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A comparative analysis of multiple ML models for fake news detection

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ABSTRACT

The rapid growth of internet usage has emerged as a defining trend in recent decades, profoundly influencing how individuals communicate, access information, and engage with digital platforms. Among these, social media has become particularly prominent, with users demonstrating increasing proficiency in leveraging multiple platforms for diverse purposes. Such web resources enable any citizen to become a publisher or a distributor of news. The people and the content are not verified on these networks. People sometimes use such media to spread misleading information. The geometric growth of disseminated false information has become a critical concern in modern culture, which largely depends on information. The proliferation of fake and misleading information raises serious problems for societal well-being, the democratic process, and communal perception. Researchers have responded by increasingly using machine learning (ML) algorithms to develop automated systems to detect fake news. Based on this inspiration, we propose a resilient and effective system capable of appropriately identifying and combating misinformation propagation. This paper considered eight ML models to identify and evaluate fake news on two real-world datasets acquired on Kaggle. We use the Term Frequency-Inverted Document Frequency (TF-IDF) method in feature extraction. The best performance was recorded in the Passive Aggressive Classifier (PAC) among the other eight models, with an average accuracy of 97.26%.

Contribution/Originality: This study is among the few that evaluate multiple ML models for accurately identifying fake news on social media. It determines the most suitable and efficient model by conducting a comprehensive assessment of precision, recall, accuracy, and F1-score. The objective is to identify an ML model that offers strong overall performance with a balanced trade-off between precision and recall.

1. INTRODUCTION

The battle between truth and deception has accordingly become more intricate in the present digital era, where the amount of information accessible is immense and sometimes intimidating [1]. The emergence of social network services in the contemporary cyber-physical setting has been critical in the concentration and spread of data [2]. But it has also resulted in the uncontrolled distribution of misinformation and outright fabrication of content, also known as fake news, which has become an issue of paramount importance in recent years. The digital age is a reality, and with great benefits comes great adversity. The spread of fake or misleading news is one of the numerous issues associated with digitalization. The Internet is a good source of information for people [3], but the rapid growth of online platforms like Facebook and Twitter, combined with the effects of globalization, has created an unprecedented medium for information exchange [4]. Such platforms are convenient and preferred by users and thus are widely used to consume news. Moreover, they allow people to interact by commenting, reacting, and using other interactive elements. Despite their usefulness, these platforms have attracted malicious participants as well. Hackers and malicious individuals use these networks to spread fake information, often exploiting the sharing of posts or news stories to increase the reach of misinformation. The intentional spread of fake or false information presented as real news has become a common and troubling tendency, designed to deceive and disorient audiences. This phenomenon poses a significant threat to media integrity, national discourse, and the foundations of democratic processes.

The speed at which false information travels has rendered it difficult to distinguish between authentic and false information. Information sharing has never been so rapid on social media networks, making it challenging for anyone to determine whom or what to trust. This explosion of easily spread misinformation has harmful consequences for individuals, organizations, and society [5]. As people moved to online resources, such as social media, search engines, and online news publishers, as the primary sources of information, the potential impact of fake stories is larger. Posting such stories may alter the thinking of people, influence the outcome of elections, and create social issues. It may also damage reputations and contribute to confusion and anger, particularly on important events [6]. False data can likewise undermine civic confidence in news sources and the entire news framework, which people need to be aware of so as to know what is happening in a democracy [7]. Therefore, it is highly significant to identify fake news so that its negative influence can be reduced [8] since the information presented has a great impact on the way individuals perceive things and make their choices [9]. The recent past has given an example of how citizens can become irrational over news that was proven to be incorrect. As another example, in the case of the COVID-19 pandemic, much misinformation regarding the origins, characteristics, and biology of the virus was circulating on the Internet [10]. The US election in 2016 also demonstrated the extent to which fake news could influence the thoughts of people and their overall ideas [11]. Machine learning (ML) algorithms are the key to the effectiveness of ML, as they form the computational basis of automated learning, adaptation, and gradual enhancement. Scholars have conducted extensive research to understand how ML can be utilized to combat misinformation. As an example, Shu, et al. [8] have used the data mining method to detect the presence of made-up information that was spread via social media. They showed the relevance of the study of network topology, user activity patterns, and content attributes to detect deceptive data. [12] conducted another research, in which they analyzed fabricated news articles, proving the success of analyzing syntactic and lexical characteristics in distinguishing between trustworthy and non-trustworthy sources. Moreover, a variety of ML models have been developed to categorize fake news, and their number of potential applications is quite broad [13].

Machine learning has proven to be a very effective method in identifying fake news. Through training on large datasets consisting of social media posts, news stories, and other pieces of information, ML algorithms learn to recognize patterns and other characteristic features that may assist in distinguishing between genuine and fake content. Fake news detection is a task that has received considerable attention, and ML is especially important because it can learn and improve the detection results based on the data [14]. With the help of ML-based techniques, it is easier to create powerful systems that can detect false information, as these systems can use advanced methods to evaluate textual and contextual factors. ML algorithms analyze textual data through computational means, identify patterns, and capture latent linguistic features that can aid in assessing authenticity. Through training on large coverage of data that include real and generated news content, ML models can identify linguistic patterns and writing styles that are generally related to misleading information [15]. It is common to represent and analyze text with Natural Language Processing (NLP) techniques, which integrate features like sentiment analysis, phrase structure, and word usage. The textual features, such as the frequency of words, syntactic, and grammatical patterns, can be extracted automatically by ML algorithms and subsequently used to train models that can help to detect deceptive news. Moreover, ML models have the ability to compare the consistency of the information with the confirmed facts and real events in the world, at which they can identify contradictions or inconsistencies. Such supervised learning methods make it possible to train with labeled data that distinguish news stories as true or false [5]. In cases where labeled data is not accessible, unsupervised learning methods, including clustering and anomaly detection, may be applied to identify suspicious patterns that are characteristic of misinformation [16].

Misinformation, whether formed with the intent to deceive or spread accidentally, may have dire social ramifications, including divisions of societal faith, the control of mass opinion, and the disruption of elections. The best way to deal with this problem of fake news detection is to have automated systems that will reliably and efficiently separate reliable and misleading information sources. Many scholars have delved into examining how ML can be used to reduce the effects of misinformation spread by considering both textual and contextual features. Baarir and Djeffal [15] suggested a fake news detection model, which adopted a TF-IDF approach to extract features based on a Support Vector Machine (SVM) classifier as the core learning model. TF-IDF, likewise, was applied in the work of Shaikh and Patil [5] however, contrary to using a single classifier, the authors tested a variety of classification algorithms, such as the Passive Aggressive Classifier (PAC), Naive Bayes (NB), and SVM, and compared their performance to figure out the most efficient method. In a separate analysis, Sharma, et al. [17] prepared and evaluated a design utilizing four classifiers, namely RF, NB, LR, and PAC. In a more recent work [18], six ML algorithms, LR, LSVM, DT, SVM, SGD, and KNN, were compared regarding their ability to identify fake news.

In this work, several machine learning algorithms, including Naive Bayes (NB), Decision Tree (DT), Logistic Regression (LR), Random Forest (RF), Passive Aggressive (PA), K-Nearest Neighbors (KNN), Gradient Boosting (GB), and Support Vector Machine (SVM), are employed to determine which model offers the most robust and effective results in identifying fake news posts and misleading content spread online on social media. To identify the optimal algorithm for detecting false news, this study evaluates the performance of these algorithms based on common evaluation metrics, including accuracy, precision, recall, and F1-score. The models are trained and tested using two different datasets comprising fake and true news. The study also provides a comparison of the average model accuracy across these datasets. Additionally, the performance of these models is compared with state-of-the-art methods. The research objectives are outlined as follows.

- To perform a thorough comparison of different ML algorithms in terms of their effectiveness in detecting fake news. This objective aims to systematically assess the accuracies of different algorithms in differentiating between true and false news content in order to highlight their strengths and limitations.
- To identify the most suitable and efficient ML algorithm for detecting falsified news, a comprehensive assessment of precision, recall, accuracy, and F1-score should be conducted. This objective aims to find an algorithm that achieves overall good performance by balancing precision and recall.
- The third objective aims to determine whether algorithms consistently outperform others across different data contexts or if their performance depends on specific data attributes. The process involves running the same set of algorithms on multiple datasets and comparing the outcomes.

The paper is organized as follows: Section 2 reviews related literature and comparative models. The methodological approach is described in Section 3. Section 4 analyzes the experimental results and the performance measures. Section 5 discusses the study's contributions and limitations.

2. RELATED WORK

Massive publishing of false information and fiction stories is an urgent social problem in a modern digitized world. Scholarly research has firmly investigated the consequences of misinformation on modern societies, with research studies revealing how cognitive perceptions of real-life phenomena can be distorted after being exposed to misleading information repeatedly and how this can hamper the ability to make sound judgments [19].

The authors in Jain, et al. [20] introduced a framework for disinformation detection, integrating linguistic analysis NLP with ML classifiers such as Naive Bayes (NB) and SVM. Experimental results were benchmarked against existing solutions using a curated dataset of RSS feeds compiled from aggregated news sources. The SVMdriven model outperformed comparative systems, achieving 93.6% classification accuracy, and was supplemented by a corrective mechanism that suggests verified alternative articles when misinformation is detected. This work underscores the complexity of disinformation mitigation, advocating for hybrid methodologies that combine feature engineering with algorithmic synergy. Complementing this, Shaikh and Patil [5] conducted a systematic evaluation of classifier efficacy in fake news identification. Their analysis identified ensemble architectures combining linguistic features and behavioral metadata as particularly effective for improving detection robustness. The study emphasizes iterative model refinement and data diversity as critical factors for optimizing accuracy in dynamic information ecosystems. This study included three distinct classification techniques, namely SVM, PA, and NB. This research utilized a news dataset with a size of 63,354. Among the methods tested, SVM demonstrated the highest level of accuracy, with a precision of 95.05%. However, it is worth noting that SVM requires a longer processing time compared to PA or NB. Other machine learning algorithms can be employed to enhance the outcomes as a progression in their task. Specifically, for the Bengali language, Mugdha, et al. [21] investigate how well various machine learning systems can identify fabricated news stories. The study accomplishes this by developing a unique dataset specifically for the Bengali language. They used the Gaussian Naïve Bayes model and obtained an accuracy rate of 87.4%. Through the utilization of more refined data, their objective is to construct a model that exhibits enhanced precision and efficiency in feature identification.

Several types of ML techniques and strategies for spotting false news have been explored in a recent work [22]. The study also addressed the difficulties linked to identifying false news and emphasized the significance of recognizing fake news. Acquired the dataset on fake news from Kaggle for the research. The DT algorithm outperforms all other ML techniques with an accuracy of 99.36%. Future research directions include integrating additional classifiers and refining feature engineering to improve model robustness in identifying unreliable content. In Elyassami, et al. [23] the efficacy of five ML classifiers such as LR, RF, GB, NB, and SVM were evaluated for binary news classification (authentic vs. deceptive). Performance analysis, based on classification accuracy metrics, revealed RF and GB as superior in handling textual and contextual features. The article Hiramath and Deshpande [24] proposed a disinformation detection framework that benchmarks ML approaches (RF, LR, NB, SVM, deep neural networks/DNN) across computational efficiency, accuracy, and resource utilization. Using a news dataset derived from web-based news platforms, their DNN model achieved 91% accuracy with optimized inference times, outperforming traditional methods. Future extensions of this work could explore hybrid architectures or adaptive training protocols. These studies collectively highlight the importance of algorithmic adaptability and computational efficiency in scalable fake news detection systems.

2.1. Improvement of ML Strategies with Feature Extraction Methods

This section emphasizes research that employed particular feature extraction techniques to improve the efficiency of ML algorithms.

The study published by Baarir and Djeffal [15] developed a framework that uses n-gram analysis and term frequency-inverse document frequency (TF-IDF) to identify fake news. They employ a bag of words as a technique for feature extraction and use SVM as the classifier. In their strategy, a software tool known as WEKA and the SMO library are used to enhance the decision model and achieve improved precision. The researchers determined that the most influential parameters for the SVM were Cost C, gamma γ, and epsilon ϵ. The findings demonstrated the efficacy of the proposed framework. There is potential for conducting the same study using a larger dataset in the future. In a similar direction, Deepak and Ameer [25] concentrated on constructing an ML model that can detect false information. They employed PA and NLP approaches, such as TF-IDF feature extraction. The ML club gathered the UTK dataset from Kaggle for this purpose. The study further demonstrated enhanced model performance through TF-IDF-based classification, achieving 96% classification accuracy. Smitha and Bharath [26] proposed a multimodal framework integrating TF-IDF vectorization, count vectorization, and word embedding techniques to enable granular linguistic analysis. Using the Kaggle fake news corpus, they implemented an SVM classifier with TF-IDF feature engineering, attaining 94% accuracy. Recognizing the limitations of conventional ML approaches, the authors augmented their architecture with DNNs to exploit hierarchical feature learning, further elevating detection precision. This hybrid methodology underscores the value of combining feature diversity with computational linguistics for robust disinformation analysis.

2.2. Ensemble and Advanced ML Models

The research by Tian and Baskiyar [27] explored the viability of KNN and quantum KNN algorithms for disinformation detection, leveraging the Buzzface dataset for empirical validation. To optimize model efficacy, the team integrated Genetic and Evolutionary Feature Selection (GEFeS), a metaheuristic technique for dimensionality reduction, which enhanced KNN's discriminative power to achieve 91.3% accuracy. While classical KNN demonstrated robust performance, the study highlighted unexplored opportunities in quantum-inspired machine learning for parallelized pattern recognition in high-dimensional data spaces. These findings underscore the necessity for expanded experimentation with quantum-classical hybrid architectures to advance computational efficiency in large-scale misinformation analysis.

Research by Neeraj, et al. [28] evaluated DT and KNN alongside established ensemble classifiers such as RF and GB. To enhance detection capabilities, they designed novel hybrid architectures, including stacked generalization and majority voting classifiers, for binary news classification. Using temporally stratified datasets (2016–2017) containing both factual and deceptive articles, their composite framework integrating NB, SVM, and LR achieved 91.5% accuracy. In Patel and Hassan [29] the authors introduced a credibility assessment framework that evaluates semantic coherence and contextual plausibility to flag disinformation. Comparative analysis of classifiers (NB, RNN, SVM, KNN, LSTM) revealed that long short-term memory (LSTM) networks are superior, achieving 97% accuracy through sequential pattern recognition. Agarwal and Dixit [30] proposed an NLP-driven pipeline for high-stakes news verification, leveraging the synthesized WEL Fake dataset. Through eight experimental configurations, SVM achieved peak performance with 98% accuracy, outperforming RF and baseline models. This work underscores the scalability of DL in addressing disinformation when paired with curated, multimodal datasets, emphasizing the need for adaptive architectures in evolving information landscapes.

The work by Aljabri, et al. [31] introduces a multimodal framework for detecting medical disinformation, integrating ten machine learning algorithms with seven feature extraction methods spanning lexical, structural, and domain-specific attributes. Training and evaluation were performed on a verified ground-truth dataset of health-related articles, with reliability ensured through stratified 5-fold cross-validation. This approach demonstrated consistent performance metrics such as precision of 92% and recall of 89% across validation splits, emphasizing the role of multi-algorithm benchmarking and domain-aware feature engineering in combating health misinformation. The study advocates for adaptive validation protocols and computational epidemiology techniques to minimize algorithmic bias in high-stakes applications. LR demonstrated superior performance compared to the other methods, achieving an accuracy rate of 99.87%. As part of their plans, they contemplated developing a framework that encompasses data in languages other than English. The work authored by Elhadad, et al. [32] conducted a comprehensive analysis of ML models, including LSVM, SVM, RNN, CNN, KNN, Naïve Bayes, DT, Stochastic Gradient Descent, and LR. The study found that CNN achieved a superior accuracy rate of 99.8%. Their primary objective was to detect and classify misinformation utilizing ML and AI methodologies.

2.3. Comparative Analysis

Ongoing research on detecting false news involves a thorough examination of ML techniques that are specially developed to improve accuracy. The authors Shaikh and Patil [5] utilized a simple methodology and performed a comparative analysis of three classification techniques. The researchers found that SVM provided the highest level of accuracy, although it necessitated a longer computing time. In contrast, Jain, et al. [20] employed a comprehensive methodology that integrated many attributes and ML techniques, achieving an accuracy of 93.6%, comparable to that of SVM. The linguistic particularities of the Bengali language were explored by Mugdha et al. [22], which resulted in a somewhat lower accuracy of 87% when using GNB.

The studies conducted by Gupta, et al. [22] and Tian and Baskiyar [27] achieved accuracy rates over the 90% threshold, although employing distinct methodologies [27]. Combined quantum algorithms with Genetic and Evolutionary Feature Selection to reach an accuracy of 91.3% utilizing the KNN method. In contrast, Gupta, et al. [22] utilized a DT strategy and achieved an impressive accuracy of 99.36%. This exemplifies the diverse range of methodologies at one's disposal, each offering distinct benefits [30]. Highlighted the significance of having a diverse dataset and achieved significantly better results than Gupta et al. by an impressive proportion of 98% utilizing SVM. Nevertheless, the meticulous approach employed by Baarir and Djeffal [15] which focuses on optimizing parameters in SVM, highlights that the choice of algorithm does not solely determine the effectiveness of the outcomes but also the extent of algorithm refinement. The study conducted by Neeraj, et al. [28] examined ensemble methodologies that combine the strengths of many algorithms. The results, with an accuracy rate of 91.5%, demonstrate the promise of these hybrid models. This aligns with the emphasis of Deepak and Ameer [25] on feature extraction approaches, in which their model highlights the importance of obtaining high-quality data representation to achieve successful outcomes.

The studies conducted by Elyassami, et al. [23] and Elhadad, et al. [32] explored various ML techniques. However, they obtained contrasting results, with Elhadad, et al. [32] using CNN and Elyassami, et al. [23] employing GB and RF. This suggests that the efficacy of the algorithm may be dependent upon the context [29]. Examined the LSTM and demonstrated its dynamic nature in the field by employing advanced DL techniques. The significance of domain specificity and data representation is emphasized by the health-specific approach of Aljabri, et al. [31] and the focus on feature extraction approaches by Smitha and Bharath [26]. Both had impressive accuracies exceeding 90%, indicating that employing specialized tactics in specific contexts has advantageous outcomes. To summarize, the comparison study demonstrates that the different strategies employed in the research all strive for reasonable accuracy in detecting false news. However, it is crucial to strike the right balance between selecting the appropriate algorithm, extracting relevant features, and ensuring the uniqueness of the dataset. The accuracy range, spanning from 87% to over 99%, underscores the intricacies and challenges inherent in this ever-evolving field.

2.4. Critical Assessment

The investigator's collective efforts in the domain of ML to detect false news demonstrate an impressive dedication to addressing a critical issue in the current information ecosystem. Their research employs a diverse array of algorithms, datasets, and methodologies, all aimed at improving the accuracy of fake news detection. While these efforts have yielded promising results, some important issues require consideration. The use of several ML approaches, such as NB, DT, and SVM, has shown high levels of accuracy, indicating potential for practical implementation. However, the research often concentrates on specific algorithms, possibly overlooking the advantages of integrating alternative methods to enhance resilience. Additionally, the model's applicability to real-world scenarios may be limited due to its reliance on particular datasets, which could introduce biases. To enhance the effectiveness and reliability of machine learning models in fake news detection, future research should explore hybrid methodologies, diverse datasets, and robust verification techniques on a broader scale.

Notable scholars have conducted in-depth research that has provided valuable insights closely related to the purpose of our proposed technique; examples are [33]. We are even more dedicated to developing precise ML models after reading their in-depth analysis and evaluation of numerous ML techniques, such as SVM and DT, for the detection of false information. The focal point of our research revolves around achieving enhanced accuracy rates, which are notably prominent in all articles. These experiments showcase the feasibility and importance of our desired objective by employing a range of ML approaches to classify news stories as either genuine or fraudulent. Their research establishes a robust structure for our attempts to enhance the precision of ML-based false news detection.

3. METHODOLOGY

In this section, we explain the procedures used to implement the proposed approach. It includes methods for data collection and preparation, as well as explanations of the models used for analysis and prediction.

3.1. Data Collection

As information spreads rapidly through digital channels, the ability to identify and challenge fake news has assumed heightened significance, necessitating a comprehensive exploration within the realm of data-driven solutions; we set out to choose an appropriate dataset from the Kaggle community site. We made our pick based on numerous crucial factors, each of which had a substantial impact on our decision-making process.

3.1.1. The Size and Quality of a Dataset

The quantity and quality of the dataset are crucial elements in the selection process. We were seeking a dataset that includes a substantial quantity of diverse news stories encompassing a wide range of themes and originating from numerous sources. Due to the wide variety of writing styles, tonalities, and subject areas, the model will have undergone training, allowing it to distinguish between genuine and fabricated news more effectively.

3.1.2. Balanced Distribution

A proper balance between authentic and fake news examples is essential. If the distribution is skewed, the model may perform well for the majority group while ignoring essential details for the minority [5]. A balanced dataset will ensure that the model is not biased and can accurately classify both forms of news.

3.1.3. Review and Community Feedback

Our methodology incorporated systematic reviews of peer assessments and experiential data from prior studies using the dataset. These insights into the dataset's capabilities, constraints, and operational risks informed our feasibility analysis for achieving project goals. Collaborative knowledge-sharing with domain specialists enhanced our evaluation framework for dataset alignment with investigative requirements. Following rigorous evaluation of these parameters, we developed two Kaggle-hosted repositories optimized for disinformation detection systems. These datasets balance technical robustness for misinformation analysis with practical utility to support operational objectives in countering deceptive content, validated through iterative testing and cross-disciplinary peer validation. We selected the Fake and true news dataset [18] as our first dataset, and the second dataset is the Fake News and misinformation text data sets. The initial dataset comprises 44,898 records, which are then categorized into two separate datasets: true and fake. The dataset of fake news has 23,481 entries, whereas the dataset of true news consists of 21,417 records. Both datasets possess four attributes: Subject, Title, Date, and Text. Table 1 displays the data pertaining to the first dataset.

Table 1. First dataset.

News type	Dataset entries
True news	21417
Fake news	23481
Total news	44898

There are a total of 79,000 records in the second dataset, and they are split between two groups: DatasetMisinfoFAKE, which has 43,642 records, and DatasetMisinfoTRUE, which has 34,975 records. There are two characteristics present in both examples: an index and a body of text. The data from the second set are listed in Table 2.

Table 2. Second dataset.

News type	Entries
True news	34975
Fake news	43642
Total news	78617

3.2. Dataset Pre-Processing

Due to the rapid dissemination of false information on the internet, reliable methods of identifying fake news are more important than ever. Only high-quality data must be fed into these systems. The pre-processing of the dataset consisted of the following procedures.

3.2.1. Merging and Labelling of the Data

We added a column labeled "class," where "class 0" indicates false news and "class 1" indicates true news in both of our datasets. Samples of fake and accurate news from both sets were combined to create a third set. To obtain more valuable insights from the predictive model, the data must first be cleansed. The groundwork for our essential pre-processing operations is our newly combined dataset.

3.2.2. The Process of Data Cleaning

A dataset may contain information that is wholly or partially structured, semi-structured, or unstructured. Therefore, data cleaning is crucial for ensuring the reliability, precision, and applicability of test and training data in the ML model. This will improve the quality of the data and eliminate any noise that could prevent the model from correctly identifying bogus news. After combining the datasets, we eliminated columns such as subject, title, and date because only the text and class columns were needed for training. All punctuation, URLs, HTML tags, and newline characters were removed from the dataset. The text was converted to lowercase for consistent processing. Any text enclosed in square brackets that might have contained metadata or citations was eliminated. Alphanumeric strings containing numbers, which might have been identifiers or other irrelevant information, were removed. Non-word characters that separated words were replaced with spaces. The cleaned text was then stored for later use in the research. The second dataset also underwent these meticulous cleaning procedures to ensure standardization.

3.2.3. The Removal of Stopwords

A "stopword" is a word or phrase that has been deemed unnecessary for a given text analysis activity. The NLTK library allows us to filter out these terms by downloading a list of stopwords. Common words like "the," "is," "and," "in," etc., are called "stopwords," and they are taken out of our text data because they are not beneficial to our text analysis. In our situation, we have processed each text to eliminate all instances of stopwords in English and replaced them with the original content.

3.2.4. Data Splitting

It is a method used to generate distinct subsets from a given dataset, which are then used for testing and training purposes. Seventy-five percent of each dataset is used for training, while the remaining 25 percent is used for evaluation in both datasets. The model's learning and generalization capabilities improve significantly when it is trained on a larger dataset. As opposed to being used during model training, the test dataset is only used to evaluate how well the model performs on entirely new data. The quantity of the dataset, the complexity of the model, and the existence of class imbalances are only a few of the factors that influence the decision of the data-splitting ratio. The

75:25 split was chosen for this research because it strikes an appropriate balance between training the model thoroughly and keeping the evaluation reliable.

3.2.5. Feature Extraction

We used the TF-IDF vectorizer technique for feature extraction. TF-IDF enables the conversion of text data into a numerical format, allowing for the identification of unique characteristics in each document. This numerical representation can then be utilized as input for a variety of machine learning methods. TF is a statistical measure of how often a certain word appears in a given text. A higher TF value indicates that the document places greater emphasis on that word. The IDF evaluates how distinctive a term is across the entire corpus. The ratio of total papers to documents containing the word in question is used to derive this measure.

$$\mathrm{TF-IDF} = \mathrm{TF} \times \mathrm{IDF} \tag{1}$$

The final score indicates how significant a term is within a specific text in comparison to how often it occurs across the entire corpus. The ML model is trained using the TF-IDF vectors to identify associations between words and fake news and real news labels.

3.3. Machine Learning Algorithms

Misinformation can be identified using different ML algorithms. We use NB, DT, RF, GB, KNN, LR, PA, and SVM algorithms for additional analysis and predictions.

Decision tree: The Decision Tree (DT) classifier is a widely used machine learning technique known for its high accuracy and precision in classification tasks [34]. Our research findings indicate that DT effectively identifies key factors influencing classification, such as distinctive word patterns or combinations that differentiate real from fake news. Its adaptability to both numerical and categorical data, along with its ability to handle missing values, makes it well-suited for processing the diverse information found in news articles.

Logistic Regression: Logistic Regression (LR) is a widely used approach in both statistical analysis and machine learning for binary classification problems [35]. In this study, LR is employed due to its ability to learn optimal feature weights, enabling it to determine whether a given piece of content is authentic or not. The model estimates the probability of an instance belonging to a particular class, assigning a score between 0 and 1 using the logistic function.

K-Nearest Neighbours: Among the ML toolkits, the KNN is the most basic and least intricate classifier. In this method, training is done using a labelled dataset of news articles that have been manually labelled as fraudulent or genuine. Article features, such as text, are extracted from the dataset during pre-processing. In the prediction stage, KNN finds the unseen news articles using a distance metric of choice and then labels the article according to the distribution of its neighbour classes.

Random Forest: The RF classifier, similar to the DT classifier, is a popular tree-based method extensively employed for classification purposes. The ensemble approach is a technique that enhances accuracy and robustness by combining numerous decision trees [36]. The RF model exhibits a lower error rate than other models due to its low tree correlation, as demonstrated by Liu, et al. [37]. The problems it has previously solved with complicated data structures and nonlinear relationships are well-suited to the ones we are working on.

Support Vector Machine: The SVM classifier performs well in binary classification by utilizing support vectors as anchor points to identify an optimal hyperplane that maximizes class separation [38]. The SVM algorithm is highly proficient at discerning between various categories of news stories, making it a valuable tool for our research. Moreover, SVM can effectively process intricate textual patterns by utilizing kernel functions, enabling it to stand out in scrutinizing linguistic subtleties and detecting deceptive information.

Passive Aggressive: The PA is an online learning algorithm that performs binary classification. It can adjust its parameters based on incorrect predictions, which makes it particularly suitable for scenarios involving sequential data with concept drift. Our study's computational efficiency and low memory consumption make it well-suited for processing large, streaming datasets such as Internet news.

Naive Bayes: The NB algorithm is a probabilistic model that computes probabilities by considering the independence of features given class labels. This property makes it efficient in spaces with many dimensions [37, 38]. NB employs observed characteristics to compute the probability of an article's category and has demonstrated significant outcomes, mainly when dealing with a scarcity of training data or when processing in real-time.

Gradient Boosting: It iteratively merges multiple weak decision tree models sequentially to generate a robust predictive model. By iteratively rectifying errors in the prior ensemble and modifying the weights of data points, it acquires knowledge from incorrectly classified examples, resulting in precise forecasts. The study demonstrates that the system's ability to adjust to complex patterns and manage datasets with noise improves its ability to subtly detect deceptive information.

3.4. Evaluation Metrics

Metrics are used to evaluate the performance and quality of ML algorithms. These indicators provide an essential understanding of the model's strengths and weaknesses. Most of them are based on the confusion matrix. A classification model's effectiveness on a test set is displayed in a confusion matrix. False negative (FN), true negative (TN), true positive (TP), and false positive (FP) are the four variables that make up this matrix, as listed in Table 3.

Table 3. Confusion metrics.

	Predicted positive	Predicted negative
Actual positive	TP	FN
Actual negative	FP	TN

We used the following matrices to evaluate all the classifiers on both datasets:

Accuracy: Accuracy is the most straightforward metric because it simply indicates whether or not the prediction was correct. Correctly predicted samples are divided by the total number of samples in the dataset to determine the accuracy rate.

$$Accuacy = \frac{(\text{Number of Correct Predictions})}{(\text{Total Number of Samples})} \tag{2}$$

A better model is represented by one with a higher accuracy score. However, there is still a potential for the forecast to be incorrect. Therefore, three additional metrics were used to account for misclassified observations: recall, precision, and F1-score.

Precision: The accuracy of a model is measured by how many correct predictions it makes relative to the total number of predictions. It indicates the ratio of correctly predicted events to the total predicted events.

Recall: The recall measures how many correct predictions were made out of a total number of events. This exemplifies the model's ability to identify favourable outcomes accurately.

F1-Score: It is the average of the two measures: recall and precision. It is an excellent all-around metric because it considers both recall and precision.

3.5. Tools and Software used in Our Experiment

Our system uses Jupyter Notebook as the development environment and Python 3.9 for all coding, which reduces the time it takes to complete the project. We are using Python because, unlike many other programming languages, it can be deployed on multiple platforms without any additional modifications. It makes our code easier to read and more concise. Numerous libraries have been utilized, such as Pandas, NLTK, Scikit-Learn, Seaborn, NumPy, and Matplotlib.

3.6. Proposed Method

The following steps (see Figure 1) will be employed in this work to achieve the goal: In the first stage, we will perform pre-processing on the dataset and extract features. The pre-processing is explained earlier. Separate training and test sets will be created from the entire dataset. The next phase involves training the model with training data. Standard assessment criteria, including Recall, Precision, Accuracy, and F1-Score, will be used to evaluate the models after their performance has been recorded. We will analyze the model's output and select the most effective approach based on its performance and accuracy in recognizing the target. We will also consider the computation time and accuracy level of all the models.

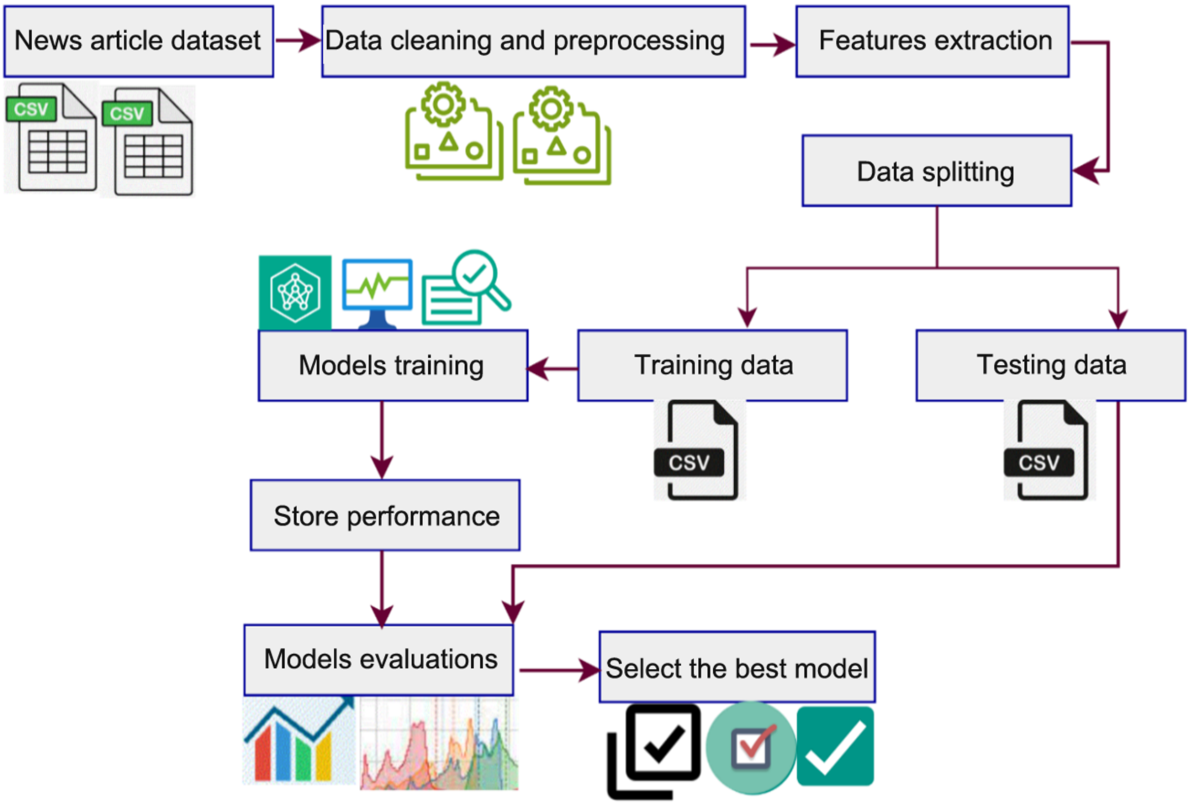


Figure 1. Working architecture of the proposed methodology.

4. ANALYSIS OF RESULTS

We have thoroughly explained the analysis of the collected results in this section. It also includes the subsections listed below.

4.1. Classes Distribution

We used a count plot to show how the datasets were split between true and false labels. The count plot is a vital tool for evaluating the balance or imbalance of the two classes in the dataset shown in Figure 2 and Figure 3.

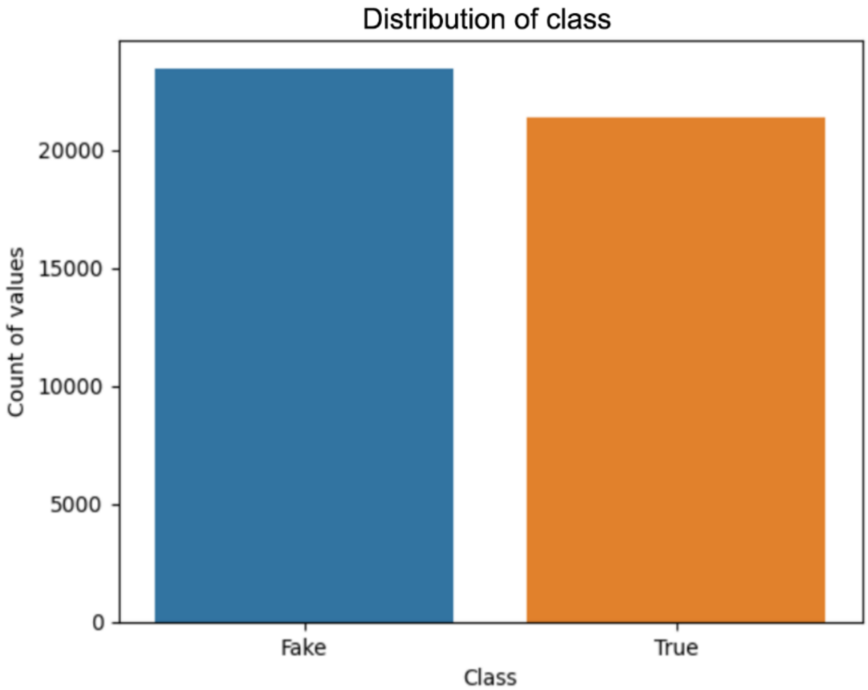


Figure 2. True and False label class distribution for DS1.

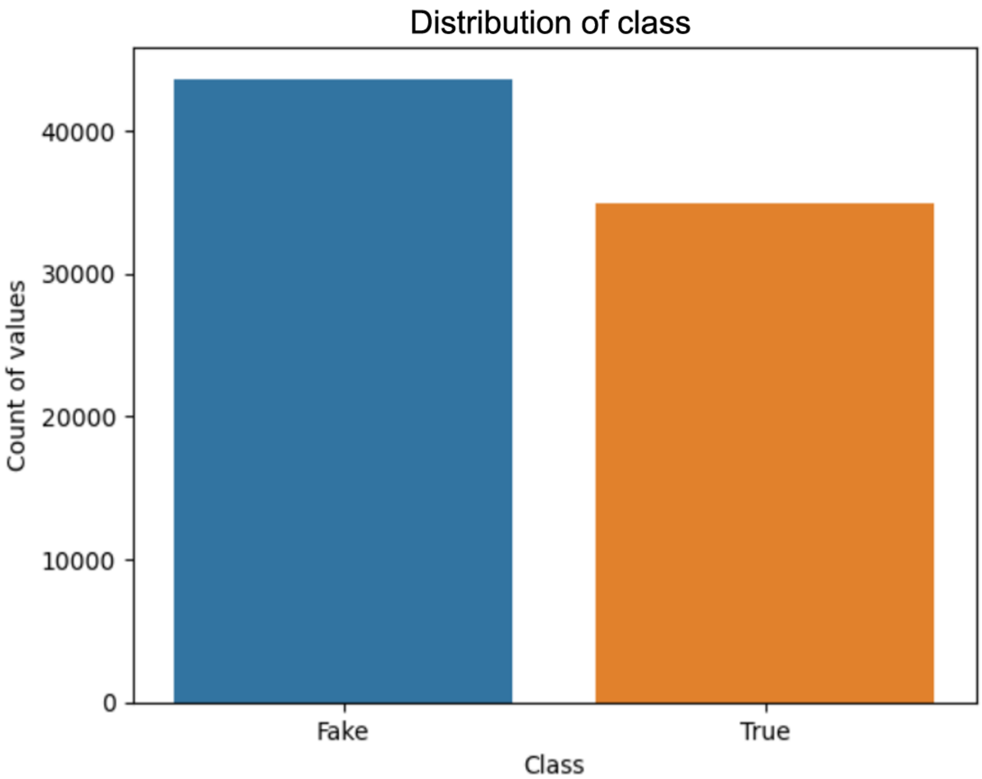


Figure 3. True and False label class distribution for DS2.

4.2. Text Distribution

Using a bar chart, we compared the number of texts representing different topics, as shown in Figure 4. This is useful for seeing how the DS1 text data is dispersed across various subjects, which in turn aids in identifying trends and disparities among those subjects.

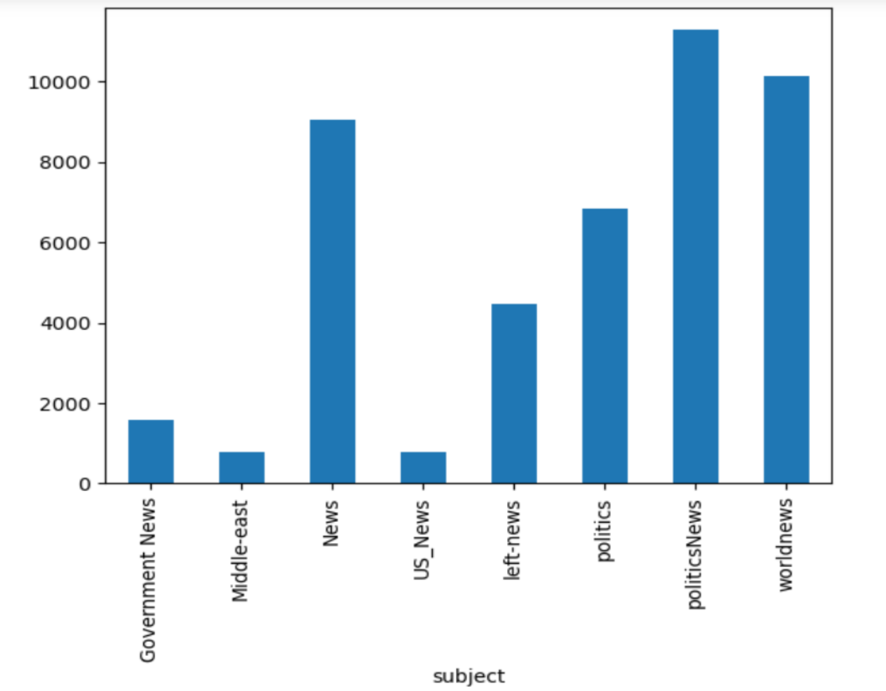


Figure 4. Text data subject classification for DS.

4.3. Top Bigrams in the Text

A bigram is a pair of consecutive components in a text or data set, usually words or letters. Bigrams are frequently utilized for text analysis and processing in the fields of NLP and computational linguistics. A bigram is a particular case of an n-gram, a series of n-consecutive elements. For example, n = 2 for bigrams. We examined the most common pairs of words (bigrams) in the combined dataset. This aids in the identification of critical phrases, pattern recognition, etc., all of which improve the accuracy of our model, as shown in Figure 5 and Figure 6.

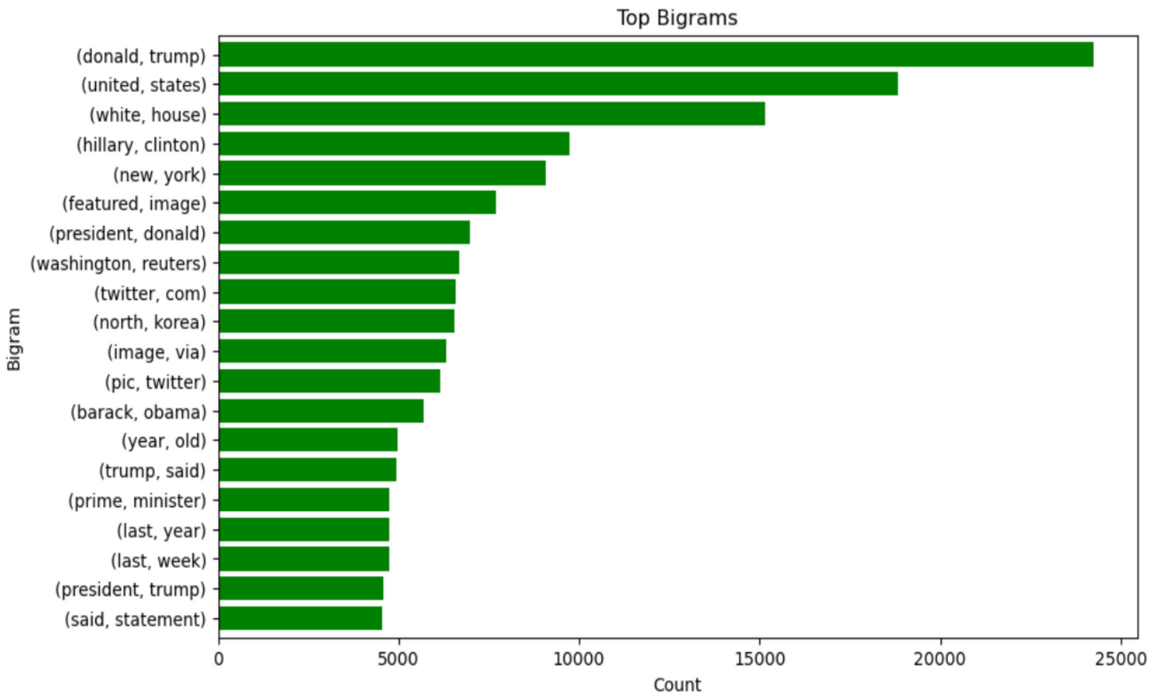


Figure 5. DS1 words data set for top bigrams.

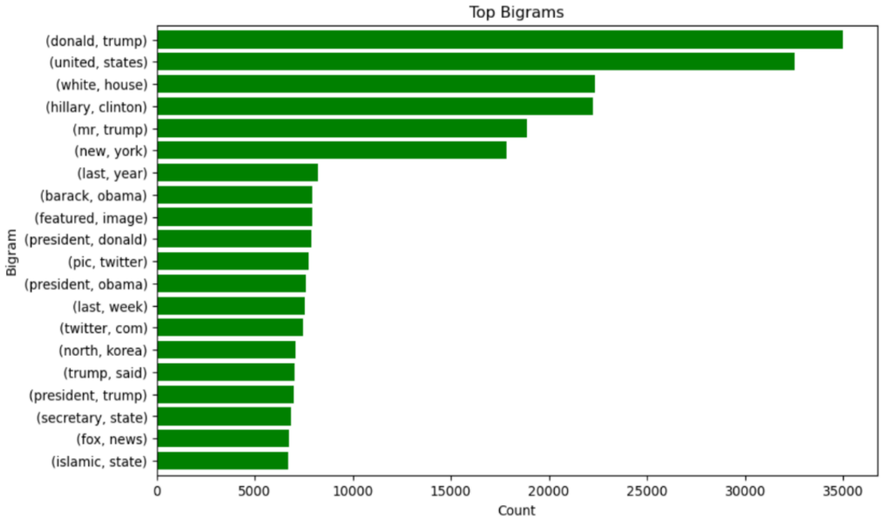


Figure 6. DS2 words data set for top bigrams.

4.4. The Discussion of Results we Obtained using Eight ML Models

Eight distinct machine learning algorithms, including GB, DT, RF, LR, NB, PA, SVM, and KNN, have been applied to the separated training and testing data. Figure 7 and Figure 8 display the accuracy of these eight methods on two separate datasets. The decision tree (DT) algorithm outperforms other algorithms in DS1 with an impressive 99.591% accuracy. The gradient boosting (GB) classifier, with its accuracy of 99.537%, is very close to this performance. The passive-aggressive (PA) algorithm achieved a maximum accuracy of 99.511%. The 99.341% precision rate achieved by the support vector machine (SVM) is also noteworthy. When applied to DS2, the SVM method again demonstrates its robustness by achieving an accuracy of 95.179%, solidifying its position as the top performer. The PAC is equally reliable after SVM, with an accuracy of 95.027%, while the logistic regression (LR) shows an accuracy of 93.882%. Notably, the random forest (RF) algorithm's performance remains consistent, with an accuracy of 93.434% in Dataset 2, which is still substantial. K-nearest neighbors (KNN) performs poorly, with accuracy levels of 64.134% and 67.399% in Dataset 1 and Dataset 2, respectively, as shown in Figure 7 and Figure 8. This indicates a lower level of efficacy. Due to its limited ability to capture complex decision boundaries in high-dimensional environments, KNN is highly susceptible to background noise.

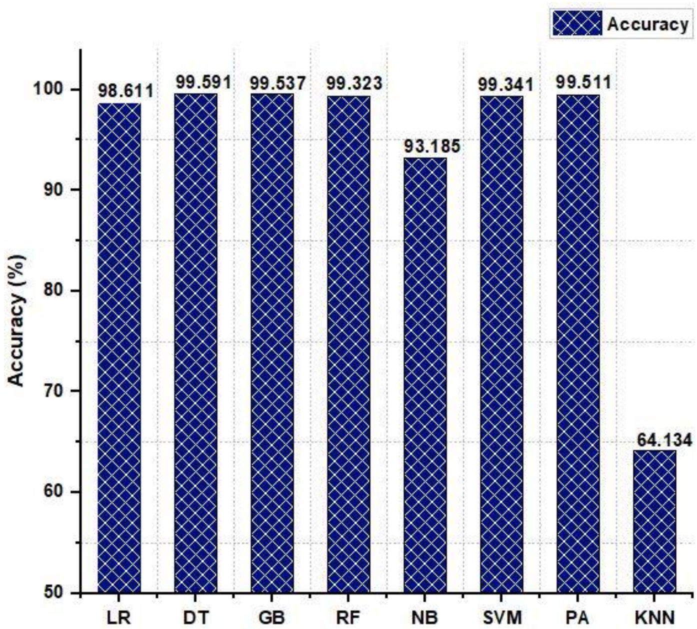


Figure 7. Accuracy of Dataset 1.

Figure 8. Accuracy of Dataset 2.

Figure 9 displays the average accuracy of both models on both datasets. The average accuracy of PA and SVM is 97.269% and 97.26%, respectively, while the average accuracy of KNN is 65.766%. In addition to the accuracy score, we employ recall, precision, and F1-score to evaluate the effectiveness of the learning models.

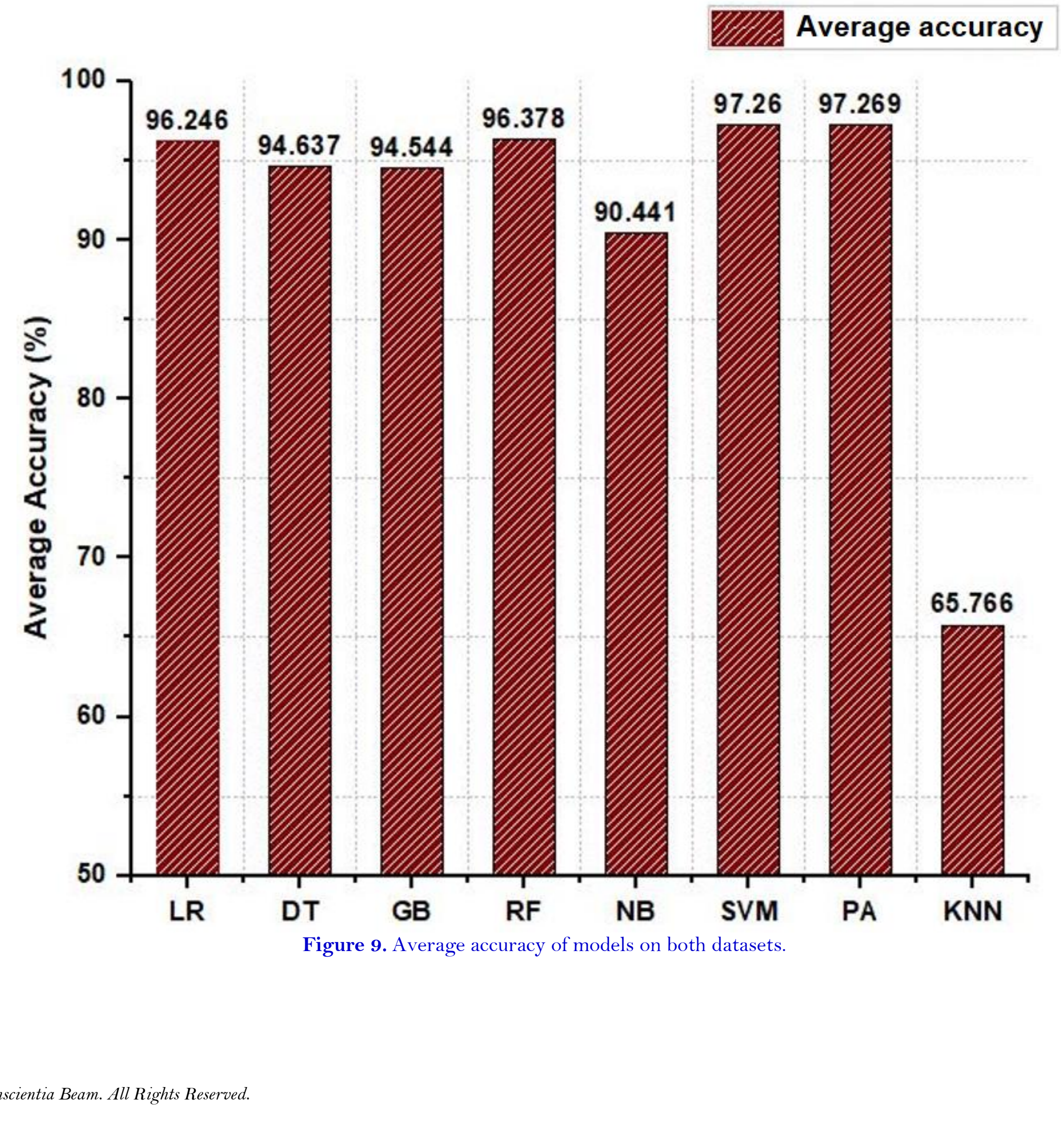


Figure 9. Average accuracy of models on both datasets.

Figure 10 and Figure 11 for data set 1 and Figure 12 and Figure 13 for data set 2 display precision, recall, and F1 scores for each model across two datasets. In DS1, the Recall, Precision, and F1-score metrics remain stable across both classes for all models. The high accuracy and recall of DT, LR, and RF confirm their effectiveness in distinguishing between real and fake news. Meanwhile, GB's strong recall, precision, and F1-score highlight its strength in detecting authentic news. SVM stands out as a top performer, achieving consistently high recall and precision across both classes, demonstrating its robustness in classification. PA maintains a balanced trade-off between recall and precision, ensuring reliable differentiation between genuine and fabricated content. However, KNN struggles with precision for the real news class, indicating challenges in accurately identifying authentic news articles.

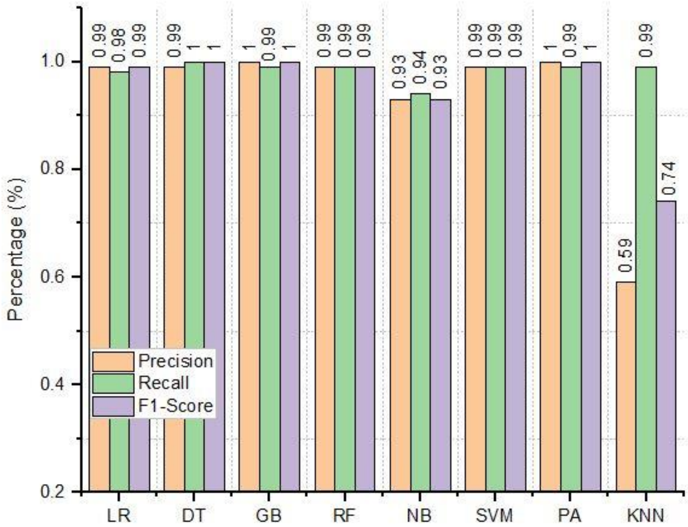


Figure 10. Evaluation metrics of fake news of dataset 1.

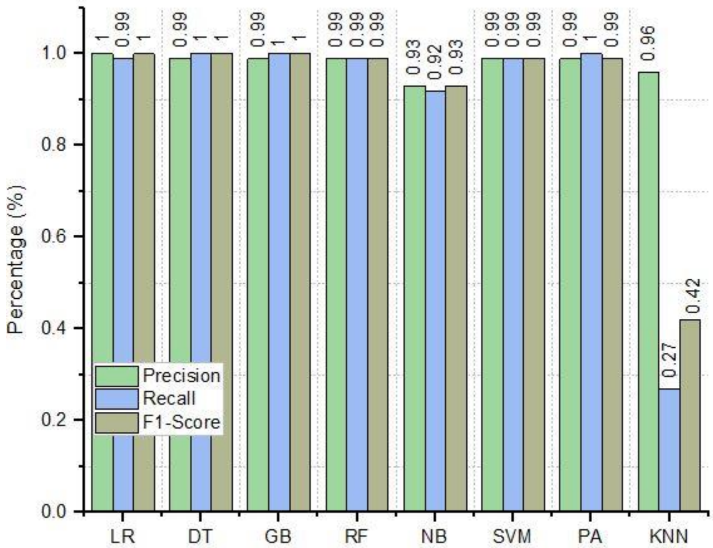


Figure 11. Evaluation metrics of true news of dataset 1.

When evaluating classifiers based on several performance parameters, the PAC and SVM models demonstrate remarkable performance. Through comprehensive research and rigorous testing, they have demonstrated an exceptional capacity to outperform their rivals in several tasks. Consistently, they have surpassed other classifiers in terms of recall, precision, and F1-score metrics, establishing themselves as the optimal choices for a wide range of applications.

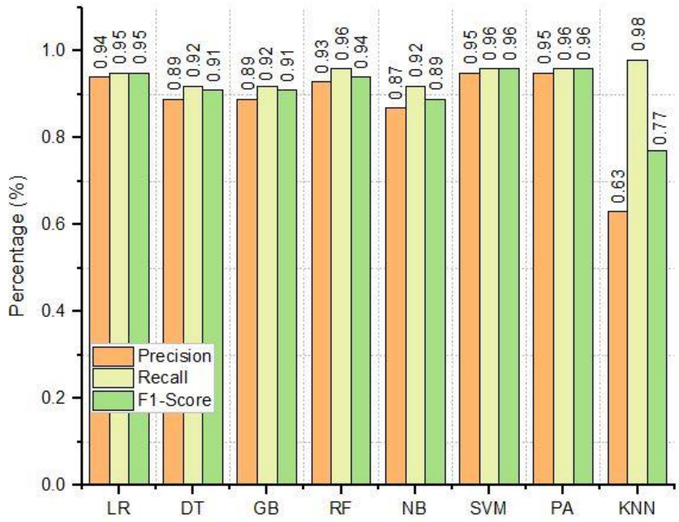


Figure 12. Evaluation metrics of fake news of dataset 2.

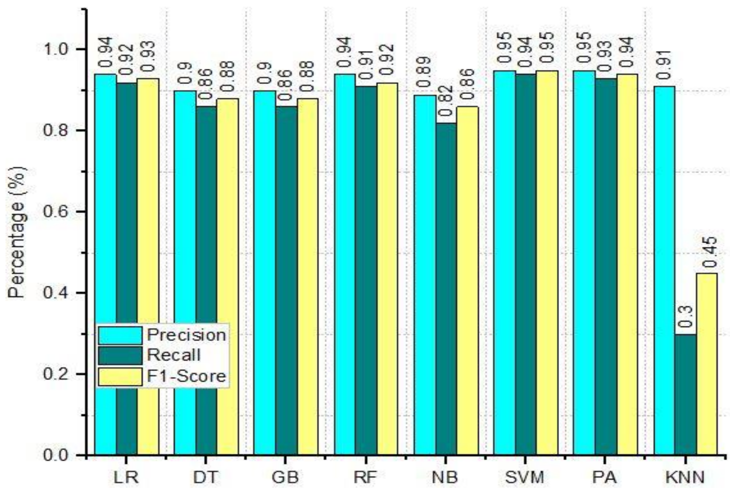
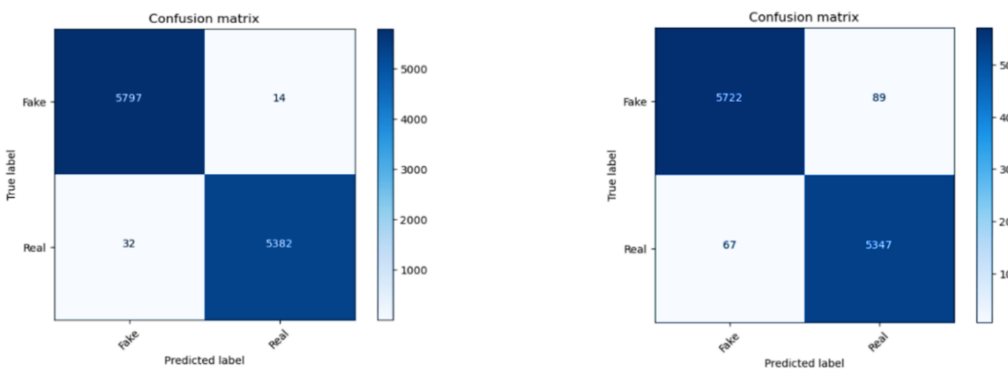


Figure 13. Evaluation metrics of fake news in dataset 2.

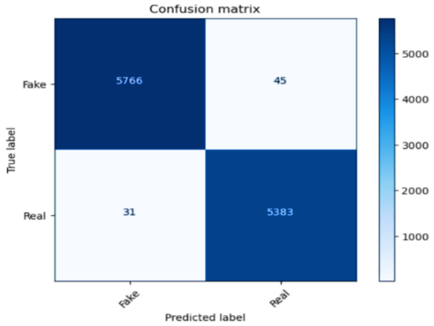
4.4.1. Confusion Matrix

Evaluating the performance of a classification model can be accomplished by employing a confusion matrix, as shown in Figure 14. Given the challenges associated with classification, a system with two or more classes may be required. Confusion matrices determine the precise count of accurate, inaccurate, and uncertain classifications by comparing the predicted labels from the classification technique with the actual classes from the original dataset.

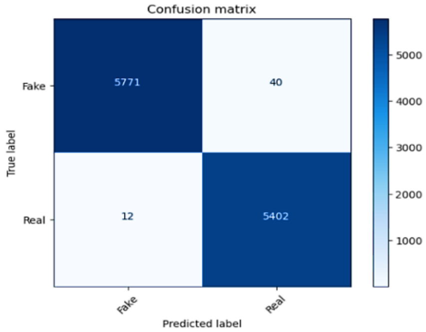


(a)

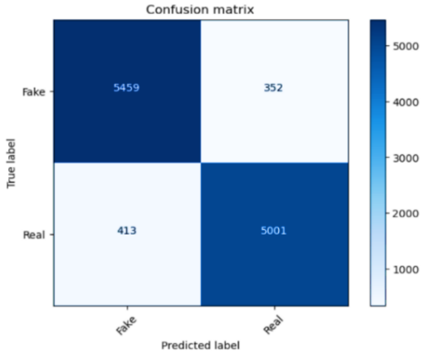
(b)



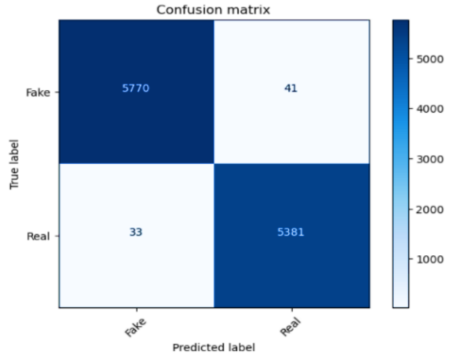
(c)



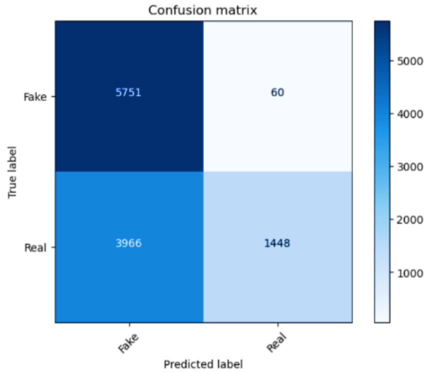
(d)



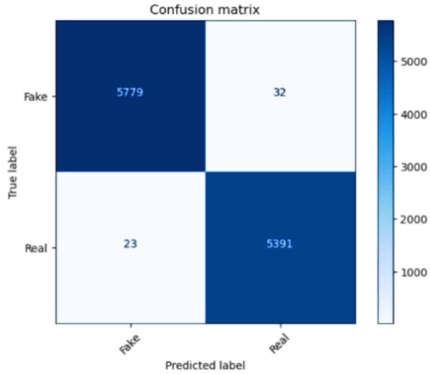
(e)



(f)



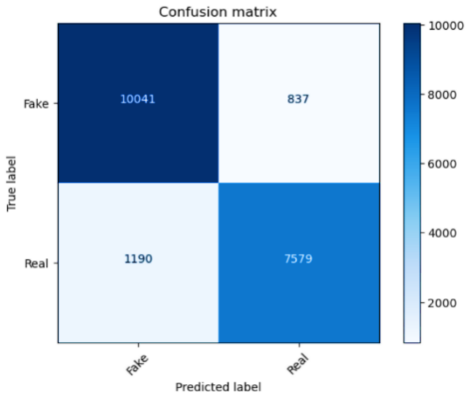
(g)



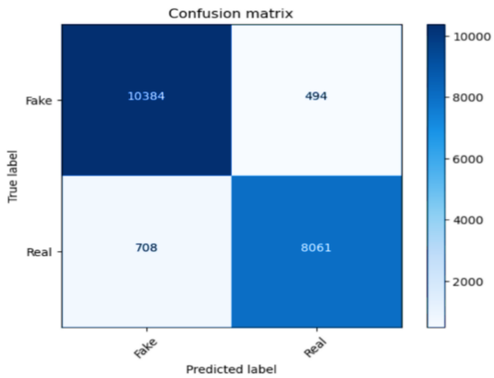
(h)

Figure 14. Confusion matrix of Dataset 1: (a) DT (b) LR (c) RF (d) GB (e) NB (f) SVM (g) KNN (h) PA.

The confusion matrix tree of various techniques in two datasets is illustrated in Figure 14 and Figure 15. Based on Figure 15, the GB classifier and the DT classifier demonstrated superior performance, whereas KNN did not meet expectations and yielded the lowest results. Figure 15 demonstrates that SVM and PA exhibited the most impressive achievements. Similarly, in the DS1 scenario, KNN displayed the lowest results.



(a)



(b)

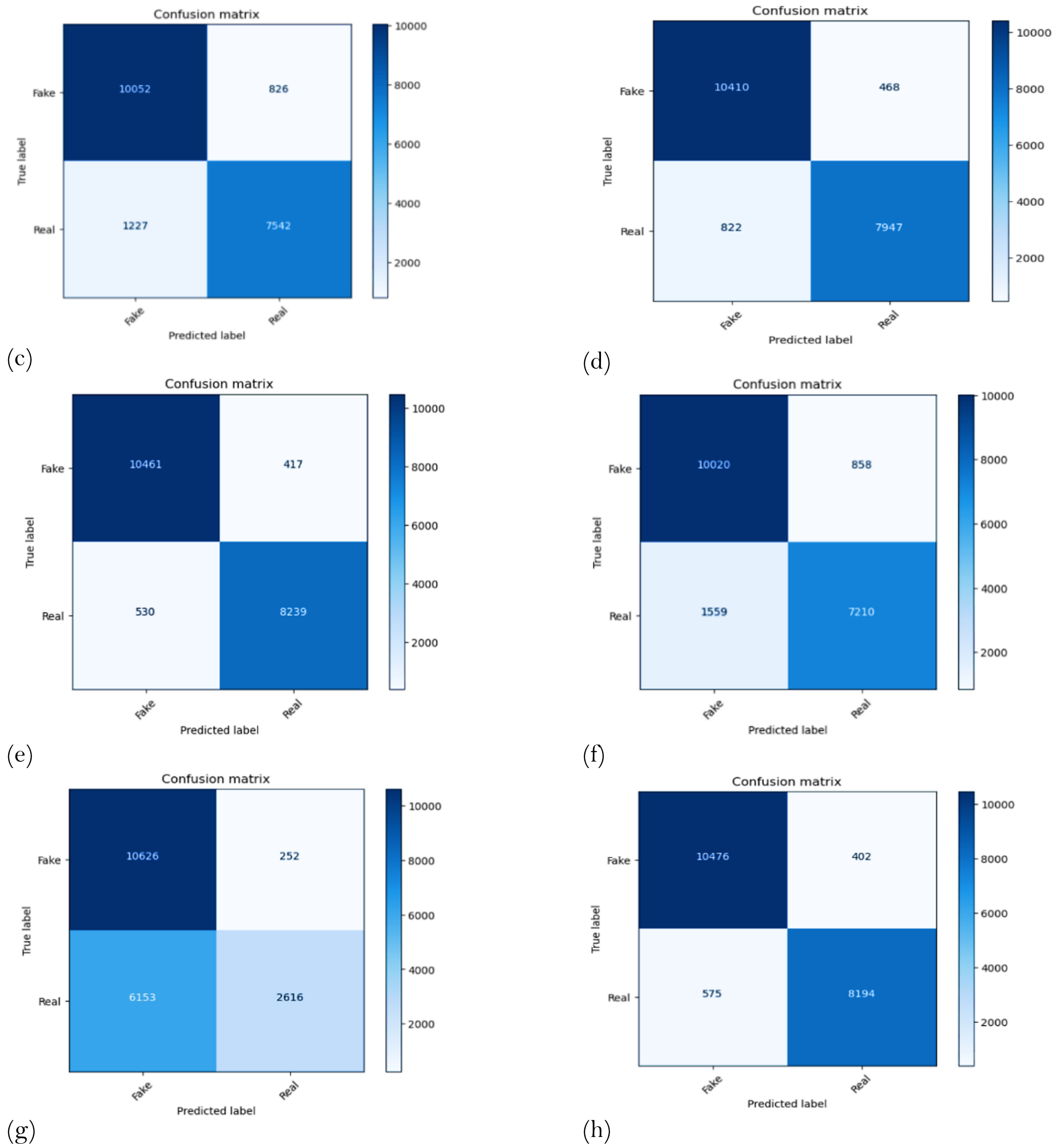


Figure 15. Confusion matrix of Dataset 2: (a)DT (b)LR (c)GB (d)RF (e)SVM (f)NB (g)KNN (h)PA.

5. FINDING AND PERFORMANCE EVALUATION

We have presented the results of our study on identifying false news by employing various ML algorithms on two separate datasets, DS1 and DS2. Our goals were to determine the most suitable ML algorithm and to investigate how the size and complexity of the dataset impact the efficacy of different ML techniques. All models exhibited comparable accuracy and performance across metrics on the smaller DS1 dataset. However, as the DS2 dataset expanded to 79,000 instances, most models experienced a notable decline in performance. This highlights the difficulty of maintaining detection precision when handling larger and more diverse datasets.

5.1. Automated News Classifier

In an era where news credibility is increasingly contested, automated verification systems are critical for systematically evaluating content legitimacy [39]. Our research advances this objective through a computational framework designed to classify news articles as authentic or deceptive with high precision. By integrating eight machine learning classifiers, the system employs a structured framework for evaluating textual patterns, semantic coherence, and contextual anomalies. Users can input articles to receive a consensus-driven classification, leveraging ensemble predictions to minimize individual model biases. For validation, we applied the system to textual datasets derived from verified news repositories. Each classifier generates probabilistic outputs, enabling granular analysis of algorithmic confidence. Empirical results indicate consistent alignment across all models (excluding KNN) in classifying test articles, with robust correspondence to ground-truth labels. This underscores the framework's reliability in supporting evidence-based assessments of information integrity, equipping users to navigate complex media ecosystems with data-driven insights.

5.2. Research's Novelty

This study's unique contribution stems from its broad evaluation of multiple ML algorithms, including passive-aggressive classifiers, a less common choice in prior fake news detection research. By testing these models on two distinct datasets, the work demonstrates their adaptability to varied data structures and sources, reinforcing their applicability across different misinformation scenarios. The analysis acknowledges the contextual complexity of disinformation, where deceptive patterns shift across sociopolitical or topical domains. Detailed accuracy metrics (ranging from 84% to 96%) provide actionable guidance for researchers and developers to select context-appropriate techniques. For instance, the underperformance of KNN in cross-dataset validation underscores challenges in handling high-dimensional text features or sparse data common in misinformation datasets. This research presents a groundbreaking framework that broadens the scope of methodological approaches in the ongoing struggle against disinformation.

5.3. Comparison with State-of-the-Art Methods

Previous studies on ML-based false news detection have systematically evaluated various algorithms to measure their effectiveness in addressing key challenges. These comparisons typically involve multiple classifiers, including DT, RF, SVM, NB, and others. Researchers assess these models using metrics such as recall, F1-score, precision, and accuracy to improve the distinction between fake and authentic news articles.

5.3.1. Decision Tree

The study by Gupta, et al. [22] evaluated six different ML algorithms for detecting and classifying fake news. After extensive testing and analysis, DT emerged as the most effective approach. It achieved an impressive accuracy of 99.36%, providing clear and interpretable classification rules. Our research using a DT yielded an accuracy of 99.591% on DS1 and 89.683% on DS2. While DS1's accuracy improved slightly, DS2's accuracy dropped by approximately 10% compared to this current model. Both experiments utilize datasets sourced from Kaggle. The study conducted by Gupta, et al. [22] utilized a dataset consisting of 20,000 records. In comparison, our DS1 dataset contains 49,000 entries, while DS2 contains 79,000 entries. There has been a notable enhancement in utilizing the DS1 dataset for the purpose of identifying and detecting fake news.

5.3.2. Logistic Regression

The article authored by Elhadad, et al. [32] examined ten ML algorithms in conjunction with seven feature extraction approaches to analyse fake news pertaining to healthcare. The researchers achieved an impressive accuracy rate of 99.87% using the LR algorithm. According to our research, DS1 accuracy is 98.611%, and DS2 accuracy is 93.882%, respectively, by utilizing LR. When combining both datasets, we observed a lower accuracy compared to previous research.

5.3.3. Gradient Boosting

The approach developed by Smitha and Bharath [26] utilizes seven ML frameworks and three distinct feature extraction techniques. The GB technique, along with the TF-IDF feature extraction method, yielded a 90% accuracy rate. Conversely, DS1 attained a precision level of 99.537 percent, and DS2 achieved a precision level of 89.551 percent when utilizing GB.

5.3.4. Random Forest

The research conducted by Gupta, et al. [22] achieved a high accuracy of 99.29% using the RF algorithm, which was somewhat lower than the accuracy achieved by the DT algorithm. In contrast, the research conducted by Sharma, et al. [17] reported a minimum accuracy of 59% when employing the RF algorithm. However, in our given scenario, DS1 and DS2 achieved better levels of accuracy utilizing the RF model, with individual scores of 99.323% and 93.434%, respectively.

5.3.5. Naïve Bayes

The study conducted by Mugdha, et al. [21] evaluates the effectiveness of different ML algorithms in detecting fake news in the Bengali language. This is achieved by developing a unique dataset specifically for the Bengali language. They achieved their objective by employing the NB method and obtained an accuracy of 87.4%. Our accuracy rates for DS1 and DS2 were 93.185% and 87.698% respectively. The research conducted was superior to previous studies, and NB outperformed other methods when applied to our English Language datasets.

5.3.6. Support Vector Machine

SVM consistently demonstrated superior performance in the majority of prior studies. The study conducted by Shaikh and Patil [5] utilized a reduced dataset obtained from Kaggle. They employed SVM as an ML method and achieved an impressive accuracy of 95.05%, surpassing the performance of other ML techniques. The authors Jain, et al. [20] only employed NB and SVM as the ML algorithms. SVM exhibited superior performance compared to NB, achieving an accuracy of 93.6%. In contrast to RF, the SVM model was used in the study conducted by Aljabri, et al. [31]. Achieved superior performance. The inclusion of several supplementary fake news datasets allowed for this, resulting in a 98% accuracy rate. Seven ML models and three different feature extraction algorithms were used in another investigation, Smitha and Bharath [26]. With the use of SVM and a variety of TF-IDF extraction algorithms, they were able to achieve a remarkable 94% accuracy. Our research outperformed the vast majority of prior studies, with an accuracy of 99.341% for DS1 and 95.179% for DS2. Our analysis confirms that SVM outperformed all other methods, with the exception of the study conducted by Aljabri, et al. [31].

5.3.7. Passive Aggressive Classifier

In a study conducted by Deepak and Ameer [25], only the PAC method was employed for false news identification, achieving an accuracy of 96% with the utilization of TF-IDF as the feature extraction technique. The accuracy of our DS1 model was 99.511%, while DS2 obtained an accuracy of 95.027%. DS1 achieved a remarkable accuracy compared to DS2 and the previous research.

5.3.8. K-Nearest Neighbour

The authors of Tian and Baskiyar [27] explored using machine learning models, especially KNN and QKNN, to identify instances of fake news. They observed that the KNN algorithm had the highest accuracy, reaching 91.3%. However, when applying KNN to our scenario, neither of the datasets performed exceptionally well. The accuracy for DS1 was 64.134%, while for DS2 it was 67.399%. Regarding previous research, the authors employed the genetic engineering feature selection method, which outperforms TF-IDF when applied to KNN. The methods selected for this study include Decision Tree (DT), Logistic Regression (LR), Naive Bayes (NB), Random Forest (RF), Gradient Boosting (GB), Passive-Aggressive (PA), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), based on previous model evaluations. The news articles were successfully classified using these classifiers on the dataset.

The PA classifier demonstrated superior average accuracy, with a rate of 97.269%, surpassing previous models. This research has enhanced the process of identifying fake news in online media by utilizing the passive-aggressive classifier. The study resulted in the development of a sophisticated automated system that employs eight machine learning classifiers to accurately differentiate between authentic and falsified news stories. This system promotes well-informed decision-making in the current complex information environment.

5.4. Findings Explanation

5.4.1. Dataset's Robustness

In our results, the PA and SVM demonstrated excellent performance on both datasets, consistently achieving high accuracy. The proficiency in efficiently overseeing varied data characteristics underscores its potential for practical application in real-life scenarios.

5.4.2. Accuracy Complexity

In DS1, the GB and DT showed excellent accuracy, indicating their ability to understand subtle relationships within the data. However, RF's reduced accuracy suggests a trade-off between complexity and precision.

5.4.3. KNN's Sensitivity

Due to its reduced accuracy in both datasets, KNN's sensitivity to noise and difficulties in high-dimensional spaces are further reinforced. This result is consistent with its poor ability to record intricate patterns.

6. CONCLUSION

Manual news classification requires subject knowledge and can be affected by text inconsistencies. This study employs machine learning (ML) algorithms to detect fake news. Eight ML models were used for classification, utilizing two Kaggle datasets containing numerous examples of both fake and real news. The learning models were trained and parameterized to enhance accuracy. Only text and class features from the datasets were used for detection. The developed ML model was evaluated, resulting in improved accuracy in identifying false news. The study successfully achieved its objective by thoroughly analyzing the strengths and weaknesses of different ML models for fake news detection. Standard evaluation metrics were employed to compare the performance of all models. The ML algorithms used include Naive Bayes (NB), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Passive Aggressive (PA), Random Forest (RF), Gradient Boosting (GB), and Support Vector Machine (SVM). PAC demonstrated a superior average accuracy of 97.269% compared to other models. Detecting fake news presents several unresolved issues that require further investigation. Recognizing the fundamental components involved in news transmission is a critical initial step in curbing the spread of false information. Graph theory and transformer techniques, combined with multimodal analysis, can be employed to identify primary sources responsible for disseminating fake news. Another potential future trend is the real-time detection of fake news in videos. The limited availability of labeled data can be addressed by developing unsupervised or semi-supervised algorithms, which may be effective in identifying patterns or clusters in data without relying heavily on labeled samples.

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Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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