International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 25 Issue 04, APR, 2025

Machine Learning Approach for Fake News Detection

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Abstract – Indian politics has experienced major setbacks due to the rapid spread of fake news. Fake news is intentionally crafted to mislead the public and promote false propaganda, making it difficult to detect based on content alone. Its widespread circulation has negatively influenced the mind-set of common people, causing confusion and distrust. Given the serious impact of fake news, it has become crucial to verify the authenticity of news content. The unchecked spread of misinformation poses a significant threat to social stability and public trust.

In this project, we propose using machine learning techniques to detect fake news. Our approach involves vectorizing news titles, analyzing tokenized words, and training models on a curated dataset labeled as fake or real. The goal is to develop an accurate model that can classify any given news article as true or fake. We will apply Natural Language Processing (NLP) methods like TF-IDF and Count Vectorization for feature extraction and experiment with various machine learning algorithms such as Logistic Regression, Naive Bayes, and Support Vector Machines. Model performance will be assessed using metrics like Accuracy, Precision, Recall, and F1-Score.Our aim is to build an efficient and reliable fake news detection system that can help combat misinformation in today's digital world.

Keywords - Fake News, Artificial Intelligence, Natural Language Processing, Word2Vec, Pattern Matching

I. INTRODUCTION

The term "fake news" has taken on various meanings, but in this paper, it is defined as news stories that are entirely false, lacking verifiable facts, sources, or quotes. Such stories are often created as propaganda to mislead readers or as clickbait to gain economic benefits. The rise of social media has accelerated the spread of fake news, making it a major concern today.

This study focuses on detecting fake news based only on textual information using traditional machine learning techniques. Before building detection models, it is important to first understand and characterize fake news. Two main aspects define fake news: authenticity, meaning the information is provably false, and intent, meaning it is created to deceive. Conspiracy theories are generally excluded since they are harder to verify as true or false.

Theories from human behaviour and cognition, especially from social sciences and economics, provide useful insights for analyzing fake news. These theories can guide the development of more explainable and accurate detection models. They fall into two categories: news-related theories, which examine differences in writing style, quality, and emotions between true and fake news, and user-related theories, which study how both malicious users and vulnerable normal users contribute to the spread of fake news due to social influence and psychological factors. Understanding both the content and user behavior is essential for building effective fake news detection systems.

II. LITERATURE REVIEW

The problem of fake news has gained considerable attention in recent years, with multiple datasets and studies addressing the detection and impact of misinformation. Risdal provided an extensive dataset for fake news classification through Kaggle, offering a valuable resource for machine learning applications [1]. Historical analyses by Soll et al. demonstrated that fake news is not a modern phenomenon but has deep historical roots [2], while Wardle emphasized the complexity involved in defining and detecting fake news [3].

Ahmad et al. explored satire detection from web documents using machine learning techniques, bridging the gap between humor and misinformation [4]. Real-world consequences of fake news were highlighted by Kang and Goldman, where a fabricated story led to a violent incident at a pizzeria [5]. Moreover, Domonoske revealed the alarming inability of students to distinguish fake news from real news, emphasizing the need for better digital literacy [6].

Several studies have leveraged spam detection techniques to counter fake news. Banday and Jan discussed the effectiveness and limitations of statistical spam filters [7], while Sedhai and Sun proposed a semi-supervised approach for spam detection on Twitter [8]. Similarly, Bhowmick and Hazarika reviewed various machine learning techniques used in email spam filtering, many of which are adaptable to fake news detection [9].

The Fake News Challenge provided a competitive environment for researchers to develop stance detection models, further boosting innovation in this field [10]. Wang introduced the "LIAR" dataset, providing labeled claims for fake news detection research [11]. Genes discussed the application of Natural Language Processing (NLP) techniques for fake news identification [12].

Perez-Rosas et al. proposed an automatic fake news detection system using linguistic features [13], while Pennebaker et al. developed LIWC, a linguistic tool frequently employed in fake news studies [14]. Ruchansky et al. introduced CSI, a hybrid deep model that combines text, user, and propagation information for fake news detection [15].

Efforts to automate fake news detection in social networks were addressed by Tacchini et al. [16], and Thorne et al. demonstrated the use of ensemble classifiers for stance detection in fake news articles [17]. Granik and Mesyura employed a Naive Bayes classifier for simple yet effective fake news detection [18].

Recent advances in deep learning have led to the use of CNN-based models for fake news detection, such as the TI-CNN proposed by Yang et al. [19]. Wang et al. proposed EANN, an event-adversarial neural network designed to improve multi-modal fake news detection [20]. Other major contributions include the Transformer architecture introduced by Vaswani et al., which greatly impacts NLP tasks including fake news detection [21].

Recurrent Neural Network (RNN) variants like the Independently Recurrent Neural Network (IndRNN) by Li et al. [22] and the Hierarchical Attention Networks by Yang et al. [23] also offer promising frameworks. Adversarial training techniques for semi-supervised text classification, as presented by Miyato et al., further enhance model robustness [24]. Kim's work on CNNs for sentence classification is fundamental for short text fake news detection [25].

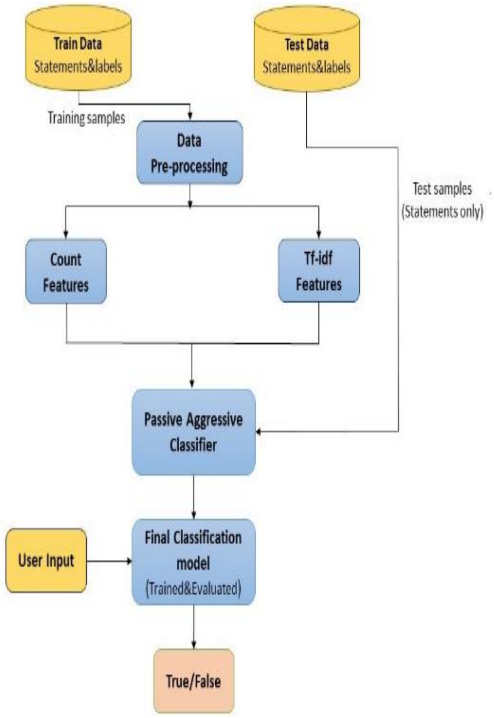
Kowsari et al. introduced RMDL, a random multimodel deep learning framework that applies multiple deep learning architectures simultaneously for improved classification performance [26]. Distributed representations of sentences and documents proposed by Le and Mikolov offer strong feature embeddings that are useful in fake news classification tasks [27].

Moreover, Karger et al. proposed iterative learning models for reliable crowdsourcing, an approach that could enhance the labeling quality of fake news datasets [28]. Finally, the Fake News Corpus by Szpakowski remains a significant open-access resource for developing and benchmarking fake news detection models [29].

III. METHODOLOGY

In this research, I followed a systematic methodology to classify news articles as true or fake. Initially, three publicly available datasets containing news articles from multiple domains such as politics, entertainment, technology, and sports were selected from Kaggle. These datasets included both truthful and fake articles and were merged into a single, large dataset for comprehensive analysis. Data pre-processing steps such as text cleaning, tokenization, and removal of irrelevant information were performed to prepare the dataset for model training.

Linguistic features were extracted using the Linguistic Inquiry and Word Count (LIWC) tool, which captures psychological and linguistic characteristics from the text. Following featureextraction, multiple machine learning models including Naïve Bayes, Logistic Regression, Support Vector Machine (SVM), Decision Tree, and Random Forest were trained and evaluated.



To enhance performance, ensemble techniques were applied by combining predictions from different models. Model performance was assessed using various evaluation metrics such as accuracy, precision, recall, and F1-score to ensure a robust comparison between individual and ensemble learners.

IV. PROPOSED SYSTEM

In my proposed framework, I aim to extend the existing research by incorporating ensemble techniques combined with various linguistic feature sets to classify news articles from multiple domains as either true or fake. The novelty of this work lies in the use of ensemble methods along with the Linguistic Inquiry and Word Count (LIWC) feature set for improved fake news detection.

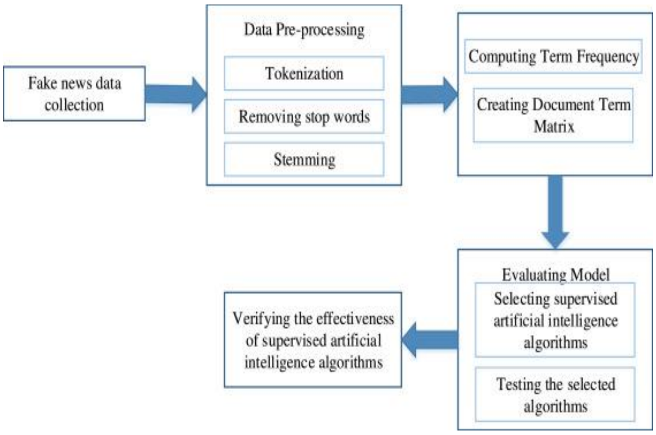


Fig a: Shows how model works

Several reputable websites publish legitimate news content, which are often used for fact-checking purposes. Additionally, open repositories maintained by researchers provide updated collections of datasets and links to fact-checking resources that help combat the spread of false information. For this study, I selected three publicly available datasets from Kaggle that include news articles across various domains, such as politics, entertainment, technology, and sports. These datasets, containing a mix of true and fake articles, were merged into a single, large dataset for experimental analysis.

V. ALGORITHMS DESCRIPTION

I used the following learning algorithms along with the proposed methodology to evaluate the performance of fake news detection classifiers.

NaiveBayes - Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming that features are conditionally independent. Despite this assumption often being unrealistic, it performs surprisingly well in many cases with low computational cost.

$$P(\mathbf{X} \mid C_i) = \prod_{k=1}^{n} P(x_k \mid C_i) = P(x_1 \mid C_i) \times P(x_2 \mid C_i) \times \ldots \times P(x_n \mid C_i)$$

LogisticRegression- Logistic Regression is used for binary classification and applies the logistic (sigmoid) function to map input values between 0 and 1. It models the relationship between features and output using a linear combination of input variables.

Support Vector Machine (SVM) - SVM is a supervised learning algorithm mainly used for classification. It finds the best hyperplane that separates data points into different classes, using support vectors (key data points) to define this boundary.

$$h(\boldsymbol{x}_i) = sign\left(\sum_{j=1}^{s} \alpha_j \; y_j \; K(\boldsymbol{x}_j, \boldsymbol{x}_i) + b \right)$$

$$K(\boldsymbol{v}, \boldsymbol{v}') = \exp\left(\frac{||\boldsymbol{v} - \boldsymbol{v}'||^2}{2\gamma^2}\right)$$

Decision Tree Learning - Decision Trees split data into branches based on feature values, ending with leaf nodes that represent outcomes. It is a simple yet powerful supervised learning technique for both classification and regression.

Random Forest - Random Forest is an ensemble of decision trees where each tree votes, and the majority class is selected as the final output. It reduces overfitting and improves accuracy by using multiple trees trained on random subsets of the data.

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2$$

VI. RESULTS AND DISCUSSION

Below graph summarizes the accuracy achieved by each algorithm on the final dataset. It is evident that the maximum accuracy achieved on Decision Tree which is 99.73%. The next highest accuracy is achieved on Support Vector Machine (SVM) which is 99.52%. The next highest accuracy is achieved on Random Forest of 99.22%. The next highest accuracy is achieved on Logistic Regression which is 98.91%. The least accuracy is achieved on Naïve Bayes which is 94.91%. Below Table Represents the name of the classifier and accuracy achieved by classifier.

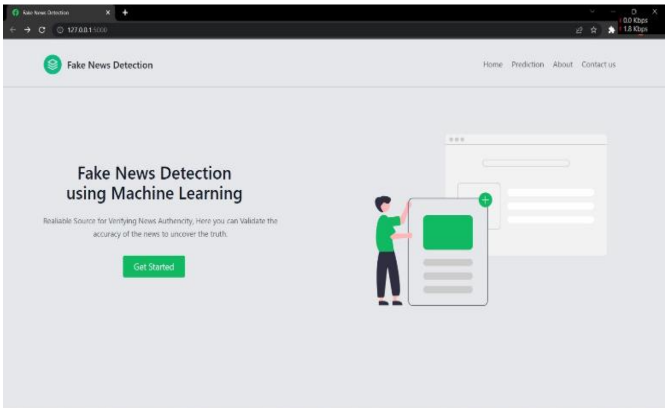


Fig-1 Fake News Detector

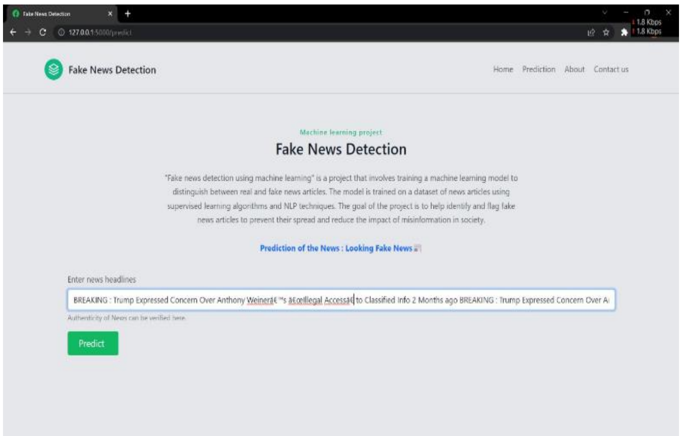


Fig-2 Fake News Detector

A streamlined prediction page where users paste a news headline into a text box and click “Predict” to have the machine-learning model instantly flag it as real or fake.

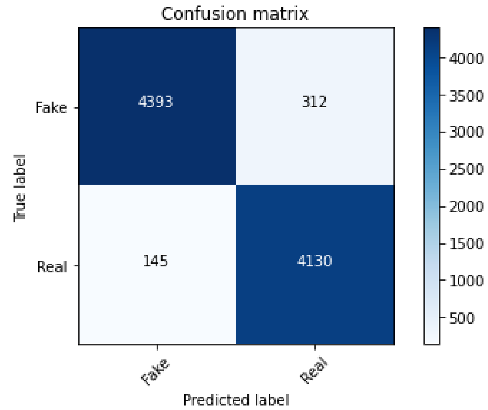


Fig b: Confusion matrix for Naïve Bayes model

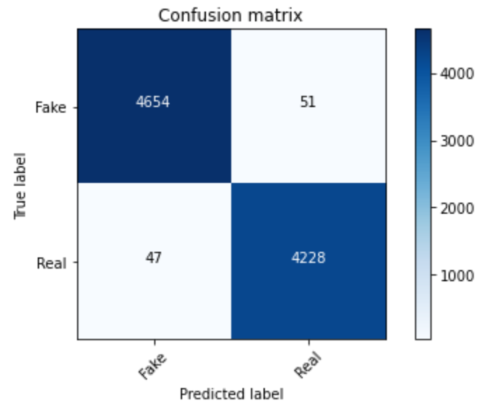


Fig c: Confusion matrix for Logistic Regression model

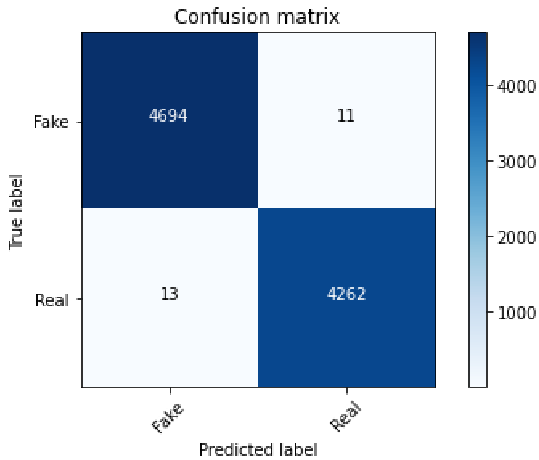


Fig d: Confusion matrix for Decision tree model

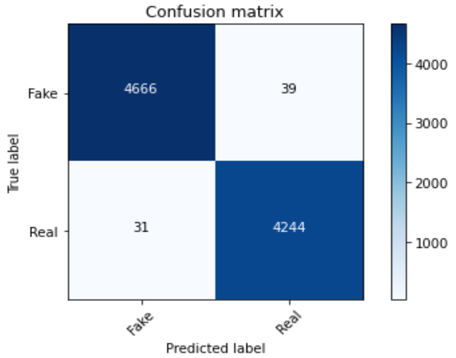


Fig e: Confusion matrix for Random Forest model

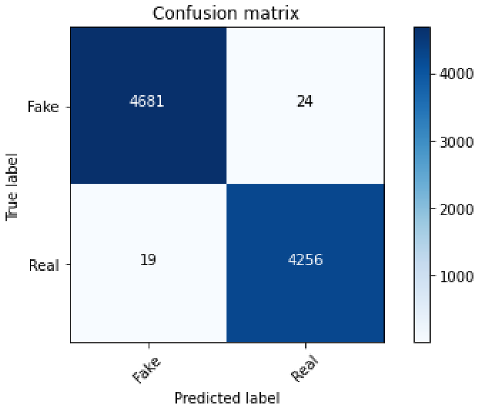


Fig f:Confusion matrix for Support Vector Machine model

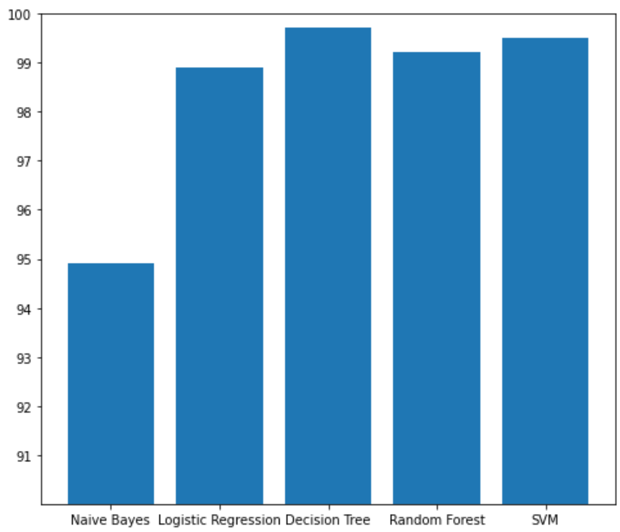


Fig g: Bar chart representing models

Classifier	Accuracy
Naïve Bayes	94.91%
Support Vector Machine (SVM)	99.52%
Random Forest	99.22%
Logistic Regression	98.91%
Decision Tree	99.91%

Table 1: Accuracies of the models

VII. CONCLUSION

Manually classifying news requires deep domain expertise to spot anomalies in text. This research focuses on classifying fake news articles using machine learning models and ensemble techniques. We used a Kaggle dataset containing news articles from various domains, aiming to distinguish fake from real news beyond just politics.

Our models were trained and tuned for optimal accuracy, with ensemble methods outperforming individual models across multiple performance metrics.

Fake news detection still has open challenges. Identifying key sources spreading fake news usinggraph theory and machine learning is a potential future direction, as is real-time detection in videos.

Ultimately, this work represents just one part of a larger fake news detection system. Building complementary tools like fact-checkers and stance detectors, and integrating them through a unified model, would improve overall detection accuracy.

VIII. FUTURE WORK

In the future, research can focus on identifying the key individuals and platforms responsible for the spread of fake news using techniques like graph theory and machine learning. Another important direction is developing real-time fake news detection models, especially for videos and multimedia content. There is also a need to build an integrated system that combines multiple tools, such as fake news classifiers, fact detectors, and stance detectors, to improve overall accuracy. Creating specialized models for fact verification and stance analysis, and combining their outputs, could make detection systems more robust. Expanding datasets to cover various domains and handling fake news in multimedia formats are other important areas. Additionally, developing explainable AI models that provide clear reasons behind each decision would help in building user trust and improving the effectiveness of fake news detection systems.

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