2015. The score is either 1 for positive or 0 for negative. The source websites for the collection of these sentences were imdb.com, amazon.com and yelp.com. Again, with each website context, 500 positive and 500 negative review sentences were randomly drawn. This paper has tried to curate such sentences that are unambiguously positive or negative, so any sentences that are neutral have been deliberately avoided.

The IMDB site corresponds to the movie review sentiment dataset that comprises of 100,000 reviews about movies, where 50,000 of them are unlabeled, and the other 50,000 are categorized as 25,000 reviews set aside for training and another 25,000 for testing. Every tagged review has one of two sentiment labels, which are either positive or negative. For the experiments of this paper, only the labeled portion of the training set was utilized. The Amazon website that McAuley and Leskovec gathered contains reviews and ratings on the mobile phone and accessories that are sold within those respective categories. The scores are given on a scale from 1 to 5 where in this paper, the comments with ratings of 4 and 5 are treated as positive, and ones with 1 and 2 are treated as negative. This information has been split randomly into two halves comprising 50 percent each, one for testing and one for training, each containing 35,000 documents. The Yelp site contains the dataset of reviews of restaurants that was extracted in this paper. The scores remain the same, from 1 to 5, and similarly, comments with scores of 4 and 5 are termed positive while those with 1 and 2 are termed negative.

An arbitrary division of the documents into test and training sets was conducted, resulting in approximate equal volumes of 300,000 documents for each category. The ASU Fake News Network dataset [41] is a repository relying on ongoing collection of data for fake news research at ASU and contains all fabricated newspapers capturing their news content "characteristics" as shown in the Table 6. From all previously mentioned datasets, 1000 sentences were taken from the test set, where manual annotation was done, marking 50% as positive emotions, while the remaining 50% were negative. These sentences are only used for evaluating the sample-level classifier, value 3. They are not employed for model training, so as to support, authenticate our claim of ensemble-level learning and sample-level prediction [36].

Table 6. 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

In order to examine the effectiveness of the application of Fuzzy-BIEM method, which is built using the machine learning paradigm, some criteria like accuracy (Acc), Precision (Pre), Recall (Rec) and Fscore have been defined. The mathematical definitions of all these criteria can be found in Equation

11 to 14 to be proposed in [13]. In these equations, TP refers to number of comments which have a positive feeling and they are correctly recognized as positive by the designed Fuzzy-BIEM method. TN has number of comments that have a positive sentiment and they are detected as negative by the designed Fuzzy-BIEM method. FP is the number of comments that have a negative feeling and are acknowledged as positive by the Fuzzy-BIEM method. Lastly, FN is the number of comments which have a negative feeling and are incorrectly recognized as negative by the Fuzzy-BIEM method [33].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{11}$$

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

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 Equation 14.

$$Execution\ Time = \sum_{i=1}^{n} t_i \tag{14}$$

4.4 Analysis and Evaluation of Results

In Table 7, the comparison of the performance of the proposed Fuzzy-BIEM method on the Amazon dataset and the proposed criteria without applying and with applying the fuzzy logic approach is shown.

In Fuzzy-BIEM's performance evaluation presented in Table 7, it is evident that it outshines the other methodologies employed at lower sentiment value thresholds in metric integration. It would appear that the merit of the Fuzzy-BIEM is due to the flexible logic systems that determine the user sentiments and the features that has maximum disregard whenever attempts are made to understand the essence of the user sentiment. Such features are designated as outstanding. The fuzzy logic system approach has enabled BIEM to utilize a simpler model that increases the accuracy of the sentiment analysis process. There is an extent to which the Bi-LSTM deep neural network based on fuzzy logic signal important received sample can result to higher expectations. Having more samples signals increased expectation for accurate output. The results show that compared to the ordinary state together with other methods, lowers the error margins utilizing Fuzzy-BIEM augmented accuracy in detection a variety of data.

Figure 4. Performance on the Amazon dataset by using the metrics defined in prior sections.

The Figure 4 delineates performance on the Amazon dataset by using the metrics defined in prior sections. Here, the performance of proposed Fuzzy-BIEM method is contextualized in relation to other methods. Here, the performance of proposed Fuzzy-BIEM method is contextualized in relation to other methods. The results in Figure 5 illustrate that the averages of accuracy, precision and sensitivity for emotion detection of users in Amazon are evenly distributed between 98.72%, 73.83% and 74.83% respectively, which is 1.83% improvement on the CSO-LSTMNN approach.

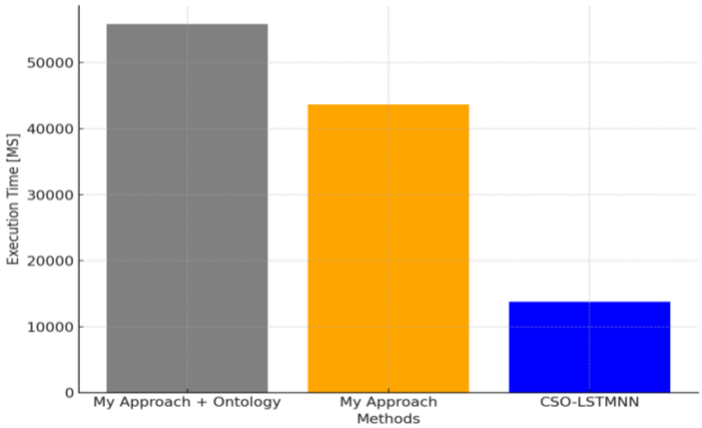

Figure 5. Comparison for the execution time (In Ms) for the application Of Fuzzy-BIEM method with other approaches.

The proposed Fuzzy- BIEM method outperforms CSO-LSTMNN methods [36] in the attempts to perform user emotion detection using BIEM hybrid fuzzy reasoning method. It has been observed that as the number and size of samples taken increases, so does the performance in terms of accuracy of the emotion recognition system. As the samples are increased, the performance of the algorithm becomes

Table 7. Comparison of sentiment analysis performance with and without Fuzzy Logic across different sample sizes.

Sample Size	Error (%) (Without Fuzzy)	Precision (%) (Without Fuzzy)	Recall (%) (Without Fuzzy)	Accuracy (%) (Without Fuzzy)	Error (%) (With Fuzzy-BIEM)	Precision (%) (With Fuzzy-BIEM)	Recall (%) (With Fuzzy-BIEM)	Accuracy (%) (With Fuzzy-BIEM)
100	11.2	89.5	91.4	88.7	6.3	94.2	96.5	93.9
500	13	92	88.3	87.2	7	97	92.3	92.1
1000	17	83.5	87.5	83	9	91.5	95.5	91
10,000	9	83	80	90.8	5	87	84	94.8
100,000	5.5	7.7	72.5	94.5	1.5	74	73	98.5

better and the errors reduce to a desired level. Figure 5 outlines the task completion time (in milliseconds) of the Fuzzy-BIEM method implemented on the Amazon dataset in comparison to the other existing methods.

Fuzzy-BIEM execution average timing with a sample amount ranging between 100 to 100,000 records using fuzzy logic is 13765 milliseconds. The average timing without fuzzy logic said approach is 43680 milliseconds. The CSO-LSTMNN method equals to 55887 milliseconds. The improved rates of proposed Fuzzy – BIEM method with respect to the assumed Fuzzy-BIEM method without semantics and the CSO-LSTMNN approach are 29915 and 42122 millisecond respectively. Thus, the proposed Fuzzy-BIEM with the aid of Bi-LSTM deep neural network extension of Markov and fuzzy logic, given diverse data volumes, outperforms the most recent methodologies like CSO-LSTMNN.

Additionally, regarding the data provided in Figure 6, it is clear that in all cases, the amount of time taken for execution tends to rise with the increase in data volume, but the fuzzy logic approach does outshine the others with best time performance equated as 112 milliseconds to 61000 milliseconds. This is Fuzzy-BIEM method optimized which uses fuzzy logic approach outperforms the rest in time performance. The sequence of steps in modeling the emotion detection system using fuzzy logic is to extract effective rules while creating a simpler model. By creating a simple model and not processing all available features, the execution time of user emotion recognition is reduced.

For many practitioners of the discipline, the importance of the data in Figure 6 is clear because they show the comparison of the average accuracy of the proposed Fuzzy-BIEM method and other methods, which include the so called deep neural network of Long Short Term Memory, deep neural networks of Recursive Deep Neural Network, Multi-Perceptron Neural Network, C4.5 decision tree, K-Nearest neighbor, and support vector machine.

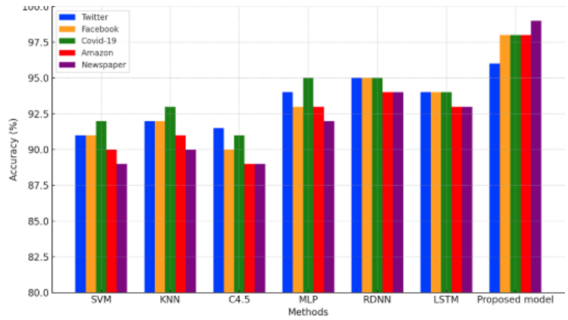

Figure 6. Comparison on the accuracy of sentiment detection of the user using Fuzzy-BIEM method and the other techniques.

We note that, in comparison with other techniques such as LSTM, RDNN, MLP, C4.5, KNN, and SVM, the Fuzzy-BIEM method achieved Twitter dataset improvement percentages of 0.44%, 0.97%, 3.61%, 4.34%, 6.54%, and 7.81%. For the Facebook Facebook dataset, in comparison with the other techniques, the Fuzzy-BIEM Method achieved 1.32%, 1.89%, 5.58%, 6.59%, 4.96%, and 10.06%. In addition, for the COVID-19 fake news dataset, the Fuzzy-BIEM method achieved improvment percentages of 1.32%, 1.9%, 5.6%, 6.63%, 4.99%, and 10.09%. Similarly, for the Amazon dataset the percentages achieved via the Fuzzy BIEM method in comparison to the other techniques were 1.06% and 1.8%. 4.84%, 5.16%, 7.16% and 8.64%. In the novel Fuzzy-BIEM method, the Fuzzy-BIEM method improves the monitoring of opinion precision on the false news network dataset when compared to other methods like LSTM, RDNN, MLP, C4.5, KNN, and SVM, achieving improvements of 1.74%, 2.34%. 6.12%, 7.15%, 5.48%, and 10.67%. It was determined that the Fuzzy-BIEM method outperformed all other approaches.

The results obtained from the implemented Fuzzy-BIEM method clearly show that the model based on fuzzy logic approach, shown in Figure 6, is not only accurate but also simple. The increased simplicity of the model with respect to a high number of hidden layers is indeed a great encouragement to the recognition of user emotion. In Figure 7, the

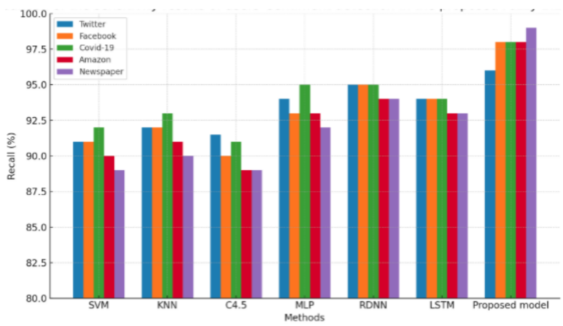

Figure 7. Results of user sentiment detection precision using the new Fuzzy-BIEM technique alongside other techniques.

results of the sensitivity of user sentiment detection from other methods are compared with the new method Fuzzy-BIEM, where LSTM, RDNN, MLP, C4.5, KNN, and SVM were used.

From the findings, it can be observed that there was an improvement in Facebook opinion mining precision, given that the proposed fuzzy BI-EMM method increased the accuracy relative to the LSTM, RDNN, MLP, C4.5, KNN, and SVM methods by 1.32%, 1.89%, 5.58%, 6.59%, 4.96%, and 10.06%. Moreover, an improvement in precision of opinion mining on the fake news dataset of covid 19 was noted in the new fuzzy BI-EMM method when compared to other methods including LSTM, RDNN, MLP, C4.5, KNN, and SVM by 1.32%, 1.9%, 5.4%, 6.63%, 4.99%, and 10.09%. Likewise, the sentence you provided describing an improvement in precision for a dataset (Amazon dataset) using a fuzzy BI-EMM approach compared to other methods, including LSTM, RDNN, MLP, C4.5, KNN, and SVM were observed to be: 1.06%, 1.8%.4.84%,5.16%,7.16% and 8.64%. The culmination was the achievement of the Fuzzy-BIEM approach concerning opinion mining precision on the fake news network dataset. Improvement over all other methods, including LSTM, RDNN, MLP, C4.5, KNN, and SVM, is 1.74%, 2.34%, respectively, 6.12%, 7.15%, 5.48%, and 10.67%. It was discovered that the Fuzzy-BIEM method was far more effective than all the other approaches taken.

In proper articulation according to the results obtained from the proposed Fuzzy-BIEM method in Figure 8, it was noted that a model generated based on a fuzzy logic approach results in a simpler class structure which works with high accuracy. Therefore, due to the high level of simplicity given to the model in addition to a large number of hidden layers, the accuracy in the emotion recognition of users is far more accurate. In Figure 8, sensitivity results of user sentiment detection for the proposed Fuzzy-BIEM technique against results obtained from other techniques, such as LSTM, RDNN, MLP, C4.5, KNN, or SVM is presented.

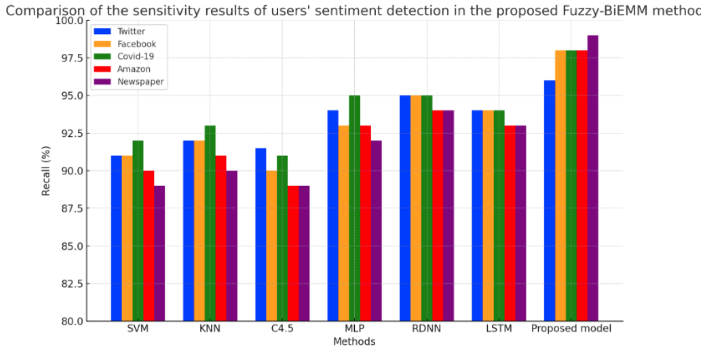

Figure 8. Comparison of the sensitivity results of user sentiment detection in the proposed Fuzzy-BIEM method with other methods.

The results of Figure 8 show that Fuzzy-BIEM performs better than its competitors. This is due to the fact that the Fuzzy-BIEM method has managed to focus on useful elements that help in emotion detection through the application of the cyclic Bi-LSTM deep neural network, thus achieving a far greater level of performance and accuracy than the other approaches.

It is noted that the incorporation of fuzzy logic into the Fuzzy-BIEM method leads to great improvements in emotion detection because it manages to resolve the ambiguity surrounding users' sentiments. The model is able to classify with greater flexibility and precision due to the fuzzy rules created from sentiment words. In addition, the Extended Markov Model (EMM) that was applied here refines these rules by eliminating the less useful ones using transition probabilities, thereby improving the classification accuracy. As seen in our experimental results, the Fuzzy-BIEM method attained an accuracy increase of as much as five percent over the traditional Bi-LSTM models, while surpassing the CSO-LSTMNN method by seven percent.

Despite the complex nature of the Fuzzy-BIEM model, which is already complicated in the structure of BERT or Transformer, the interpretability feature remains dominant. Each classification of sentiment is within the boundary of a set of fuzzy rules, which are capable of being rendered graphically for visualization and interpretation. In this way, the model can be understood and its functions elucidated." "For example, if a highly engaged tweeter has a positive attitude, then the fuzzy rules logic states that for classification, words like 'extremely happy' operate at a high degree of belief coverage.

5 Conclusion & Future Work

One of the objectives of this document was to carry out a survey model focusing on the two-way LSTM deep neural network, EMM approach and fuzzy logic. Fuzzy logic methods were applied to effective rule extraction, Bi-LSTM deep neural network was used for emotion classification, and EMM was applied to enhance user emotion recognition model. The results obtained proved that fuzzy logic approach increases the accuracy in detecting emotions and identifying sentiment of the tweets, classifying COVID19 user comments, and so on. The implementation of EMM which is capable of learning from tweets, comments, and other sources enables the prediction of new tweets based on the weighting of significant words. The process of enhancing the final Bi-LSTM deep neural network model led to an increase in the accuracy of emotions expression recognition. We achieved an accuracy of 94.33% on average when implementing the proposed Fuzzy-BIEM method for sentiment detection, by simulating the approach to the Twitter, Facebook, Covid-19 Fake News, Amazon, and the Fake News Network datasets. Therefore, an application of the fuzzy logic approach helps towards improving execution speed and recognition accuracy in the deep neural network architecture of cellular Bi-LSTM. Because of its rule-based description, the Fuzzy-BIEM approach is easily adaptable for sentiment analysis in different languages and domains. Work will be done in the future on the implementation of the fuzzy logic rules for sentiment determination in various other languages besides English and customising the model to particular fields like politics, healthcare, and finance. We trust that the multicross and domain applications of the framework will be effective and useful across various languages and domains using the fuzzy logic's interpretability and reasoning attributes. Using deep learning algorithms GMDH and CNN or combinations of machine learning methods with gray wolf, advanced cats, dragonfly, etc. instead of the fuzzy logic approach and Bi-LSTM deep neural network are some of the important recommendations. These are the recommendations that can be made to enhance the outcomes of this study.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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. [CrossRef]

[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. [CrossRef]

[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. [CrossRef]

[4] Balazs, J. A., & Velásquez, J. D. (2016). Opinion mining and information fusion: a survey. *Information Fusion, 27*, 95-110. [CrossRef]

[5] Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile networks and applications*, 19, 171-209. [CrossRef]

[6] Injadat, M., Salo, F., & Nassif, A. B. (2016). Data mining techniques in social media: A survey. *Neurocomputing, 214*, 654-670. [CrossRef]

[7] 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*. [CrossRef]

[8] Narayanan, V., Arora, I., & Bhatia, A. (2013). Fast and accurate sentiment classification using an enhanced Naive Bayes model. In *Intelligent Data Engineering and Automated Learning–IDEAL 2013: 14th International Conference, IDEAL 2013, Hefei, China, October 20-23, 2013. Proceedings 14* (pp. 194-201). Springer Berlin Heidelberg. [CrossRef]

[9] Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: tasks, approaches and applications. *Knowledge-based systems, 89*, 14-46. [CrossRef]

[10] Prasad, S. S., Kumar, J., Prabhakar, D. K., & Pal, S. (2015). Sentiment classification: an approach for Indian language tweets using decision tree. In *Mining Intelligence and Knowledge Exploration: Third International Conference, MIKE 2015, Hyderabad, India, December 9-11, 2015, Proceedings 3* (pp. 656-663). Springer International Publishing. [CrossRef]

[11] Rezaee, M. R., Goedhart, B., Lelieveldt, B. P., & Reiber, J. H. (1999). Fuzzy feature selection. *Pattern Recognition, 32*(12), 2011-2019. [CrossRef]

[12] 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. [CrossRef]

[13] 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. [CrossRef]

[14] 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. [CrossRef]

[15] Mdhaffar, S., Bougares, F., Esteve, Y., & Hadrich-Belguith, L. (2017). Sentiment analysis of tunisian dialects: Linguistic ressources and experiments. In *Third Arabic Natural Language Processing Workshop* (*WANLP*) (pp. 55-61). [CrossRef]

[16] 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. [CrossRef]

[17] 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. [CrossRef]

[18] 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. [CrossRef]

[19] 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. [CrossRef]

[20] Alahmary, R. M., Al-Dossari, H. Z., & Emam, A. Z. (2019). Sentiment analysis of Saudi dialect using deep learning techniques. In *2019 International Conference on Electronics, Information, and Communication* (*ICEIC*) (pp. 1-6). IEEE. [CrossRef]

[21] Ramanathan, V. (2019). Prediction of Individual's Character in Social Media Using Contextual Semantic Sentiment Analysis. *Mobile Networks and Applications*, *24*(6), 1763-1777. [CrossRef]

[22] 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. [CrossRef]

[23] 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. [CrossRef]

[24] 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. [CrossRef]

[25] Chauhan, D., & Sutaria, K. (2019). Multidimensional sentiment analysis on twitter with semiotics. *International Journal of Information Technology*, *11*(4), 677-682. [CrossRef]

[26] 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. [CrossRef]

[27] Han, H., Bai, X., & Li, P. (2019). Augmented sentiment representation by learning context information. *Neural Computing and Applications*, *31*(12), 8475-8482. [CrossRef]

[28] Choi, S., & Segev, A. (2020). Finding informative comments for video viewing. *SN Computer Science*, *1*(1), 1-14. [CrossRef]

[29] 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. [CrossRef]

[30] 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. [CrossRef]

[31] 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. [CrossRef]

[32] 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. [CrossRef]

[33] 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).

[34] Siami-Namini, S., Tavakoli, N., & Namin, A. S. (2019). 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. [CrossRef]

[35] 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. [CrossRef]

[36] Kaggle. (n.d.). Sentiment140 dataset. Retrieved from https://www.kaggle.com/datasets/kazanova/sentiment140

[37] Kaggle. (n.d.). Fake/real news dataset. Retrieved from https://www.kaggle.com/datasets/techykajal/fakereal-news

[38] Kaggle. (n.d.). COVID19 fake news dataset NLP. Retrieved from https://www.kaggle.com/datasets/elvinagammed/covid19-fake-news-dataset-nlp

[39] Kaggle. (n.d.). Sentiment labelled sentences data set.

Retrieved from https://www.kaggle.com/datasets/marklvl/sentiment-labelled-sentences-data-set

[40] Zhou, C., Sun, C., Liu, Z., & Lau, F. (2015). A C-LSTM neural network for text classification. *arXiv preprint arXiv:1511.08630*. [CrossRef]

[41] Almansour, B. Y., Almansour, A. Y., J, J. I., Zahid, M., & Abbas, T. (2024). Application of Machine Learning and Rule Induction in Various Sectors. In *2024 International Conference on Decision Aid Sciences and Applications* (pp. 1-8). Manama, Bahrain. [CrossRef]

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