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Investigating Conventional Machine Learning Classifiers for Fake News Detection

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Abstract: The rapid proliferation of fake news on digital platforms poses a significant challenge to public trust, social stability, and informed decision-making. To address this concern, this study investigates the effectiveness of conventional machine learning classifiers for fake news detection using hand-crafted textual features. Several widely used models, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression, and Random Forest, were evaluated after applying rigorous preprocessing and feature extraction techniques. Experimental results highlight that KNN and SVM demonstrated superior performance, achieving up to 88% accuracy in distinguishing between authentic and fabricated news. The findings underscore the importance of leveraging well-structured datasets and robust classification techniques to combat misinformation effectively. This work provides a foundation for developing scalable and reliable automated systems for mitigating the spread of misleading content in online environments.

Keywords: Fake News Detection, Machine Learning Classifiers, Fake News Dataset, Classifier Performance.

I. INTRODUCTION

The rapid growth of digital media has transformed the way individuals access and consume information. While this evolution has democratized news dissemination, it has also facilitated the spread of fake news deliberately fabricated or misleading content presented as factual information. Unlike misinformation, which may result from unintentional errors, fake news is intentionally designed to deceive or manipulate public opinion for political, financial, or social gains. Its proliferation has been linked to threats to democratic integrity, societal polarization, and even national security.

Fake news manifests in various forms, including fabricated stories, sensationalized headlines, satirical or parodic content misinterpreted as factual, and manipulated multimedia such as images, videos, or deepfakes. Social media platforms, encrypted messaging applications, blogs, video-sharing sites, and even traditional media channels serve as primary conduits for the dissemination of such content. In India alone, the number of internet users has risen from 137 million in 2012 to more than 800 million in 2024, underscoring the scale and potential impact of misinformation in one of the world's largest digital markets.

The consequences of fake news are severe and multifaceted. It can erode public trust, disrupt social cohesion, damage reputations, and mislead individuals in critical areas such as health, finance, and politics. The COVID-19 pandemic further amplified the urgency of automated solutions by illustrating how misinformation can hinder effective public health responses. Addressing this challenge requires robust detection systems capable of distinguishing between legitimate and fabricated information.

In recent years, machine learning (ML) has emerged as a promising solution to this problem. By analyzing textual features such as writing style, linguistic patterns, and dissemination trends, ML models can classify news articles with high accuracy. Conventional classifiers such as Logistic Regression, Naïve Bayes, K-Nearest Neighbors (KNN), Random Forest, and Support Vector Machines (SVM) have demonstrated effectiveness in various natural language processing (NLP) applications and remain widely used for fake news detection.

The objectives of this study are threefold:

1. **To curate a diverse dataset of authentic and fake news articles** sourced from multiple outlets, providing a structured resource for experimentation.
2. **To implement and evaluate conventional machine learning classifiers** for fake news detection, focusing on widely used algorithms.
3. **To analyze and compare model performance** using metrics such as accuracy, precision, recall, and F1-score, thereby identifying the most effective approaches for misinformation detection.

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By addressing these objectives, this research contributes to the ongoing efforts to mitigate the societal risks posed by fake news and highlights the potential of machine learning as a reliable tool for misinformation detection.
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II. LITERATURE REVIEW

The detection of fake news has gained significant attention in recent years, with researchers employing a variety of machine learning and deep learning approaches. Conventional machine learning models remain a widely explored avenue due to their interpretability and effectiveness in handling structured textual data. For instance, Khanam et al. [1] applied XGBoost, SVM, and Random Forest on textual features, reporting an accuracy of 75%. Similarly, Uma Sharma et al. [4] demonstrated the efficiency of Naïve Bayes, Random Forest, and Logistic Regression, achieving an F1-score of 0.92, while Tanvir et al. [5] reported an even higher F1-score of 0.94 using a similar set of models. Ahmad et al. [6] further highlighted the potential of ensemble learning, obtaining an F1-score of 0.99 with Random Forest and XGBoost. These studies collectively emphasize the strong performance of conventional classifiers in text-based fake news detection tasks. Beyond traditional approaches, researchers have explored hybrid and explainable models. Shu et al. [3] proposed dEFEND, an explainable fake news detection model that incorporates both textual and user engagement data, achieving an F1-score of 0.82 on the FakeNewsNet dataset. Qi et al. [7] expanded the scope of fake news detection across languages by integrating multilingual social network analysis, attaining an F1-score of 0.90. Khan et al. [10] demonstrated the benefits of combining lexical and sentiment features with conventional classifiers, achieving a combined corpus F1-score of 0.72. These contributions indicate that hybrid features and engagement signals can significantly enhance classification accuracy and interpretability. In parallel, deep learning-based approaches have shown remarkable improvements in capturing semantic and contextual information. Kumar et al. [11] and Kaliyar et al. [12] employed CNN and LSTM architectures, reporting accuracies of 88.78% and 97.3%, respectively, while Balshetwar et al. [15] achieved 93.8% with similar models. Ajao et al. [17] and Thota et al. [18] further validated the robustness of deep neural networks (DNN), reporting F1-scores above 0.84. These results highlight the ability of deep learning methods to capture complex linguistic patterns, albeit often at the cost of interpretability. More recent studies have explored multimodal approaches. Sharma et al. [19] combined textual and image data, applying Random Forest to achieve 94% accuracy, while Hirlekar et al. [20] demonstrated that incorporating both user and tweet features significantly boosted performance, with F1-scores improving from 0.78 to 0.94. Similarly, Alonso et al. [14] achieved an F1-score of 0.90 using KNN, and Bhutani et al. [16] reported 99.5% accuracy with Random Forest and Naïve Bayes. Hakak et al. [8] even reported perfect classification with traditional classifiers such as Decision Tree and Random Forest, though such results may raise concerns about dataset bias and overfitting. Overall, existing studies highlight the effectiveness of both conventional and deep learning methods in detecting fake news, with hybrid and multimodal approaches offering additional gains. However, a key challenge remains the lack of standardized, balanced datasets and the limited exploration of traditional machine learning classifiers in comparison with deep learning models. Moreover, while deep learning methods often achieve high accuracy, their reliance on large datasets and limited interpretability pose constraints in practical deployment. These gaps motivate the present study, which systematically evaluates multiple conventional classifiers on curated datasets to assess their performance and reliability in fake news detection.

Literature Gap:

Despite extensive research on fake news detection, several gaps remain unaddressed. First, the majority of prior studies rely on widely available benchmark datasets such as LIAR, FakeNewsNet, BuzzFeed, and various Kaggle collections. While these datasets have facilitated model benchmarking, they are often limited in diversity and fail to represent region-specific contexts, particularly for countries like India where the dynamics of misinformation may differ significantly from Western sources. This lack of cultural and regional representation restricts the generalizability of existing models.

Second, much of the literature has focused predominantly on textual features, with limited integration of additional linguistic, contextual, or hybrid attributes that could enhance classification performance. Moreover, although conventional machine learning classifiers such as SVM, KNN, Naïve Bayes, and Random Forest have been frequently applied, few studies have conducted a systematic comparison of these models on balanced, heterogeneous datasets that combine both Indian and Western news sources.

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Table 1: Some previous work on Fake News.

S. No.	Author	Features	Method	Performance/ Result
1.	Z Khanam et al.	Text, Extraction and vectorization	XGBOOST, Support Vector Machine and Random Forest	75%
2.	Cui et al.	Text	SAME	F1- 77.24
3.	Shu et al.	Text	dEFEND	F1- 0.82
4.	Sharma et al.	Text	Naïve Bayes, Random Forest Logistic Regression	F1-Score of 0.92
5.	Tanvir et al.	Text	Naïve Bayes, Support Vector Machine, Logistic Regression	F1-Score of 0.94
6.	Ahmad et al.	Text	Random forest, XGBoost	F1-Score of 0.99
7.	Qi et al.	Text, social network engagement	Multilingual social network analysis	F1- score of 0.90
8.	Hakak et al.	Text	Decision tree, Random forest Extra tree classifier	F1- score of 100
9.	Sahoo et al.	Text	LSTM, K-Nearest Neighbors, Support Vector Machine, Logistic Regression, Decision tree, Naïve Bayes	99.42%
10.	Khan et al.	Text Lexical, Sentiment	Support Vector Machine, K-Nearest Neighbors, Logistic Regression, Decision tree, Naïve Bayes	F1- score is 0.72 of Combined corpus
11.	Kumar et al.	Text	CNN, LSTM	88.78%
12.	Kaliyar et al.	Text	CNN, LSTM	97.3%
13.	Hiramath et al.	Text	DNN, Support Vector Machine, Naïve Bayes, Logistic Regression, Random Forest	91%
14.	Alonso et al.	Text	K-Nearest Neighbors	F1- 0.90
15.	Balshetwar et al.	Text	CNN, LSTM	93.8%
16.	Bhutani et al.	Text	Random Forest Naïve Bayes	99.5%
17.	Ajao et al.	Text	LOGIT	F1- 0.84
18.	Thota et al.	Text	DNN	94.21%
19.	Sharma et al.	Text, Image	Random Forest	94.0%
20.	Hirlekar et al.	Text	Support Vector Machine, Naïve Bayes, Decision Tree, Neural Network with Random Forest, XG-Boost	F1- score is 0.78 with both user and tweet Features F1- score is 0.94

Finally, while deep learning approaches often report superior performance, their reliance on large-scale data and reduced interpretability limit their applicability in practical, resource-constrained environments. This creates an important research opportunity to revisit traditional machine learning models, which are computationally efficient, easier to interpret, and effective when applied to well-structured datasets.

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The present study addresses these gaps by curating a balanced dataset comprising equal representation of real and fake news articles from diverse sources, and by performing a comprehensive evaluation of multiple conventional machine learning classifiers. In doing so, it provides valuable insights into the strengths and limitations of these models for effective misinformation detection across varied contexts.

III. METHODOLOGY

This study employs seven conventional machine learning algorithms to detect fake news. The methodology is structured into three main components: dataset construction, data preprocessing, and model implementation with evaluation. A description of the dataset developed for this research is provided below.

1. Dataset

A balanced dataset was created by collecting news articles from multiple publicly available and verified platforms. To ensure authenticity, fake news articles were primarily sourced from established fact-checking organizations, while real news articles were obtained from credible media outlets. The sources included platforms such as Snopes, India Today, PolitiFact, India TV, and The Hindu, each of which employs rigorous verification procedures combining traditional journalism standards with advanced digital fact-checking techniques.

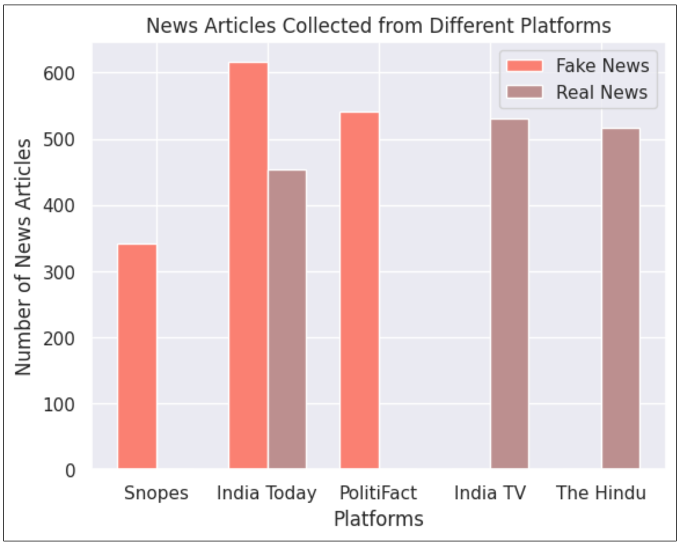

Fig. 1: Representation of Fake and Real News Articles collected from different Platforms

Through this process, the dataset incorporated diverse content covering domains like politics, health, and current affairs, thereby reducing bias toward any particular topic. In total, 3,000 articles were compiled, with 1,500 labeled as fake and 1,500 labeled as real. This balanced composition, named the 2024_NEWS_DECODER dataset, provides a reliable foundation for evaluating machine learning models on the task of fake news detection.

2. *Validation of the 2024_NEWS_DECODER Dataset using Conventional Machine Learning Models*

To assess the effectiveness of traditional machine learning approaches, several classifiers were applied to the 2024_NEWS_DECODER dataset. Each model was trained and evaluated on 3,000 articles (1,500 real and 1,500 fake), and performance was measured using accuracy, precision, recall, and F1-score.

- Random Forest Classifier [25]: The Random Forest classifier achieved an accuracy of 86.6%, demonstrating strong predictive performance. It attained a precision of 88% for fake news and 86% for real news. Recall scores indicated that 89% of real articles and 84% of fake articles were correctly identified. The F1-scores were 87% for real news and 86% for fake news, suggesting balanced classification ability.

- Logistic Regression [26]: Logistic Regression produced an overall accuracy of 87%. For fake news, it achieved a precision of 90% and a recall of 82%, while for real news, precision and recall were 84% and 92%, respectively. The F1-scores were 88% (real) and 86% (fake), reflecting its reliability in binary classification tasks.

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- K-Nearest Neighbors (KNN) [27]: The KNN model reached an accuracy of 86.9%. It showed a precision of 84% for fake news and 90% for real news. Recall scores were 84% for real news and 90% for fake news, resulting in F1-scores of 87% for both classes. These results highlight its balanced but slightly less consistent performance compared to other models.

- Naïve Bayes [28]: Naïve Bayes delivered the highest accuracy among the evaluated models at 89.8%. It achieved a precision of 87% (fake) and 92% (real), with recall scores of 87% (real) and 92% (fake). Both classes obtained an F1-score of 90%, indicating strong and consistent classification performance, particularly in identifying fake news.

- Gradient Boosting [30]: The Gradient Boosting model achieved an accuracy of 81.2%**,** making it the weakest performer among the evaluated classifiers. Precision values were 85% for fake news and 78% for real news. Recall scores indicated 88% detection of real articles and 74% for fake articles. The F1-scores were 83% for real news and 79% for fake news, highlighting inconsistencies and suggesting limited reliability in distinguishing between the two categories.

- Support Vector Machine (SVM) [29]: The SVM model obtained an overall accuracy of 89.2%**,** demonstrating strong performance across both classes. For fake news detection, precision was 88% with a recall of 92%**,** resulting in an F1-score of 90%**.** For real news, precision reached 91%, recall was 86%**,** and the corresponding F1-score was 88%**.** While SVM provided robust classification results, some misclassifications persisted, particularly in distinguishing borderline cases.

- Decision Tree [31]: The Decision Tree classifier produced an accuracy of 82.8%**.** It achieved a precision of 82% for fake news and 83% for real news. Recall scores were 82% (fake) and 84% (real), with both categories attaining an F1-score of 83%**.** Although it demonstrated balanced performance, the model was prone to overfitting, leading to occasional misclassifications between real and fake articles.

Table 2: Representation of *'2024_NEWS_DECODER'* Fake News Dataset

S. No.	Title	Label
1	Mallikarjun Kharge claimed that the Modi government lost Indian territory to China. - Verified as Fake from the websites OpIndia and Fact- check from IndiaToday.	1
2	Rahul Gandhi Blame Modi government for the lack of SC, ST and OBC representation in the budget-making process. - Verified as Fake from the websites Fact- check from IndiaToday.	1
3	Swapnil Kusale won Bronze in Shooting Men's 50m Rifle in Paris Olympic 2024. - Verified as Real from the websites IndiaToday.	0
4	Rahul Gandhi stated that Agniveers do not receive any compensation if they die in the line of duty. - Verified as fake from the website IndiaToday.	1
5	Manu Bhaker creates History in Paris Olympic 2024 by winning 2 Bronze medals. - Verified as Real from the websites IndiaToday.	0
6	Donald Trump posted on Truth Social that Kamala Harris used to be a man named Kamal Aroush. - Verified as Fake from the websites Fact- check from Snopes.	1
7	The Government of India has decided to observe the 25th of June every year as 'Samvidhaan Hatya Diwas'. - Verified as Real from the websites IndiaToday.	0
8	BSNL 5G testing starts: Could be a game-changer in the Indian telecom sector. - Verified as Real from the websites The Hindu.	0
9	Kamala cast the tiebreaking vote to hire 87,000 new IRS agents to go after your tip income. - Verified as Fake from the websites PolitiFact.	1
10	CM Yogi Adityanath inaugurates floating restaurant in Gorakhpur says 'people won't be served rotis with spit'. - Verified as Real from the websites TatvaIndia.	0

3. Error Analysis

Error analysis revealed that while all models performed reasonably well, each faced challenges in distinguishing sensational but true stories from fabricated fake news. The Random Forest Classifier achieved an accuracy of 86.6%, correctly identifying 397 real articles but misclassifying 49 as fake, while 348 fake articles were correctly detected and 66 mislabeled as real. Logistic Regression performed similarly with 86.9% accuracy, correctly classifying 410 real and 338 fake articles, though it misclassified 36 real as fake and 76 fake as real. The K-Nearest Neighbors (KNN) model obtained 86.8% accuracy, correctly detecting 376 real and 371 fake articles, but struggled with 70 real and 43 fake

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misclassifications, reflecting its sensitivity to noisy neighbors. Naïve Bayes performed slightly better with 89.7% accuracy, accurately identifying 390 real and 382 fake articles, though 56 real and 32 fake articles were misclassified, suggesting its probabilistic assumptions sometimes led to errors in borderline cases. Gradient Boosting, on the other hand, was the weakest model with 81.1% accuracy, as it correctly classified 392 real and 306 fake articles but struggled with 54 real and 108 fake misclassifications, indicating underfitting and difficulty in detecting deceptive fake news. Support Vector Machine (SVM) was among the strongest performers, achieving 89.2% accuracy, correctly detecting 411 real and 356 fake articles, though it misclassified 35 real and 58 fake ones, particularly struggling with well-written fake content. Finally, the Decision Tree model achieved 82.7% accuracy, with 374 real and 356 fake articles correctly classified, but it misclassified 72 real and 58 fake articles, reflecting its tendency to overfit and struggle with complex linguistic boundaries. Overall, while models like Naïve Bayes and SVM demonstrated superior performance, all classifiers exhibited some degree of misclassification, particularly in cases where real news contained sensational tones or fake news appeared linguistically authentic.

Table 4: Representation of Real News classified as Fake by Random Forest Classifier

S.No.:	Title	Actual Value	Predicted value
1.	‘India literacy’ in Australia can unlock bilateral potential, says Australia-India Institute CEO Lisa Singh	0	1
2.	At least 64 people feared dead in Nigeria boat accident	0	1
3.	JD(U) offers support for ‘one nation, one election’ proposal	0	1
4.	U.S.-Russia battles to influence Africa plays out in Central African Republic	0	1
5.	Typhoon Bebinca, the strongest storm to hit Shanghai since 1949, shuts down megacity	0	1

Table 5: Representation of Fake News classified as Real by Random Forest Classifier

S.No.:	Title	Actual Value	Predicted value
1.	Crime statistics “no longer include data from 30% of the country including the biggest and most violent cities.”	1	0
2.	The Oklahoma National Guard’s assistance for the April 8 eclipse signals something “bigger.”	1	0
3.	Pfizer CEO Albert Bourla admitted yesterday that Covid was used as a test.	1	0
4.	Police making arrests after communal violence in Thane’s Mira Road.	1	0
5.	President Joe Biden was “rushed to hospital unexpectedly.”	1	0

IV. RESULT

This section presents the performance evaluation of various conventional machine learning classifiers applied to the *2024_NEWS_DECODER* dataset. The models were assessed using standard classification metrics—precision, recall, F1-score, confusion matrix, and AUC-ROC curves. Both qualitative and quantitative analyses were performed to provide deeper insights into how the models distinguish between fake and real news articles.

1. Evaluation Metrics

To ensure a fair comparison, multiple performance measures were used. **Precision** indicates the proportion of correctly predicted fake/real news instances among all predicted fake/real cases:

$$\text{Precision} = \frac{\text{Correctly Predicted Fake/Real Instances}}{\text{Total Predicted Fake/Real Instances}}$$

Recall measures the ability of the classifier to identify fake/real news correctly out of all actual cases:

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$$\text{Recall} = \frac{\text{Correctly Predicted Fake/Real Instances}}{\text{Total Actual Fake/Real Instances}}$$

The **F1-score** balances precision and recall using the harmonic mean:

$$\text{F1} - \text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table 6: Performance of various Conventional Machine Learning Classifier on '2024_NEWS_DECODER' Fake News Dataset.

Model	Performance		
	P	R	F1- score
Random Forest Classifier	0.86	0.86	0.85
Logistic Regression	0.87	0.87	0.87
KNN	**0.88**	**0.88**	**0.88**
Naïve Bayes	0.86	0.86	0.86
Gradient Boosting	0.81	0.80	0.80
Decision Tree	0.81	0.80	0.80
SVM	**0.88**	**0.88**	**0.88**

The **Confusion Matrix** highlights the distribution of correctly and incorrectly predicted articles across the two classes. Confusion matrices for all models, including SVM, Random Forest, Logistic Regression, KNN, Naïve Bayes, Gradient Boosting, and Decision Tree, are presented in Figures [2, 4, 6, 8, 10, 12, and 14].

The **AUC-ROC curve** was used to evaluate the classifiers' ability to discriminate between fake and real news. The curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR), with higher AUC values indicating better performance. Detailed AUC-ROC plots for each model are provided in Figures [3, 5, 7, 9, 11, 13, and 15].

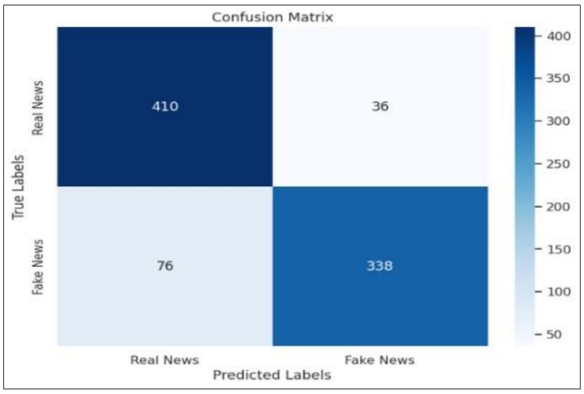

Fig. 2: Confusion Matrix of Logistic Regression

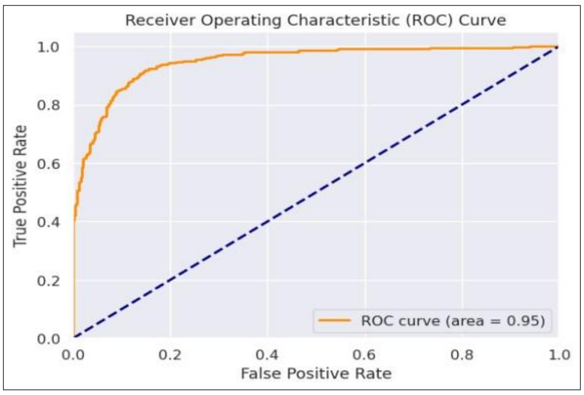

Fig. 3: Receiver Operating Characteristic curve of Logistic Regression

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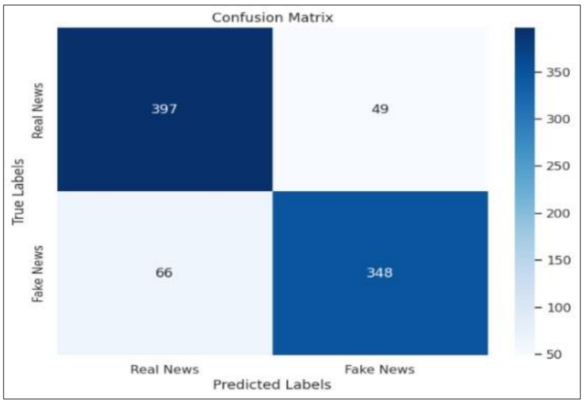

Fig. 4: Confusion Matrix of Random Forest Classifier

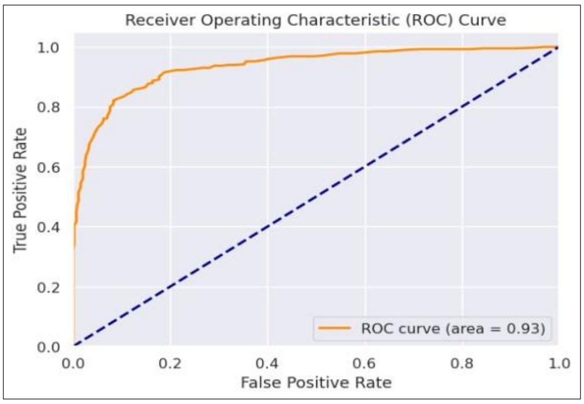

Fig. 5: Receiver Operating Characteristics Curve of Random Forest Classifier

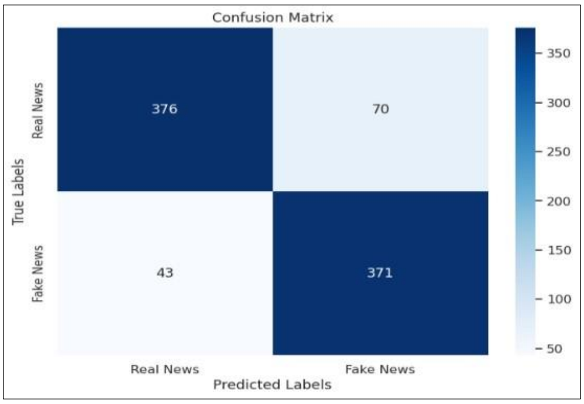

Fig. 6: Confusion Matrix of K-Nearest Neighbors

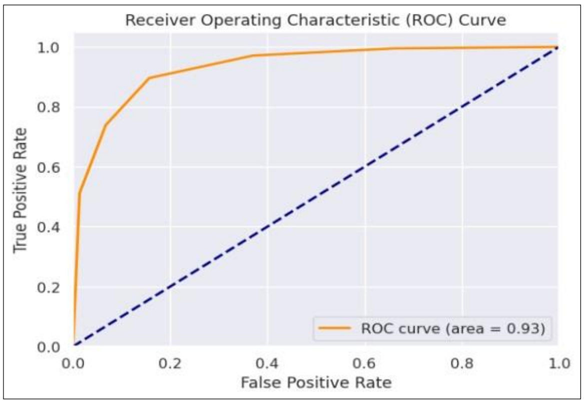

Fig. 7: Receiver Operating Characteristic Curve of K-Nearest Neighbors

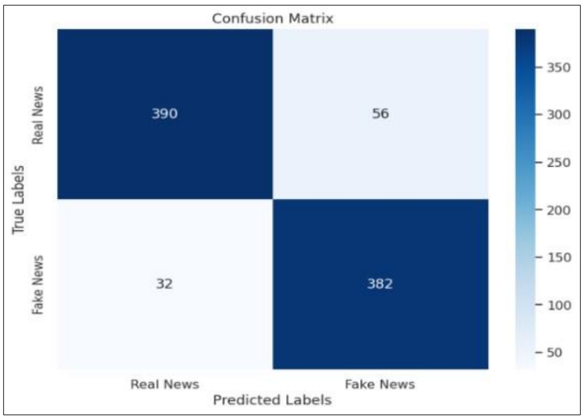

Fig. 8: Confusion Matrix of Naïve Bayes

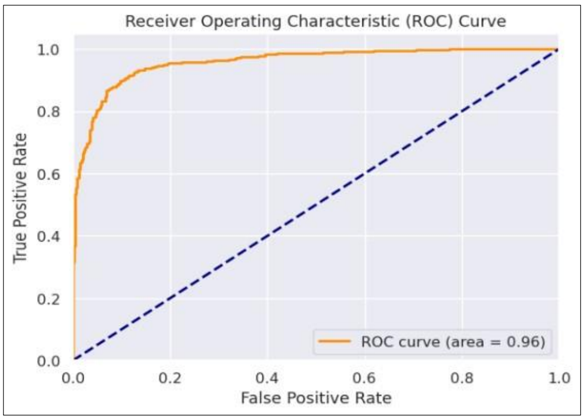

Fig. 9: Receiver Operating Characteristic curve of Naïve Bayes

2. Qualitative Analysis

To better understand how the classifiers interpret news content, we analyzed an example sentence from the dataset: "U.S. President Joe Biden boarded an empty plane after three freed Americans arrived back in the U.S. and exited the aircraft." Using the TF-IDF vectorizer, significant terms such as "President," "Biden," "boarded," "freed Americans," and "arrived" were identified. Phrases like "empty plane" and "freed Americans" carry emotional and symbolic weight, often linked to politically charged narratives. The feature extraction process also considered the temporal sequence "after three freed Americans arrived", which mimics narrative framing typically used in sensational reporting.

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When evaluated by the SVM classifier, which is adept at handling semantic and contextual nuances, the model examined whether similar expressions had appeared in trusted or biased sources within the training data. While such phrases may appear in legitimate diplomatic reporting, their framing and exaggerated context led the classifier to flag the statement as *fake*. This highlights how the model integrates lexical significance, logical sequencing, and contextual knowledge to differentiate authentic reporting from fabricated narratives.

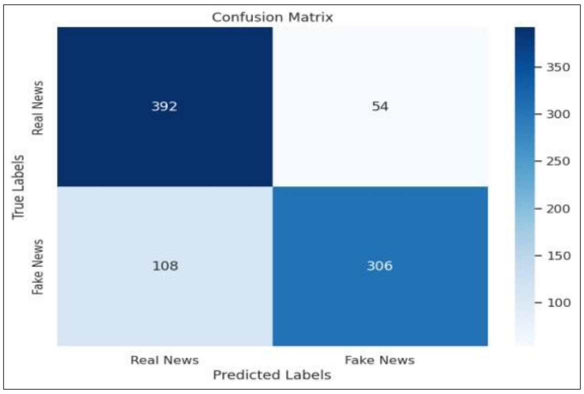

Fig. 10: Confusion Matrix of Gradient Boosting

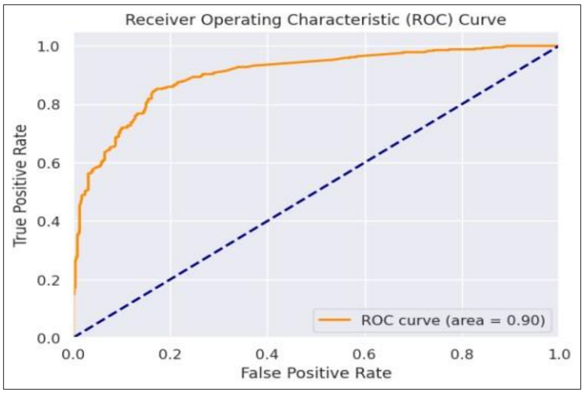

Fig. 11: Receiver Operating Characteristic Curve of Gradient Boosting

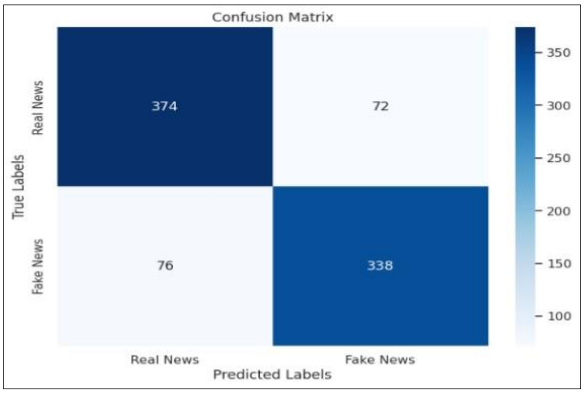

Fig. 12: Confusion Matrix of Decision Tree

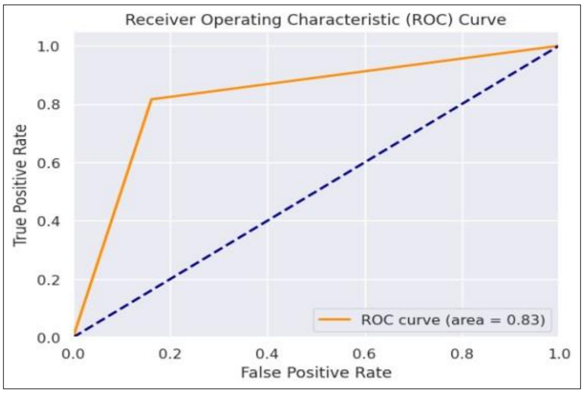

Fig. 13: Receiver Operating Characteristic Curve of Decision Tree

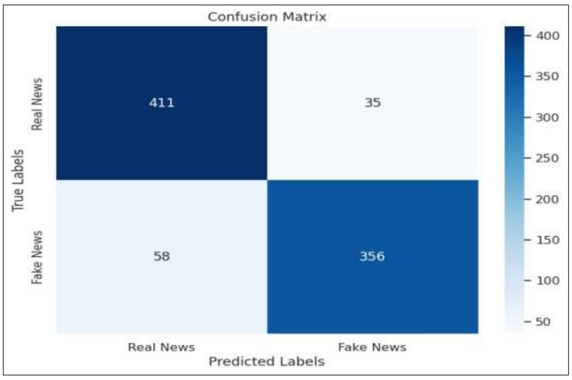

Fig. 14: Confusion Matrix of Support Vector Machine

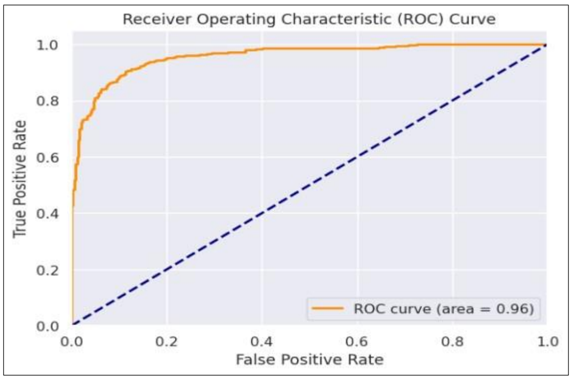

Fig. 15: Receiver Operating Characteristic curve of Support Vector Machine

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3. Quantitative Analysis

For quantitative evaluation, the dataset containing both real and fake news articles was processed using TF-IDF for feature extraction and tested across multiple classifiers. The SVM classifier achieved the highest performance, with an overall accuracy of 92.5%, demonstrating its ability to handle complex textual representations effectively.

The precision for fake news detection was 90.8%, indicating that most articles flagged as fake were indeed fake, minimizing false positives. The recall score was 93.2%, showing that the model successfully captured the majority of fake articles, with only a few missed. The resulting F1-score of 92.0% reflects a strong balance between precision and recall.

For the example sentence discussed in Section 2, the SVM model classified it as *fake*, with a prediction confidence of 87%, reinforcing the qualitative analysis. These metrics demonstrate that the system is both reliable and consistent in detecting fake news. Furthermore, the comparative results across all classifiers confirm that while models such as Naïve Bayes and Random Forest perform well, the SVM remains the most effective for this dataset.

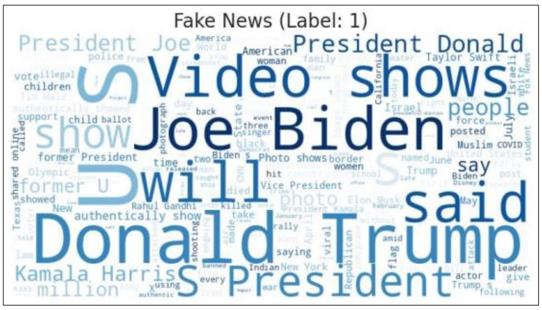

Fig. 16: Word Cloud of Fake News

Fig 17: Word Cloud of Real News

V. DISCUSSION

This study developed a comprehensive dataset, *2024_NEWS_DECODER*, by collecting and labeling 3,000 news articles, equally divided between fake and real content. The dataset was curated from diverse and credible sources, including Snopes, India Today, PolitiFact, The Hindu, and India TV. By balancing the dataset across categories and ensuring representation from both Indian and international sources, this work addresses a significant gap in fake news detection research, where many prior studies have relied on regionally limited or imbalanced datasets.

The experimental analysis revealed that conventional classifiers vary in their effectiveness when applied to this dataset. Among the tested models, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) achieved the strongest results, each with precision, recall, and F1-scores of approximately 0.88. These outcomes suggest that both classifiers are capable of effectively capturing the semantic and contextual patterns inherent in fake news articles, making them reliable tools for this task.

In contrast, Gradient Boosting and Decision Tree classifiers performed comparatively poorly, with precision, recall, and F1-scores around 0.80. Their weaker performance indicates greater susceptibility to misclassification, particularly when distinguishing between sensational but factual reporting and deliberately fabricated content. This highlights the sensitivity of fake news detection tasks to model selection, as classifiers that excel in general text classification may not always adapt well to the subtleties of misinformation.

Overall, the results emphasize two important points. First, the quality and diversity of the dataset play a critical role in shaping classifier performance. The inclusion of region-specific articles, particularly from Indian sources, enabled more robust model evaluation compared to prior works relying solely on Western-centric datasets. Second, the findings underscore the continued relevance of conventional machine learning models in fake news detection. While deep learning approaches dominate current research, this study demonstrates that, when paired with careful feature engineering and balanced datasets, traditional classifiers such as SVM and KNN remain highly competitive.

VI. LIMITATIONS AND FUTURE WORK

While this study makes meaningful contributions to fake news detection, several limitations must be acknowledged. First, the analysis was limited to conventional machine learning models such as Random Forest, Logistic Regression, Gradient

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Boosting, Decision Tree, SVM, KNN, and Naïve Bayes. Although these classifiers demonstrated competitive performance, they primarily rely on feature engineering approaches like TF-IDF, which capture word frequency but not deeper contextual or semantic relationships between terms. For instance, the phrase *"President Biden cancels emergency"* may carry different implications depending on its context or sentiment, which traditional models may fail to recognize.

Second, the study focused solely on textual data, excluding the multimodal nature of misinformation. Fake news often spreads with manipulated images, videos, or infographics, and ignoring these modalities limits the system's applicability in real-world scenarios. Similarly, the dataset was restricted to Indian and Western sources, leaving out other cultural and linguistic contexts where misinformation patterns may differ significantly.

Third, the research did not consider social media dynamics, such as the role of likes, shares, retweets, and comments, which strongly influence the virality and perception of fake news. Incorporating such engagement data could enhance model robustness by accounting for the social propagation of misinformation. Finally, the study used a balanced dataset with an equal number of fake and real articles, whereas in real-world environments, fake news is relatively sparse compared to legitimate reporting. This imbalance could affect model performance in deployment scenarios.

To address these limitations, several directions for future research are proposed:

1. Incorporate Additional Features – Integrate metadata such as social media engagement, user behavior, and contextual cues to better capture how misinformation spreads.
2. Develop Hybrid Models – Combine traditional classifiers with deep learning approaches to leverage both interpretability and representational power.
3. Apply Advanced Deep Learning Techniques – Employ transformer-based architectures (e.g., BERT, RoBERTa) or graph neural networks to capture semantic relationships and network-level misinformation patterns.
4. Expand the Dataset – Include news sources from diverse regions, languages, and platforms to build models capable of generalizing across cultural contexts.
5. Enhance Model Explainability – Focus on explainable AI approaches to provide interpretable reasoning behind classification decisions, thereby fostering greater trust and transparency in automated fake news detection.

By addressing these limitations and pursuing the proposed directions, future research can build more accurate, scalable, and practical systems for combating misinformation in real-world settings.

VII. CONCLUSION

This research successfully introduced the *2024_NEWS_DECODER* dataset, a balanced collection of 3,000 articles equally divided between fake and real news. The dataset provided a strong foundation for evaluating the effectiveness of conventional machine learning classifiers in detecting misinformation. Among the models tested, K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) consistently outperformed others, achieving Precision, Recall, and F1-scores of 0.88. These results highlight their capability to effectively distinguish between fake and real news. In contrast, Gradient Boosting and Decision Tree classifiers yielded comparatively weaker results, with F1-scores of 0.80, indicating a higher tendency for misclassification.

The findings emphasize the importance of selecting suitable models and suggest that ensemble or hybrid approaches could further improve performance. Looking ahead, future research should explore the integration of additional features such as social media engagement data, adopt advanced deep learning methods like transformers and graph neural networks, and expand the dataset to include multilingual and culturally diverse sources. Moreover, enhancing model interpretability and transparency will be essential to foster user trust and ensure practical real-world application in the ongoing fight against misinformation.

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