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Fake News Detection Using Traditional Machine Learning Approaches

Shivani Pandey[1], Rajnish Pandey[2], Aanchal Mishra[3], Awadhesh Maurya[4], Akhilesh Mauriya[5]

Department of Information Technology, Institute of Engineering and Technology, Dr. Rammanohar Lohia Avadh University, Ayodhya, U.P., India[1-5]

Abstract: The rapid growth of digital media has made the detection of fake news an essential task, as misinformation can quickly spread online and influence public opinion, decision-making, and social trust. This study explores the effectiveness of traditional machine learning techniques in classifying news articles as fake or real. Using the WELFake dataset, which contains 72,134 news articles from the Kaggle platform, classifiers such as Support Vector Machine (SVM), Random Forest, Decision Tree, and Gradient Boosting were evaluated. Initial experiments achieved strong results, with several models reaching an F1-score of 0.90. Further improvements were obtained by engineering additional features, leading to an enhanced F1-score of 0.96. The findings highlight the capability of traditional machine learning approaches for fake news detection and provide insights into building effective models to mitigate the spread of misinformation.

Keywords: Include at least 4 keywords or phrases.

I. INTRODUCTION

The rapid growth of the internet and social media platforms has made information more accessible than ever before [1–3]. However, this ease of access has also facilitated the widespread circulation of fake news, which can mislead audiences, influence public perception, and even disrupt democratic and societal processes [4]. Detecting fake news is therefore essential for safeguarding the integrity and credibility of information in the digital age. Machine learning has emerged as a powerful tool for addressing this challenge, leveraging techniques such as natural language processing (NLP), deep learning, and network analysis to automate fake news detection [5]. By examining textual patterns, sentiment, and source credibility, machine learning models can effectively differentiate between authentic and fabricated content [6]. This study focuses on evaluating traditional machine learning algorithms—including Naïve Bayes, Support Vector Machines (SVM), Random Forest (RF), and Decision Trees (DT)—to determine their effectiveness in detecting fake news. While advanced deep learning models have also been explored extensively in recent years, this research emphasizes traditional approaches for their interpretability, efficiency, and strong baseline performance. Fake news can be defined as deliberately false or misleading information presented as factual news, often distributed through various channels such as websites, social media, television, radio, and print media, with the intent to deceive or manipulate audiences. In the context of machine learning, fake news detection involves applying algorithms to analyse textual content, source reliability, and dissemination patterns to accurately classify news as real or fake.

Modes of Fake News Dissemination Fake news spreads through multiple channels, each playing a significant role in shaping public perception and fuelling misinformation. Among these, social media platforms are the most prevalent [13]. With millions of users sharing content instantly, false information can go viral before fact checking measures are applied. Social media algorithms often prioritize sensational or emotionally charged content, further amplifying the reach of misinformation. Another major source is online news websites, some of which deliberately publish misleading or fabricated stories to attract traffic and generate advertising revenue [15]. Sensational headlines and images are often used to gain attention, regardless of the credibility of the content. Similarly, blogs and online forums can act as breeding grounds for unverified claims, where personal opinions and conspiracy theories are easily circulated across wider networks. Even traditional media outlets are not immune to spreading misinformation [17]. In some cases, established news organizations may publish inaccurate reports due to reliance on unverified sources or the urgency to release breaking news, as seen in several high-profile incidents. Organized misinformation campaigns also contribute significantly to the spread of fake news [12]. These campaigns are often politically, financially, or ideologically motivated, using coordinated strategies to influence specific groups of people and manipulate public opinion. A more recent and highly concerning development is the use of deep fakes and manipulated content [17,18]. Advances in artificial intelligence have made it possible to create realistic but false videos, images, and audio recordings that are difficult for the public to distinguish from authentic content. This has heightened the challenge of combating misinformation. Fake news dissemination occurs across a wide spectrum of digital and traditional channels, ranging from social media platforms and online news portals to organized propaganda efforts and emerging AI-driven content manipulation. These factors highlight the urgent need for media literacy, fact checking practices, and advanced detection technologies to mitigate the harmful effects of misinformation. Importance of Fake News Detection The detection of fake news has become a critical issue in the modern digital landscape, where information is exchanged rapidly and extensively across a multitude of online platforms. The growth of social media platforms such as Facebook, X (formerly Twitter), Instagram, and WhatsApp has transformed the way people consume information. News updates, opinions, and narratives now spread instantly to millions of users around the globe, often without undergoing the traditional processes of verification or editorial review [21]. This unprecedented speed and scale of information dissemination create a fertile environment for misinformation and fake news to thrive. The COVID-19 pandemic served as a striking example of the dangers posed by unchecked misinformation. During this period, social media was flooded with unverified claims regarding treatments, vaccines, and preventive measures, many of which had no scientific basis. False narratives promoting unsafe remedies, such as consuming bleach or relying solely on herbal cures, caused significant confusion, fear, and even health hazards. Such incidents demonstrate that misinformation is not merely a matter of distorted truth but a public health concern that can result in severe consequences, including illness and loss of life. Beyond health, misinformation has influenced a range of social and political events, shaped narratives and fostering division within communities. Elections in several countries have been influenced by fabricated stories targeting specific candidates or voter groups, eroding public confidence in democratic processes and institutions [23]. The spread of fake news also has profound psychological and societal effects. When individuals are repeatedly exposed to misinformation, even if it is later debunked, they may continue to believe and share it due to cognitive biases such as confirmation bias and the illusory truth effect. Over time, this weakens trust in legitimate news sources, making it increasingly difficult for individuals to distinguish between credible information and falsehoods. This erosion of trust in the media ecosystem undermines the foundation of informed decision-making, polarizing communities and weakening social cohesion. In addition to its political and societal implications, fake news has significant economic consequences. Fabricated news stories can manipulate stock markets, harm brand reputations, and disrupt financial stability. For instance, a single viral false report claiming that a large company has declared bankruptcy can lead to stock price fluctuations and investor panic. Similarly, misinformation about economic policies or trade relations can trigger widespread market volatility. This illustrates that fake news is not only a social or political threat but also an economic liability for nations and corporations. Traditional media outlets, once considered the cornerstone of credible information dissemination, have not been entirely immune to the risks of spreading misinformation. In the era of 24-hour news cycles and competition for breaking stories, journalists and media organizations sometimes rely on unverified sources or hastily reported facts. This has occasionally led to the accidental publication of incorrect information, further contributing to the overall atmosphere of uncertainty and mistrust. Notable incidents, such as the misidentification of suspects during the Boston Marathon bombing in 2013, highlight the dangers of reporting without thorough verification. The influence of fake news campaigns is amplified when organized groups or entities deliberately use misinformation to serve political, financial, or ideological agendas. For example, investigations into global election interference have revealed how state-sponsored campaigns have deployed targeted fake news stories to manipulate voter perceptions and behaviours. These campaigns often use sophisticated techniques such as microtargeting advertisements, bots, and coordinated inauthentic accounts to reach specific groups of people, making detection even more challenging. This level of coordination demonstrates that fake news is not just random misinformation but, in many cases, a calculated tool used to influence public opinion on a large scale. Adding to these concerns is the rise of deepfakes and other AI-generated content, which represent a new and particularly dangerous form of misinformation. Deepfake technology uses artificial intelligence to create hyper-realistic videos, images, or audio clips of individuals saying or doing things they never actually did. This makes it significantly harder for audiences to differentiate between genuine and fabricated content, further eroding trust in media and online platforms. For example, deepfake videos of world leaders have been circulated online, with the potential to spark political crises or damage reputations. As this technology becomes more accessible, the threat it poses to information integrity continues to grow [17,18]. The consequences of misinformation extend beyond the immediate effects of individual stories. Over time, repeated exposure to fake news undermines confidence in democratic institutions, public health organizations, and journalistic integrity. A population that cannot distinguish fact from fiction becomes more susceptible to manipulation, ultimately weakening the very foundations of a free and informed society. As seen during the Brexit campaign, targeted misinformation efforts fuelled political polarization and deepened divisions within communities, illustrating the societal harm that fake news can cause when left unchecked. To address this global challenge, researchers and policymakers have increasingly emphasized the importance of fake news detection. Detecting misinformation is not simply a matter of identifying false statements; it involves analysing the mechanisms through which misinformation spreads, understanding user behaviour, and developing robust systems capable of handling massive amounts of data. Machine learning and artificial intelligence (AI) have emerged as vital tools in this effort. By analysing linguistic patterns, sentiment, metadata, and source credibility, machine learning models can efficiently classify and detect fake news. While advanced deep learning techniques are gaining popularity, traditional machine learning models such as Support Vector Machines (SVM), Random Forests, and Naïve Bayes classifiers remain critical because of their interpretability, efficiency, and effectiveness. However, technology alone is not sufficient. Combating fake news requires

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a multi-pronged approach that combines machine learning advancements with fact-checking initiatives, regulatory measures, and improved public awareness. Media literacy programs are essential in helping individuals critically evaluate online content and identify misinformation. Additionally, social media platforms must take greater responsibility in detecting and flagging false content, while also providing users with reliable information. Governments and organizations are increasingly collaborating with technology companies and academic researchers to develop scalable and transparent systems for misinformation detection. In summary, fake news detection is vital for maintaining a healthy, informed society. The rise of social media, deepfake technology, and organized misinformation campaigns has made it increasingly difficult for the public to differentiate between truth and falsehoods. Without effective detection strategies, misinformation has the potential to destabilize economies, erode trust in democratic systems, and endanger public safety. By integrating machine learning techniques, raising public awareness, and fostering collaboration between stakeholders, society can build a more resilient information ecosystem capable of mitigating the far-reaching consequences of fake news. This research investigates the effectiveness of conventional machine learning algorithms in detecting fake news, leveraging the WELFake dataset from Kaggle, which contains a large collection of labelled news articles. Initially, a baseline evaluation was conducted using classifiers such as Support Vector Machines (SVM), Naïve Bayes, Decision Trees, and Random Forest, trained on the raw dataset without additional feature engineering. While these models demonstrated reasonable accuracy, the complexity and subtlety of misinformation highlighted the need for advanced feature extraction techniques to improve detection capabilities. To address this, multiple preprocessing and feature engineering methods were incorporated. The preprocessing stage involved cleaning the text data by removing stop words, punctuation, and irrelevant tokens, followed by tokenization and normalization to prepare the dataset for effective analysis. TF-IDF (Term Frequency–Inverse Document Frequency) was then applied to convert text into numerical feature vectors, capturing the importance of words across the dataset. In addition to TF-IDF, several handcrafted features were introduced to capture deeper linguistic and structural cues within the news articles. These included sentiment analysis scores to assess the emotional tone of content, word and character counts to identify stylistic differences between real and fake news, and entropy values to measure information distribution within text. Such enriched features provide machine learning algorithms with a broader representation of the data, enabling them to detect subtle patterns of deception that may not be evident through raw text alone. For example, Support Vector Machines are particularly effective at identifying non-linear decision boundaries in high-dimensional feature spaces, making them suitable for detecting patterns like exaggerated or emotionally charged language that often characterizes fake news. Research during the 2016 U.S. presidential election demonstrated how SVM-based approaches could identify overly sensational headlines and clickbait-style phrasing commonly used to mislead readers. Similarly, Naïve Bayes classifiers, which rely on probabilistic reasoning, have been widely applied to misinformation detection tasks, including studies on COVID-19-related fake news, by analysing word frequency distributions and co-occurrence patterns [18, 24]. By retraining these models with the enriched feature set, significant improvements in classification performance were observed. The overarching aim of this study is to systematically assess the capability of traditional machine learning algorithms in detecting misinformation when provided with both raw and feature-enhanced data. This dual-phase evaluation offers a comparative understanding of how feature engineering influences model performance and contributes to developing scalable, automated tools for combating fake news. Ultimately, this approach emphasizes the importance of combining linguistic analysis, statistical modelling, and computational techniques to effectively distinguish between authentic and deceptive content in large-scale datasets [25]. This study focuses on evaluating how the inclusion of advanced text processing techniques and additional handcrafted features can improve the performance of machine learning models in detecting fake news. To achieve this, the classification results of different algorithms were systematically compared in two phases: first, by training the models on the original dataset without any added features, and then by retraining them on a feature-augmented version of the same dataset. The enhanced dataset included several additional attributes, such as sentiment analysis scores, word and character counts, entropy values, and TF-IDF-based representations, all of which were designed to capture deeper linguistic and structural patterns in the news articles. By carrying out this comparison, the study not only demonstrates the measurable impact of these advanced techniques but also highlights the importance of feature engineering in building effective fake news detection systems. The findings from this research provide valuable insights into how machine learning models can be optimized to handle misinformation more accurately and efficiently. Traditional models like Support Vector Machines, Naïve Bayes, Decision Trees, and Random Forests benefit significantly from well-structured input features, which enable them to detect subtle cues such as sensational language, biased wording, and unusual writing styles often present in fake news. Moreover, by carefully analysing model performance with and without feature augmentation, this study emphasizes the role of interpretable models that not only achieve high accuracy but also offer transparency in decision making. These insights contribute to the broader goal of designing scalable, robust, and reliable detection frameworks that can be applied across various digital platforms to limit the spread of false information and protect users from misinformation.

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II. LITERATURE REVIEW

In recent years, the problem of fake news detection and misinformation analysis has attracted significant attention from researchers, leading to the development of a variety of machine learning and deep learning-based models. These approaches aim to improve the accuracy, interpretability, and scalability of automated fake news detection systems by leveraging linguistic, social, and network-level features. Researchers have experimented with a wide range of techniques, from traditional classifiers to advanced neural networks, achieving promising results on benchmark datasets. A summary of some prominent studies is provided in Table 1. Sahoo et al. [1] proposed a hybrid deep learning model that integrates Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), using GloVe word embeddings to represent text semantically. This combination allowed the model to capture both sequential dependencies and contextual meaning, resulting in a remarkably high precision score of 0.994. Similarly, Yang et al. [2] explored a Bayesian Network Model with Collapsed Gibbs Sampling to analyse user behaviour and engagement patterns on social media platforms. This probabilistic approach effectively modelled relationships between users and content, achieving a precision of 0.720. In another study, Ozbay et al. [7] carried out a comprehensive comparison of multiple machine learning algorithms, including Logistic Regression (LR), Naïve Bayes, Decision Trees (DT), Random Forests, Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), Gradient Boosting Machines (GBM), Neural Networks, LSTM, and CNNs. They used Term Frequency (TF) and Document-Term Matrix (DTM) representations to capture textual information and reported a recall score of 0.780, demonstrating the effectiveness of both traditional and neural network-based models for misinformation classification. Aldwairi et al. [8] focused on a logistic regression classifier built using key textual features, such as news titles and posts, and achieved a perfect ROC score of 100%, highlighting that even simpler models can perform exceptionally well when combined with carefully chosen features. Han et al. [9] introduced a Graph Neural Network (GNN)-based approach, which goes beyond text analysis by modelling propagation patterns and leveraging social context. Their model demonstrated strong performance, achieving a precision of 0.746, and showcased the power of graph-based modelling for detecting misinformation in complex social networks. Shu et al. [11] contributed significantly to the field with their Tri-FN model, which combines three critical dimensions of fake news detection: news publisher credibility, user engagement patterns, and relationships between different pieces of news. Their method achieved an F1-score of 0.880 ± 0.015. In a related study, Shu et al. [12] developed a deep learning framework that integrates linguistic and social engagement features, achieving a recall score of 0.919. This demonstrated that combining textual analysis with user and platform-level behavioural data can significantly boost fake news detection performance. Researchers have explored a wide range of approaches to fake news detection, combining both traditional machine learning methods and modern deep learning techniques. For instance, Shu et al. [14] developed a framework that integrates traditional algorithms such as Logistic Regression, Decision Trees, and Random Forests with deep learning models like Neural Networks. Their study utilized both content-based features and social network data, achieving a recall score of 0.976, showing that incorporating social engagement metrics can significantly improve detection accuracy. Similarly, Ju Lu et al. [16] introduced the Graph-aware Co-Attention Networks (GCAN) model, which analyses sequences of retweets and short-text tweets to capture the structure of information spread. This innovative graph-based approach achieved an F1-score of 0.86, demonstrating the effectiveness of modelling propagation patterns in identifying misinformation. Shu et al. [21] further extended this research by experimenting with a mix of machine learning algorithms (such as Logistic Regression and SVM) and deep learning architectures (CNNs, RNNs, Transformers). Using popular feature representation techniques like Word2Vec, GloVe embeddings, and TF-IDF, their system obtained an F1-score of 0.80, showing that combining linguistic and contextual features enhances model robustness. Vedova et al. [20] presented the HC CB-3 model, which leverages both social interactions and content signals to detect deceptive content, reaching a remarkable F1-score of 0.98. Other researchers have also explored multimodal techniques. Yang et al. [22] proposed the IT-CNN model, which fuses textual and image-based features, integrating both explicit and latent information for classification. Their approach achieved an F1-score of 0.80, emphasizing the role of visual data in identifying misinformation. Similarly, Singhal et al. [10] developed the SpotFake model, which combines BERT-based textual features with VGG-19 image embeddings, achieving an F1-score of 0.73. Z. Pan et al. [5] proposed the B-TransE model, leveraging knowledge graph embeddings to enhance semantic understanding, and reported an F1-score of 0.87, highlighting the usefulness of structured knowledge in fake news detection. Hybrid deep learning architectures have also been widely explored. Roy et al. [15] designed a CNN BiLSTM-MLP framework, where feature representations extracted through CNN and BiLSTM layers are fed into a multilayer perceptron (MLP) for classification. This pipeline achieved an F1 score of 0.87, illustrating the power of layered models in capturing both local and sequential features of news text. Reddy et al. [3] applied ensemble techniques like Random Forest and Bagging, along with external IFCN chatbot data, to improve classification reliability, achieving an F1-score of 93.32%. An emerging research trend focuses on emotion-aware modeling. Ghanem et al. [25] proposed the Emotionally Infused Network (EIN), integrating emotional features with textual data and LSTM based networks. This model achieved an impressive F1-score of 96%, suggesting that emotional cues in language play a crucial role in identifying fake news. Collectively, these studies demonstrate that fake news detection benefits greatly from multi-dimensional approaches that combine content analysis, social engagement

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Table 1: Some previous related works

S.No.	Author	Model	Features	Performance
1.	Sahoo et al. [1]	Hybrid Model based on LSTM, CNNand RNNs	GloVe	P =0.9
2.	Yang et al.[2]	Bayesian Network Model	Users Engagement on social media	P =0.70
3.	Ozbay et al. [7]	LR, NB, DT, RF, SVM, K- NN, GBM, Neural Network, LSTM, CNN.	Term Frequency (TF) Document – Term Matrix (DTM)	R=0.780
4.	Aldwairi et al. [8]	Logistic Classifier.	Title and Post features.	ROC = 100%
5.	Han et al. [9]	GNNs	Propagation patterns, Social Context features.	P=0.746
6.	Shu et al. [11]	Tri FN	News publisher, User engagements, Interrelationship.	F1-score =0.880 ± .015
7.	Shu et al. [12]	Deep learning-based solution.	Linguistic and social engagement features.	R=0.919
8.	Shu et al. [14]	LR, DT, RF	Content features, Social Network features.	R=0.976
9.	Ju Lu et al. [16]	GCAN	Sequence of retweets Source short - text – tweet.	F1-score = 0.86
10.	Shu et al. [21]	LR, SVM, CNN, RNN, Transformers	Word2 vec, GloVe, TF – IDF.	F1-score = 0.80
11.	Vedova et al. [20]	HC – CB – 3	Social signals, Content Signals.	F1-score = 0.98
12.	Yang et al. [22]	IT – CNN	Include explicit features and latent features.	F1-score = 0.80
13.	Z.Pan et al.[5]	B-Trans E-model	Based on knowledge graphs.	F1-score = 0.87
14.	Singhal et al. [10]	Spot Fake model	BERT and VGG – 19	F1-score = 0.73
15.	Roy et al. [15]	CNN, Bi– LSTM, MLP	CNN and Bi – LSTM	F1-score = 0.87
16.	Reddy et al. [3]	Ensemble methods	Style metric, Word2Vec	F1-score = 0.75
17.	Qi et al. [17]	MVNN Framework. Multimodal models.	Frequency domain features, Pixel domain features, Multimodal information, Sentiment alignment between image and text.	F1-score = 0.69
18.	Umer et al. [19]	CNN, LSTM, CNN – LSTM, Tree–Base Learning.	Quality features, Textual features.	Accuracy = 97.8%
19.	Patwa et al. [24]	Machine Learning Algorithms, SVM Based classifier.	Social media posts and articles on Covid – 19, IFCN chatbot.	F1-score = 93.32%
20.	Ghanem et al. [25]	EIN, LSTM Network, Baseline models.	Emotional features, Text data from, Language – related features.	F1-score = 96%

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signals, knowledge graphs, and even emotional sentiment. The progression from traditional models to advanced multimodal and hybrid frameworks reflects the growing complexity of misinformation detection and the need for scalable, high-accuracy solutions. Many researchers have explored different approaches to text classification and fake news detection by experimenting with a wide range of machine learning and deep learning models. For instance, some studies have utilized boosting and voting-based classification models, along with traditional algorithms such as Logistic Regression and Naïve Bayes. These models often incorporate stylistic metrics and word vector representations, such as Word2Vec embeddings, to enhance their predictive performance, achieving F1-scores around 0.75. Qi et al. [23] proposed a Multi-View Neural Network (MVNN) framework that integrates multimodal information by analyzing visual content, frequency and pixel-level features, and aligning sentiment between images and text. This innovative multimodal approach achieved an F1-score of 0.69, highlighting the potential of combining visual and textual data for misinformation detection. Similarly, Umer et al. [19] explored a variety of models, including Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and hybrid CNN-LSTM models, alongside tree-based algorithms. By incorporating feature selection techniques such as Principal Component Analysis (PCA) and Chi-square analysis along with textual features, their approach achieved a notable accuracy of 97.8%, demonstrating the strength of combining advanced feature engineering with deep learning models. Patwa et al. [24] focused on detecting misinformation during the COVID-19 pandemic by applying machine learning techniques, particularly a Support Vector Machine (SVM) classifier, to social media posts and articles. Their dataset also included fact-checking information from the IFCN chatbot, helping them achieve an impressive F1-score of 93.32%. Furthermore, Ghanem et al. [25] developed the Emotionally Infused Network (EIN), a deep learning model that integrates emotional cues and linguistic features, coupled with LSTM networks and baseline models. This method achieved an outstanding F1-score of 96%, emphasizing the importance of emotional and language based signals in improving classification accuracy. These studies collectively demonstrate the effectiveness of various machine learning and deep learning strategies for text classification and misinformation detection. By combining traditional statistical methods, advanced neural architectures, multimodal learning approaches, and emotional or sentiment-based cues, researchers have made significant progress in building more accurate and reliable models for identifying fake news and misleading content across digital platforms.

Literature Gap

The reviewed studies highlight significant progress in fake news detection, showcasing the use of advanced models like LSTM, CNN, GNN, and Bayesian networks, along with features such as social engagement patterns, content-based signals, and emotional cues. While some models, such as Vedova et al.'s HC-CB-3 (F1-score = 0.98) and Ghanem et al.'s EIN (F1-score = 0.96), have achieved impressive results, other approaches, like Qi et al.'s MVNN framework, have demonstrated comparatively lower performance (F1-score = 0.69). This indicates a gap in the consistent effectiveness of classifier models across studies. Furthermore, while certain research efforts, like Patwa et al.'s, focus on detecting misinformation in specific contexts (e.g., COVID-19), there is still a need for the development of more generalized and versatile models that can accurately identify misinformation across multiple domains, platforms, and scenarios.

III. METHODOLOGY

This research adopts a systematic and structured approach to fake news detection, making use of seven widely recognized traditional machine learning classifiers. The methodology is designed to provide a clear understanding of each step involved in building an effective fake news detection framework. It begins with a comprehensive description of the dataset, including its source, size, and composition, as well as an explanation of its relevance to the study. To ensure data consistency and improve model performance, several preprocessing steps were applied, such as text cleaning, tokenization, stop-word removal, and normalization. Additionally, feature extraction techniques, including Term Frequency-Inverse Document Frequency (TF-IDF) and handcrafted features such as sentiment scores, word count, and character count, were incorporated to enrich the dataset and capture deeper textual and structural patterns. Following data preparation, each of the selected machine learning classifiers—Support Vector Machine (SVM), Random Forest, Decision Tree, Gradient Boosting, Logistic Regression, Naïve Bayes, and K-Nearest Neighbors (KNN)—is discussed in detail. The methodology highlights their working principles, mathematical foundations, advantages, and suitability for solving text classification problems. By providing a step-by-step overview of model implementation, training, and evaluation, this section ensures transparency, reproducibility, and a clear justification for the techniques employed. This approach emphasizes a comparative analysis of classifier performance to identify the models most effective in detecting misinformation. By combining robust preprocessing, feature engineering, and well-established machine learning algorithms, the methodology aims to deliver a comprehensive framework for fake news detection. This detailed explanation also serves as a guide for future researchers seeking to replicate or extend this work across different datasets and domains, contributing to the advancement of misinformation detection techniques.

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1. Dataset

This study utilizes the WELFake dataset, a widely used benchmark dataset for fake news detection, which is publicly available on the Kaggle platform. The dataset consists of 72,134 news articles, including 35,028 real news articles and 37,106 fake news articles, providing a balanced and comprehensive resource for experimentation. Each entry in the dataset contains four key attributes: a serial number (index starting from 0), the title of the news article, the full text content, and a label, where 0 indicates fake news and 1 indicates real news. To improve the quality of the data and enhance the accuracy of classification, this research extended the original WELFake dataset by introducing several engineered features. A Cleaned_Description attribute was generated to remove unnecessary elements such as stop words, punctuation, and irrelevant characters, thereby improving the clarity and structure of the text. A Sentiment_Score feature was also added to quantify the sentiment of each article (positive, negative, or neutral), which can help capture emotional and stylistic differences between fake and real news. Furthermore, Word_Count and Char_Count attributes were included to examine variations in text length, while Extracted_Features provided additional linguistic and statistical attributes useful for classification. Another key addition was Entropy, a measure of textual randomness, designed to distinguish well-structured and coherent real news articles from misleading or manipulated content. After feature engineering, multiple traditional machine learning classifiers—including Support Vector Machines (SVM), Random Forest, Decision Tree, and Gradient Boosting—were applied to the dataset. The models were evaluated both before and after feature augmentation to systematically analyse the contribution of these newly introduced features. This comparison highlights the effectiveness of feature engineering in improving the accuracy, interpretability, and robustness of fake news detection models, reinforcing the importance of combining preprocessing techniques with machine learning approaches for misinformation analysis.

Table 2: Statistics of dataset 'WELFake'

S No.	Types of News	Number of News
1.	Real	35,028
2.	Fake	37,106

2. Machine Learning Models

This study employs seven widely used conventional machine learning classifiers for the task of fake news detection: 1. Random Forest Classifier 2. Logistic Regression 3. K-Nearest Neighbors (KNN) 4. Naïve Bayes 5. Gradient Boosting 6. Support Vector Machine (SVM) 7. Decision Tree.

These models were chosen for their proven effectiveness in text classification tasks and their ability to handle diverse data characteristics. Each classifier was initially trained on the raw dataset, and later re-evaluated after incorporating the engineered features to assess their contribution to classification performance. The Random Forest Classifier demonstrated strong performance, initially achieving an F1-score of 0.90. With the addition of handcrafted features, its F1-score improved to 0.95, highlighting its ability to leverage structured data for better predictions. Similarly, Logistic Regression achieved an F1 score of 0.90 on the raw dataset, which increased to 0.95 after feature augmentation. Its simplicity, interpretability, and efficiency make it a reliable choice for text-based classification tasks. The K-Nearest Neighbors (KNN) algorithm struggled with high-dimensional text data, achieving an F1-score of only 0.18 on the raw dataset. However, with the integration of engineered features, its performance improved significantly to 0.67, demonstrating the importance of feature engineering in enhancing distance-based classifiers. In contrast, Naïve Bayes maintained relatively stable performance, achieving an F1-score of 0.86 both before and after feature augmentation, benefiting from probabilistic modeling but showing limited gains from additional features. The Gradient Boosting model initially achieved an F1-score of 0.83, which increased substantially to 0.94 after feature integration. Its sequential learning approach, where each weak learner focuses on correcting previous errors, allowed it to capitalize on sentiment-based and statistical features effectively. Support Vector Machine (SVM) and Decision Tree classifiers were also evaluated, offering further insights into model interpretability and adaptability. Overall, the comparison of these models before and after feature engineering demonstrates the significant impact of handcrafted features in improving classification accuracy and robustness. Models like Random Forest and Gradient Boosting particularly benefited from the added sentiment, entropy, and statistical attributes, underlining the value of feature engineering in fake news detection research.

Algorithm 1: Detect Fake or Real News Using Machine Learning Classifiers

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Input:
- feature_enhanced_dataset: Combined TF-IDF and handcrafted feature matrix = Fake)
- classifier: Selected machine learning model (e.g., SVM, Random Forest, etc.)

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Output:
- predictions: Model-generated labels (Fake/Real)
- performance_metrics: Accuracy, Precision, Recall, F1-Score

1. Begin
2. Split feature_enhanced_dataset and labels into training_set (X_train, y_train) and testing_set (X_test, y_test)
3. Initialize selected classifier (e.g., SVM, Random Forest, XGBoost)
4. Train classifier using X_train and y_train
5. For each article_vector in X_test Do
6. predicted_label ⟵ classifier.predict(article_vector)
7. If predicted_label = 0 Then
8. Classify article as RealNews
9. Else
10. Classify article as Fake News
11. End If
12. End For
13. Compare predicted_labels with y_test to compute:
    a. Accuracy ⟵ correct_predictions / total_predictions
    b. Precision ⟵ TP / (TP + FP)
    c. Recall ⟵ TP / (TP + FN)
    d. F1-Score ⟵ 2 × (Precision × Recall) / (Precision + Recall)
14. RETURN predictions, performance_metrics 15. End

The architectural framework of the machine learning models employed in this study is illustrated in Figure 1, which provides a step-by-step workflow for detecting fake news, beginning with raw text input and culminating in a binary classification outcome. The workflow is designed to systematically process, transform, and analyze textual data to ensure effective and accurate detection of misinformation.

The process starts with text preprocessing, a critical step that prepares unstructured news data for computational analysis. During this stage, the text is tokenized into smaller units (tokens), and nonessential elements such as stop words (e.g., to, for, and) are removed to reduce noise. This is followed by vectorization using the Term Frequency–Inverse Document Frequency (TF-IDF) technique, which transforms textual content into a numerical format, capturing the significance of individual terms relative to the entire dataset. This numerical representation enables machine learning algorithms to process textual data effectively and identify underlying patterns.

Once preprocessing is complete, feature engineering and extraction are applied to enhance the dataset with handcrafted attributes that provide deeper insights into linguistic and structural properties of the news content. The engineered features include:
- Cleaned Description, which eliminates unnecessary symbols, punctuation, and irrelevant text elements;
- Sentiment Score, which quantifies the emotional tone (positive, negative, or neutral) of an article;
- Word Count and Character Count, which capture stylistic and length-based patterns;
- Extracted Features, which represent additional statistical and linguistic characteristics; and
- Entropy, which measures randomness or unpredictability in text, often higher in deceptive content.

These enriched features collectively improve the model's ability to identify subtle differences between fake and real news articles. The enhanced dataset is then fed into seven traditional machine learning classifiers: Random Forest, Support Vector Machine (SVM), Gradient Boosting, Decision Tree, Logistic Regression, K-Nearest Neighbors (KNN), and Naïve Bayes. Each classifier applies its unique mathematical approach to analyze patterns within the text and engineered features. For example, ensemble-based models like Random Forest and Gradient Boosting leverage multiple decision trees for robust prediction, while algorithms like SVM separate data into distinct classes based on optimal hyperplanes.
Finally, the trained classifiers produce a binary classification output, labeling news articles as either Fake or Real. This structured pipeline—from raw text preprocessing to feature engineering and classification—demonstrates the importance of integrating multiple stages of analysis to enhance model accuracy and reliability. By incorporating both linguistic and statistical features, the workflow provides a comprehensive strategy for combating misinformation.

3. Hand-Crafted Features

To enhance the accuracy of fake news detection, this study incorporates six key hand-crafted features that capture both linguistic and statistical properties of news articles. These features provide additional context beyond standard text vectorization techniques, allowing machine learning models to better distinguish between fake and real content. The selected features are:

- Cleaned Description – Represents the news text after preprocessing steps such as tokenization, stop word removal, and punctuation cleaning, ensuring a refined textual representation for analysis.
- Sentiment Score – Quantifies the emotional tone of the text (positive, negative, or neutral), as fake news often employs emotionally charged language to influence readers.
- Word Count – Measures the total number of words in an article, helping to identify stylistic patterns such as excessively short or verbose headlines.
- Character Count – Represents the total number of characters, providing insight into text structure and length-based variations.
- Extracted Features – Includes additional statistical or linguistic attributes, such as keyword frequency and n-gram distributions, to capture subtle textual characteristics.
- Entropy – Measures the level of unpredictability or randomness in text, which can often be higher in misleading or deceptive content.

These features collectively complement the numerical representations generated by TF-IDF, enabling classifiers to leverage richer contextual information. For example, consider the news headline: "Bobby Jindal, raised Hindu, uses story of Christian conversion to woo evangelicals for potential." After preprocessing and feature engineering, these attributes are systematically extracted, as illustrated in Table 3.

Algorithm 2: Generate Handcrafted Features for Fake News Detection

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Input:

- raw_dataset: News articles with title, text, and label columns
- stopwords_list: Standard stop word list for cleaning
- NLP Tools: Tokenizer, Lemmatizer, Sentiment Analyzer, NER/POS Tagger

Output:

- handcrafted_features: Set of extracted features per article • cleaned_descriptions: Preprocessed text descriptions

1. Begin
2. For each article in raw_dataset Do
3. description ← concatenate(title, text)
4. cleaned_text ← to_lowercase(description)
5. cleaned_text←remove_punctuation_and_special_chara-cters(cleaned_text)
6. tokens ← tokenize(cleaned_text)
7. tokens ← remove_stopwords(tokens, stopwords_list)
8. lemmatized_tokens ← lemmatize(tokens)
9. Cleaned_Description ← join(lemmatized_tokens)
10. Word_Count ← count_words(Cleaned_Description)
11. Char_Count ←count_characters(Cleaned_Description)
12. Sentiment_Score←analyze_sentiment(Cleaned_Description)
13. Extracted_Features←extract_named_entities_and_pos(Cleaned _Description)
14. Entropy ← compute_shannon_entropy(Cleaned_Des cription)
15. Store all above values as a record in handcrafted_features
16. End For
17. RETURN handcrafted_features, Cleaned_Descriptions
18. End

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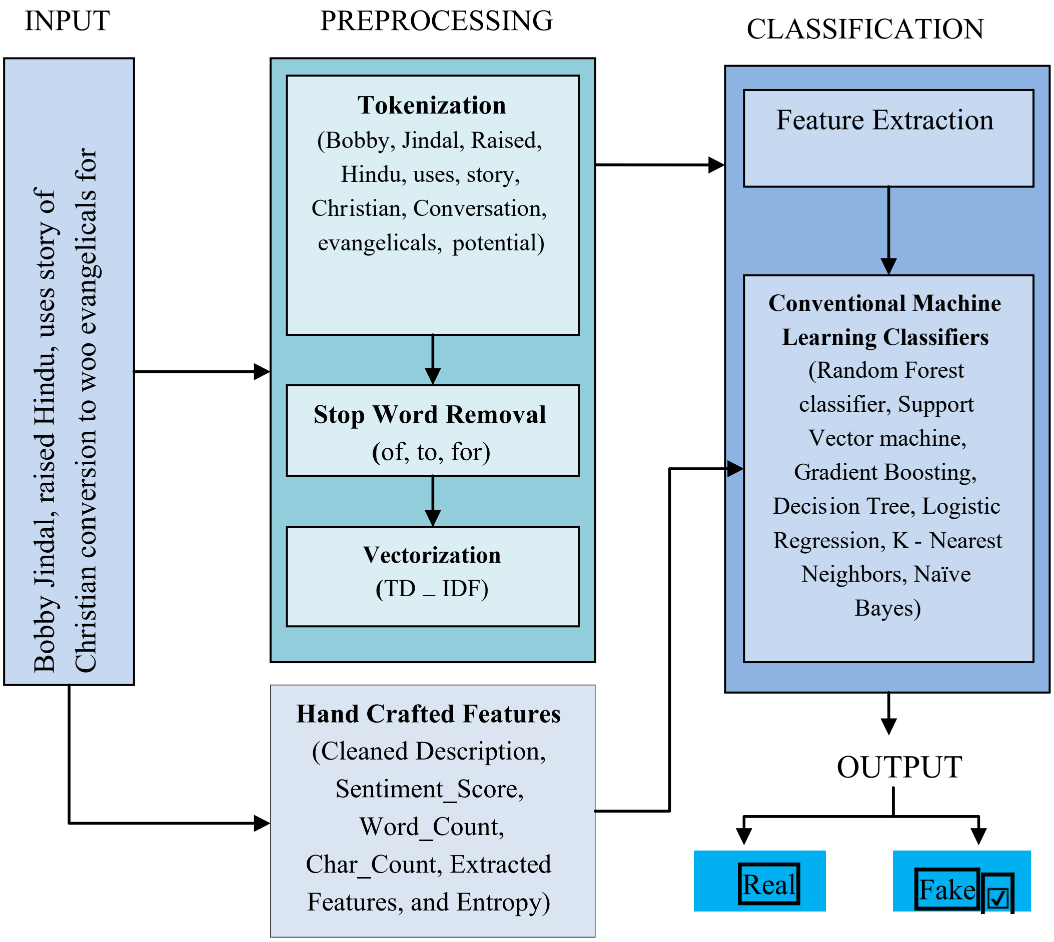

Fig. 1: Architectural Representation of Machine Learning Models with Hand Crafted Feature

IV. RESULT

This section presents a detailed evaluation of the performance of various machine learning classifiers used for fake news detection on the WELFake dataset. The primary goal of this analysis is to assess how well each model can distinguish between real and fake news articles, both when applied to the raw dataset and when enhanced with additional handcrafted features. The evaluation is based on three key performance metrics: Precision (P), Recall (R), and F1-score (F1), each providing a different perspective on model effectiveness:

- Precision (P): Precision measures the proportion of correctly identified fake news articles out of all articles predicted as fake. In other words, it evaluates the accuracy of positive predictions and shows how many of the flagged articles are truly fake.
- Recall (R): Recall indicates the model's ability to correctly detect all actual fake news articles. A higher recall value means fewer fake news items are being overlooked, making this metric critical in misinformation detection scenarios.
- F1-score (F1): The F1-score is the harmonic mean of precision and recall, offering a balanced measure of both. This metric is particularly valuable when there is an imbalance in the dataset, as it provides a single indicator of overall classification performance.

The experimental results are presented for two scenarios:
Raw Dataset: Classifiers were first applied to the dataset without additional processing beyond basic text preprocessing.
Enhanced Dataset with Handcrafted Features: Additional features—such as Cleaned Description, Sentiment Score, Word Count, Character Count, Extracted Features, and Entropy—were incorporated to improve the models' ability to detect fake news.

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This study demonstrates the impact of handcrafted feature engineering on classification accuracy and provides insights into which models perform best under different conditions.

1. Classifier Performance on the Raw WELFake Dataset

In the initial stage of experimentation, various machine learning classifiers were evaluated on the original WELFake dataset without incorporating any additional handcrafted features. The results of this evaluation are presented in Table 4.

As shown in the table, classifiers such as Random Forest, Logistic Regression, and SVM demonstrated strong performance, each achieving an F1-score of 0.90. In contrast, the K-Nearest Neighbors (KNN) classifier performed poorly, with a significantly lower F1-score of 0.18. This result highlights KNN's limitations in processing high-dimensional textual data effectively when feature engineering is not applied.

Table 3: Hand-Crafted Features and their Performance

S.No.:	Hand Crafted Features	Overview	Extracted Value (Performance based on News Headline)
1.	Cleaned Description	Raw text often contains noise, such as stop words, punctuation, and unnecessary characters. We preprocess the text to remove these elements while retaining the most meaning words.	Bobby Jindal raised Hindu uses story Christian conversion woo evangelicals potential
2.	Sentiment Score	This metric quantifies whether the text expresses a positive, negative, or neutral sentiment.	**Neutral (0.02)** (Minimal emotional tone)
3.	Word Count	A straightforward feature that counts the number of words in the sentence.	12
4.	Character Count	The total number of characters in the sentence, including spaces.	97
5.	Extracted Features	These include linguistic patterns such as Named Entity Recognition (NER) and Part-ofSpeech (POS) tagging.	Named Entities: "Bobby Jindal" (Person), "Hindu" (Religion), "Christian" (Religion), "evangelicals" (Group) POS Tags: "Bobby Jindal" (Proper Noun), "uses" (Verb), "story" (Noun).
6.	Entropy	A measure of text randomness and complexity. Higher entropy suggests more diverse or unpredictable word choices.	3.1 (Moderate Complexity)

2. Classifier Performance After Feature Enhancement

To improve classification accuracy, additional handcrafted features were created and incorporated into the dataset. These included Cleaned_Description, Sentiment_Score, Word_Count, Char_Count, Extracted Features, and Entropy. The classifiers were retrained and evaluated on this enhanced dataset, with the results summarized in Table 5.

Overall, all classifiers demonstrated improved performance after feature engineering, with models such as Random Forest, Logistic Regression, Gradient Boosting, Decision Tree, and SVM achieving F1-scores above 0.93. The most notable improvement was observed in KNN**,** which initially performed poorly with an F1-score of 0.18 but rose to 0.67 after incorporating the new features. These findings highlight the effectiveness of feature engineering in improving classification performance.

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Table 4: Performance of Classifiers on the Original WELFake Dataset

Model	Performance		
	P	**R**	**F1 – score**
Random Forest Classifier	0.91	0.89	0.90
Logistic Regression	0.91	0.89	0.90
KNN	0.96	0.10	0.18
Naïve Bayes	0.87	0.85	0.86
Gradient Boosting	0.85	0.80	0.83
Decision Tree	0.87	0.85	0.86
SVM	**0.91**	**0.88**	**0.90**

3. *Performance Comparison and Analysis*

The findings of this study strongly emphasize the critical role of feature engineering in enhancing the effectiveness of fake news detection models. By incorporating additional features such as Cleaned_Description, Sentiment_Score, Word_Count, Char_Count, Extracted Features, and Entropy**,** the classifiers were able to capture a wider range of textual and statistical patterns in the dataset. This, in turn, resulted in measurable improvements in classification metrics, including precision, recall, and F1-score.

Machine learning models such as Random Forest, Logistic Regression, and SVM demonstrated substantial performance gains, reinforcing their suitability for fake news classification tasks. Similarly, Gradient Boosting and Decision Tree classifiers also exhibited consistent improvements, with all these models achieving F1-scores above 0.93 after feature enhancement. This high level of performance indicates that the selected features effectively contributed to distinguishing between real and fake news articles.

An especially noteworthy observation is the improvement in the K-Nearest Neighbors (KNN) classifier. Initially, KNN struggled to generalize effectively, achieving an F1-score of only 0.18 on the raw dataset. However, after incorporating the engineered features, its performance improved significantly, reaching an F1-score of 0.67**.** This improvement demonstrates that even relatively weaker classifiers can achieve meaningful accuracy gains when provided with a carefully engineered and informative feature set.

The results clearly demonstrate that incorporating linguistic, statistical, and entropy-based features substantially enhances model performance, making the detection of fake news more accurate, robust, and reliable**.** The findings validate the importance of a comprehensive feature engineering strategy in strengthening classification models, highlighting that the choice and design of features play a crucial role in achieving state-of-the-art results in fake news detection.

Table 5: Performance of Classifiers on the Enhanced WELFake Dataset

Model	Performance		
	P	**R**	**F1 – score**
Random Forest Classifier	0.95	0.95	0.95
Logistic Regression	0.95	0.95	0.95
KNN	0.76	0.70	0.67
Naïve Bayes	0.86	0.86	0.86
Gradient Boosting	0.94	0.94	0.94
Decision Tree	0.93	0.93	0.93
SVM	**0.96**	**0.96**	**0.96**

4. *Performance Analysis*

The comparison of results highlights the crucial role of feature engineering in improving fake news detection. By adding new features to the dataset, the machine learning classifiers achieved better precision, recall, and F1-scores. Models like

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Random Forest, Logistic Regression, and SVM showed strong performance improvements, confirming their effectiveness for this task. Even KNN**,** which initially performed poorly, demonstrated significant gains, showing that the right choice of features can improve the performance of weaker classifiers as well.

Overall, the findings confirm that incorporating linguistic, statistical, and entropy-based features enhances the accuracy and reliability of fake news classification, making the models more robust and effective in distinguishing between real and fake news articles.

V. DISCUSSION

This study used the WELFake dataset from Kaggle, which contains 72,134 news articles (35,028 real and 37,106 fake), to evaluate the effectiveness of seven traditional machine learning classifiers for fake news detection. On the raw dataset, models such as Random Forest, Logistic Regression, and SVM performed relatively well, each achieving an F1-score of around 0.90, whereas KNN performed poorly with an F1-score of 0.18. These results highlight the limitations of applying traditional machine learning algorithms directly to raw textual data without additional feature engineering. To improve performance, six hand-crafted features—Cleaned Description, Sentiment Score, Word Count, Character Count, Extracted Features, and Entropy—were added to the dataset alongside the existing 10,000 TF-IDF features, increasing the total feature space to 10,006. These additional features introduced richer linguistic and statistical information that complemented the TF-IDF representation. After retraining the models on the enhanced dataset, all classifiers demonstrated noticeable performance improvements, with the greatest gains observed in KNN, Gradient Boosting, and Decision Tree, which initially struggled with raw textual features alone.

Among all classifiers, SVM achieved the highest accuracy of 96%, demonstrating the value of combining TF-IDF features with carefully engineered linguistic and statistical attributes. This hybrid approach provided a deeper contextual understanding of the text, improving classification performance and robustness. Overall, the results confirm that integrating structured handcrafted features with traditional text-based representations can significantly enhance fake news detection, making machine learning models more accurate and reliable in distinguishing between real and fake news articles.

VI. FUTURE WORK

While this study has contributed valuable insights into fake news detection using machine learning and topic modeling, there remains considerable scope for further exploration and advancement in this field. Future research can focus on several promising directions:

1. Exploring Advanced Deep Learning Architectures: Future studies could investigate deep learning techniques such as Long Short-Term Memory (LSTM) networks, Transformer based models, and CNN-LSTM hybrid architectures. These advanced approaches are capable of capturing intricate linguistic patterns, semantic nuances, and contextual dependencies, which may lead to more accurate and scalable fake news detection systems.
2. Incorporating Multimodal Data: This research primarily focused on textual data, but fake news often spreads through images, videos, and audio content. Future work could involve developing multimodal detection frameworks that integrate and analyze multiple data types simultaneously, enabling a more comprehensive understanding of misinformation and improving detection performance.
3. Modeling Contextual and Temporal Dynamics: Fake news is often tied to real-time events, trending topics, and dynamic online discussions. Future research should explore techniques that incorporate contextual and temporal factors to track topic evolution and detect misinformation early, allowing systems to adapt to rapidly changing information landscapes.
4. Transfer Learning and Cross-Domain Adaptation: Another area for future work is leveraging transfer learning approaches to adapt models trained on one dataset, language, or domain to other contexts. This would facilitate the creation of robust, generalizable fake news detection systems capable of performing effectively across diverse scenarios and linguistic environments.
5. Addressing Ethical and Privacy Challenges: As fake news detection systems rely on large scale data collection and processing, ethical considerations and privacy concerns must be prioritized. Future studies should examine methods to ensure fairness, transparency, and user data protection while maintaining strong detection performance. 6. Standardized Benchmarking and Evaluation Metrics: To advance research in this domain, there is a need for standardized benchmarks and evaluation protocols. Developing consistent metrics and datasets for comparing machine learning techniques will promote more rigorous assessments of model performance, reproducibility, and generalizability.

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VII. CONCLUSION

This research focused on fake news detection using the WELFake dataset, which contains 72,134 news articles, including 35,028 real and 37,106 fake articles. The dataset, compiled by merging multiple sources, provided a robust foundation for evaluating the effectiveness of traditional machine learning classifiers in distinguishing real news from fake news. Seven machine learning models were examined: Random Forest, Logistic Regression, K-Nearest Neighbors (KNN), Naïve Bayes, Gradient Boosting, Decision Tree, and Support Vector Machine (SVM). When applied to the raw dataset, Random Forest, Logistic Regression, and SVM demonstrated strong performance with F1-scores of 0.90, whereas KNN struggled significantly, achieving an F1-score of only 0.18. To improve detection accuracy, several handcrafted features were engineered and integrated into the dataset, including Sentiment Score, Cleaned Description, Word Count, Character Count, Extracted Features, and Entropy. These enhancements significantly improved model performance, with SVM achieving the highest F1-score of 0.96, while Random Forest, Logistic Regression, and Gradient Boosting all exceeded 0.93. Even KNN showed notable improvement, increasing its F1-score to 0.67, highlighting the effectiveness of feature engineering in enhancing classification outcomes. Looking ahead, future research in fake news detection should explore advanced deep learning methods, such as Transformer-based models (e.g., BERT, RoBERTa) and hybrid CNN-LSTM approaches, to capture more complex textual structures and semantic relationships. Additionally, adopting multimodal analysis that combines text with images, videos, and metadata could lead to more comprehensive misinformation detection systems. Incorporating contextual and temporal dynamics will also help track the evolution of misinformation over time, improving early detection capabilities. Techniques like transfer learning and domain adaptation may further enhance the adaptability of models across multiple languages and domains. Moreover, future studies should address ethical and privacy considerations to ensure responsible and transparent AI practices, and work toward establishing standardized benchmarks to improve reproducibility, reliability, and scalability in fake news detection research.

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BIOGRAPHY

Shivani Pandey is a master's student at IET, Ayodhya. She holds a B.Tech degree in information technology from IET, Ayodhya. Shivani research areas include machine learning, natural language processing, misinformation detection. She has worked extensively on fake news detection, applying advanced text-processing techniques and feature engineering to improve classification performance. She aims to contribute to the development of efficient and reliable AI-driven solutions for combating misinformation.

Rajnish Pandey received his B.Tech. degree in Computer Science from the Institute of Engineering and Technology, Sitapur, affiliated with AKTU, and his M.Tech. degree in Computer Science from SRM University, Chennai. He earned his Ph.D. from the National Institute of Technology, Patna, in sarcasm identification from news headlines and tweets using deep learning approaches. He has a teaching experience of more than 10 years, from 2014 till present. Currently, he serves as an Assistant Professor in the Department of Information Technology at the Institute of Engineering and Technology, Dr. Rammanohar Lohia Avadh University, Ayodhya. He has authored or coauthored more than 20 research publications, including 10 conference proceedings and 5 journal articles. His research contributions have earned him an H-index of 19 with over 120 citations.

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Aanchal Mishra is a master's student with a specialization in Information Technology.She has received her B.Tech. degree in Information Technology from the I.E.T., Ayodhya. Aanchal's first research paper focuses on creating a new dataset of fake and real news, implementing machine learning classifiers, and analyzing their performance. Her research interests include machine learning, natural language processing, and misinformation detection. She is passionate about exploring AI-driven solutions to enhance the reliability of news classification.

Awadhesh Kumar Maurya received his B.Tech. degree in Information Technology from the BIET Jhansi, affiliated with AKTU, and his M.Tech. degree in Information Technology from IIIT Allahabad. He has a teaching experience of more than 14 years, from 2011 till present. Currently, he serves as an Assistant Professor in the Department of Information Technology at the Institute of Engineering and Technology, Dr. Rammanohar Lohia Avadh University, Ayodhya. He has authored or coauthored more than 10 research publications, including 4 conference proceedings and 6 journal articles. His research contributions have earned him an H-index of 04 & i10 index of 03 with over 108 citations.

Akhilesh kumar received his B.Tech. degree in computer science and engineering from the MGM college of engineering and technology Noida affiliated with AKTU, and his M.Tech. degree in computer science and technology from knit Sultanpur. He has a teaching experience of more than 13years, from 2012 till present. Currently, he serves as an Assistant Professor in the Department of Information Technology at the Institute of Engineering and Technology, Dr. Rammanohar Lohia Avadh University, Ayodhya.
He has authored or coauthored more than 10 research publications, including 4 conference proceedings and 6 journal articles. His research contributions have earned him an H-index of 04 & i10 index of 03 with over 108 citations.