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Enhancing the Fake News Classification Model Using Find-Tuning Approach

Mohammed A. M. Ali[1], S. N. Lokhande[2], Safwan A. S. Alshaibani[3], Abdulrazzaq H. A. Al-Ahdal[4]

[1, 2, 3] School of Computational Sciences S.R.T.M. University, Nanded, MS, 431606, India
[4]Dept. of Computer Science & Engineering, Hodeidah University, Yemen
[1]moh.srtmu@gmail.com, [2]lokhandesn19@gmail.com, [3]safwan.srtmu@gmail.com, [4]alahdal201211@gmail.com

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Abstract

In recent years, fake news on social media has become a pressing concern, posing significant threats to individuals, organizations, and society as a whole. we present a novel strategy to enhance the accuracy of fake news classification models through fine-tuning. Our proposed model involves adding new layers and freezing some layers in the BEART model, resulting in improved performance. To facilitate our research, we constructed a comprehensive fake news dataset by combining real and fake datasets obtained from secondary sources. Firstly, the dataset underwent rigorous preprocessing, including data cleaning, text normalization, tokenization, stop word removal, and other techniques, ultimately enabling binary classification. Subsequently, the proposal model (DCNN) was trained on this dataset to classify news articles as either real or fake. Notably, experimental results demonstrate that our approach outperforms several recent studies in detecting fake news, achieving high accuracy. To evaluate the effectiveness of our proposed model, we employed various evaluation methods. Firstly, we utilized the Tag Cloud technique, which visually represents the most frequently used words in the text or documents, enabling us to distinguish between real and fake news. Additionally, we employed the Classification report, which provides precision, F1, recall, and support scores, to comprehensively assess the model's performance. Furthermore, we employed the confusion matrix, a tabular layout that effectively visualizes the classification algorithm's performance, thereby enabling a clear interpretation based on known true values. Therefore, the proposed model was trained to classify news articles as real or fake, and the experiments on the dataset show that this approach performs better than several recent studies for detecting fake news, achieving high accuracy.

Keywords

Fake News, BERT model, Transfer Learning, Text Classification, NLP

1. Introduction

Nowadays, Fake news has emerged as a major challenge in the era of social network and online information sharing. The spread of fake news can have serious consequences, including public distrust, social polarization, and even threats to democratic institutions. As a result, there has been growing interest in developing automated methods for detecting fake news. Natural language processing (NLP) techniques have proven to be effective in this task, as they can analyze the content and context of news articles to identify misleading or false information [1]. However, Natural Language Processing (NLP) is a specialized area within the field of artificial intelligence that focuses on the ways in which human language and computer systems interact. It involves using various tools and algorithms to analyze, understand, and generate human language. In addition, one of the most essential techniques is analyzing the content and context of news articles to identify misleading or false information. This involves identifying patterns and inconsistencies in the language used and cross-checking the information presented against reputable sources to verify its accuracy. Other techniques used in fake news detection such as sentiment analysis, entity recognition...etc. One of the most common applications of DL in NLP is building language models, which can be used for various tasks such as text classification, sentiment analysis, machine translation, question-answering, and many more. Various NLP tasks employ deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers [2]. Furthermore, with the increasing availability of large datasets and powerful computing resources; For many NLP tasks, deep learning has emerged as the leading method, surpassing traditional rule-based or statistical approaches. We will propose an improved and novel study to detecting and classification fake news. Our proposal involves developing a deep learning model that classifies news articles as either real or fake. We plan to conduct experiments using a benchmark dataset to demonstrate that our approach outperforms several state-of-the-art models used for fake news detection. Python is a highly popular programming language that finds extensive usage in natural language processing (NLP) applications such as detecting and classifying fake news. There are various libraries and tools available in Python that can be used for this purpose, such as Scikit-learn, NLTK, SpaCy, and Keras.Overall, Python provides a rich ecosystem of Techniques and libraries for fake news classification and detection, allowing researchers and practitioners to build and deploy effective models for identifying misleading or false information in news articles and other text sources.

2. Existing Studies

In this part, there are several of studies that have focused on detecting and classifying fake news using NLP and DL algorithms. These techniques are important for identifying and responding to fake news quickly and effectively, in order to minimize potential damage or loss for individuals, companies, and organizations. In this section, we discuss previous studies in the last years. Zichao Wang et al. [3] observed that the GCN method achieves a satisfactory accuracy of around 85% for detecting fake news when compared with other neural network models. The authors also noted that there is a lack of a standardized training dataset in this field and suggested that future fake news detection models should give a lot of attention to semi-supervised learning and unsupervised learning techniques. Nida Aslam et al. [4] used the LIAR dataset and proposed an ensemble-based deep learning model to get classification news as fake or real . The dataset attributes were such that two deep-learning models were used; the Bi-LSTM-GRU-dense deep learning model was used for the textual attribute "statement," while the dense deep learning model was used for the other attributes. The experimental results demonstrated that the proposed study achieved high accuracy, recall, precision, and F-score, with an accuracy of 89.8%, recall of 91.6%, a precision of 91.3%, and F-score of 91.4%, respectively, when only a statement attributes were used. The authors also noted that the performance of their proposed models was significantly better than that of previous studies for fake news detection using the LIAR dataset. According to Akshay Aggarwal et al. [5] proposed a Natural Language Processing (NLP) technique that utilizes the Bidirectional Encoder Representations from Transformers (BERT) language model to classify news articles as fake or real. Their findings indicate that the fine-tuned BERT model performs exceptionally well on news article classification even with minimal text pre-processing. The researchers also developed LSTM and Gradient Boosted Tree models for the same task, and the comparative results are presented for all three models. The fine-tuned BERT model outperformed the other two models by approximately eight percent, achieving an accuracy of 97.021% on the NewsFN dataset. Sonal Garg et al. [6] proposed the identification of fake news by concentrating on diverse categories of linguistic features, including complexity, readability, psycholinguistics, and stylometrics. They developed a linguistic model that can assess language-based features by learning the properties of news content. They selected 26 significant features and applied various machine learning models for implementation. To extract features, they used three techniques: term frequency-inverse document frequency (tf-idf), count vectorizer (CV), and hash-vectorizer (HV). The models were tested with different training dataset sizes to obtain accuracy for each model, and the results were compared. The study employed four existing datasets, and the proposed framework achieved 90.8% accuracy on the Reuter dataset. The Buzzfeed dataset had the highest accuracy of 90%, while the Random Political and Mc_Intire datasets achieved accuracy levels of 93.8% and 86.9%, respectively. Rohit Kumar Kaliyar et al. [7] developed a deep learning technique called "FakeBERT" that uses BERT (Bidirectional Encoder Representations from Transformers) and a combination of parallel blocks of a one-layer deep Convolutional Neural Network (CNN) with diverse kernel sizes and filters. This approach helps tackle ambiguity, a major hurdle in natural language comprehension. The study demonstrated that their proposed FakeBERT model surpassed current models, attaining 98% accuracy in classification.. However, the literature highlights the importance of obtaining fake news data from social networks for detecting and classifying news. Various deep learning models have been employed for fake news analytics, particularly in natural language processing. Future research is expected to focus on analyzing both real and fake news. Prior studies have used deep DL algorithms to identify all references to a given topic and determine whether the news is real or fake.

3. Fake News Dataset

A Fake News Dataset is a compilation of data utilized to train and test ML and DL models for detecting and classify and categorizing fake news. The dataset contains both authentic and deliberately falsified news articles or statements that mislead readers. The dataset is algorithms to recognize the discrepancies between them. We obtain from various online sources, such as social media platforms and news websites [8]. A comprehensive fake news dataset should be diverse and representative of multiple types of fake news, covering various topics, genres, and sources. It should also be large enough to provide adequate training data for ML and DL algorithms to learn accurately. Properly labeled datasets are crucial for the precision of machine learning and deep learning models; thus, datasets that have undergone a thorough annotation and validation process are generally preferred. FakeNewsNet, LIAR, Buzzfeed News, Kaggle, and several other publicly available resources for fake news datasets exist for research purposes [9 typically marked to specify which news items are genuine and which are fake, allowing machine learning and deep learning] [10]. Figure 1 shown in our dataset contains two classes' real dataset and fake dataset. Fake dataset has around 21417 observations with 4 features, as well as the real dataset has around 23481 observations with 4 features.

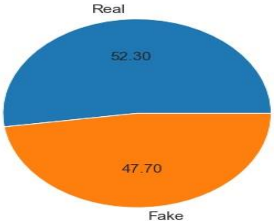

Figure 1. Types of Dataset

4. Data Handling Stages

The increase of fake news is becoming an increasingly alarming issue in contemporary society, as it can cause serious harm by spreading misinformation and influencing people's decisions. With the advancement of technology, deep learning models have shown promising results in detecting and classifying fake news [11]. Thus, our approach will use the DCCN model to improve the BERT model. However, before training the model, a series of preprocessing steps must be carried out to clean and transform the raw data into a suitable format for the deep learning algorithms. These steps include data cleaning, text normalization, tokenization, stop word removal, and others shown in figure 2. The effectiveness of the model greatly depends on the quality of the preprocessed data. This article aims to present a comprehensive explanation of the necessary preprocessing measures for improving the detection of fake news using the BERT model in deep learning. We will explain in details in below:

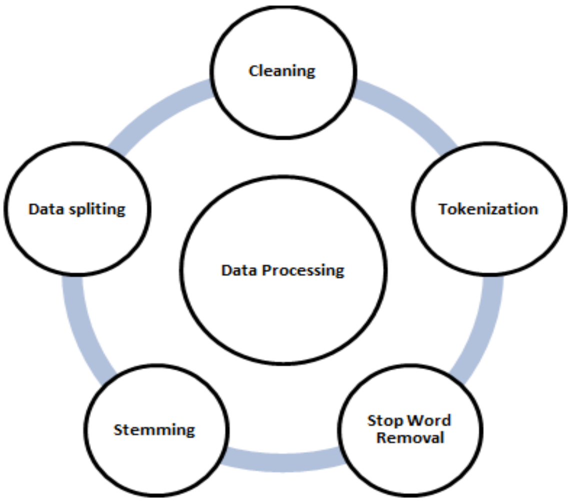

Figure 2. Data Preprocessing Stages

4.1. Data Preprocessing

Data preprocessing, also known as Data wrangling, is a crucial step in preparing and cleaning raw data for analysis. The goal of data wrangling is to transform the data into a structured and consistent format that is suitable for analysis and visualization. This process involves several stages to ensure that the data is accurate, complete, and relevant to the analysis at hand. By performing data wrangling, researchers and analysts can obtain more accurate and useful insights from the data [13]. In this discussion, we will study the preprocessing stages in detail:

a) **Data Cleaning:** This step involves removing any unwanted characters, punctuations, or special symbols from the text data. It also involves converting the text data to lowercase.

b) **Tokenization:** Tokenization is the process of segmenting textual data into smaller units, known as tokens. Tokens are usually words or phrases that represent a single unit of meaning. This is typically done using a tokenizer, which can be a pre-built function or a custom function.

c) **Stop Word Removal**: Stop word removal is the process of eliminating frequently occurring words that do not contribute significantly to the meaning of the text data. Examples of stop words include "the", "a", "an", "in", and "is". Stop word removal can help to improve the efficiency of the algorithm.

d) **Stemming:** it also known as lemmatization, this step involves reducing words to their base form, also known as the lemma. Unlike stemming, which reduces words to a root form; lemmatization reduces words to their dictionary form. This can help to improve the accuracy of the algorithm.

e) **Data splitting**: Data splitting is the procedure of dividing the preprocessed data into three sets: training, validation, and test sets. The machine learning or deep learning algorithms are trained on the training set, while the hyper parameters are optimized using the validation set. The performance of the algorithm on new data is assessed using the test set.

The classification of news types and their frequency in the database is displayed in Figure 3, which was obtained by analyzing and processing the data in the preceding stages. Furthermore, this information can be used to gain a better understanding of the contents of the database and to make informed decisions about how to use the data for various purposes, such as research or marketing.

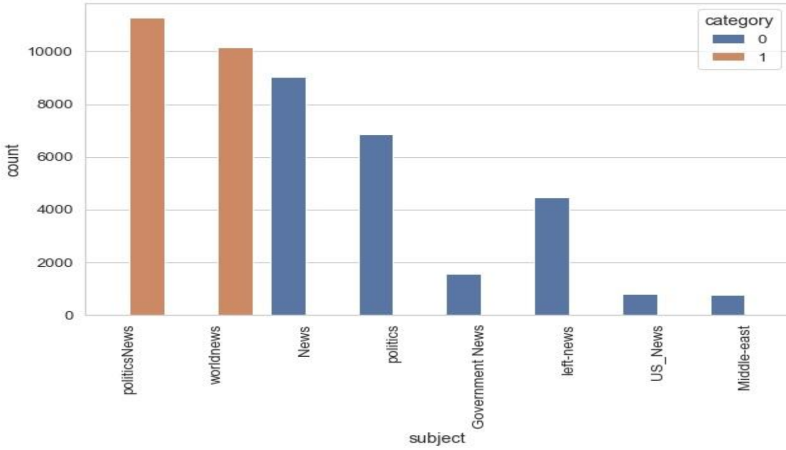

Figure 3. Classification of Types of Dataset

5. Deep Transfer Learning

Nowadays, transfer learning has become a widely well-known technique in NLP which allows efficient solving of new NLP tasks with less data. Traditionally, NLP models were built from scratch for each new task, necessitating a considerable amount of labeled data and computational resources. Transfer learning allows for fine-tuning of pre-trained models using a smaller dataset that is specific to the task at hand, which enables the adjustment of the model's parameters for the new task. Pre-trained models can be trained using various unsupervised techniques, such as language modeling or masked language modeling, and learn representations of words as well as phrases that capture their syntactic and semantic properties. These learned representations can then be used in downstream tasks, including text classification or sentiment analysis [11]. Transfer learning in NLP has resulted in significant performance improvements on different tasks involving question answering, machine translation, and text classification. BERT, GPT-2, and RoBERT are among the most popular pre-trained models used in transfer learning for NLP [16]. Overall, transfer learning in NLP has allowed for state-of-the-art outcomes on a range of neural language processing tasks with less labeled data and computational resources.

5.1. BERT Model

Bidirectional Encoder Representations from Transformers (BERT) is a deep learning model that Google has developed for NLP tasks. Using an unsupervised learning approach called masked language modeling, BERT is pre-trained, where a percentage of the input tokens are masked, and then the model is trained to predict them based on the context of surrounding words. As a result, BERT has accomplished state-of-the-art performance on a wide range of neural language processing benchmarks and competitions [17]. Furthermore, To fine-tune BERT for this task, a labeled dataset of real and fake news articles is used to further train the pre-trained model with a supervised learning approach. During fine-tuning, the final layer(s) of the model are modified to match the number of output classes for the task. BERT has accomplished state-of-the-art performance on various NLP benchmarks, including fake news detection, making it a useful tool for this application. When we use Masked Language Model (MLM) as a pre-training objective, BERT breaks free from the limitation imposed by the unidirectional approach. With its impressive performance on eleven NLP tasks, BERT has introduced a novel approach that does not rely on extensively engineered and task-specific architectures. Its input representation comprises three embedding layers, namely Token Embeddings, Segmentation Embeddings, and Positional Embeddings. BERT has approximately 110M parameters. Figure 4 indicates the block diagram of the BERT model [5].

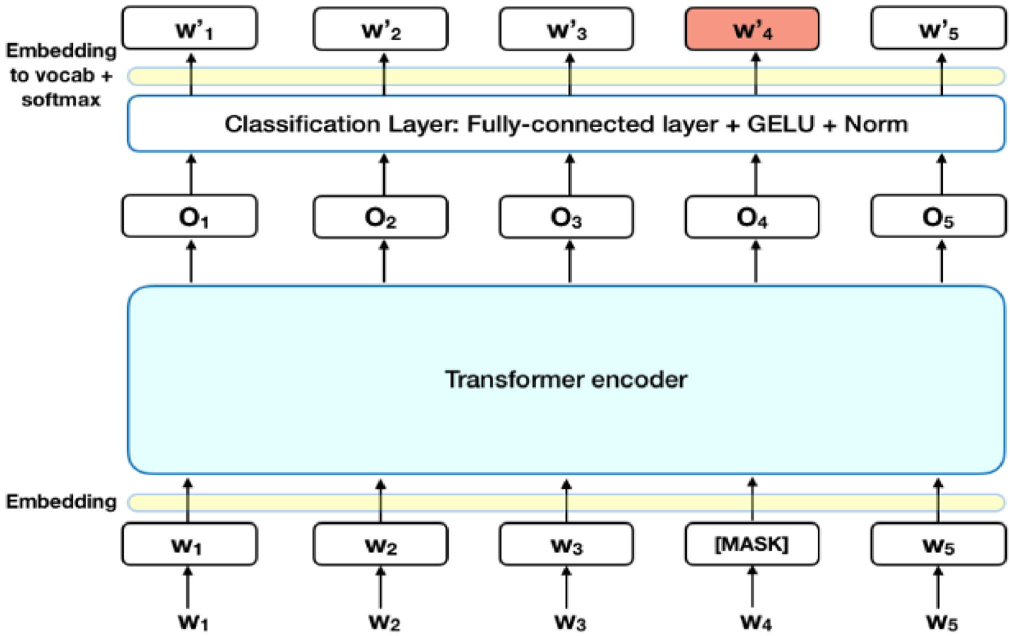

Figure 4. Block Diagram of BERT for classification [5]

6. Proposal Model

The Fake news dataset is prepared using a model that combines both real and fake data. In addition, the model conducts both data preprocessing and NLP preprocessing to make the dataset suitable for use with a deep learning model. To facilitate model training, the dataset is provisionally split into 70% for training and 30% for testing. Moreover, a BERT model is selected from the list of TensorFlow applications, which is a widely used pre-trained language model for natural language processing tasks such as classification. The model freezes layers and adds new layers without modifying their weights, a technique commonly used in transfer learning, where pre-trained models are fine-tuned for specific tasks by modifying only the top layers. Furthermore, our proposed model, DCNN, generates fresh weights for the new layers in addition to the previous weights trained on the dataset. The model provides binary classification for Fake news. The workflow of the proposed model and how it detects and classifies fake news is illustrated in Figure 5. Specifically, the model takes input from the fake news dataset after combining the real data and fake data datasets. It trains all the data in the model with the previous weights of the BERT model and new weights generated by the DCNN.

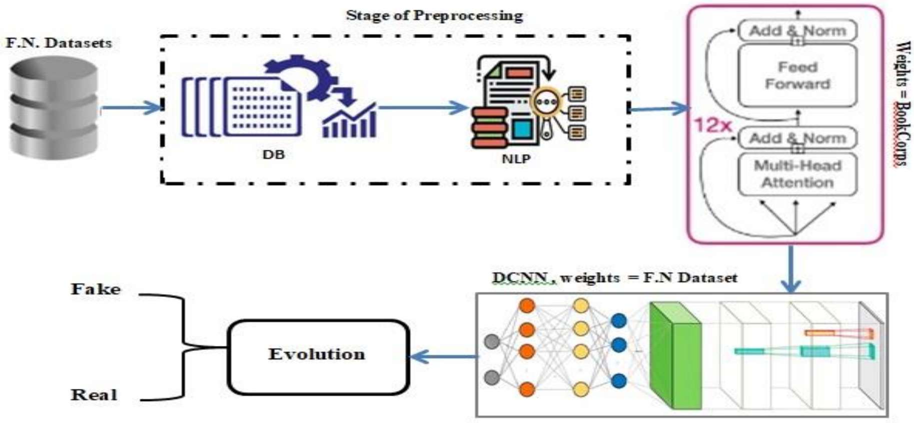

Figure 5. Block Diagram of Proposed Model

7. Result and discussion

This section will cover the outcomes of the accuracy and precision of our Proposal model. We made adjustments by adding new layers and freezing some from the BERT model. Figure 6. Illustrates the results of our work using the Proposal model (DCNN) to detect and classify fake news, which achieved an impressive accuracy of 99.6%.

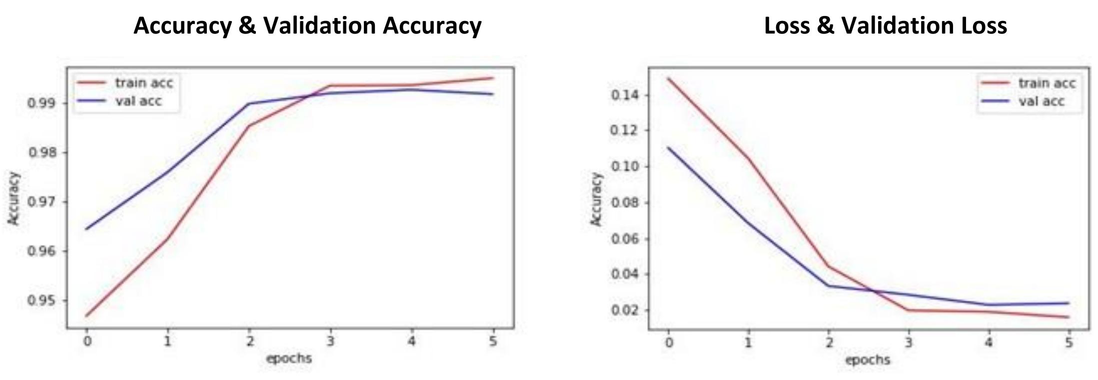

Figure 6. Performance of Loss and Accuracy in (Training and Validation)

We utilized the Tag Clouds method, also referred to as the word cloud technique; to create a visual representation of text or documents, highlighting the most commonly used words. This approach enabled us to conduct a comparative analysis of different documents or texts. We observed that the word cloud visualization was useful in distinguishing between real and fake news. Figure 7 displays the word cloud visualization fake news.

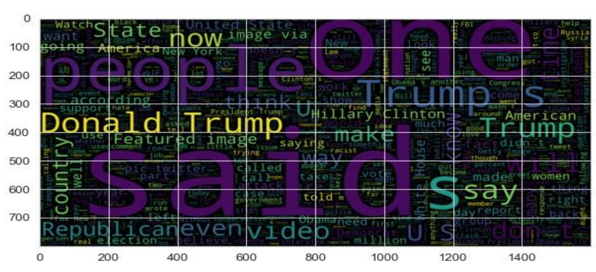

Figure 7. Word cloud of fake news

We also utilized the Classification report, which employs precision, F1, recall, and support scores, to evaluate our model's performance. This report can be used to identify problems and facilitate clear interpretation in any classification scenario.
The first factor of classification is precision also called "positive predictive value. However, defined as the ratio of true positives to the sum of false and true positives. Where fp is false positive and tp is true positive that can be defined below:

$$Precision = \frac{\mathrm{tp}}{\mathrm{tp+fp}} \tag{1}$$

The second element of the classification report is Recall, also referred to as "sensitivity." It aims at answering the question, "What proportion of actual positives was identified correctly?" The recall is obtained through dividing the number of true positives by the sum of true positives and false negatives. False negative (fn) and other factors in precision remain the same. The mathematical equation for Recall is as follows:

$$Recall = \frac{\mathrm{tp}}{\mathrm{tp+fn}} \tag{2}$$

The third factor of classification report is known F1 value When We note the balance among Recall and Precision, F1 value is required and showing that the good score is 1.0 and the bad score is 0.0, hence F1 Score may be best measure to selected if we need to search a balance among Recall and Precision. Generally speaking, F1 scores are lower than accuracy measures as they integrate precision and recall into their computation. We will follow formula as below:

$$F1 = \left(\frac{2}{\mathrm{recall}^{-1}+\mathrm{precision}^{-1}} \right) 2.\frac{\mathrm{precision}\ .\ \mathrm{recal}l}{\mathrm{precision} + \mathrm{recal}l} \tag{3}$$

The final Factor of classification report is called the Receiver Operating Characteristics (ROC) is a tool for evaluating the effectiveness of a binary classification model at different classification thresholds. It represents the relationship between the true positive rate (sensitivity) and false positive rate at various thresholds. The AUC, or area under the ROC curve, provides a summary of the model's performance across all possible thresholds. It measures the overall ability of the model to distinguish between positive and negative cases, with a higher AUC indicating better performance. **Figure 8** displays the Receiver Operating Characteristics and we will follow formula as below:

$$\mathrm{FPR} = \frac{\text{False Postive}}{\text{False Postive+True Negative}} \tag{4}$$

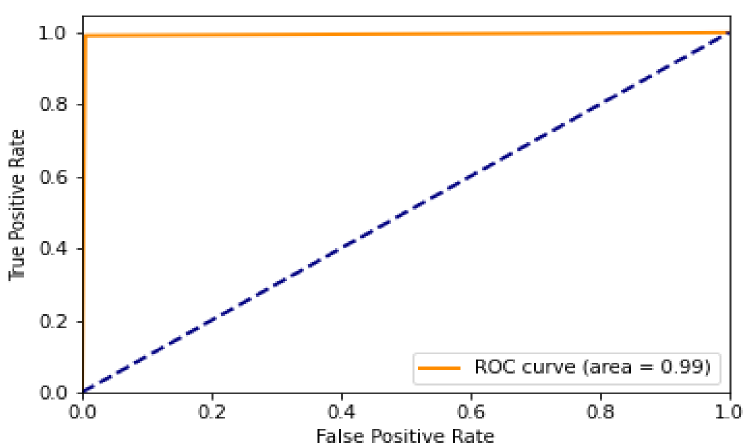

Figure 8. Receiver Operating Characteristics

We executed the confusion matrix, also known as an error matrix, is a tabular layout used to visualize the performance of a classification algorithm. It consists of rows representing instances in a predicted class and columns representing instances in an actual class, on the basis of a set of test data where the true values are known [18]. **Figure 9** displays the relationship between the predicted and actual values.

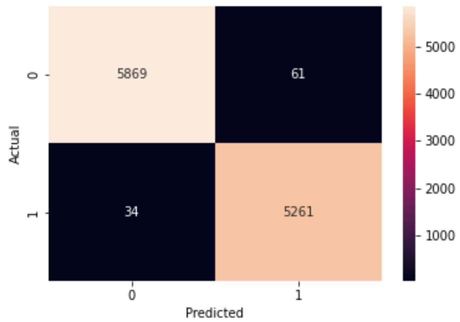

Figure 9. confusion matrix

8. Performance Comparison Literature

Here are more details related to the table that presents various methods, NLP techniques, accuracy, and sources related to previous studies on the identification and classification of fake news:. As shown in below Table 1:

Table 1. Comparative Pervious Studies

Method	NLP Techniques	Accuracy	Sources
CNN	TF-IDF	98%	Kaliyar [19]
Deep CNN	GloVe	98.36%	Kaliyar et at.[20]
CNN	TensorFlow embedding Layer	96%	Amine et at. [21]
CNN+LSTM	GloVe	94.71%	K.Shu et at. [22]
Bi-directional LSTM-RNN	GloVe	98.75%	Bahad et at. [23]
Passive aggressive	TF-IDF	83.8%	Mandiacl et at. [24]
Fake BERT	GloVe, BERT	89.90%	Kaliyar et at. [25]
CNN+LSTM	PCA	97.7%	UMer et at. [26]
Proposed Model	TensorFlow embedding Layer	99.6%	--

In this table, different methods for fake news identification and classification are listed in the "Method" column. The corresponding NLP techniques utilized for each method are described in the "NLP Techniques" column. The accuracy achieved by each method in detecting fake news is reported in the "Accuracy" column. Lastly, the sources, which refer to the references from where the methods and their associated accuracy values are obtained, are mentioned in the "Sources" column.

9. Conclusions

The article emphasizes the significance of detecting and classifying fake news in today's society, where misinformation can spread rapidly and cause harm. Deep learning models have shown great potential in achieving high accuracy for fake news detection and classification. This paper explores the use of the proposed model (DCNN) for fake news detection and classification, and the experiments showed that the model achieved high accuracy in identifying fake news articles. However, it is essential to consider the potential limitations and biases of the model so that the quality of the data used can significantly impact its performance. Therefore, continued research and development are necessary to improve the model's performance and mitigate potential limitations and biases. As result, the training of the model achieved an accuracy rate of 99.6 %. The improvement of effective fake news detection and classification models is vital for promoting information integrity and protecting individuals and society from the harmful effects of fake news.

References

[1]. W. Li, J. Wu, X. Jia, and Y. Huang, "Fake news detection using deep learning: A survey," *Journal of Autonomous Intelligence*, vol. 2, no. 1, pp. 24–33, 2019.

[2]. T. Young, D. Hazarika, S. Poria, and E. Cambria, "Recent trends in deep learning based natural language processing [review article]," *IEEE Comput. Intell. Mag.*, vol. 13, no. 3, pp. 55–75, 2018.

[3]. Z. Wang, "Deep learning methods for fake news detection," in *2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA)*, pp. 472-475, 2022.

[4]. N. Aslam, I. Ullah Khan, F. S. Alotaibi, L. A. Aldaej, and A. K. Aldubaikil, "Fake detect: A deep learning ensemble model for fake news detection," *Complexity*, vol. 2021, pp. 1–8, 2021.

[5]. Aggarwal, A., Chauhan, A., Kumar, D., Verma, S., & Mittal, M. (2020). "Classification of fake news by fine-tuning deep bidirectional Transformers based language model". *EAI Endorsed Transactions on Scalable Information Systems*, vol. 7, no. 27, e10, 2020. https://eudl.eu/pdf/10.4108/eai.13-7-2018.163973

[6]. S. Garg and D. Kumar Sharma, "Linguistic features based framework for automatic fake news detection," *Comput. Ind. Eng.*, vol. 172, no. 108432, p. 108432, 2022.

[7]. R. K. Kaliyar, A. Goswami, and P. Narang, "'FakeBERT: Fake news detection in social media with a BERT-based deep Learning Approach," *Multimedia Tools Appl*, vol. 80, no. 8, pp. 11765–11788, 2021.

[8]. M. R. Khan, S. A. A. Shah, and A. Rehman, "Fake news dataset: a comprehensive analysis," *Human-centric Computing and Information Sciences*, vol. 10, no. 1, pp. 1–23, 2020.

[9]. K. Shu, D. Mahudeswaran, S. Wang, D. Lee, and H. Liu, "FakeNewsNet: A data repository with news content, social context, and spatiotemporal information for studying fake news on social media," *ArXiv preprint arXiv: 1906.01370*. 2019. https://doi.org/10.48550/arXiv.1809.01286

[10]. V. Pérez-Rosas, B. Kleinberg, A. Lefevre, and R. Mihalcea, "Automatic detection of fake news," *In Proceedings of the 27th International Conference on Computational Linguistics, pp. 3391-3401*, 2017. https://aclanthology.org/C18-1287

[11]. J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language Understanding". *ArXiv preprint arXiv: 1810.04805*. 2019. https://doi.org/10.48550/arXiv.1810.04805

[12]. W. Zhang, C. Liu, and Y. Wu, "Deep learning models for fake news detection: A review of recent progress and challenges," *Expert Systems with Applications*, vol. 172, 2021.

[13]. K. Shu, D. Mahudeswaran, S. Wang, D. Lee, and H. Liu, "FakeNewsNet: A data repository with news content, social context, and spatiotemporal information for studying fake news on social media," *Big Data*, vol. 8, no. 3, pp. 171–188, 2020.

[14]. A. Thota, P. Tilak, S. Ahluwalia, and N. Lohia, "Fake news detection: a deep learning approach," *SMU Data Science Review*, vol. 1, no. 3, 2018.

[15]. M. Farokhian, V. Rafe, and H. Veisi, "Fake news detection using parallel BERT deep neural networks," *arXiv [cs.CL]*, 2022.

[16]. J. Brownlee, "A gentle introduction to transfer learning for deep learning," *Machine Learning Mastery*, 2017.

[17]. S. Kumar, R. Asthana, S. Upadhyay, N. Upreti, and M. Akbar, "Fake news detection using deep learning models: A novel approach," *Trans. Emerg. Telecommun. Technol.*, vol. 31, no. 2, e3767, 2020.

[18]. J. Xu, Y. Zhang, and D. Miao, "Three-way confusion matrix for classification: A measure driven view". *Information Sciences*, vol. 507, pp. 772-794. 2020. https://www.sciencedirect.com/science/article/abs/pii/S0020025519306024

[19]. R. K. Kaliyar, ''Fake news detection using a deep neural network,'' *in Proc. 4th Int. Conf. Comput. Commun. Autom. (ICCCA),* pp. 1–7, 2018.

[20]. R. K. Kaliyar, A. Goswami, P. Narang, and S. Sinha, ''FNDNet—A deep convolutional neural network for fake news Detection,'' Available: http://www.sciencedirect.com/science/article/pii/S138904172030 085

[21]. O. Ajao, D. Bhowmik, and S. Zargari, "Fake news identification on twitter with hybrid CNN and RNN models," in *Proceedings of the 9th International Conference on Social Media and Society*, New York, NY, USA, pp. 226-230, 2018.

[22]. A. S. K. Shu, D. M. K. Shu, L. G. M. Mittal, L. G. M. Mittal, and M. M. J. K. Sethi, ''Fake news detection using a blend of neural Networks: An application of deep learning,'' *Social Netw. Comput. Sci.,* vol. 1, no. 3, pp. 1–9, Jan. 1970. [Online]. Available: https://link.springer. com/article/10.1007/s42979-020-00165-4.

[23]. P. Bahad, P. Saxena, and R. Kamal, ''Fake news detection using bi-directional LSTM-recurrent neural network,'' *Proc.* Available: http://www.sciencedirect.com/science/article/pii/S138904172030 085.

[24]. R. R. Mandical, N. Mamatha, N. Shivakumar, R. Monica, and A. N. Krishna, ''Identification of fake news using machine Learning,'' *in Proc. IEEE Int. Conf. Electron., Comput. Commun. Technol. (CONECCT),* pp. 1-6, 2020.

[25]. R. K. Kaliyar, A. Goswami, and P. Narang, "'FakeBERT: Fake news detection in social media with a BERT-based deep learning Approach," *Multimedia Tools Appl*, vol. 80, no. 8, pp. 11765–11788, 2021.

[26]. M. Umer, Z. Imtiaz, S. Ullah, A. Mehmood, G. S. Choi, and B.-W. On, ''fake news stance detection using deep learning Architecture (CNN LSTM),'' *IEEE Access*, vol. 8, pp. 156695–156706, 2020. https://ieeexplore.ieee.org/document/9178321