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Fake News Detection using Ensemble Methods: an Empirical Evaluation of Bagging and Boosting Algorithms

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ABSTRACT: The proliferation of fake news has become a significant concern in today's digital age, especially where social media platforms and online news outlets have made it easy for false information to spread rapidly. To combat this issue, we propose an ensemble-based approach for fake news detection, leveraging the strengths of both bagging and boosting algorithms. Our empirical evaluation employs Random Forest andCatBoost algorithms, and the results are promising. Our findings indicate that Random Forest algorithm achieves an accuracy of 99%, outperforming the CatBoost algorithm which achieves an accuracy of 98%. These results demonstrate the effectiveness of ensemble methods in detecting fake news and highlight the potential of Random Forest and CatBoost algorithms in this domain. Our study contributes to the ongoing efforts to develop reliable fake news detection systems, essential for maintaining the integrity of online information.

KEYWORDS: Fake,news, social media, Machine Learning, ensemble learning.

I. INTRODUCTION

Fake news has become a significant threat to modern society, with the potential to influence political decisions, damage reputations, and erode trust in institutions (Allcott & Gentzkow, 2019). The proliferation of social media and other online platforms has made it easier for false information to spread rapidly, making it challenging to distinguish fact from fiction (Benkler et al., 2018). Fake news detection has become a significant concern in today's digital age, where social media platforms and online news outlets have made it easy for false information to spread rapidly.

Machine learning techniques have shown promise in detecting fake news, with various studies employing supervised learning methods (Kumar et al., 2018) and deep learning approaches (Ruchansky et al., 2017). The power of natural language processing (NLP) and machine learning algorithms have been leveraged to identify and classify fake news articles. However, these methods have limitations, such as the risk of overfitting and the need for large amounts of labeled training data (Wang et al., 2019).

Ensemble learning methods, which combine the predictions of multiple base models, have been shown to improve the performance of fake news detection models (Zhang et al., 2020). Ensemble methods can reduce overfitting, improve generalizability, and provide more robust predictions (Hossain et al., 2020). Despite the advances in fake news detection, the task remains challenging, particularly in the face of evolving tactics used by fake news creators (Benkler et al., 2018). Therefore, there is a need for more sophisticated ensemble methods that can adapt to changing patterns in fake news data.

This study proposes a machine learning ensemble approach for fake news detection, with a view to comparatively evaluating the performance difference between bagging and boosting ensemble learners, selecting one of the best algorithms for each category, Random Forest for Bagging-based and CatBoost for Boosting-based ensembles. The proposed approach is evaluated on two open-source datasets from Kaggle, one on world political news articles and the other on Covid-19 related news articles and posts, and the results show improved performance compared to many existing results on Fake News Detection. The findings of this study contribute to the development of more effective fake news detection methods, which are essential for maintaining the integrity of online information.

II. RELATED WORKS

Fake news detection has become a significant concern in today's digital age, where social media platforms and online news outlets have made it easy for false information to spread rapidly. Machine learning approaches have been widely applied to tackle this issue, leveraging natural language processing (NLP) and machine learning algorithms to identify and classify fake news articles. One of the earliest studies in this area was conducted by (Pérez-Rosas et al., 2018) [1], who proposed a machine learning approach using linguistic features to detect fake news. Their model achieved an accuracy of 75% in classifying news articles as fake or real.

Several studies have since explored the use of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to improve fake news detection. For instance, Wang et al. (2019) developed a CNN-based model that achieved an accuracy of 92.5% in detecting fake news articles. Zhang et al. (2023) also proposed a convolution-based neural computing framework to detect fake news trained on short Chinese text, Rumor dataset, and tested on Chinese social media post, CHEF dataset

Other researchers have investigated the use of attention mechanisms and transfer learning to enhance the performance of fake news detection models. Zhang et al. (2020) proposed a hierarchical attention network that achieved an accuracy of 95.2% in classifying news articles as fake or real.

In addition to these approaches, some studies have focused on analyzing the spread of fake news on social media platforms. Chen et al. (2020) developed a machine learning model that predicted the likelihood of a news article being shared on social media, which can help identify potential fake news articles.

While machine learning approaches have shown promising results in fake news detection, challenges still exist. One major concern is the lack of labeled data, which can limit the training and evaluation of machine learning models. Kumar et al. (2021), addressed this issue by proposing a weakly supervised learning approach that leverages unlabeled data to improve fake news detection.

More so, recent studies have also explored the use of multimodal features, including text, images, and videos, to improve fake news detection. (Wang et al., 2022) proposed a multimodal fusion model that achieved an accuracy of 96.5% in detecting fake news articles. Athira et al. (2022), also employed a multi-modal approach by combining news contents with news image and built a model based on SpotFake+ model to detect fake news. They achieved 87% accuracy on GossipCop dataset. Another study by (Hossain et al., 2022) developed a deep learning model that leveraged social media user behavior to detect fake news.

Other researchers have also investigated the use of graph neural networks (GNNs) to model the propagation of fake news on social media networks. Zhang et al. (2022) proposed a GNN-based model that achieved an accuracy of 94.1% in detecting fake news articles, Zhang et al. (2024), also proposed the adoption of subgraph transformer approach to detecting fake news and achieved 93% accuracy.

Furthermore, some studies have focused on explaining the decisions made by fake news detection models. Chen et al. (2022) proposed an interpretable machine learning approach that provided insights into the features used by the model to classify news articles as fake or real.

Finally, recent research has also explored the use of transfer learning and domain adaptation to improve the generalizability of fake news detection models across different domains and languages. Kumar et al. (2022), proposed a transfer learning approach based on pretrained BERT model for sentence encoding to capture long-term dependencies between words, and BiLSTM for news article encoding, then concatenated both left-right encoding and right-left encoding to form the final encoding of the news article. Their model achieved an accuracy of 52.7% in detecting fake news articles on the CLEF-2022 news article dataset.

A number of machine learning approaches have been employed for fake news detection which include the use of machine learning algorithms such as Xgboost, BERT, Logistic Regression, Support Vector Machine, Naïve Bayes, Decision Tree, Random Forest, XGBoost among others (Varshney

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& Wadhwani, 2023). Other non-machine learning approaches include manual and NLP techniques while the two (2) approaches have been combined in many cases (Al Ghamdi, 2022; Algamdi et al., 2024).

Ensemble learning methods have shown promise in improving the accuracy of fake news detection models (Zhang et al., 2020). Previous studies have employed various machine learning techniques, including supervised learning methods (Kumar et al., 2018) and deep learning approaches (Ruchansky et al., 2017). However, these methods have limitations, such as the risk of overfitting and the need for large amounts of labeled training data (Wang et al., 2019).

Ensemble learning methods, which combine the predictions of multiple base models, have been shown to improve the performance of fake news detection models (Zhang et al., 2020). For example, a study by (Hossain et al., 2020) used an ensemble of decision trees and random forest classifiers to achieve an accuracy of 93.5% on a dataset of news articles. Other studies have used ensemble methods such as stacking (Wang et al., 2020) and voting (Kumar et al., 2020) to combine the predictions of multiple models. These approaches have been shown to improve the robustness and generalizability of fake news detection models.

Despite these advances, fake news detection remains a challenging task, particularly in the face of evolving tactics used by fake news creators (Benkler et al., 2018). Our work aims to fill the gap of limited dataset by combining a world Political dataset with covid-19 datasets covering two (2) common areas, Politics and Health, where effects of fake-news may be very disastrous, as well as evaluate the performances of Boosting against Bagging ensemble learning algorithms on fake news detection.

III. METHODOLOGY

The system model for the adopted methodology is shown in fig. 1 below. As shown in fig. 1, news articles datasets were sourced from open-sources, then subjected to some preprocessing including data aggregation, feature extraction and generation, data cleaning, text (feature) encoding. The preprocessed and encoded data were then split into training and testing set. The training set was used to train a Random Forest and Catboost classifier algorithm. The trained models were then evaluated on the test set to classify the news articles as fake or real news on the basis of their predictive accuracy, precision, recall, roc-auc and f1 measure.

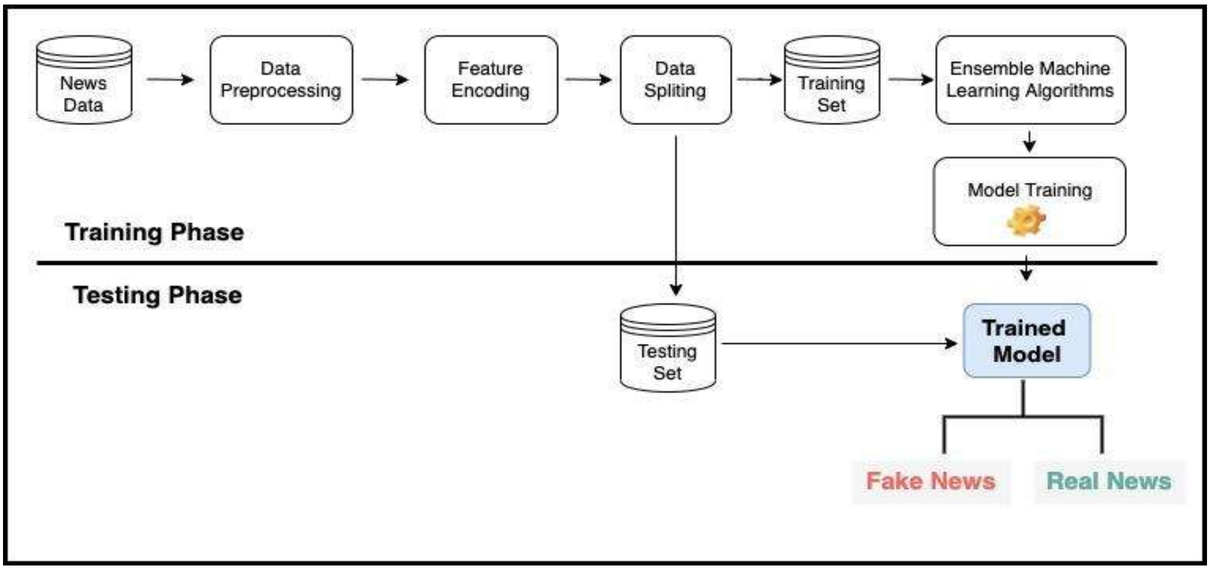

Fig. 1: System Model

Dataset Description

Two open-source datasets are combined and used for this work, both were obtained from Kaggle, an open-source data repository. The first dataset was ISOT Fake News dataset. This dataset contains both real and fake news collected with focus on articles between 2016 and 2017. The real news were crawled from reuter.com (news website), while the fake news were scrapped from various unreliable sources flagged by Wikipedia and Politifact (a fact-checking USA organization). The news article covers different news types but primarily on political and world news articles. The dataset contains 21,417 real news articles and

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23,481 fake news articles organized into a csv file containing the news article title, text, subject (type) and the published date of the news article. Table I shows the details of this dataset.

The second dataset is the COVID-19 Fake News dataset also obtained from Kaggle. The dataset contains various misinformation on COVID-19 from both websites and social media platforms, as well as users engagements about such posts. It is made up of 4,251 news, 296,000 related user engagements, 926 social platform posts about COVID-19, and ground truth labels.

TABLE I: ISOT FAKE NEWS DATASET

News	Size (Number of articles)	*Subjects*	
Real-News	21417	Type	Articles size
		World-News	*10145*
		Politics-News	*11272*
Fake-News	23481	Type	Articles size
		Government-News	*1570*
		Middle-east	*778*
		US News	*783*
		left-news	*4459*
		politics	*6841*
		News	*9050*

(Source:https://www.kaggle.com/datasets/emineyetm/fake-news-detection-datasets/data)

Data Preprocessing

The COVID-19 dataset is made up of 33 csv files each holding specific information category such as tweets, tweet replies, news articles, user data, other post metadata. The actual files used are "NewsRealCOVID-19.csv", "NewsRealCOVID-19_5.csv", "NewsRealCOVID-19_7.csv" for real news, and "NewsFakeCOVID-19.csv", "NewsFakeCOVID-19_5.csv", "NewsFakeCOVID-19_7.csv" for fake news. The choice of this selection was based on the fact that they are the only files containing actual news contents while other files were simply holding some meta-data and other identification details. The real news files were merged into one dataset, constituting 3,610 observations, while the merged fake news files constitute 894 total observations. The merged real-news contains column name different from the fake news. We therefore selected only the type, title and content features from both of the merged cells as these are the most useful, yet common features. Using these selected features, we derived a new feature to be used for training which is concatenation of the news title, content and type, to capture the various components of the news for appropriate representation. The cleaned COVID-19 dataset 4,504 covid-19 news observations (news articles), 3,610 of which are real news and 894 fake news.

For the ISOT dataset also, we derived a new feature to be used in the training by concatenating the news title, text and subject features. The ISOT dataset contains 44,898 total observations, 21,417 of which are real news articles while the remaining 23,481 observations are fake news articles.

The newly derived feature for real news of both datasets were merged into a single "real-

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news" dataset and assigned a label of "0", while the newly derived feature for fake news of both datasets were extracted and merged into a single "fake-news" dataset and assigned a label of "1". These labelled datasets of both the real-news and fake news were then merged into a single dataset making up the final dataset to be used for our study. This new dataset contains only two columns "derived-news-article" and "label". Our final merged dataset is made up of 49,402 observations made up of 25,027 real news and 24,375 fake news.

In other to prevent bias that may be introduced due to data imbalance we randomly selected 20,000 observations each for the real news and fake news, making-up 40,000 observations to be used for training and testing our machine learning algorithm for fake-news detection.

Then, each of the news articles was cleaned by decapitalizing the news articles, thus preventing the same word in different casing being treated as separate words. Also, we removed all English stop words, this was necessary to ensure that redundant words that would not contribute in any way to the classification process is removed, thereby reducing the vocabulary size and by implication reduces computational complexity. The remaining words were then stemmed using nltk's "WordNetLemmatizer" class. This step was necessary to retain only the root word of polymorphic words that could appear in different forms. For example, rather than treat the words "love", "loved" and "loving" or the words "eat", "ate", "eaten", "eating" differently as separate words in the corpus, the root word "love" and "eat" are used respectively instead.

The cleaned textual news-article now in our derived feature needs to be vectorized using some form of encoding into a numeric form suitable for use by our machine learning algorithm. To achieve this, we encoded the text-based news article into vectors of numbers using Term-Frequency Inverse Document Frequency encoding (TF-IDF) method. TF-IDF computes a numeric weight value that measures the importance of a term (word) to a document (news article) in a collection (all articles set). Mathematically, the computation of the TF-IDF score can be as follows:

$$\mathrm{tf}(t,d) = {k_t}/{n_d} \quad (1)$$

$$\mathrm{idf}(t) = \log\left(\frac{N}{\mathrm{df}(t)+1}\right) \quad (2)$$

$$\mathrm{tfidf}(t,d) = \mathrm{tf}(t,d) * \mathrm{idf}(t) \quad (3)$$

$$\mathrm{tfidf}(t,d) = \left(\frac{k_t}{n_d}\right) * \log\left(\frac{N}{\mathrm{df}+1}\right) \quad (4)$$

As shown in the equations (1) to (4) above, t represents the term. d is the current document (news article). k_t is the number of times the term, t, occur in a given news article, d. n_d is the total number of terms in news article, d. N represents the count of corpus (all unique words in all the news articles). tf(t,d) is the term-frequency, which is the weight of the term, t, in a single news article, d. df(t) represents the number of news articles containing the term, t. The inverse document frequency, idf(t) measures the informativeness of the term, t, by computing a higher weight for rarer words and lower weights for stop-words that naturally occur most frequent. The addition of 1 to the value of df(t) in the estimation of idf(t) is to smoothen the df(t) in order to prevent the possibility of division by zero. Also, to address the explosion of idf(t) value in situations involving large corpus, as is our case, we regularize the value by taking its log (see equation (2)).

The encoded tf-idf-encoded text was then divided into 80% training set and 20% testing set. The training set was used to train a random forest classifier algorithm and a CatBoost classifier algorithm.

Experimental Setup

The experiment was carried out with Python 3 programming language on Google Colab running a T4-GPU on NVIDIA-SMI with CUDA v12.2, 12.7GB System RAM, 15GB GPU RAM and 78.2GB Disk strorage. The Random Forest Classifier model was implemented using sci-kit learn package and the CatBoost Classifier was implemented using the catboost package. The Random Forest Classifier was setup for training using the following configurations n_estimator=100, criterion='gini', mi_samples_split=2, min_samples_leaf=1, max_features='sqrt' and boostrap=True. The default values were taken for the rest of the hyperparameters.

For the CatBoost configuration on the other hand, we set the learning rate to 0.01, eval_metric was set to 'Accuracy', early_stopping_roundswas set to 20 to enable the model watch for overfitting and stop the training before the end of the entire iterations if the accuracy does not change significantly after 20 rounds. We also set use_best_model to True to allow the model return the weights of the best model during the training, and the verbose level set to 50, to show report of the training process. Finally, we set the iterations to 200 to allow the model repeat the training process 200 times provided there is no overfitting detected that would warrant an early stopping. Each of the two (2) algorithms with their configurations was then fitted with tf-idf-encoded training set comprising 80% of the pre-processed and encoded dataset that is made up of 16,000 observations with 85,071 columns (corpus length). The test set comprising 20% of the dataset had the shape of (4000, 85071).

Evaluation Metrics

We employed five (5) evaluation metrics extensively used in text classification tasks to evaluate the performances of our trained models:

Accuracy: The ratio of correct classification to the total number of predictions made. This is calculated as follow:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (5)$$

Precision: This measures exactness. It is a measure of how many of the correct predictions actually turned out to be positive. In our case, we measure how many correct predictions/detections actually turned out to be fake news articles. This is calculated as the ratio of the correct positive (TP) predictions to the total number of positive predictions (TP + FP).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (6)$$

Recall: This is also called sensitivity. It is a measure of how many true positive were correctly predicted. i.e. how many actually fake news were correctly classified as fake news. It is represented as the ratio of true positive (TP) predictions to the total number of actual positive observations presented for evaluation (TP + FN)

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (7)$$

F1 Score: This is a harmonic mean of precision and recall. It combines the precision and recall measure by allocating equal weight to both measures.

$$\text{f1} = 2 \cdot \left(\frac{\text{precision} \ \text{x recall}}{\text{precision} \ + \text{recall}}\right) \quad (8)$$

ROC-AUC: The Receiver Operator Characteristic (ROC) is a probability curve that plots the TPR(True Positive Rate) against the FPR(False Positive Rate) at various threshold values and separates the 'signal' from the 'noise'. The **Area Under the Curve (AUC)** is the measure of the ability of a classifier to distinguish between classes. An AUC score of 1 indicates the classifier is able to perfectly distinguish between the positive and negative class points. i.e. in our context, the ability to perfectly distinguish all the fake news from all real news. Roc-AUC of 0.5 implies a random guess. Roc-AUC below 0.5 shows the model ranks negative cases higher than the positive cases and vice-versa. A high value of 0.8 and above is often a good score.

IV. RESULTS AND DISCUSSION

After training the Random Forest (bagging) and CatBoost (boosting) ensemble algorithms, the trained models were evaluated on the test set and the results obtained are shown below in fig. 2 to fig. 5.

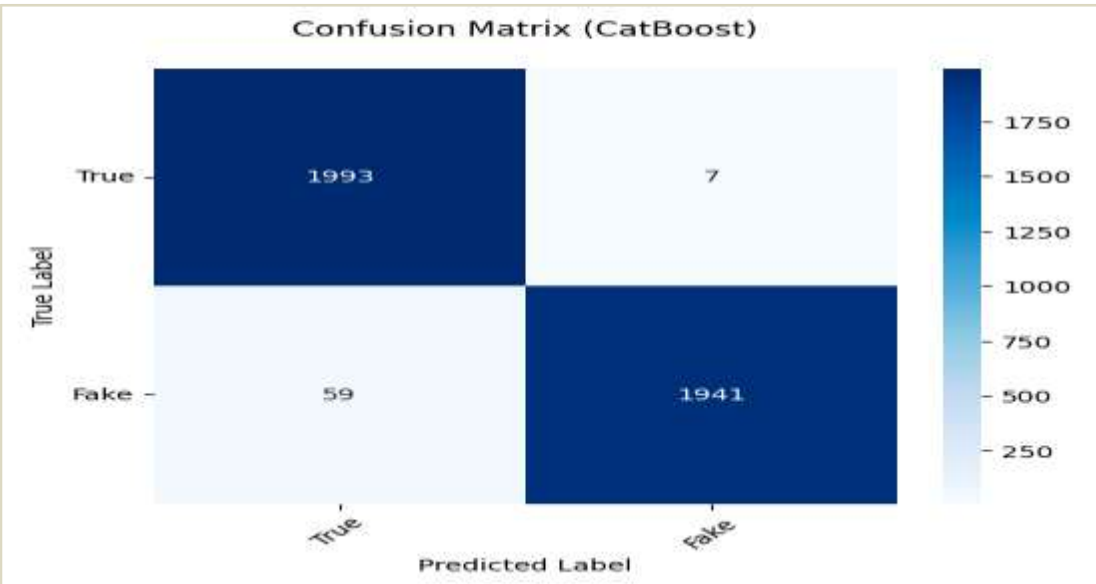

Fig. 2: Confusion Matrix for CatBoost (Boosting Ensemble) Classifier

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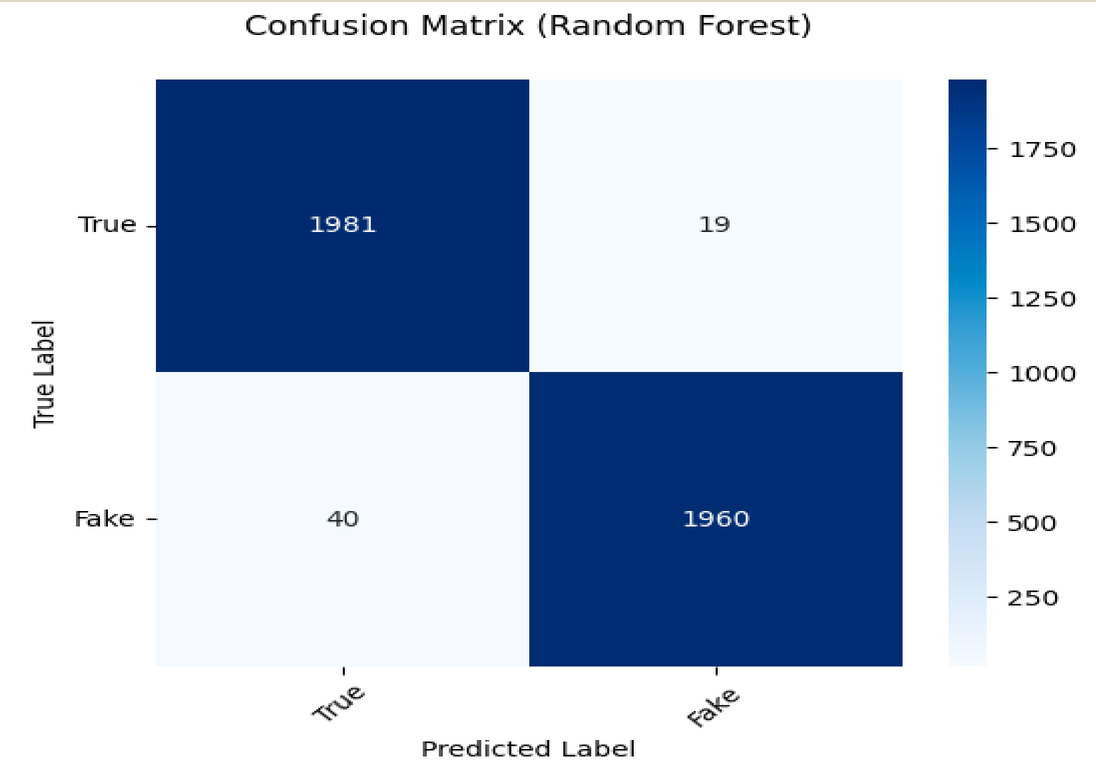

Fig. 3: Confusion Matrix for Random Forest (Bagging Ensemble) Classifier

The results obtained from the trained catboost classifier on the test set is shown in Fig. 2, Out of the 1,979 fake news presented for evaluation, 1,941 were correctly classified, constituting 97% correct classification, with 59 (3%) misclassification of fake news. 1,993 (99.7%) of the 2,052 real news evaluated were correctly classified, with only 7 (0.3%) misclassifications. From this result, Catboost is doing a bit better on real news classification than fake news classification.

As shown in fig. 3, The random Forest classifier correctly classified 1,960 (98%) fake news and misclassified only 40 (2%) fake news out of the 1,979 fake news presented for evaluation. Out of the 2,021 real news evaluated, 1,981 (99.1%) were correctly classified, leaving only 19 (0.9%) real news misclassifications.

TABLE II. RESULTS ON EVALUATION SET

	CatBoost Classifier		Random Forest Classifier	
	cb_test	cb_train	rf_test	rf_train
Accuracy	0.984	0.984	0.985	1.000
Precision	0.996	0.995	0.990	1.000
Recall	0.971	0.974	0.980	1.000
ROC-AUC	0.984	0.984	0.985	1.000
F-Measure	0.983	0.984	0.985	1.000

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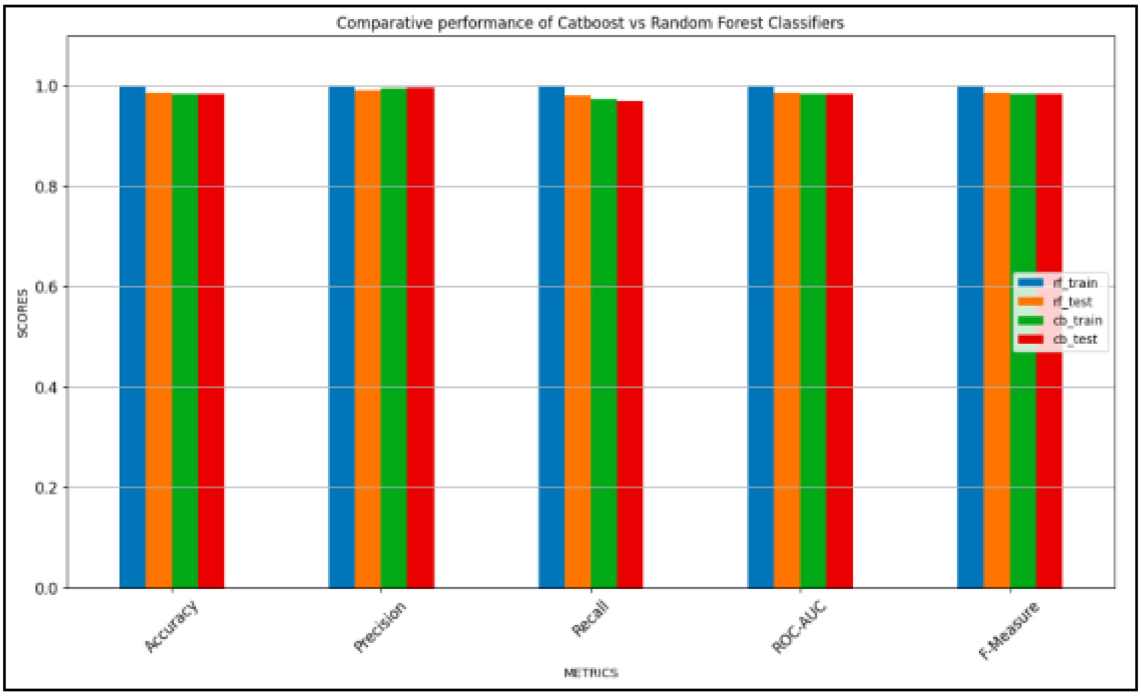

Fig. 4: Comparative Result of CatBoost (Boosting) vs Random Forest (Bagging) Ensembles

Table II and Fig 4 show the results obtained from both models trained. As shown, the two (2) ensemble models performed comparatively good with the best being Random Forest (Bagging) ensemble having overall classification accuracy of 99%, while CatBoost (Boosting) ensemble model had a predictive accuracy of 98% which is comparatively just a marginal difference.

Taking the whole metric into account, Random Forest (bagging) ensemble performed consistently better than Catboost (boosting) ensemble learner in terms of accuracy, recall and roc-auc and f1-measure, except for precision where catboostrecorded 0.006 improvement in precision than random forest.

V. CONCLUSION

As shown in our work, machine learning approaches have demonstrated effectiveness in detecting fake news articles. Most notably is the adoption of ensemble methods, as our results showed that both bagging and boosting ensemble algorithms are good predictors for fake news detection with the least having as much as 98% accuracy. More so, our work also showed that Random Forest (bagging) ensemble is a more stable choice for fake news detection across multiple evaluation metrics over catboost (boosting) ensemble, although the performance difference is fairly marginal, as our results showed.

We have been able to demonstrate that both bagging and boosting ensemble methods are good choice for fake news detection and that when faced with a decision to choose, bagging-based algorithm such as Random Forest is a good choice with a more stable performance. Future research should focus on addressing the challenges of labelled data scarcity and exploring new techniques to improve the accuracy and robustness of fake news detection models.

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