International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Fake News Detection Using TF-IDF Weighted with Word2Vec: An Ensemble Approach

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Submitted: 25/04/2023 **Revised**: 26/06/2023 **Accepted**: 06/07/2023

Abstract: Social media platforms' utilization for news consumption is steadily growing due to their accessibility, affordability, appeal, and ability to propagate misinformation. False information, whether intentionally or unintentionally created, is being disseminated across the internet. Certain individuals spread inaccurate information on social media to gain attention, financial benefits, or political advantage. This has a detrimental impact on a substantial portion of society that is heavily influenced by technology. It is imperative for us to develop better discernment in distinguishing between fake and genuine news. In this research paper, we present an ensemble approach for detecting fake news by using TF-IDF Weighted Vector with Word2Vec. The extracted features capture specific textual characteristics, which are converted into numerical representations for training the models and balanced dataset with the Random over Sampling technique. The implementation of our proposed framework utilized the ensemble approach with majority voting which combines 2 machine learning models like Random Forest and Decision Tree. The proposed strategy was adopted empirically evaluated against contemporary techniques and basic classifiers, including Gaussian Naïve Bayes, Logistic Regression, Multilayer Perceptron, and XGBoost Classifier. The effectiveness of our approach is validated through the evaluation of the accuracy, F1-Score, Precision, Recall, and Auc curve, yielding an impressive accuracy score of 94.24% on the FakeNewsNet dataset.

Keywords: *Convolutional Neural Networks, Machine learning, TF-IDF Weighted Vector; Word2Vec*

1. Introduction

In the current online environment, the spread of fake news has emerged as a pressing concern that threatens the integrity of information dissemination and public discourse. It is often crafted to sway opinions among people, create confusion, or serve specific agendas. The propagation of fake news has gotten easier since the introduction of social networking sites as well as the accessibility for exchanging data online faster and more widespread than ever before. The consequences of fake news are far-reaching and impactful. It can sway elections, incite social unrest, damage reputations, and erode trust in traditional news sources. Moreover, the sheer volume and rapid dissemination of fake news make it increasingly challenging for individuals to distinguish between reliable information and fabricated content. This phenomenon of creation and dissemination of false information poses a significant threat to democratic societies that rely on an informed citizenry for decision-making and governance. Developing effective detection algorithms and tools, promoting media literacy and critical thinking skills, and fostering a culture of responsible information sharing is necessary. Research in the field of fake news encompasses various disciplines, including computer science, journalism, psychology, and communication studies. Scholars and experts are continuously exploring methods to detect, analyze, and counteract the spread of fake news. This research aims to equip individuals, organizations, and platforms with the necessary tools and strategies to identify and combat misinformation effectively. By shedding light on the mechanisms, implications, and challenges surrounding fake news, researchers strive to promote media literacy, strengthen information integrity, and safeguard the democratic principles of transparency, accountability, and truth. Through interdisciplinary collaboration and innovative approaches, the battle against fake news is being fought on multiple fronts, with the ultimate goal of fostering a more informed and resilient society. The given text discusses the problem of fake news and presents a paper that focuses on principles and fundamental ideas behind spotting fake news. The paper investigates various kinds of linguistic and machine learning-based detection techniques. It additionally offers a qualitative evaluation of these methods for spotting fake news. The article points out the use of machine learning and ensemble learning techniques, particular taking advantage of the technique of counting and TF-IDF vectorization methods, and discusses the difficulties of fake news detection. [1]. In our research paper, we incorporate the TF-IDF (Term Frequency-Inverse Document Frequency) technique, a widely used approach in natural language processing and information retrieval, to assess the significance of words within a document relative to a larger collection of documents. TF-IDF combines term

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frequency (TF), which measures how frequently a term appears in a document, with inverse document frequency (IDF), which evaluates the rarity or uniqueness of a term across the document collection. By calculating a TF-IDF score [2] for each term in a document, we can determine its importance in that specific context**.** This technique enables us to represent documents as numerical feature vectors, facilitating subsequent analysis using machine learning algorithms. The inclusion of TF-IDF enhances the effectiveness of our research by capturing the relevance and distinctiveness of terms within the document collection, thus contributing to a comprehensive and accurate analysis of the research topic.

The research paper introduces a novel approach for context-free fake news detection by combining Word2Vec and LSTM-based deep learning techniques. By leveraging word embeddings and the sequential processing capabilities of LSTM, the proposed framework aims to accurately identify fake news articles without relying on contextual cues. The paper likely presents experimental results and evaluations to demonstrate the effectiveness of the approach in detecting fake news [3]. Word2Vec is a popular algorithm in the field of natural language processing that has revolutionized the way we represent and analyze textual data. It has gained significant attention and achieved remarkable success in various NLP tasks, including language modeling, sentiment analysis, and document classification. In this research paper, we explore the concept and applications of Word2Vec in the context of fake news detection. Word2Vec is an unsupervised learning algorithm that learns word embeddings, which are vector representations of words, from large amounts of unlabeled text data. The fundamental idea behind Word2Vec to elicit semantic information meaning and relationships between words by mapping them to dense numerical vectors in a continuous vector space. These word embeddings encode the distributional properties of words, enabling them to capture syntactic and semantic similarities.

The authors likely present a dataset consisting of labeled news articles, with some articles labeled as fake and others as real. This dataset is used to train and evaluate the machine learning models. The paper likely discusses the preprocessing steps performed on the data and the features selected for training the models. The evaluation of the proposed approach is presented, where the performance of the machine learning models in detecting fake news is assessed. The evaluation likely includes metrics such as accuracy, precision, recall, and F1-score [4] to measure the effectiveness of the models.

The paper emphasizes the significance of adopting advanced deep learning techniques, such as FakeBERT, to combat the spread of fake news on social media platforms. The proposed model offers a promising solution by leveraging the strengths of BERT and CNN, thereby improving the accuracy and effectiveness of fake news detection [5].

The research paper makes several contributions in the field of fake news detection using ensemble methods.

Data Preprocessing: The paper addresses the crucial step of data preprocessing, where techniques are employed to clean and prepare the raw data for further analysis. The authors likely discuss the steps involved in cleaning and preprocessing the dataset, such as Text normalization methods like the stemming process or either lemmatization are used to remove irrelevant data, handle values that are missing, and normalize text.

Feature Extraction: The paper explores the use of two powerful feature extraction techniques, TF-IDF and Word2Vec. TF-IDF enables the extraction of important keywords and phrases from the news articles, while Word2Vec captures the semantic relationships between words. By incorporating both techniques, we enhanced the representation of textual data and contribute to the improvement of feature extraction in fake news detection and balanced with the Random over sampling technique.

Ensemble Method: Instantiate two machine learning models, such as Random Forest and Decision Tree. These models will form the ensemble. Apply the majority voting strategy to make predictions. Each base model in the ensemble predicts the class label and the majority class is selected as the final prediction.

Evaluation: Evaluate the performance of the ensemble approach using various metrics such as accuracy, F1-Score, Precision, Recall, and AUC curve. Compare the results with other state-of-the-art methodologies and base classifiers like Gaussian Naïve Bayes, Logistic Regression, Multilayer Perceptron, and XGBoost Classifier.

Results and Analysis: Analyze the performance of the proposed approach and highlight its effectiveness in detecting fake news. Discuss the achieved accuracy score and other relevant metrics to demonstrate the contribution of the research.

The paper's structure is organized as follows: In Section 2, the literature pertaining to this subject is examined, providing a thorough analysis of different methodologies such as machine learning, deep learning, and ensemble techniques.
In Section 3, the paper outlines the proposed approach, which involves the utilization of a hard voting classifier comprising two machine learning algorithms: Logistic Regression and Random Forest. The outcomes and evaluation of the recommended approach are discussed in Section 4. The efficiency of the recommended approach is evaluated against traditional machine learning algorithms and state-of-the-art methodologies.

2. Related Works

The cooperative deep learning-based model presented in the paper leverages user feedback to estimate news trust levels and ranks the content accordingly. The model exhibits superior accuracy in fake news detection compared to existing approaches and proves to be highly efficient in combating the spread of fake news on social media. The model utilizes temporal language processing to analyze news articles. Less important news is subjected to further whereas highest important information is recognized as authentic news, language processing is employed to verify its truthfulness. A convolutional neural network (CNN) is employed in the deep learning layer to convert user feedback into rankings. The negatively rated news is then feedback into the system to train the CNN model. The suggested model achieves an impressive 98% accuracy rate in detecting fake news, surpassing many existing language processing-based models. It is also compared to cutting-edge techniques using Metrics like area under the curve (AUC), recall, F-measure, and precision demonstrating its high efficiency [5].

The complexity of various languages poses a challenge for fake news detection, as it requires understanding the logic behind fake stories and drawing conclusions about the people involved. Existing methods struggle to gather sufficient semantic and contextual information from multilingual text corpora. To address these challenges, a new semantic approach to identifying fake news is proposed, which focuses regarding related parameters such as feelings, entities, and facts extracted directly from the text. The model presented in this study outperforms average of 3.97% for English to English, 1.41% for English to Hindi, 5.47% for English to Indonesian, 2.18% for English to Swahili, and 2.88% for English to Vietnamese when compared to the most recent methods employing the TALLIP fake news dataset for translations. This study is the first to use a capsule neural network to identify fake news in multiple languages [6]. The paper gives a summary of the state of the art of research on the identification of fake and fabricated news using machine learning. It emphasizes the need for automated methods to verify information and categorize it accurately. The review explores the limitations of existing approaches and suggests the potential benefits of incorporating deep learning techniques[7].

The research focuses on the detection of fake news on social media platforms, considering the challenges posed by the widespread dissemination of misinformation. Fake news negatively impacts individuals and society, necessitating effective detection methods. Traditional algorithms may not be applicable due to evolving challenges in identifying fake news. Fake news is intentionally crafted to mislead readers, making content-based detection alone insufficient. Auxiliary information, such as user social engagements on social media, needs to be considered for improved detection. However, utilizing such auxiliary information is challenging due to noisy and unstructured nature of users' social engagements [8]. This research focuses on exploring the feasibility of using deep learning techniques to detect fake news solely based on their text content. The study proposes three different neural network architectures, including one based on BERT, a cutting-edge language model developed by Google known for achieving state-of-the-art results in natural language processing tasks. By leveraging deep learning and specifically considering the text of news articles, the research aims to develop effective methods for discriminating between genuine and fake news on the internet. The study's findings and insights contribute to addressing the challenges posed by fake news and have implications for improving the accuracy and reliability of news verification processes[9].

The proposed model utilizes a combination of deep learning techniques to enhance the detection process. The ensemble approach incorporates multiple neural network architectures, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. By leveraging the strengths of these models, the ensemble model aims to improve the overall accuracy and robustness of fake news detection. The study describes the implementation and evaluation of the Fake Detect model on a dataset comprising both real and fake news articles. Performance metrics such as accuracy, precision, recall, and F1 score are used to assess the effectiveness of the model[10].The study formulates the fake news detection task as a sequential decision-making process, where the model interacts with the environment and learns to make optimal decisions based on rewards and punishments. By using reinforcement learning, the model can adapt and generalize well to diverse domains, enhancing its ability to identify fake news across different contexts.

The paper describes the implementation and evaluation of the domain adaptive fake news detection model on real-world datasets from various domains. The results demonstrate the effectiveness of the proposed approach in improving the model's performance and adaptability compared to traditional detection methods. The research contributes to the field of fake news detection by introducing a domain adaptive approach that leverages reinforcement learning techniques. By adapting the model to different domains, it addresses the challenge of detecting fake news in various contexts, ultimately enhancing the reliability of fake news detection systems [11]. The study describes the implementation and evaluation of the approach using a large-scale dataset collected from social networks. Convolutional neural networks (CNN) and recurrent neural networks (RNN) are two examples of deep learning techniques that are used to analyse the multiple features and classify news articles as fake or genuine.

The results demonstrate the effectiveness of the proposed approach in accurately detecting fake news on social networks. By leveraging deep learning and considering multiple features, the model achieves improved performance compared to traditional methods that rely solely on content analysis[12]. The paper describes the implementation and evaluation of the weak supervision approach for identifying fake news on real-life data sets. The results demonstrate the efficiency of the recommended approach in achieving high accuracy and robustness, even with limited labeled data compared to traditional supervised learning approaches.

The research contributes to the field of fake news detection by offering a solution to the challenge of limited labeled data. By leveraging weak supervision and reinforcement learning, the approach enables training effective fake news detection models with fewer annotated examples, thus reducing the annotation effort and expanding the applicability of such models[13]. The authors propose a two-step approach: pre-processing and classification. In the pre-processing step, various NLP techniques such as tokenization, stemming, and part-of-speech tagging are employed to prepare the data for further analysis. for classification, the authors use a machine learning model trained on a large dataset of labeled fake and genuine news articles. They employ a combination of textual and non-textual features, including linguistic patterns, metadata, and user engagement metrics, to enhance the accuracy of the classification process. The proposed method is evaluated on multiple platforms and languages, demonstrating its effectiveness in detecting fake news across different contexts. The results indicate that the approach achieves high accuracy and performs well in identifying fake news articles across various platforms and languages[14].

The paper discusses the importance of reliable training data for the supervised learning approach. A labeled dataset consisting of both fake and genuine news articles is utilized to train the algorithms. The authors highlight the significance of selecting relevant features from the news articles, such as textual content, metadata, and user engagement metrics, to improve the accuracy of the classification. Several supervised learning algorithms are employed in the study, including Multinomial Naive Bayes, Random Forest, and Support Vector Machines (SVM). The authors compare the performance of these algorithms based on evaluation metrics such as accuracy, precision, recall, and F1-score[15].

Based on the literature provided, here are some potential research gaps that can be identified:

What alternative feature extraction techniques remain unexplored and how do they compare to traditional approaches in terms of their effectiveness for fake news detection?

To what extent does the utilization of an ensemble approach for feature extraction enhance the accuracy and reliability of classification models in the context of fake news detection

How can the interpretability of models used for fake news detection be improved, and what impact does the incorporation of interpretable elements have on the overall performance and trustworthiness of the detection system?

To what extent do fake news detection models build using ensemble approaches generalize to unseen data, and how well do they perform when externally validated on different datasets and across diverse contexts?

3. Proposed Methodology

Figure 1 represents a proposed methodology. Firstly, the FakeNewsNet dataset is employed as the foundation for the study, providing a diverse collection of labeled fake and real news articles and social media posts. To prepare the data for analysis, pre-processing techniques are applied, including text cleaning, tokenization, and lemmatization. This ensures that the text is in a standardized format and reduces noise in the data. Next, feature extraction is performed using a TF-IDF weighted vector representation combined with Word2Vec. This approach captures the semantic meaning of words and their context within the documents, resulting in more informative and meaningful features for classification.

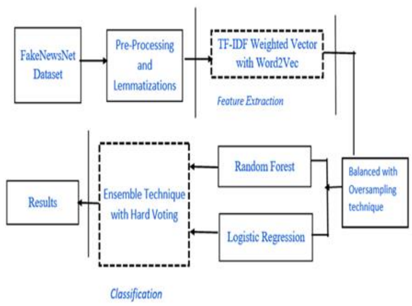


Fig 1. Block Diagram of Proposed methodology

In the ensemble approach, both Random Forest and logistic regression classifiers are employed. These algorithms have been selected for their ability to handle high-dimensional data and capture complex relationships between features and target variables. A hard voting scheme is utilized to combine the predictions of these classifiers, allowing for a more robust and accurate final prediction. The results obtained from this proposed methodology are evaluated and analyzed, comparing them with other conventional machine learning algorithms and state-of-the-art methodologies in fake news detection. This comprehensive assessment provides insights into the effectiveness and performance of the ensemble approach in accurately distinguishing between fake and real news.

3.1 Dataset Details

We have used the FakeNewsNet dataset for this research to identify fake news. The FakeNewsNet dataset comprises data from two platforms, namely PolitiFact and Gossipcop. It includes information about the number of users (after removing bots), the total number of shared news articles, and the count of true news and fake news articles. Specifically, the dataset consists of a user count, the number of shared articles, and the number of articles [16] classified as true news and fake news for both the PolitiFact and Gossipcop platforms represented in table 1.

Table 1. FakeNewsNet Dataset Details

Dataset	***Platform***	***Users (without filtering bots)***	***Sharing***	***True News***	***Fake News***
Fake News Net	***Politifact***	***159,699***	***271,462***	***361***	***361***
	Gossipcop	***209,930***	***812,194***	***4,513***	***4,513***

3.2 Data Processing

To prepare the tweet data for analysis, a text preprocessing step was applied using the preprocessing function. This function employs a series of cleaning and normalization techniques to enhance the quality of the tweet text. Firstly, HTML tags were removed from the tweets using the BeautifulSoup library, ensuring that only the relevant textual content remained. Subsequently, special characters were eliminated through the utilization of regular expressions, which replaced non-alphabetic and non-characters[17] with spaces. Moreover, URLs were removed from the text using another regular expression pattern. To facilitate further analysis, the text was converted to lowercase and tokenized into individual words.

To remove commonly occurring and non-informative words, a set of English stop words from the NLTK library was employed. These stop words encompass common language articles, pronouns, and conjunctions, which typically do not carry significant meaning in the analysis. By filtering out these stop words, the resulting text became more focused on informative content. Lastly, lemmatization was performed using the WordNet Lemmatizer from the NLTK library. This process reduced words to their base or dictionary form, ensuring consistency in word representation and aiding in reducing lexical variations. The preprocessing function served as an effective means of cleaning and normalizing the tweet data, enhancing the accuracy and reliability of subsequent analysis tasks. By removing HTML tags, special characters, URLs, and stop words, the function successfully reduced noise and eliminated irrelevant information. Moreover, the lowercase conversion, tokenization, and lemmatization steps ensured consistency and improved the representation of words in the processed text.

3.21 Feature Extraction using TF-IDF Weighted Word2Vec

To ensure the relevance of the words, we establish certain criteria for word validity. This could involve checking if the word exists in both the Word2Vec and TF-IDF vocabularies, adheres to specific linguistic or semantic requirements, or aligns with the research objectives. Oncethe word is deemed valid, we retrieve its Word2Vec vector representation from our trained Word2Vec model.

3.22 Computing TF-IDF weights

TF-IDF is a statistical measure that combines term frequency (TF) and inverse document frequency (IDF) to quantify the importance of a word within a document or corpus. In this step, we calculate the TF-IDF weight for each valid word by leveraging the IDF values obtained from the TF-IDF analysis and the term frequency of the word within the given text. This weight reflects the significance of the word in the context of the entire corpus[19].

3.23 Incorporating TF-IDF weighted Word2Vec vectors

By multiplying the Word2Vec vector of each word by its corresponding TF-IDF weight, we obtain TF-IDF weighted Word2Vec vectors. These vectors encapsulate both the semantic representation of the word obtained from Word2Vec and the contextual importance derived from TF-IDF. Additionally, we accumulate the TF-IDF weights to capture the overall importance of the words in the research paper. By following these steps, we successfully integrate the advantages of TF-IDF and Word2Vec techniques, enabling us to extract informative features from the text data and enhance the representation of words in our research paper which is represented in algorithm 1.

Algorithm 1: Feature extraction with TF-IDF Weighted with

Word2Vec

Input: title (collection of text data)

Output: Listed weighted vectors of features

1. Initialize an empty list tfidf_w2v_vectors

2. Compute TF-IDF vectors:

- Initialize a TfidfVectorizer and compute TF-IDF vectors
- Obtain feature names and compute IDF values

3. Initialize a Word2Vec model:

- Convert *title* into a list of sentences, where each *sentence* is a list of *words*
- Initialize a Word2Vec model with the *sentences* and desired parameters (e.g., vector size)

4. Get the vocabulary *words* from the Word2Vec model

5. For each *title* in the *title*:

- Initialize a vector of zeros called a vector
- Initialize tf_idf_weight to 0
- Split the title into *words*
- For each *word* in the title:

Check if the word is present in both the Word2Vec and TF-IDF vocabularies

If the word is valid:

- Retrieve the Word2Vec vector for the word
- Compute the TF-IDF weight for the word using the IDF value and term frequency
- Multiply the Word2Vec vector by the TF-IDF weight and add it to the vector
- Accumulate the TF-IDF weight in tf_idf_weight

6. If tf_idf_weight is not zero:

- Divide the vector by tf_idf_weight to compute the weighted average

7. Append the resulting TF-IDF weighted Word2Vec vector to tfidf_w2v_vectors

Output: list of TF-IDF weighted Word2Vec vectors

3.24 Voting Classifier for classification

The research methodology employed in this study involves two key steps: dataset balancing and prediction using a voting ensemble classifier. To address the issue of class imbalance in the dataset, the TF-IDF weighted word2vec vectors are utilized as extracted features. These vectors are assigned as labels to the variables 'X' and 'y'. Subsequently, random oversampling with the RandomOverSampler technique is applied to the dataset, ensuring a balanced representation of classes. The resulting balanced dataset serves as a reliable foundation for training the subsequent classification models.

For prediction purposes, the balanced dataset is split into training and testing subsets using a predetermined test size. Two classification models, namely Random Forest and Logistic Regression, are selected for their respective strengths and compatibility with the dataset. To leverage the collective knowledge of these models, a voting ensemble classifier is created using the VotingClassifier [20] module from scikit-learn. By employing the 'hard' voting strategy, the ensemble classifier consolidates the predictions from each individual model and selects the majority vote as the final prediction. This approach maximizes the predictive accuracy of the ensemble classifier. The balanced dataset generated through oversampling ensures that each class is appropriately represented, enhancing the reliability of subsequent analysis. The voting ensemble classifier combines the predictive capabilities of Random Forest and Logistic Regression to deliver accurate and robust predictions, making it a valuable tool for classification tasks in various domains.

Algorithm 2: Predictive Performance through Dataset Balancing and Voting Ensemble Classification

Input: Extracted Features *F*(TF-IDF weighted word2vec vectors)

Output: Balanced Dataset, Predictions

Procedure: Balanced_dataset (*F*)

- Assign the TF-IDF weighted word2vec vectors to the variable *'X'* and *'y'* as a label
- Apply random oversampling using *RandomOverSampler* with a specified *random_state* to balance the dataset and obtain *X_balanced* and *y_balanced*.
- Calculate and print the counts of each class in the balanced dataset.

Return Balanced dataset

Procedure: SPLIT_DATA(Balanced_dataset)

- Training_data, Testing_data=split(Balanced_data, Test_Size)
- Return Training_data, Testing_data

Procedure: Predictions(Balanced Dataset)
Voting="hard"

M1=Random Forest

M2=Logistic Regression

Create the voting ensemble classifier *voting_ensemble*:

- Use the *VotingClassifier* with *estimators* parameter containing a list of tuples:
- Each tuple consists of a unique name and the corresponding model instance.
- Set *voting* parameter to *'hard'* for majority voting.

Return *Predictions*

4. Experimental Results

The proposed methodology uses ensemble methods TF-IDF Weighted Vector with Word2Vec for feature extraction. Balanced dataset with Random Over Sample technique before which has 13168 and for 0 class and 1 class 4346 distribution, after applying Random Over Sampling technique distributes equal distribution in each class with 16460 which represented in figure 2.

Fig 2. Balanced dataset distribution

For Classification used a combination of a couple of machine learning techniques, such as Logistic Regression and Random Forest, and a Classifier with hard voting. The FakeNewsNet dataset has been used for exploration. The dataset includes which has Politifact and gossipofact in terms of real and fake news. This section compares all the traditional machine learning algorithms for categorizing Fake and Real classes. It has been done to evaluate and compare the accuracy of all traditional algorithms. The results of different machine learning algorithms using the FakeNewsNet dataset are compared in Table 1. Table 1 shows that the ensemble Hard voting classifier outperformed all other algorithms with regard to of precision and accuracy, F1 score, recall, and AUC.

The evaluation metrics mentioned below are commonly used in research articles to assess the performance of classification models:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \quad (1)$$

$$Roc\ Curve = TPR = \frac{TP}{TP+FN} \quad (2)$$

$$FPR\ \frac{FP}{FP+FN}$$

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP + FN}} \quad (3)$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})} \quad (4)$$

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (5)$$

Based on the results, the Random Forest algorithm achieves the highest accuracy of 93% and a strong F1 score of 92%, indicating excellent overall performance. The Hard Voting Classifier also performs well, with an accuracy of 94.24% and high precision, recall, and AUC values, demonstrating its effectiveness in combining multiple classifiers. The Decision Tree algorithm also shows good accuracy and F1 score, indicating its ability to capture patterns in the data. Other algorithms, such as Logistic Regression, SVM, Gradient Boosting, and Multi-Layer Perceptron, also exhibit respectable performance, albeit slightly lower than Random Forest and the Hard Voting Classifier. Gaussian Naive Bayes has the lowest accuracy and F1 score among the listed algorithms in table 2. The performance of each algorithm is evaluated in terms of its accuracy, highlighting the effectiveness of different approaches in detecting fake news. The graph provides a visual representation of the results obtained from applying the ML algorithms to the FakeNewsNet dataset. Each algorithm is represented by a distinct line or bar, depicting its performance metric on the dataset.

By analyzing the graph, insights can be gained regarding the comparative performance of the ML algorithms. The accuracy metric is particularly emphasized, as it reflects the proportion of correctly classified instances by each algorithm. Higher bars or lines indicate algorithms with better accuracy, thus indicating their superior ability to discern between fake and real news within the FakeNewsNet dataset. Figure 3. illustrates the comparison of various machine learning (ML) algorithms on the FakeNewsNet dataset.

Algorithms	Accuracy	F1 Score	Precision	Recall	Roc
Gaussian Naive Bayes	65%	68%	65%	64%	0.70%
Logistic Regression	71%	72%	71%	80%	76%
Decision Tree	87%	88%	86%	78%	92%
SVM	70%	71%	70%	69%	75%
Random Forest	93%	92%	92%	90%	92%
Gradient Boosting	73%	73%	73%	72%	78%
Multi-Layer Perceptron	73%	73%	74%	74%	78%
Hard Voting Classifier	94.24%	94%	93%	97%	97%

Table 2. Comparative Performance of Machine Learning Algorithms on the FakeNewsNet Dataset

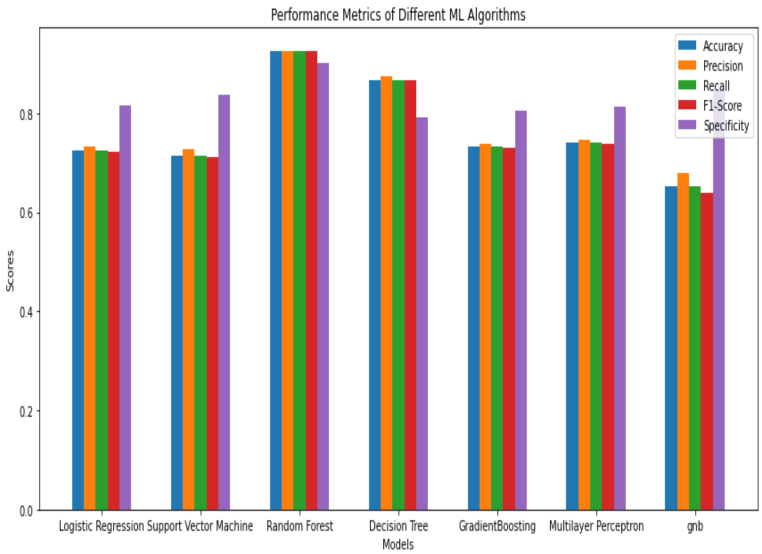
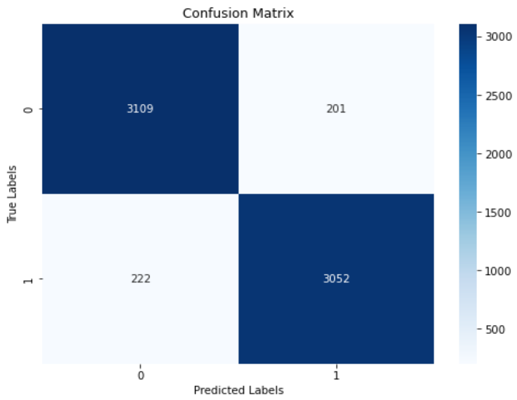


Fig 3. Comparative Performance of Machine Learning Algorithms on the FakeNewsNet Dataset

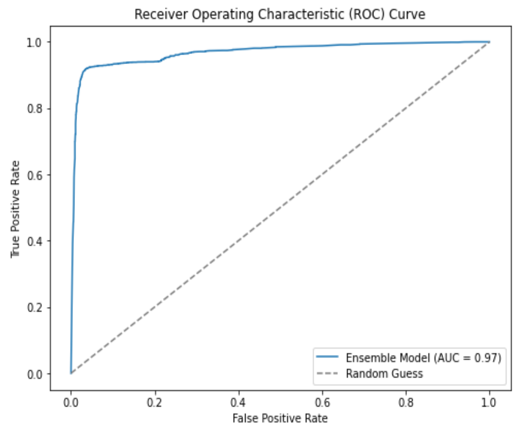
In the Roc Curve which is in figure 4, each point represents the TPR and FPR at a specific threshold. The curve is obtained by connecting these points.

The dotted line represents a random classifier, while a perfect classifier would have a curve that hugs the top-left corner. The area under the ROC curve (AUC-ROC) is also commonly reported as a single metric to assess the classifier's overall performance. A higher AUC-ROC value indicates better discriminative power, with 1 being the highest achievable score.

The "Our Proposed model" utilizes a Voting Classifier, which is an ensemble model, with feature extraction performed using TF-IDF weighted vectors combined with Word2Vec embeddings. This model achieves an accuracy of 94.24%, indicating strong performance.



(a)



(b)

Fig 4. Performance of Voting Classifier(a) confusion matrix (b)Roc curve

The table 3 showcases the performance of different models and their associated feature extraction techniques. An LSTM model with BERT embeddings achieves an accuracy of 84%. while an SVM model utilizing TF-IDF and FastText achieves an accuracy of 90%. Reference 23 utilizes XGBoost without specifying a feature extraction technique, resulting in an accuracy of 84%. Lastly, an LSTM model with BERT embeddings achieves an accuracy of 89%.

Table 3. Comparative performance of feature extraction techniques and models in fakenewsnet dataset

Study	***Algorithm***	***FF Feature Extraction***	***Accuracy***
Our Proposed model	***Voting Classifier (Ensemble model)***	***TF-IDF weighted vector with Word2vec***	***94.24%***
[21]	***LSTM***	***BERT***	***84%***
[22]	***SVM***	***TF-IDF and FastText***	***90%***
[23]	***XGBoost***	***---***	***84%***
[24]	***LSTM***	***BERT***	***89%***

5. Conclusion

This research study aimed to compare and evaluate various machine learning algorithms for classifying fake and real news using the FakeNewsNet dataset. The proposed model, a Voting Classifier with feature extraction using TF-IDF weighted vectors combined with Word2Vec embeddings, achieved the highest accuracy of 94.24%. This highlights the effectiveness of the ensemble approach and the importance of utilizing advanced feature extraction techniques in improving classification performance. Comparative analysis of traditional machine learning algorithms revealed that the Hard Voting Classifier outperformed other algorithms in terms of accuracy, precision, F1 score, recall, and AUC. The Random Forest algorithm demonstrated the highest accuracy of 93% and a strong F1 score of 92%, indicating excellent overall performance. The Decision Tree algorithm also exhibited good accuracy and F1 score, showcasing its ability to capture patterns in the data. Furthermore, the Roc Curve provided a visual representation of the performance of each algorithm in terms of True Positive Rate (TPR) and False Positive Rate (FPR) at different thresholds. The area under the ROC curve (AUC-ROC) was used as a metric to assess the overall discriminative power of the classifiers, with higher values indicating superior performance. The study also compared different feature extraction techniques and models. The proposed model using TF-IDF weighted vectors with Word2Vec achieved the highest accuracy of 94.24%. These findings emphasize the significance of ensemble methods, advanced feature extraction techniques, and careful selection of machine learning algorithms in accurately classifying fake and real news. The proposed model demonstrates promising results and can be further explored and refined for more comprehensive news classification systems. future research directions aim to advance the field of fake news detection by leveraging more sophisticated models, incorporating domain-specific knowledge, and improving the interpretability and robustness of the classification systems.

Acknowledgement

We would like to acknowledge that this research study was

self-funded, receiving no financial assistance from public,

private, or nonprofit organizations. We extend our appreciation to the esteemed faculty members who have provided valuable insights, advice, and academic expertise, contributing significantly to the development and execution of this research. Their continuous support and encouragement have been instrumental in shaping the research direction and ensuring its quality.

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