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Fake News Detection using Python and Machine Learning

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Abstract

In an era dominated by digital information, the unchecked proliferation of false information poses a critical threat. This has motivated to study for techniques which can tackle issues related to it, and hence the study uses machine learning algorithms to detect fake news. By systematically exploring and evaluating various machine learning models, the research enhances decision-making, fortifies information integrity and addresses the adverse impacts of misinformation on a broader scale. Going beyond mere algorithmic efficacy, the study introduces a multifaceted approach by using evaluation metrics like precision and accuracy. This strategic analysis identifies the optimal machine learning algorithm for classifying articles as real or fake news. The contents covered by the study include literature review, dataset selection, data preprocessing and cleaning, vectorization, model and metric selection, model training, optimization and evaluation. The study extends its impact beyond technical proficiency, actively contributing to bolstering trust across media, democratic processes, and ensuring content authenticity. This inclusive approach benefits a wide array of stakeholders including news organizations, social media platforms and government entities. Through rigorous evaluation, the study significantly enhances information credibility, providing a countermeasure against the growing threat of misinformation.

Keywords: Applied machine learning; Detection of Fake News

1. Introduction

To prevent relentless dissemination of fake news in the digital era, advanced techniques have to be developed or

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existing techniques have to be improved. Current techniques in fake news detection include ML, DL. NLP and metadata analysis. Each technique has its own strengths and limitations and calls for a more comprehensive and adaptive approach. For instance, NLP struggles with nuanced context and adversarial attacks. Similarly, machine learning has some limitations such as the dependency on standard and representativeness of data to be trained and potential bias in training data which is why this study is being done. The study hopes to find the best ML model to differentiate a news document as Fake or Not. Furthermore, the dynamic nature of machine learning models allows for continuous learning and adjustment, making them well-suited to counter the diverse and evolving strategies used to spread misinformation. This study advocates for the exploration of machine learning algorithms as powerful tools to address these challenges, aims to propel the field forward and fill any gaps in the current landscape of fake news detection.

2. Related Works

A thorough literature review was conducted to obtain a proper understanding of applied ML models in the area of news of type hate/fake news.. Prior research has explored various techniques, revealing their strengths and limitations. Notably, Sharma et al. [1] made a system which uses applied ML and NLP to detect fake news , utilizing classifiers like Passive Aggressive Classifier, Random Forest and Logical Regression. Khanam et al. [2] employed XGBoost, while Pandey et al. [3] achieved high accuracy and F1-scores using classifiers like Decision Tree and Logistic Regression. To provide a comprehensive overview, Table 1 was crafted to summarize related works on fake news detection. It condenses information on research papers, authors, classifiers employed, model performance metrics, issue dates, and references. Noteworthy classifiers include Decision Tree, Random Forest, PAC (Passive Aggressive Classifier), XGBOOST, Naïve Bayes, SVM , Logistic Regression and KNN , each applied in various studies. Evaluation of ML models using various metics like F1-score, precision, and accuracy were crucial for evaluation. Table 1 allows for easy comparison of different classifiers across multiple research papers, shedding light on variations in their success rates in detecting fake news but limitations include the absence of recall and, unavailability of F1-score and precision in some studies. Direct comparative analysis and discussion of the strengths and weaknesses of each classifier could offer additional insights for researchers and practitioners. Moreover, understanding the specific dataset or problem domain for which these classifiers were applied is crucial for interpreting their performance. Addressing these limitations would contribute to a more thorough and actionable understanding on how to deal with fake news. The study strategically narrowed down the selection to six classifiers: logistic regression , gradient boosting ,random forest , passive aggressive classifier decision tree and XGBoost. This decision was informed by a thorough consideration of the classifiers' performance in previous research, as well as the specific strengths and limitations revealed in Table 1. The aim is to build upon the insights gained from existing literature, contributing to a more nuanced understanding of how effective these classifiers are in detecting fake news. Ensemble classifier methods can improve accuracy [6]. Comparing machine learning algorithms and selecting the best and then implementing them using python libraries, is the conventional method of implementation [7] [9] [14]. These ML models can be implemented after extracting features manually, and engineered features are sent to the model for prediction. Fake news were detected automatically in social media through many features are present, where a deep learning analyzer was used for the detection [8]. Novel approaches like BERT based in ML are also existing with each method having its own advantages and disadvantages [10] [11]. To overcome outdated labeled samples for training, authors proposed a reinforcement method for fake news detection based on weakly supervised classification technique [12] [15].

Table 1. Related works

Author(s)	Classifiers	Accuracy	Precision	F1 Score	Issue Date	Reference
Sharma U., Saran S., Shankar M. P.	Naïve Bayes	0.60	0.59	0.72	2020	[1]
	Random Forest	0.59	0.62	0.67		
	Logistic Regression	0.65	0.69	0.75		

	PAC	0.9273	0.93	0.9257		
Alwasel B.N., Khanam Z, Sirafi, M Rashid H.	XGBOOST	0.75	-	-	2020	[2]
	SVM	0.73	-	-		
	Random Forest	0.73	-	-		
Prabhakaran S., Pandey S., N. V. S. Reddy, Acharya D.	SVM	0.8933	-	-	2021	[3]
	Decision Tree	0.7333	-	-		
	Naïve Bayes	0.8689	-	-		
	Logistic Regression	0.9046	-	-		
	KNN	0.8998	-	-		

3. Exploratory Data Analysis

Choosing the right dataset is an important step in constructing an effective classifier to detect news which are fake, as the data quality directly impacts model performance. The ISOT fake news dataset [4][5] which is a widely recognized and reputable source, consists of articles from various domains such as media, democratic processes, content authenticity, news organizations, media platforms, and government agencies. This dataset includes two distinct categories: fake and real news, with parameters like title, text, type, and publication date. Exploratory Data Analysis (EDA) assumes a central role in uncovering crucial insights about the dataset. It involves the analysis and summarization of data to identify relevant elements such as patterns, relationships and anomalies. This process aids in revealing missing values, outliers, correlations, distributions, and potential features. Visualizations, such as bar graphs help to examine subject distribution, identify key topics, and explore potential features differentiating between fake and true articles. Furthermore, data imbalance should be avoided to ensure a fair and unbiased training dataset. The ISOT Fake News Dataset was selected for its diverse topics and a well-balanced composition of articles from reputable and unreliable sources. It provides dimensions like type, text, publication date and title. As shown in Figure 1, the bar graphs give a comprehensive overview of the distribution of articles across various categories and subcategories, enabling an in-depth analysis of the topics covered in both real and fake news. It was existing in the literature about the distribution of articles across different categories and subcategories, providing valuable insights into the dataset's composition. The table categorizes articles into "Real News" and "Fake News," with further subcategories such as "World News," "Politics News," and others. Information on the number of articles per category, denoted as "Articles Size," adds a quantitative dimension to the analysis.

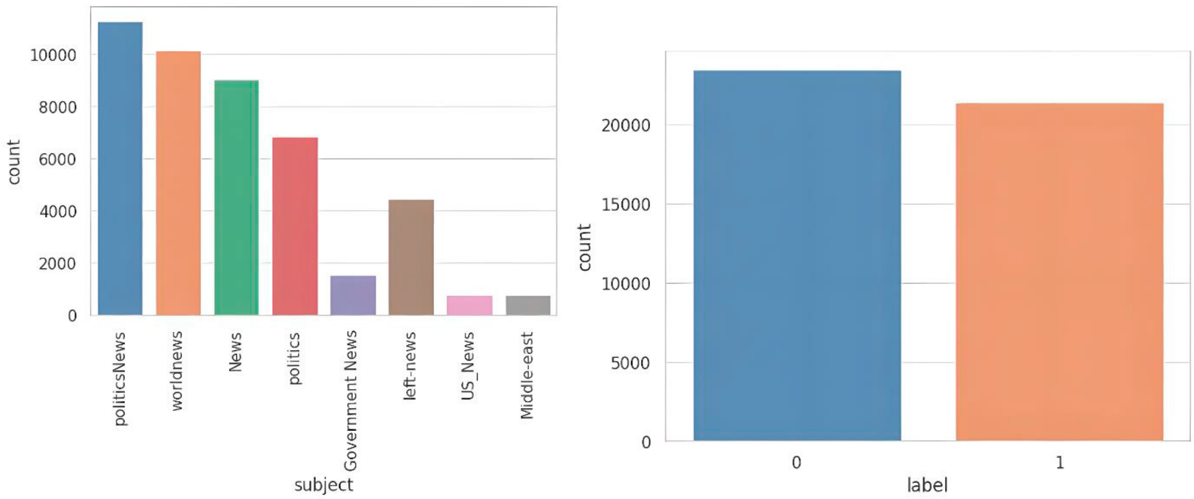

Fig. 1. (a) visualization based on subject column; (b) bar graph of categories and counts.

4. Preprocessing, Vectorization and Optimization

To ensure a higher level of accuracy, data preprocessing was done and that included the removal of numbers, punctuation, and stopwords, streamlining the text data for subsequent analysis. Features were extracted using TF-IDF. It captures the significance of words within a document and across the entire corpus. It works by assigning weights to words based on their frequency within a specific document and their rarity across the entire dataset. This process aims to identify words that are not only frequent within a document but also distinctive to that document compared to the entire corpus. The resulting TF-IDF matrix effectively transforms the raw textual data into a numerical representation. Vectors represent each document in high-dimensional space. Each unique word in the corpus is assigned a specific index for encoding, and score of TF-IDF for each word becomes respective value in the representation of vector. This encoding technique ensures that the machine learning model can process and derive meaningful patterns from the text data. For performance optimization, the application of the Intel Extension for Scikit-learn was used. It led to faster computation and better performance. It reduced the code runtime of logistic regression by 1.8x. While parameter tuning was not explicitly performed, it can be a valuable step in refining the model's hyperparameters. Techniques such as grid search or random search can be employed in future iterations to systematically explore different combinations of hyperparameter values for models like logistic regression. This iterative tuning process aims at finding the optimal configuration that strikes a balance between recall and precision, ultimately improving the ability of model to accurately differentiate between fake and non-fake documents.

5. Model Selection and Proposed work

The models selected for comparison is as shown in Table 3. Logistic regression was selected as the baseline model due to its interpretability and suitability for binary classification tasks. The subsequent models were chosen as they offered advantages such as capturing non-linear relationships, handling complex interactions, and improving predictive performance. By making use of a diverse set of models, a proper analysis of fake news detection can be ensured.

5.1 Logistic Regression

It is linear and suited for binary classification by modeling the probability of an instance belonging to a particular class.

5.2 Decision Tree

A tree-shaped model that makes decisions by recursively splitting the dataset based on features.

5.3 Random Forest

An ensemble of decision trees that collectively improve accuracy and prevent overfitting in classification and regression tasks.

5.4 Gradient Boosting

A sequential ensemble method building trees to correct errors of the previous ones, often used for regression and classification.

5.5 XGBoost

An optimized version of gradient boosting, known for its speed, efficiency, and high-performance in classification and regression.

5.6 Passive Aggressive Classifier

A type of online learning algorithm suitable for large-scale classification problems, updating its model with minimal computation and adaptability to streaming data.

6. Metric Selection

The chosen metrics for evaluation were:

6.1 Accuracy

Estimates overall correctness of model's predictions, which is crucial in determining the reliability of news classification. It consists of training and testing accuracy. Training accuracy means the proportion of correctly classified instances in the training dataset whereas testing accuracy means the same but in the test dataset. How well the model fits the data trained is accuracy during training whereas overall model performance on unseen data is obtained from the accuracy during testing.

$$Accuracy = TP + TN \tag{1}$$

6.2 Precision

Precision is a measure of positive predictions accuracy, which ensures accurate identification of true positives (real news) and minimizes false positives (classifying fake news as real), as avoiding the spread of false information is critical.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

6.3 Recall

Recall, or sensitivity, measures model ability to capture all positive instances. Helps to measure how well the model correctly classifies real news articles and avoids false negatives (misclassifying real news as fake), which is important for maintaining the credibility of legitimate news sources. It is ratio of correctly predicted positives to actual positives.

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

6.4 F1 Score

Provides a balanced measure, considering false negatives and positives, making it valuable in situations where both types of errors are equally important.

6.5 AUC of ROC

The metric area under curve (AUC) evaluates a classification problem at different threshold settings. AUC represents the capacity of model to discriminate between negative and positive instances, with higher AUC indicating better discrimination. It evaluates by ranking true positives higher than false positive***6.6 Confusion Table***

A visual representation of model performance as table, which analyzes the ability across different categories is called a Confusion Table. True Positive (TP): Fake news is correctly identified by model. True Negative (TN): Genuine news correctly identified. False Positive (FP): Model mistakenly classifies genuine news as fake. False Negative (FN): Fake news is labelled as genuine.

7. Model Evaluation and Result Analysis

Figure 2, shows the performance analysis of various models as Confusion Table

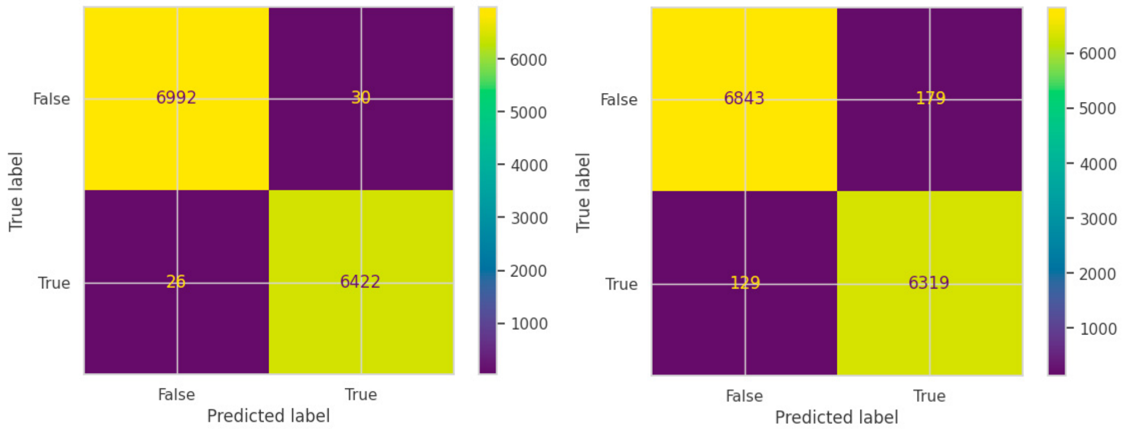

Fig. 2. (a) decision tree and (b) logistic regression.

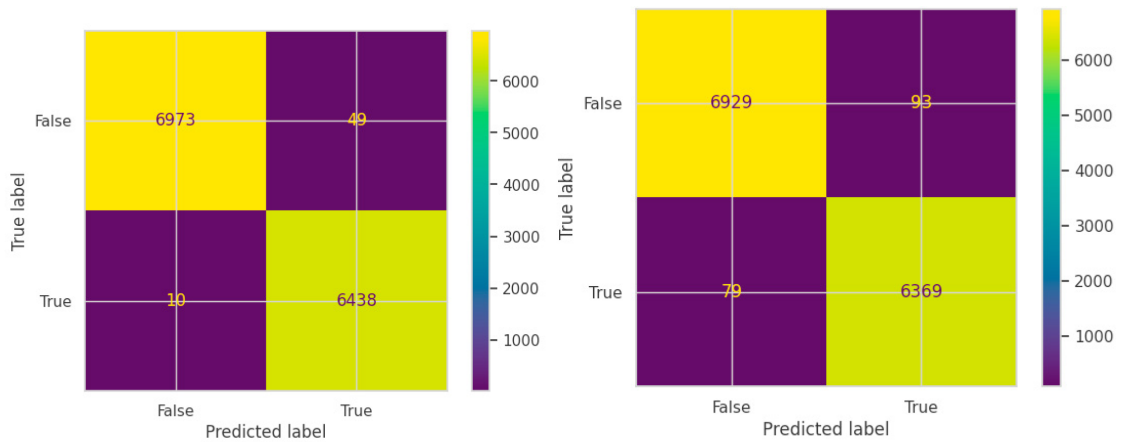

Fig. 2. (c) gradient boosting and (d) random forest.

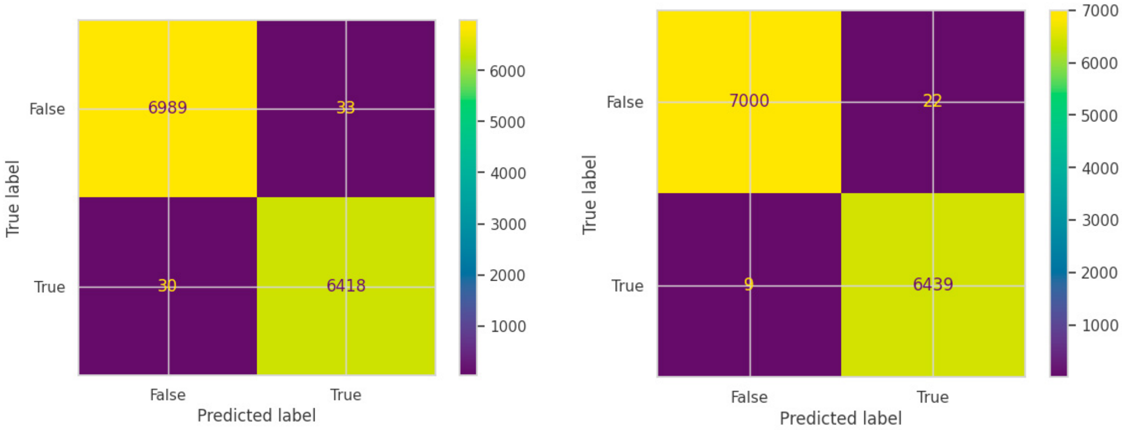

Fig. 2. (e) passive aggressive classifier and (f) xgboost.

Table 2. Algorithm performance metrics

Machine Learning Algorithm	Recall	Testing Accuracy	Precision	F1-Score	AUC	Training Accuracy
Logistic Regression	0.979994	0.977134	0.972453	0.976209	0.977251	0.979954
Decision Tree	0.995968	0.995843	0.995350	0.995659	0.995848	1.0
Random Forest	0.987748	0.987231	0.985608	0.986677	0.987252	1.0
Gradient Boosting	0.998449	0.995620	0.992446	0.995439	0.995736	0.996786
Passive Aggressive Classifier	0.995347	0.995323	0.994885	0.995116	0.995324	1.0
XGBoost	0.998604	0.997699	0.992446	0.997559	0.997736	1.0

XGBoost performed the best, showcasing the lowest false positives and true negatives (Figure 2). With the highest training and testing accuracy (Table 2), XGBoost demonstrated minimal overfitting and excellent generalization. Furthermore, it excelled in precision, recall, F1-score, and ROC AUC score, indicating superior separability. Contrary to expectations from the literature review, where the PAC was anticipated to outperform, alternative models surpassed PAC in this study. Factors such as complexity, handling non-linear relationships, ensemble learning, regularization techniques, and dataset characteristics likely contributed to the superior performance of these models. In this specific context, the combined analysis of visual representations, diverse algorithms, and comprehensive metrics solidifies XGBoost as the optimal choice for fake news detection. This approach helps to enhance understanding of model performance and select the best one for the task.

8. Conclusion with Future Scope

The research has demonstrated success, yet practical limitations necessitate future research. The dynamic nature of fake news dissemination, as it turns out is not just through unreliable news platforms but also through social media and thus is a crucial challenge that warrants focused attention. To enhance the model's efficacy, it should adapt to the distinctive elements of different platforms. Difficulty in precisely classifying news and challenges in classifying multimedia content underscores the need for continuous adaptation and improvement. Future research should prioritize diverse data cleaning methods, testing various algorithms, and exploring alternative vectorizers like Word2Vec and BERT. Additionally, optimization through techniques such as grid and random search, and exploration of alternative machine learning models, are essential to properly understand limitations and strengths. Given how prevalent fake news is, strategies for real-time monitoring and fact-checking should be at the forefront of future investigations. This comprehensive approach will contribute to model efficiency and effectiveness across diverse applications. By addressing these challenges and leveraging emerging opportunities, the field can advance the capabilities of fake news detection models for real-world impact.

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