Engineering and Technology Journal e-ISSN: 2456-3358

Volume 10 Issue 05 May-2025, Page No.- 5177-5185

DOI: 10.47191/etj/v10i05.46, I.F. – 8.482

Fake News Detection Using Natural Language Processing (NLP) and Machine Learning

Hisham Ahmed Mahmoud[1], Ibrahim M. Ibrahim[2]

[1]Akre University for Applied Sciences Technical College of Informatics Directorate of Educational Training and Development/Duhok

[2]Akre University for Applied Sciences Computer Networks and Information Security Technical College of Informatics-Akre

ABSTRACT: Fake news has become a significant social problem that affects public opinion and social trust. The dissemination of misinformation at lightning speed through online media channels presents a serious problem in distinguishing between credible and deceptive content. Much research has been done on machine learning and natural language processing (NLP) approaches to create automated detection systems that address this problem. These methods classify news stories as synthetic or legitimate based on statistical, contextual, and language characteristics. Several machine learning techniques are presented in this book, including deeper, more complex models as well as more conventional classifiers like Logistic Regression (LR), Naïve Bayes (NB), Support Vector Machines (SVM), and Decision Trees. Additionally, the hybrid models that combine ensemble learning and natural language processing (NLP) are showcased for their potential to improve classification accuracy and dependability. Feature extraction techniques like word embeddings, N-grams, and Term Frequency-Inverse Document Frequency (TF-IDF) are credited with organizing textual data into machine learning inputs. In addition, network-based techniques and sentiment analysis are examined as substitute techniques for pattern recognition in the fight against false information. The findings provide strong evidence that combining statistics and deep learning techniques enhances the effectiveness and precision of false news detection. This study establishes the groundwork for future research to create robust and scalable systems for identifying fake news by shedding light on the capabilities and limitations of various approaches.

KEYWORDS: Fake News Detection; Natural Language Processing (NLP); Machine Learning; Deep Learning; Text Classification; Feature Extraction; Sentiment Analysis; Hybrid Models; Transformer Models; Word Embeddings; TF-IDF; Misinformation.

1. INTRODUCTION

The dissemination of false information has become one of the most urgent concerns of the digital age. With the advent of fast, user-driven models such as social media, messaging apps, and networked blogging, the distribution of false information is no longer constrained by traditional editorial screening mechanisms[1, 2]. This unfiltered information dissemination has wide-ranging effects ranging from influencing popular perceptions and dictating electoral outcomes to spreading health misinformation and inducing social unrest[3]. Particularly at such historic event such as the 2016 U.S. Presidential Election and global-wide COVID-19 pandemic, disinformation succeeded in outpacing official sources of information as far as visibility and engagement are concerned[4]. The traditional mechanisms for verifying news—relying on human fact-checkers, journalists, or regulatory agencies—are inherently slow and insufficient to deal with the amount and pace at which content is produced online[5]. Thus, there exists a pressing necessity for systems to automatically process vast amounts of text in real-time and make accurate judgments regarding false or misleading information[6]. In such a scenario, Natural Language Processing (NLP) and Machine Learning (ML) are cutting-edge technologies that can enable automated systems to read, analyze, and classify news stories based on linguistic, semantic, and statistical patterns[7]. Machine learning models can be trained to detect subtle text cues and anomalies that are typical of deceptive content[8]. These include sensationalized titles, emotive language, semantic dissonance, and stylistic deviance from genuine reporting. Coupled with NLP models such as tokenization, lemmatization, sentiment analysis, and syntactic parsing, such models can form the basis for a robust fake news detection system. Slightly more sophisticated techniques using word embeddings (e.g., Word2Vec, GloVe), vectorization techniques (e.g., TF-IDF, n-grams), and deep learning architectures (e.g., RNNs, LSTMs, CNNs) further enhance the system in learning from context and complex language constructs[9]. Further recent developments in transformer models, i.e., BERT, RoBERTa, and GPT, have changed the game in the domain by introducing pre-trained models capable of understanding fine-grained semantic dependencies between words and phrases[10]. These models far outperform traditional ML methods with the assistance of deep contextual information and transfer learning so that it is now achievable to identify fake news more precisely and effectively[11]. This paper provides a comprehensive comparison of various machine learning and NLP-based methods for detecting fake news. It puts traditional classifiers such as Logistic Regression, Naïve Bayes, and Support Vector Machines against existing deep learning models and transformer-based models. It also talks about hybrid methods that combine statistical models with neural networks to leverage the strength of both[12]. The study evaluates the performance of these models using public datasets and compares their accuracy, scalability, and generalizability to practical applications. Moreover, the paper stresses the challenge of translating disinformation tactics, such as AI-created content and multimodal fakes, and underlines the necessity of explainable AI in crafting trustworthy detection systems[13]. In general, fake news detection is a multidisciplinary problem that must be solved by integrating linguistic analysis, algorithmic creativity, and ethical concerns. By leveraging the capabilities of NLP and machine learning, this research aims to help develop intelligent systems that can aid in digital literacy, safeguard information integrity, and ultimately build a more enlightened global society.

2. RESEARCH METHODOLOGY

The methodology used to develop a false news detection system based on machine learning (ML) and natural language processing (NLP) techniques is described in this section. The method uses a systematic pipeline that starts with data gathering and ends with assessment and recommendations for further developments.

2.1 Dataset Collection

A wide range of authentic and fraudulent news stories are included in the dataset utilized in this study, which was obtained via Kaggle. To aid with supervised learning, each item has a label. The dataset, which includes a variety of news items to ensure fair representation and generalizability, is crucial for training and testing classification algorithms. The work promotes equitable model evaluation and adheres to reproducible research principles by utilizing a carefully selected and publicly accessible dataset.

2.2 Text Preprocessing

The raw text data was preprocessed using a number of methods to guarantee clean and consistent input for machine learning models. Tokenization, which divides the text into discrete tokens or words, was a step in this process. Stopwords and unnecessary letters were then eliminated. Additionally, to improve uniformity throughout the dataset, terms were reduced to their basic forms using stemming and lemmatization. In order to reduce noise and improve the quality of the input data, text normalization—which includes lowercasing and punctuation removal—was also carried out.

2.3 Feature Engineering

Numerical features were taken from the text to be used as inputs for the machine learning algorithms once the data had been preprocessed. This was achieved by employing techniques that aid in capturing word significance and sequence patterns, such as Count Vectorization, N-gram modeling, and Term Frequency-Inverse Document Frequency (TF-IDF). Feature selection methods like the Chi-Square Test and Mutual Information were applied to increase efficiency and concentrate the model on the most pertinent data. By highlighting important characteristics and reducing dimensionality, these techniques aid in precise categorization.

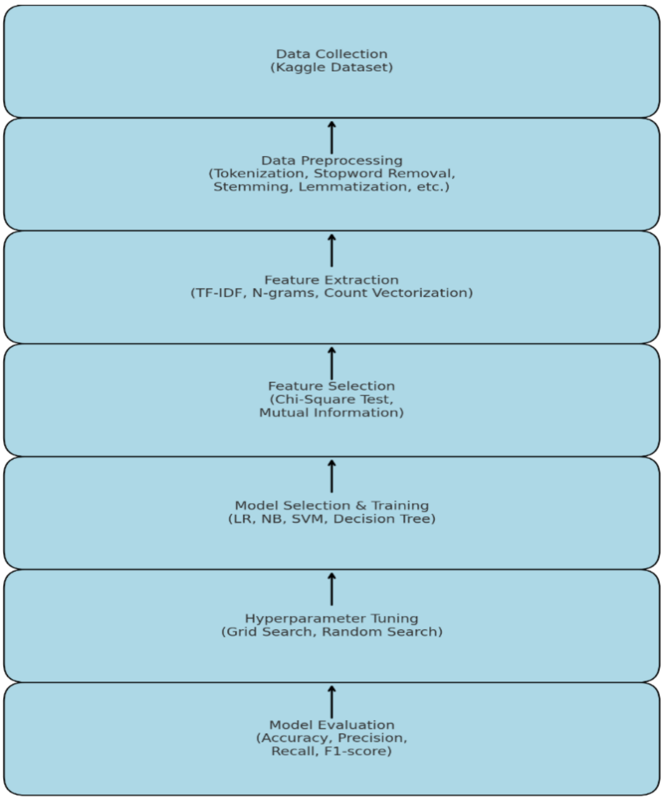
2.4 Model Development and Training

Numerical features were taken from the text to be used as inputs for the machine learning algorithms once the data had been preprocessed. This was achieved by employing techniques that aid in capturing word significance and sequence patterns, such as Count Vectorization, N-gram modeling, and Term Frequency-Inverse Document Frequency (TF-IDF). Feature selection methods like the Chi-Square Test and Mutual Information were applied to increase efficiency and concentrate the model on the most pertinent data. By highlighting important characteristics and reducing dimensionality, these techniques aid in precise categorization.

2.5 Evaluation and Future Scope

Several widely used performance measures—accuracy, precision, recall, and F1-score—were used to holistically assess the performance of the trained machine learning models. These measures provide a multi-dimensional perspective on how accurately a model can detect real and fake news. Accuracy indicates the overall accuracy of the predictions, whereas precision indicates the proportion of true fake news identified out of all items identified as fake. Recall, in contrast, measures the capability of the model to accurately detect all the existing fake news articles. The F1-score, a harmonic mean of recall and precision, is especially useful when working with imbalanced datasets, where one class may significantly dominate the other—a real-world scenario in fake news detection tasks.Despite the current models demonstrating strong classification power and producing positive outcomes, there remains ample room for improvement in adjusting to the constantly shifting landscape of misinformation. Future research has to aim at creating real-time fact-checking solutions that can perform well within dynamic environments where disinformation spreads rapidly across different platforms. Secondly, the use of Explainable

Artificial Intelligence (XAI) needs to be looked into for greater transparency and trust, particularly in high-stakes applications where model outputs need to be explainable and accountable. Another avenue with promise is researching Self-Supervised Learning, which could decrease dependence on large amounts of labeled data by enabling models to obtain beneficial representations from unlabelled, raw text. Together, these innovations hold the promise of creating more adaptive, scalable, and consistent fake news detection systems capable of addressing the advanced and adaptive techniques of modern disinformation campaigns.



Figer1: Structured Methodology for Automated Fake News Classification

4. LITERATURE REVIEW

Identification of false news has been an emerging area of research, and various studies have utilized machine learning and NLP techniques to increase precision[14, 15]. Language and semantic examination, such as sentence structure, use of vocabulary, and coherence, have been researched by scholars, and researchers have discovered that false news articles usually utilize hyperbolic word choice, lower lexical diversity, and extreme readability measures[16]. Sentiment and emotional analysis show that fake news employs intense emotions, typically playing on the reader's emotions through emotive language[17]. Stylometric analysis, examining writing style and syntactic structures, has proven successful in identifying fake content[18]. Traditional machine learning models such as Naïve Bayes, SVM, and Decision Trees have been widely employed for classification, but with the recent advancements in deep learning such as RNNs, LSTMs, CNNs, and hybrid architectures, detection accuracy has significantly improved by learning contextual relations in text data[19]. The transformer-based architectures such as BERT, GPT, and T5 employ self-attention to enhance performance[20]. Ensemble and hybrid approaches extend accuracy even more by combining statistical learning and deep learning models[21]. Real-time detection of fake news has driven innovation in user behavior analytics, network-based detection, and explainable AI models to enhance transparency[22]. All these despite, fake news detection remains challenging due to the dynamic nature of misinformation, innovation of multimodal fake news (text, images, and videos), and algorithmic bias concerns[23]. Future research promises to develop adaptive, scalable, and ethically responsible models in order to counter misinformation more effectively in a continuously changing digital space.

4.1 Linguistic and Semantic Analysis

One of the pioneer approaches in fake news detection is linguistic analysis, which inspects textual characteristics like sentence structure, use of vocabulary, and semantic coherence[24-26]. It has been observed by researchers that fake news articles tend to have:

- **Exaggerated or sensational language:** Fake news stories frequently use emotionally charged words, hyperbolic expressions, and misleading headlines to attract attention.

- **Lower lexical diversity:** Studies suggest that deceptive articles tend to reuse specific words and phrases, indicating a lack of linguistic variation.
- **Sentence complexity and readability:** Fake news articles may exhibit overly simplistic or overly complex sentence structures, deviating from journalistic norms.

Semantic analysis techniques such as Latent Semantic Analysis (LSA) and Word Embeddings (Word2Vec, GloVe, FastText) have been applied to detect hidden patterns among words and detect patterns characteristic of misinformation.

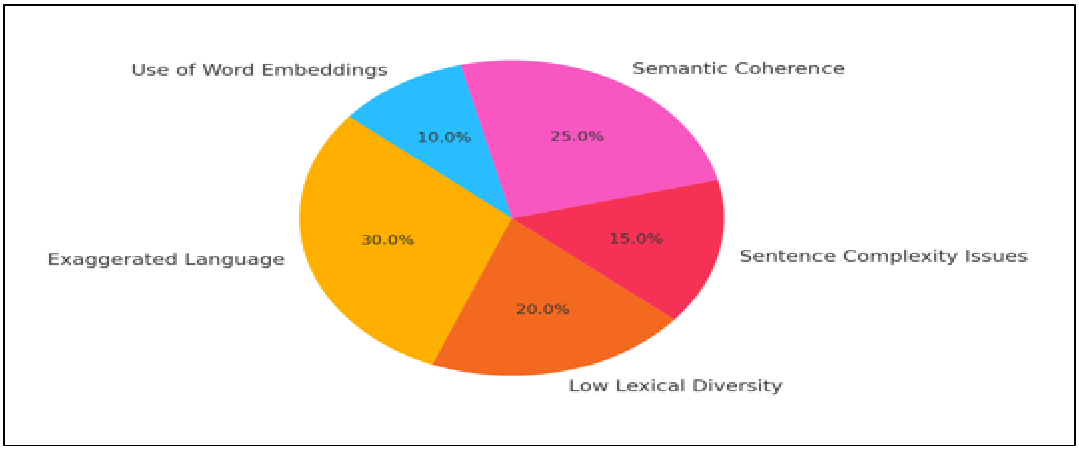


Figure 1: Distribution of Linguistic and Semantic Features in Fake News Detection

4.2 Advanced Techniques for Fake News Detection

Fake news detection has evolved through techniques such as sentiment and emotion analysis, which have shown that fake news tends to incorporate emotionally charged or subjective language, as opposed to the neutral tone of authentic news[27]. Emotion classifiers that identify fear, anger, or surprise assist in identifying deceptive content. Stylometric analysis, such as n-gram patterns, grammar, and readability scores, also assists in detecting fake news[28]. Machine learning algorithms such as Naïve Bayes, SVMs, Decision Trees, and Random Forests categorize content using linguistic features but demand heavy feature engineering. In order to combat increasingly complex disinformation, scientists are integrating deep learning and NLP for higher accuracy.

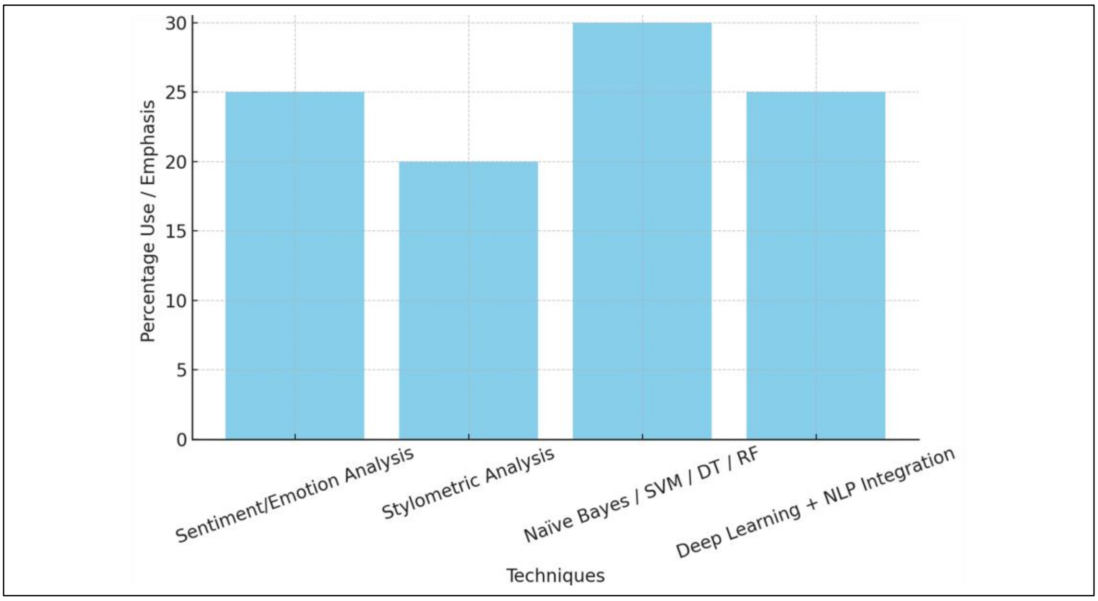


Figure 2: Distribution of Core NLP and ML Techniques for Fake News Detection

4.3 Advanced Deep Learning Techniques for Fake News Detection

With the rise of misinformation, identifying fake news is becoming more crucial with deep learning. RNNs, LSTMs, and CNNs learn textual patterns and contextual relationships, improving classification accuracy[29]. Hybrid models that employ a combination of CNNs and LSTMs, and transformer-based models like BERT, GPT, T5, and XLNet offer state-of-the-art results with deep language and contextual understanding. Researchers also use ensemble methods and combine statistical models like SVM and Naïve Bayes with deep learning to provide improved accuracy and explainability[30]. Knowledge-based systems and external fact-checkers assist in making it reliable. User behavior analysis and network-based tracking are components of real-time detection now. Explainable AI (XAI) is also used to build trust. Some of the challenges are the novel misinformation tactics, the rise of multimodal content, bias, and scalability[31]. Future work seeks to create adaptive, ethical, and robust AI systems using techniques like self-supervised, reinforcement, and federated learning.

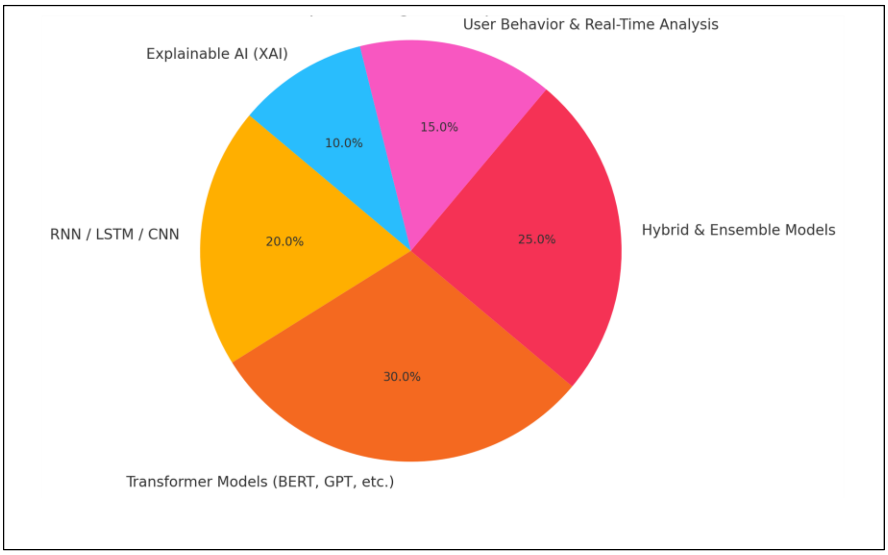


Figure 3: Proportion of Deep Learning Strategies for Fake News Classification

5. DISCUSSION AND COMPARISON

The performance of disinformation detection systems largely relies on the choice of machine learning algorithms, representativeness and quality of the dataset, feature extraction techniques employed, and hyperparameter tuning approach[32]. Here, a variety of models were explored, ranging from simple classifiers to state-of-the-art deep learning and transformer-based models[33]. Of the traditional machine learning methods, Logistic Regression (LR) and Naïve Bayes (NB) are the most basic, quickest, and efficient ones, especially for high-dimensional text classification tasks. They require similarly fast computation resources and are interpretable, making them ideal for baseline studies and quick deployment in low-resource environments[34]. Logistic Regression is able to produce good performance in cases when text features are linearly separable, but Naïve Bayes, despite relying on the strong assumption of feature independence, is surprisingly capable of producing good results for natural language processing problems due to word distribution topological properties within text[35]. Support Vector Machines with their ability to handle high-dimensional spaces of features tend to perform better than simpler models, especially after optimization using kernel functions. SVMs perform best with sparse representation such as those produced by TF-IDF or N-gram vectorization[36]. They are, however, computationally intensive and require tuning, especially for larger datasets. Decision Trees and Random Forests, as rule-based learners, enjoy the advantage of interpretability and can learn non-linear relationships. They work well in finding hierarchical decision paths but are prone to overfitting, particularly when feature engineering is weak or the dataset is imbalanced. Ensemble techniques such as Random Forest and XGBoost improve model stability by taking the average of numerous learners, which improves generalization and reduces the likelihood of bias[37]. Apart from traditional models, deep learning models have made significant advancements in identifying fake news since they are capable of learning complex semantic and syntactic patterns from texts. Convolutional Neural Networks (CNNs) are adept at extracting local features and spatial hierarchies from text, whereas Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are adept at capturing sequential dependencies, and therefore are well placed to capture context and narrative flow[38]. Deep learning models, however, typically require large labeled data and a tremendous amount of computing power for training. In this, transformer models such as BERT (Bidirectional Encoder Representations from Transformers), RoBERTa, and GPT are the state-of-the-art models[39]. The models utilize the self-attention mechanism to capture the contextual relations in the text more effectively than RNNs and CNNs. Fine-tuning pre-trained transformer models for fake news data has shown high accuracy and F1 values over traditional classifiers as well as older deep learning models[40]. Though they work excellently, transformer models come with trade-offs. They are memory-intensive and can require GPU capability and enormous memory space. Their complexity also can reduce transparency, leading to explainability and bias issues in high-stakes uses like news classification. Hybrid approaches and ensemble models combining several approaches have been especially helpful[41]. For example, stacking a logistic regression on the outputs of an SVM and an LSTM can take advantage of both linear and non-linear relationships in addition to sequential context modeling. Ensemble methods such as bagging and boosting (e.g., AdaBoost, XGBoost) have also been known to work well, usually outperforming single classifiers since they can reduce variance and bias. Additionally, the incorporation of metadata attributes (such as source of article, author credibility, and social engagement measures) and user behavior analysis will enhance the accuracy of models, particularly in real-world application where context becomes vital[42]. Work has demonstrated that combining content-based features with propagation-based signals is a better enhancement for fake news detection systems to improve their credibility. In brief, while basic machine learning models offer speed and ease, transformer models and deep learning offer improved performance in high-level textual applications[43]. Based on the requirements of the application, whether scalability, interpretability, available computing resources, or real-time execution, a model must be selected accordingl

Table1: Comprehensive Comparative Analysis of Machine Learning Models and Techniques for Fake News Detection

#	Model/Technique	Type	Key Techniques	Strengths	Limitations
	Logistic Regression (LR)	Traditional ML	TF-IDF, CountVectorizer	Fast, interpretable	Weak on non-linear patterns
	Naïve Bayes (NB)	Traditional ML	N-gram, TF-IDF	Lightweight, good for text classification	Assumes feature independence
	Support Vector Machine	Traditional ML	TF-IDF + Kernel	Handles high-dimensional data well	High computational cost
	Decision Tree	Traditional ML	Gini/Entropy splits	Easy to visualize and understand	Prone to overfitting
	Random Forest	Ensemble	Bagging, multiple trees	Robust, reduces overfitting	Slower, less interpretable
	XGBoost	Ensemble	Gradient boosting	High accuracy, regularization built-in	Complex parameter tuning
	AdaBoost	Ensemble	Weak learners + boosting	Improves weak classifiers	Sensitive to noisy data
	K-Nearest Neighbors (KNN)	Traditional ML	Distance metrics (Euclidean)	Simple, no training phase	Inefficient with large datasets
	Ridge Classifier	Regularized ML	L2 Regularization	Reduces overfitting	Not great with non-linear data
	Passive Aggressive Class.	Online ML	Hinge loss-based	Fast updates, good for large streams	Prone to instability
	Recurrent Neural Network	Deep Learning	Sequential data processing	Good for sequence learning	Vanishing gradient issue
	LSTM	Deep Learning	Gated RNN units	Solves long dependency issues in text	Slow training, many parameters
	GRU	Deep Learning	Simplified LSTM	Faster than LSTM, performs comparably	Less expressive than LSTM
	CNN	Deep Learning	Convolutional layers	Great for extracting local text features	Lacks sequential understanding

	BERT	Transformer (DL)	Pre-trained transformer	Deep contextual awareness, top-tier accuracy	Large memory & compute requirements
	RoBERTa	Transformer (DL)	Optimized BERT	Better fine-tuning, robust	Very resource-heavy
	GPT	Transformer (DL)	Generative pre-training	Contextual generation + classification	Lower interpretability
	XLNet	Transformer (DL)	Permutation Language Modeling	Handles longer dependencies than BERT	Training complexity
	T5	Transformer (DL)	Text-to-text format	Flexible for classification and generation	High training resource demand
	Hybrid (SVM + LSTM)	Hybrid	Stacking techniques	Combines strengths of both models	Hard to interpret, complex structure
	Hybrid (CNN + LSTM)	Hybrid	Local + sequential features	Enhanced feature extraction	Needs large training data
	Ensemble Voting Classifier	Hybrid	Majority voting among classifiers	Improved stability and generalization	Model selection is key
	Self-Supervised Learning	Emerging	Pretext tasks for feature learning	Reduces need for labeled data	Still under development for fake news
	Reinforcement Learning	Emerging	Reward-based feedback	Good for dynamic, adaptive systems	Not widely adopted yet in fake news
	Federated Learning	Privacy-Preserving	Distributed training	Privacy-friendly, scalable	Communication overhead
	Sentiment Analysis	NLP Technique	Polarity scores, emotion classifiers	Adds emotional dimension to analysis	May miss sarcasm or subtleties
	Stylometric Analysis	NLP Technique	Writing style, POS patterns	Authorship or style-based detection	Style can be mimicked
	Explainable AI (XAI)	Model Interpretation Tool	SHAP, LIME, attention visualization	Improves transparency & trust	May slow down prediction process

6. CONCLUSION

Fake news detection remains a significant issue in today's digital era, with the spread of misinformation affecting societal beliefs, political discourse, and public decision-making. A number of machine learning and NLP-based approaches to the classification of news articles as real or fake have been presented in the paper, demonstrating that hybrid models that integrate deep learning and statistical methods can significantly improve detection precision. Traditional machine learning models such as Logistic Regression, Naïve Bayes, and Support Vector Machines have worked well to classify deceptive content based on linguistic and statistical features. Deep learning techniques, in particular Transformer-based architectures, have however enhanced classification accuracy by capturing complex contextual dependencies within text. Feature engineering methods such as TF-IDF, N-grams, and word embeddings have played a significant role in preprocessing textual data for the machine learning models. Sentiment analysis and network-based approaches have also provided further insights on the emotional and relational content of fake news. Despite the massive progress, some limitations remain for developing fully reliable fake news detection systems. Challenges such as adversarial manipulation, emerging misinformation tactics, and real-time detection require continued research. Research in the future needs to prioritize the development of model adaptability, the inclusion of multi-modal data sources, and the advancement of explainable AI techniques to make automated detection systems more transparent and trustworthy. Overall, the combination of NLP and machine learning provides a solid foundation for tackling fake news, with ongoing innovation required to ensure scalability and effectiveness in the real world. The findings of this research contribute to the growing body of research committed to mitigating the impact of misinformation and shaping a more informed digital society.

REFERENCE

1. C.K.H. and P.G.C. Deshpande, *Fake News Detection Using Deep Learning Techniques.*

International Conference on Advances in Information Technology, 2019.

2. A Santhosh Kumar1, P.K., K Sharan Athithya1, V Sri Ajay Sundar1, *Retraction: Fake News Detection on Social Media Using Machine Learning (J. Phys.: Conf. Ser. 1916 012235).* Journal of Physics: Conference Series, 2021. **1916**(1).
3. Abdulrahman, A. and M. Baykara, *Fake News Detection Using Machine Learning and Deep Learning Algorithms*, in *2020 International Conference on Advanced Science and Engineering (ICOASE)*. 2020. p. 18-23.
4. Al Asaad, B. and M. Erascu, *A Tool for Fake News Detection*, in *2018 20th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC)*. 2018. p. 379-386.
5. Al-Asadi, M.A. and S. Tasdemir, *Using Artificial Intelligence Against the Phenomenon of Fake News: A Systematic Literature Review*, in *Combating Fake News with Computational Intelligence Techniques*. 2022. p. 39-54.
6. Chauhan, T. and H. Palivela, *Optimization and improvement of fake news detection using deep learning approaches for societal benefit.* International Journal of Information Management Data Insights, 2021. **1**(2).
7. Costin BUSIOC, S.R., Mihai DASCALU, *A Literature Review of NLP Approaches to Fake News Detection and Their Applicability to RomanianLanguage News Analysis.* TRANSILVANIA, 2020.
8. Doss, A.K.S.A.M.R., *Smart Systems: Innovations in Computing.* 2021.
9. Fatima, B.N., *Fake news detection using machine learning.* IEEE Access, 2020.
10. Faustini, P.H.A. and T.F. Covões, *Fake news detection in multiple platforms and languages.* Expert Systems with Applications, 2020. **158**.
11. Federico Monti1, F.F., 2 Davide Eynard1,2 Michael M. Bronstein1,2,3, *Fake News Detection on Social Media using Geometric Deep Learning.* IEEE Access, 2019.
12. Gerardo Ernesto Rolong Agudelo1, O.J.S.P., 2 and Julio Barón Velandia1, *Raising a Model for Fake News Detection Using Machine Learning in Python.* International Conference on Advances in Information Technology, 2019.
13. Haqi Al-Tai, M., B.M. Nema, and A. Al-Sherbaz, *Deep Learning for Fake News Detection: Literature Review.* Al-Mustansiriyah Journal of Science, 2023. **34**(2): p. 70-81.
14. Ibrishimova, M.D. and K.F. Li, *A Machine Learning Approach to Fake News Detection Using Knowledge Verification and Natural Language Processing*, in *Advances in Intelligent Networking and Collaborative Systems*. 2020. p. 223-234.
15. Jain, A., et al., *A smart System for Fake News Detection Using Machine Learning*, in *2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)*. 2019. p. 1-4.
16. Kaliyar, R.K., *Fake News Detection Using A Deep Neural Network.* International Conference on Computing Communication and Automation (ICCCA), 2018.
17. Khaleel, Y.L., *Fake News Detection Using Deep Learning.* International Conference on Advances in Information Technology, 2024.
18. Khanam, Z., et al., *Fake News Detection Using Machine Learning Approaches.* IOP Conference Series: Materials Science and Engineering, 2021. **1099**(1).
19. Kong, S.H., et al., *Fake News Detection using Deep Learning.* International Conference on Advances in Information Technology, 2020.
20. Koosha Sharifani 1, M.A., Yaser Akbari 3, Javad Aghajanzadeh Godarzi 4, *Operating Machine Learning across Natural Language Processing Techniques for Improvement of Fabricated News Model.* International Conference on Advances in Information Technology, 2022. **12**(9).
21. Madani, M., H. Motameni, and R. Roshani, *Fake News Detection Using Feature Extraction, Natural Language Processing, Curriculum Learning, and Deep Learning.* International Journal of Information Technology & Decision Making, 2023. **23**(03): p. 1063-1098.
22. Mahmud, T., et al., *Integration of NLP and Deep Learning for Automated Fake News Detection.* International Conference on Advances in Information Technology, 2024.
23. Manzoor, S.I., J. Singla, and Nikita, *Fake News Detection Using Machine Learning approaches: A systematic Review*, in *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*. 2019. p. 230-234.
24. Meesad, P., *Thai Fake News Detection Based on Information Retrieval, Natural Language Processing and Machine Learning.* SN Comput Sci, 2021. **2**(6): p. 425.
25. Mishra, S., et al., *Analyzing Machine Learning Enabled Fake News Detection Techniques for Diversified Datasets.* Wireless Communications and Mobile Computing, 2022. **2022**: p. 1-18.
26. Mridha, M.F., et al., *A Comprehensive Review on Fake News Detection With Deep Learning.* IEEE Access, 2021. **9**: p. 156151-156170.

27. Mugdha, S.B.S., S.M. Ferdous, and A. Fahmin, *Evaluating Machine Learning Algorithms For Bengali Fake News Detection*, in *2020 23rd International Conference on Computer and Information Technology (ICCIT)*. 2020. p. 1-6.
28. Nasir, J.A., O.S. Khan, and I. Varlamis, *Fake news detection: A hybrid CNN-RNN based deep learning approach.* International Journal of Information Management Data Insights, 2021. **1**(1).
29. Pandey, S., et al., *Fake News Detection from Online media using Machine learning Classifiers.* Journal of Physics: Conference Series, 2022. **2161**(1).
30. Prachi, N.N., et al., *Detection of Fake News Using Machine Learning and Natural Language Processing Algorithms.* Journal of Advances in Information Technology, 2022. **13**(6).
31. Ray Oshikawa1, J.Q., WilliamYang Wang2, *A Survey on Natural Language Processing for Fake News Detection.* IEEE Access, 2020.
32. Rodríguez, Á.I. and L.L. Iglesias, *FAKE NEWS DETECTION USING DEEP LEARNING.* IEEE Access, 2019.
33. S, D. and B. Chitturi, *Deep neural approach to Fake-News identification.* Procedia Computer Science, 2020. **167**: p. 2236-2243.
34. Saeed Amer Alameri, M.M., *COMPARISON OF FAKE NEWS DETECTION USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES.* International Conference on Advances in Information Technology, 2020.
35. Sajjad Ahmed, K.H., Flavio Corradini, *Development of Fake News Model Using Machine Learning through Natural Language Processing.* International Conference on Advances in Information Technology, 2020.
36. Shaik, M.A., et al., *Fake News Detection using NLP*, in *2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA)*. 2023. p. 399-405.
37. Shaikh, J. and R. Patil, *Fake News Detection using Machine Learning*, in *2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC)*. 2020. p. 1-5.
38. Smitha, N. and R. Bharath, *Performance Comparison of Machine Learning Classifiers for Fake News Detection*, in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*. 2020. p. 696-700.
39. Srivastava1, A., *Real Time Fake News Detection Using Machine Learning and NLP.* International Research Journal of Engineering and Technology (IRJET), 2020. **7**(6).
40. Subhadra Gurav1, S.S., Supriya Shinde3, Prachi Wabale4, Sumit Hirve5, *Survey on Automated System for Fake News Detection using NLP & Machine Learning Approach.* International Research Journal of Engineering and Technology (IRJET), 2019. **6**(1).
41. Thota, A., et al., *Fake News Detection: A Deep Learning Approach.* SMU Data Science Review, 2018. **3**(1).
42. Uma Sharma, S.S., Shankar M. Patil, *Fake News Detection using Machine Learning Algorithms.* International Journal of Engineering Research & Technology (IJERT). **9**(3).
43. Zhixuan Zhou1, Huankang Guan1, Meghana Moorthy Bhat2 and Justin Hsu2, *Fake News Detection via NLP is Vulnerable to Adversarial Attacks.* International Conference on Advances in Information Technology, 2020.