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Enhance the Detection of Fake News on Social Media with Text Vectorization and Deep Learning Algorithms

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Abstract: The prevalence of misleading information poses a significant challenge to efforts aimed at combating misinformation spread through social media, as such content can adversely affect public opinion and decision-making. Organizations that engage in the business of varied diversity face significant barriers to creating smart and sound mechanisms to detect misinformation with precision. This problem is a strategic dilemma that requires rigorous investigation and efforts to produce systematic answers and reverse the proliferation of fake information, as well as to enhance the trustworthiness of the online information infrastructure. In response to these challenges, there is an increasing demand for robust systems capable of identifying false information. The current paper presents a new way of research with the background of the previous works that use the TruthSeeker2023 dataset. The method combines neural network structures and natural language processing methods to be able to identify obscene cues of deceptive signals in the production of tweets. Multilayer perceptron topologies, or Deep Neural Network (DNN) topologies, are defined by small hidden layers with discrete activation functions. To convert the textual data to numeric attributes, sophisticated text vectorization models, Count Vectorizer and the Term Frequency-Inverse Document Frequency (TF-IDF), were used. The proposed methodology is superior to the highest accuracy rate of 96, which has been previously achieved; it has a high rate of 99. This paper elevates the levels of misinformation recognition and shows how intelligent systems can protect social media against misinformation, thus improving the credibility of the entire internet world.

Keywords: Text vectorization**,** Fake News Detection, Deep Learning, TF-IDF.

1. Introduction

Social media platforms such as Facebook, Instagram, and X have evolved to facilitate the rapid and effortless dissemination of information and news. In recent times, the society has largely relied on these available platforms to obtain news and information in all segments of the community. However, one negative aspect that has compromised the credibility of these sites is spreading the wrong content knowingly or unknowingly. Scholars have categorized this deceptive information as either rumors or media fabrications, as the intention behind spreading it is to mislead readers and followers in order to achieve objectives that are socially, politically, or commercially important to the publisher [1]. The issue of distinguishing the real news and the fake information is a major challenge facing digital-age society. The speed of sharing misleading information is enabled through social media platforms because of their ability to repost and spread unverified news, thus compromising the opinion of the masses and undermining the credibility of reliable and official news sources [2].

Based on the estimates, the world social media user base increased by 9.9 percent with an average of 13 new users every second [3]. There is also the wide age gap among the social media users, with reports

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showing that the age group of 18 to 29 years forms the biggest demographic in social media leadership, hence propelling their dominance [3]. By 2027, over 6 billion people are expected to use social media [3]. The personal and direct reliance of people on these sources of information and the exchange of news has made these platforms viable for the spread of fanciful and fictitious stories that greatly impacted the society's culture through knowledge distortion, values and behavior, critical thinking, and cultural and social segregation. Social media is regarded as a powerful tool for the rapid dissemination of information; however, it poses a significant risk to culture when used without a certain consideration. In addition, the impact of fake news could be reduced by increasing media literacy and facilitating the checking of information, which would preserve cultural and social values [3].

Tackling these problems is key to creating reliable tools that enhance information integrity within the news ecosystem. This study addresses these challenges by examining the effectiveness of advanced Deep Neural Network (DNN) models and their integration with traditional Machine Learning (ML) techniques. The researcher utilizes Term Frequency-Inverse Document Frequency (TF-IDF) alongside DNN with Leaky ReLU boosted layers for the feature extraction process, which aims to better identify topics in scenarios where information is limited or the environment is rapidly changing. Acknowledging the difficulty of obtaining a comprehensive dataset on misinformation, the current study leverages the TruthSeeker2023 dataset, which contains over 134,000 labels from 2009 to 2022 [3]. The methodology is intricate, incorporating preprocessing and advanced feature extraction to capture the subtleties of deceptive content. The framework's ability to integrate methods like Natural Language Processing (NLP) and DNN models not only enhances detection accuracy but also allows for scalability. The primary achievement of this research is the development of a novel methodology that effectively combines established techniques to yield improved results compared to previous studies. The use of the TruthSeeker2023 dataset, the integration of TF-IDF with DNN, and the comprehensive preprocessing pipeline significantly contribute to high accuracy in fake news detection and advance scientific inquiry into this topic.

The subsequent part of this work is organized subsequently. Section II presents the related works. Section III provides a summary of the research methodology and delineates the proposed strategy. The findings and analysis of our study, specifically the results and discussion, are described in Section IV. Finally, Section V focuses on conclusions and future research.

2. Related works

Several studies on fake news detection have been proposed with diverse advanced methods. Kaliyar et al. (2020) have proposed a deep Convolutional Neural Network (CNN) and trained it to learn hitch-free discriminative features of the text. This model hadan accuracy (98.36%), which demonstrates the potential of CNNs in this task [4]. Equally, Liu et al. (2020) prioritized the effectiveness of early fake news detection through a DNN, which has a position-aware attention mechanism. Their model attained more than 90% accuracy after 5 minutes of propagation of news, which is highly effective and indicates that it uses limited labeled data [5].

Researchers continue to enhance the system by incorporating multiple feature extraction techniques. Almarashy et al. (2023) presented the multifeature classification model including global, spatial, and temporal characteristics captured using the TF-IDF, CNN, and a Bidirectional Long Short-Time Memory (BiLSTM), respectively. Such combination led to the increased accuracy of the classification [6]. Likewise, Farhangian et al. (2024) attempted to investigate and declare that the combination of using different feature representation approaches and classification algorithms, provides improved generalization and performance [7].

Alghamdi et al. (2023) fine-tuned a pre-trained transformer, including Bidirectional Encoder Representations Transformers (BERT) and COVID-Twitter-BERT (CT-BERT), and appended downstream a CNN with BiGRU layers to detect COVID-19 fake news using the transformer-based framework It has had an exemplary F1-score of 98 percent suggesting the strength of fine-tuned transformers to a specialized environment [8]. Wani et al. (2023) is another work that dealt with transformer-based models where authors implemented certain Machine Learning solutions, including Support Vector Machine (SVM) and Random Forests (RF), to identify the toxic fake news on COVID-19 and described a paradigm based on toxicity [9].

Other researchers have examined new paradigms and integrations. Mahmud et al. (2023) focused on the topic of news authenticity, providing the framework that entails the blockchain, smart contracts, and incremental Machine Learning (ML). The illustration showed the prospects of this mode of decentralized truths of news verification, where accuracies reached above 93% with sequential training [10]. Through an interactive DL model, Mallick et al. (2023) have found a way to enhance the detection of fake news through user feedback and achieved a 98 percent level of accuracy in identifying it [11]. The emergence of Large Language Models (LLMs) allowed Liu et al. (2024) to propose a Few-Shot Fake News Detection (FS-FND) framework that can perform successfully in low-resource environments due to the utilization of LLMs and in-context learning [12].

Additional research has employed DL to detect misinformation. They widely use hybrid models incorporating other kinds of neural networks to model local and global text features. The " TruthSeeker2023" has become a reference point in the sphere serving as a background of multiple models with the use of BERT. Ref [3], which uses a Long Short-Term Memory (LSTM) model with an accuracy of 96 percent and focuses on it, shows the effectiveness of such architecture and also offers a very useful baseline in similar studies, which would reproduce this well-established data.The results contribute to the future trends of wider capabilities, such as identification of criminal activity and prevention of harassment [12]. In the final analysis, Sajjad et al. [13] used a combination of traditional ML methods and BERT-based strategies. Their study produced an impressive 96% accuracy on the TruthSeeker2023 dataset, which is the highest of its kind.

The proposed model has achieved an exceptional 99 percent across all evaluation metrics, including precision, recall, F1-score, and accuracy.

3. Methodology

The study has a solid research methodology of broadcasts of news that can be classified as either fraudulent or authentic by combining NLP strategies with the DNN model. The method has four main steps, including dataset overview, data preprocessing, feature extraction, and proposed work, which are presented in Fig. (1) successfully.

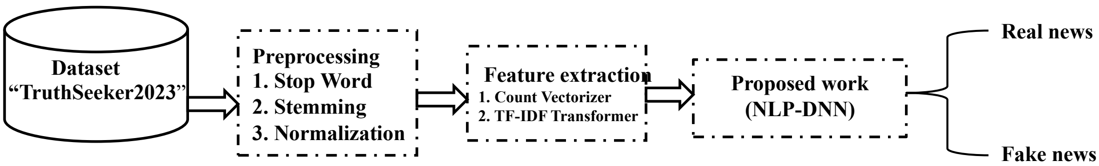

Fig. 1 A proposed framework for news classification

3.1 Dataset Overview

This research primarily relies on a comprehensive dataset, specifically, the TruthSeeker2023 [3]. The TruthSeeker2023 standard was utilized to evaluate the integrity of news items broadcast on social media sites. This collection of data, comprising around 134,000 categorized tweets, is among the largest in its category. For the purpose of annotating each tweet, the dataset was subjected to a stringent evaluation process, which included a three-factor active learning validation approach. This approach entailed four different Amazon Mechanical Turk workers who possessed a high level of expertise.. This exercise was done in order to ensure that the dataset was accurate. Through the process of extracting data from tweets connected to legitimate and misleading news that were sourced from the PolitiFact dataset in English, the TruthSeeker2023 dataset was created [3]. The primary function of Amazon Mechanical Turk is to serve as the primary technique for crowdsourcing to obtain agreement to determine whether or not a tweet is true. As a consequence of this, a ground truth database platform that is extremely thorough has been developed in order to identify fake news on X [14].

3.2 Data Preprocessing

Data preparation involves the methodical extraction of significant insights from unstructured textual data. In the preprocessing phase of the dataset, techniques such as token preprocessing, stop-word removal, stemming, and normalization were employed. These methods were utilized to clean the data, remove noise, and delete irrelevant information.

3.2.1 Stop Word

In English, sentences often include stop words to meet structural requirements; however, these words frequently do not convey the core ideas of an individual's thoughts. In text analysis, terms like "and," "these," "is," and "in" hold minimal significance. Therefore, in the experiments, we removed stop words to reduce interference and enhance the clarity of the results. By removing the following words, we can pay attention to the more significant features of the text which will enhance the quality of our text processing and classification algorithms [15]. When we take the phrase "The cat is on the mat" and remove the stop words, we get "cat mat," which preserves the essential message while eliminating extraneous words. Developing more precise and reliable machine learning models necessitates this stage [15].

3.2.2 Stemming

For the purpose of determining a word's root form, stemming involves removing prepositions, affixes, prefixes, and suffixes. To accomplish stemming, the Porter stemming algorithm is employed. This algorithm starts by inspecting the phrase and then adheres to a set of criteria. The next step is to eliminate any form of pluralization ending, such as '-s' as '-es,' past tense as '-ed,' or continuous tenses as '-ing.' After the stemmer verifies the input, it converts double suffixes to single suffixes. Several words have been removed from the list, including those that finish in "-ic," "-ful," "-ness," "-ant," or "-ence," among others. The word "use" should be used to indicate the meaning of "used," "using," and "uses" as well [15].

3.2.3 Normalization

The standardized structure of text involves the removal of dates, whitespace, abbreviations, and diacritics, along with the standardization of classification criteria. Substantive analysis cannot happen without data preparation, i.e., the elimination of extraneous or noisy elements [15]. Normalization is the conversion of all the text to lower case, eliminating characters, processing URLs and references and the additions of spaces. The method enhances the quality of data. Data purification enhances crucial NLP tasks, that is, it cleanses textual data and allows statistical analysis. The data-cleaning is the an delimiting of extraneous data and maintaining pertinent phrases [15].

3.3 Feature Extraction

Feature extraction is the process of combining variables to decrease data dimensionality while maintaining its core information. This process minimizes overfitting by refining the model, improving computational effectiveness, and improving multifaceted performance. Efficient extraction of features converts data into a more coherent and meaningful structure, which enhances the model's training and increases its ability to generalize to new inputs [15]. This research employed a Count Vectorizer and a TF-IDF Transformer to extract features in text processing.

3.3.1 Count Vectorizer

One hot encoding is a method that produces a vector that matches the size of the vocabulary. A word's occurrence in a phrase is verified in the lexicon, resulting in a rating of 1. The total number of words rises when a word is repeated multiple times within a document. The term will be included if it is not already present in the dictionary. The operation of the count vectorizer is thoroughly detailed in the example

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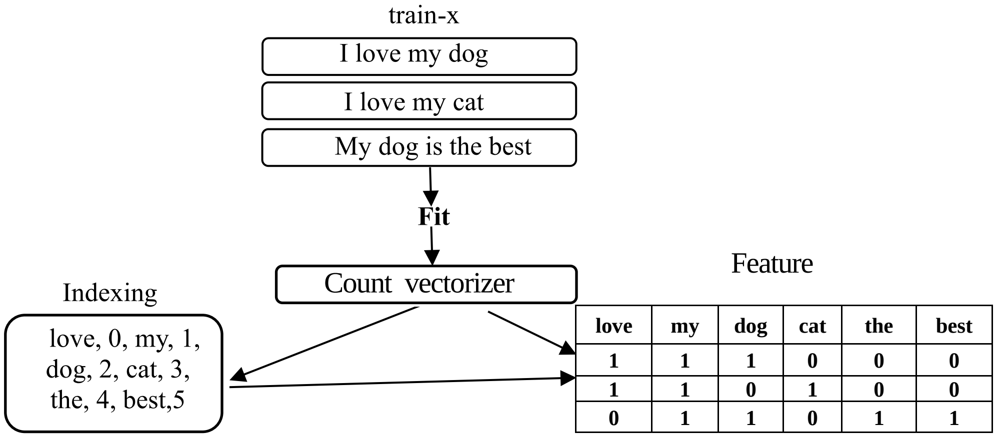
presented in Fig. (2) [16].



love	my	dog	cat	the	best
1	1	1	0	0	0
1	1	0	1	0	0
0	1	1	0	1	1

Fig. 2 Illustration of the Count Vectorizer

3.3.2 TF-IDF

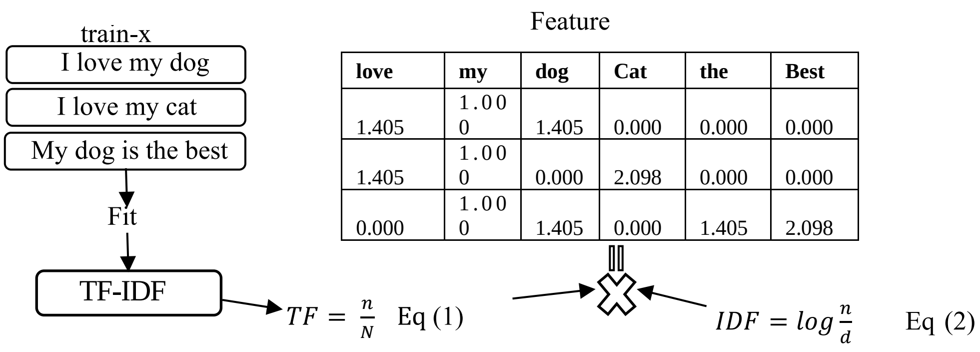
TF-IDF is a crucial instrument for machine learning applications, as it quantifies the importance of phrases in relation to a corpus of documents, facilitating accurate and relevant data representation. For a specific word (x) in a document (N), the term frequency (TF) score is calculated as the ratio of the occurrences of that word to the total word count in the document, whereas the inverse document frequency (IDF) is the ratio of the total number of documents to the number of documents containing that word. The TF_score and IDF_score are mathematically represented in Eqs 1, 2, and 3 [16].

$$TF_{score} of\ word(x) = \frac{No.appeared(n)}{total\, word\ in\ \ the\, document\ (N)} \tag{1}$$

$$IDF_{score} of\ word(x) = log\ \frac{n}{D} \tag{2}$$

$$TF\_IDFscore = \ TFscore * IDFscore \tag{3}$$

The use of these techniques provides clear data. This combination of the Count Vectorizer and the TF-IDF Transformer maintains essential information while reducing dimensionality, hence enhancing the performance and generalization capacity of the text categorization model, frequently enhancing the efficacy of ML models utilized for textual data [16]. Fig. (3) illustrates the operations of the TF-IDF.



love	my	dog	Cat	the	Best
1.405	1.000	1.405	0.000	0.000	0.000
1.405	1.000	0.000	2.098	0.000	0.000
0.000	1.000	1.405	0.000	1.405	2.098

Fig. 3 illustrates the operations of the TF-IDF

3.4 Building the Model

To enable sequential layer backing, the DNN classification model is built using the Keras Sequential API. The architecture of the neural network was nine thick layers, with each layer's neurons related to all of the neurons in the layer below it. There was an 80% training set and a 20% testing set made from the dataset. With a batch size of 128, the model proceeded through 100 epochs. It made use of the Adam optimizer for stochastic gradient descent optimization and the activation function Leaky ReLU. By going through this procedure, the model is able to comprehend the interconnections and patterns present in the training data. The dense layers analyze the supplied data to identify pertinent information. The Leaky ReLU activation layers facilitate efficient gradient propagation and incorporate non-linearity, hence augmenting the network's ability to analyze complex patterns and achieve precise estimates.

The article explains the design, training, and compilation process of a DNN model constructed using the Keras Sequential API on a binary classification problem. The objective is to label the tweets in the TruthSeeker2023 dataset as either true or false. It has nine dense layers: a total of an input layer, seven hidden layers, and an output layer. The dimensions of a TF-IDF matrix fed to the input layer are 40,511 word features. Input Layer: 40,511 dimensional TF-IDF matrix. It has non-linearity as an input by employing activation ReLU. Hidden Layers: It comprises a total of seven hidden layers. Layout of hidden layers:

1. Layers (1,2): They contain 32 ReLU-activated neurons. Each layer with the dense combination is followed by a Leaky ReLU layer with a slope of 0.3.

2. Layers (3,4): each contains 64 neurons with ReLU activations and a LeakyReLU layer whose slope is 0.3.

3. The rest of the hidden layers remain undocumented, although the tendency is that there is a dense layer (with ReLU activation), followed by a ReLU layer. ReLU is aimed at avoiding the problem of vanishing gradient and maintaining neurons in activity.

4. Output Layer: This is the final layer containing a single neuron with the ReLU activation function, giving a probability value of between 0 and 1. It is a measure of how probable a tweet is fake news (the higher it goes toward 1) or real news (the lower it goes toward 0), as illustrated in Fig. a(4). The model was created and trained with the following hyperparameters shown in Table (1).

Table 1 hyperparameters of proposed work (NLP-DNN)

Epochs	Batch size	Optimization algorithm	Loss function	Number of layers	Activation function
100	128	Adam (learning rate 0.001)	binary cross-entropy	9	ReLU, Leaky ReLU

Eq 4 is the principal applicable to all hidden layers [11]:

$$h_i = Laky\ ReLU(ReLU(W_i . h_{i-1} + b_i) \qquad (4)$$

where (i=1, 2, …, 9), W_i: Weight matrix for the 9th layer, h_{i-1}: Output of the preceding layer (or the input x if i=1), b_i : Bias for the 9th layer, $ReLU$ and $Leaky\ ReLU$ are illustrated in Eqs 5, 6 [11].

$$ReLU(z) = \max(0, z) \qquad (5)$$

$$Leaky\ ReLU(z) = \begin{cases} \propto z & if\ z < 0 \\ z & if\ z \geq 0 \end{cases} \qquad (6)$$

$\propto$: It is a small constant to ascertain the negative gradient of the z values. The value is established at 0.3.

Input (z) is given to the activation function. The product of every input multiplied by its corresponding weight together with the bias term will obtain the neural network variable z, as indicated in the Eq7 [11]. See Fig. 4(b) to illustrate. A neuron would mathematically be defined as follows [11]:

$$z = \sum_{i=1}^{m} x_i . w_i + b \tag{7}$$

The value of pre-activation is written z and the neuron input is written x. The input features are denoted by their weights, b indicates the bias equation and m is the number of input features. Sigmoid function is used to activate one neuron in the output layer. The value produced by this neuron is between 0 and 1, which denotes the likelihood that a tweet is false or true (1 or 0), respectively, as shown in Eq 8 [11].

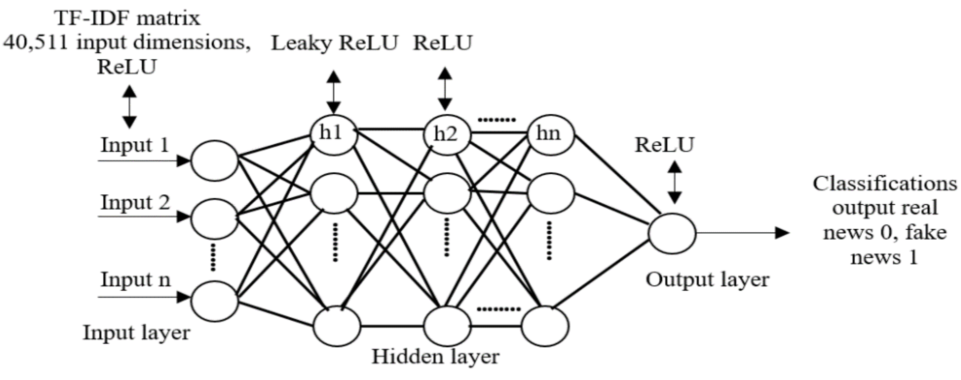
$$y = \sigma(w_{out} . h_9 + b_{out}) \tag{8}$$

In this context, 'w_{out}' denotes the weight matrix utilized in the output layer, while 'b_{out}' represents the bias vector associated with the output layer. The symbol 'σ' refers to the sigmoid function, as defined in Eq 9 [11]:

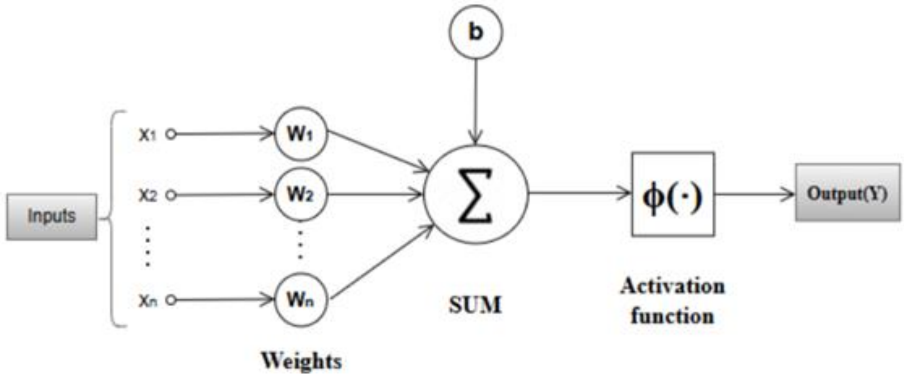
$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{9}$$

The output of the sigmoid function is represented by $\sigma (z)$, which ranges from 0 to 1. The variable z denotes the input to the sigmoid function, typically calculated using Eq 7. Euler's number (e) is approximately 2.71828 [11].

Each layer in the model does data processing and transformation, enabling it to distinguish between tweets that contain misinformation and those that contain factual news. Throughout the process, the model refines its parameters to reduce forecast inaccuracies and enhance its performance in data classification.



(a)



(b)

Fig. 4 (a) Proposed framework (NLP-DNN), (b) Function of one neuron

4. Results and Discussions

Using the TruthSeeker2023 dataset, the NLP-DNN model primarily aims to detect fake news accurately. Over 134,000 tweets that have been annotated and collected between the years 2000 and 2022 are included in this dataset [3]. These tweets are divided into two unique categories: honest and fraudulent. The proposed model is made up of five levels that are all connected to one another. The small format of the architecture enables the model to be able to absorb intricate trends in the data. The standard classification measures, such as precision, recall, F1-score, and accuracy, were used to measure the performance of the model. Fig. (5) demonstrates that the model attained an impressive 99% accuracy across all metrics for both classes, indicating its balanced and highly precise classification capabilities.

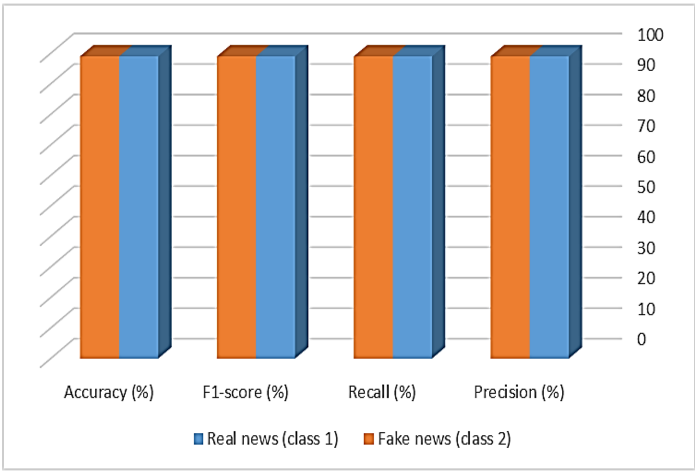


Fig. 5 NLP-DNN classification performance

Researcher used the validation set to evaluate the model's performance and find the optimal parameters for training to avoid overfitting. The researchers used a five-fold cross-validation procedure rigorously. The dataset was divided into five subsets, where the model was trained on four of them and validated on the remaining one. A detailed investigation of each fold reduced bias and improved outcome reliability. All folds show 99% accuracy, precision, recall, and F1-score in the cross-validation results shown in Fig. (6).

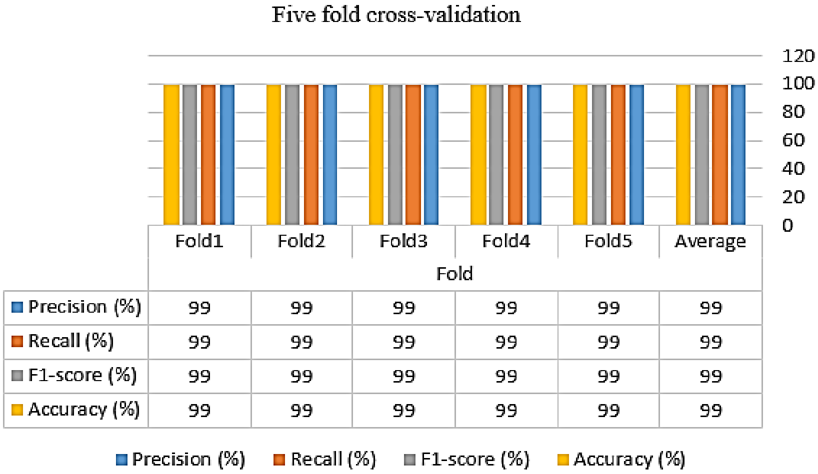


Fig. 6 result of cross-validation

Calculating a confusion matrix allows for a comprehensive analysis of the successes and failures within the categorization model. Fig. (7) presents the confusion matrix, offering a comprehensive evaluation of the proposed model's classification efficacy.. The precision and recall metrics are exceptionally high, demonstrating that the model is extremely dependable in its 'Fake' predictions and proficient at recognizing all instances of 'Fake.' The counts of false positives (26) and false negatives (15) are remarkably low in relation to the overall total of accurate predictions.

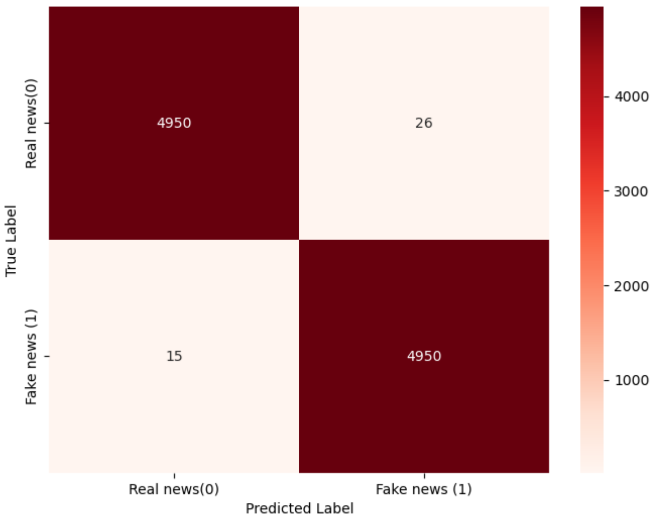


Fig. 7 Confusion Matrix for proposed work

In Table 2 the performance of the NLP-DNN model was compared with that of Ref [3], and Ref [13]on the TruthSeeker2023 dataset. Both studies, achieved the highest accuracy, attaining 96%. This research is based on the fundamental work of Ref [3], who compiled the "TruthSeeker2023" dataset. This study successfully employs the NLP-DNN on the "TruthSeeker2023" dataset to attain 99% accuracy in identifying suspect content. This method is a big step forward for detection of fake news because it uses a well-chosen dataset of more than 180,000 tweets. A 96% accuracy rate is good, but a 99% accuracy rate is a big step forward, especially when it comes to cutting down on false positives and negatives. This improved accuracy shows that the model is more advanced and can handle tiny differences in language, which is important for detection of fake news.

Table 2 Comparative analysis with relevant studies and the proposed model (NLP-DNN)

Ref	Year	Model	Accuracy (%)
[3]	2023	BERT	96
[13]	2023	LSTM-FFNN	96
Proposed work	-	NLP-DNN	99

5. Conclusions

The research results analyses and the comparisons with the studies conducted by the same authors using the same data (TruthSeeker2023) demonstrated the effectiveness of the developed methodology to build the proposed model by integrating the use of the DL and NLP techniques in the binary classification to detect fake news on social media. The effectiveness of this model can be explained by the careful design of the nine-layer neural network and the optimal application of the methods of NLP, most of all, feature extraction, Count Vectorizer and TF-IDF. The careful data processing as well as the planned combination of the dataset has significantly improved the performance of the DNN that allows it to outperform other methodologies that were utilized in similar studies in the past. In spite of the use of Multilayer Perceptron (MLP). The results of the suggested model suggest that the combination of data processing and feature extraction methods is viable to the dataset, and provides almost perfect and accurate results in binary classifications. The results obtained above proved the effectiveness of the building and design approach of this model in classifying fake news, despite a relatively high error rate of the misclassification of both genuine and fake news. It therefore follows that more research is needed in order to achieve perfect results in binary classification. Coding the algorithms that are more accurate and understandable in the data analysis.

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