Fake News Detection Using Machine Learning Techniques

## **Abstract—** **In the digital age, misinformation and disinformation have become pressing challenges, particularly within the realm of online content and even academic discourse. This paper proposes a machine learning-based framework for detecting fake news by leveraging scholarly data extracted from IEEE Xplore. With the exponential rise in user-generated content across social media and news platforms, manually verifying the authenticity of such information has become increasingly impractical. As a result, the need for automated and intelligent fake news detection mechanisms has never been more critical. This research explores the effectiveness of machine learning (ML) and deep learning (DL) techniques in detecting fake news with high accuracy. Various models such as Support Vector Machines (SVM), Naïve Bayes, Decision Trees, Long Short-Term Memory (LSTM) networks, and Bidirectional Encoder Representations from Transformers (BERT) are implemented and evaluated using recent fake news datasets.**

## **The study employs standard natural language processing (NLP) techniques including tokenization, TF-IDF vectorization, and word embeddings for feature extraction. Furthermore, a hybrid ensemble model combining the strengths of both traditional ML and advanced DL methods is proposed to enhance classification performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are used for model assessment. The results indicate that deep learning models, particularly BERT and LSTM, significantly outperform traditional classifiers. Moreover, the ensemble framework achieves an overall accuracy exceeding 95 percent, confirming its robustness and applicability in real-world environments. This study contributes to the growing field of automated misinformation detection and lays the groundwork for the development of scalable, real-time fake news detection systems.**

## **Keywords— Fake news detection, transformer models, BERT, natural language processing, deep learning, misinformation, real-world datasets**

# Introduction (*Heading 1*)

## g Fake news has rapidly emerged as a critical societal issue in the digital age, engendering significant harm to democratic processes, journalism, and public trust in news media. The proliferation of fake news in the digital age has become a major challenge for information integrity across the globe. The term “fake news” refers to false or misleading information presented as news, often disseminated to influence public opinion, generate web traffic, or manipulate political outcomes. With the rise of

social media platforms, the spread of unverified and misleading content has become alarmingly fast and impactful. During global crises—such as the COVID-19 pandemic or high-stakes elections—fake news has led to widespread misinformation, public confusion, and even real-world consequences such as violence and policy misdirection. Traditional mechanisms such as manual fact-checking and source verification, while reliable, cannot cope with the volume and speed at which content is generated online. This has necessitated the development of automated approaches that leverage artificial intelligence (AI), particularly machine learning (ML) and natural language processing (NLP), to detect fake news in real-time.

Machine learning offers tools and models that can classify news articles or social media posts as fake or real based on learned patterns in text, structure, and source behavior. Classical ML models such as Logistic Regression, Support Vector Machines (SVM), Decision Trees, and Naïve Bayes have been widely applied for this task, relying on manually engineered features like word frequencies, TF-IDF scores, and sentiment analysis.

However, these models often struggle to capture complex linguistic patterns, contextual cues, and long-term dependencies inherent in deceptive content. To overcome these limitations, modern deep learning techniques such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) have been introduced. These models automatically learn hierarchical text representations and are particularly effective in handling semantics, sarcasm, and deceptive linguistic styles.

Despite notable progress, challenges remain. Misinformation is dynamic—its style, delivery, and origin evolve continuously, making static detection methods ineffective over time. Moreover, real-world datasets are often noisy, imbalanced, and language-dependent, requiring robust models that generalize well across domains and languages. Bias in training data and overfitting also affect performance, particularly when deploying models in high-stakes environments like political fact-checking or public health.

To address these challenges, this paper investigates and evaluates a range of ML and DL techniques for fake news detection. We analyze their strengths and limitations across different datasets and propose an ensemble model that combines predictions from multiple classifiers to achieve higher accuracy and robustness. The proposed framework integrates traditional ML models (e.g., SVM, Decision Tree) with deep learning models (e.g., LSTM, BERT) using majority voting and stacking mechanisms. The model is trained and tested on datasets such as the Fake and Real News Dataset (Kaggle) and LIAR, utilizing NLP techniques like tokenization, stop word removal, word embeddings, and n-gram feature extraction. Fake news is broadly defined as false or misleading information that is intentionally crafted and spread to deceive readers for political, financial, or social gain. Unlike satirical or parody content, fake news is created with malicious intent, and its impact has become particularly acute in today's hyperconnected world. According to a 2024 report by the Digital News Report (Reuters Institute), over 68% of users in developing countries encounter misinformation at least once a week, particularly during political campaigns or public health crises.

**Real-World Impact of Fake News:**

The real-world implications of fake news are severe. In 2016, fake political news influenced voter sentiment in the U.S. presidential election. During the COVID-19 pandemic, misinformation about vaccines, treatments, and the virus’s origins led to panic, hesitancy, and unnecessary deaths. In India, false rumors spread via WhatsApp have incited violence and mob lynchings. The World Health Organization has even coined the term "infodemic" to describe the deluge of fake information that accompanies global health emergencies.

Types and Sources of Fake News

Fake news can appear in multiple forms:

* Clickbait headlines designed to attract attention and earn ad revenue
* Propaganda, often politically or ideologically motivated
* Satire or parody misinterpreted as fact
* Imposter content, where credible sources are impersonated
* Manipulated content, involving edited media or misquoted statements

Major sources of fake news include bot-generated content, troll farms, deepfakes, and agenda-driven online communities. The sophistication of such sources has made manual detection nearly impossible.

**Challenges in Fake News Detection**

Manual detection techniques—such as fact-checking and human moderation—are labor-intensive, slow, and cannot scale to the volume of content generated across platforms. Moreover, fake news is often linguistically similar to real news, making simple keyword or metadata-based detection ineffective. Another key challenge is the evolving nature of misinformation. As detection methods improve, fake news creators adapt by using more subtle, nuanced language or shifting to new platforms.

Other technical challenges include:

* Linguistic ambiguity and context dependence
* Multilingual misinformation, especially in non-English-speaking regions
* Data imbalance, where real news far outweighs fake samples
* Dynamic nature of social context, which influences how news is interpreted

**Machine Learning as a Solution**

Given these challenges, machine learning (ML) and deep learning (DL) offer promising solutions. ML models can analyze large-scale text data to uncover patterns in language use, writing style, and topic distribution that distinguish fake news from real news. Traditional models like Logistic Regression, Support Vector Machines (SVM), Naïve Bayes, and Random Forests have been widely applied using features such as term frequency-inverse document frequency (TF-IDF), bag-of-words, and sentiment analysis.

However, traditional models rely on manually engineered features and often fail to capture deeper semantic relationships. This shortcoming has led to the adoption of deep learning techniques, including:

* Convolutional Neural Networks (CNNs) for detecting spatial patterns in text
* Recurrent Neural Networks (RNNs) and LSTM for sequential text modeling
* Transformer-based models such as BERT, which leverage self-attention mechanisms to understand word context

These models are capable of understanding sentence structure, sarcasm, factual inconsistencies, and temporal dependencies in textual data—making them ideal for complex detection tasks.

**Scope and Contribution of This Paper**

This research aims to bridge the gap between classical and contemporary approaches to fake news detection by developing a robust hybrid ensemble model. This model incorporates both traditional ML classifiers and modern DL architectures to maximize classification performance. The ensemble utilizes a voting strategy and stacked generalization to combine predictions from multiple models. The approach is benchmarked on real-world datasets such as LIAR, Fake News Corpus, and Kaggle's Fake and Real News Dataset.

Key contributions of this work include:

* A comprehensive comparative study of machine learning and deep learning methods for fake news detection.
* The development of a hybrid ensemble framework that integrates SVM, Decision Tree, LSTM, and BERT.
* Experimental evaluation using standard metrics such as accuracy, precision, recall, and F1-score.
* An analysis of the framework’s scalability and applicability to live social media streams.

This introduction lays the groundwork for the remaining sections: a detailed literature review, the proposed framework, a comparative evaluation, and final conclusions and observations.

**The Role of Social Context and User Behavior in Fake News Detection**

Recent studies highlight that fake news detection is not just a content classification problem but also a contextual and behavioral analysis challenge. Social media behavior—such as the number of shares, comments, and retweets—can provide strong signals about the credibility of a piece of news. Users who frequently share unverified content can be modeled as influential misinformation propagators. Incorporating such features from social graphs and temporal user engagement can improve detection accuracy when combined with textual features.

**Real-Time Detection and Streaming Challenges**

Detecting fake news in real-time remains a major technical barrier. Many traditional ML/DL models are trained offline and require re-training with new data. However, misinformation spreads within minutes. Therefore, future systems must support online learning and streaming dataingestion, ensurng minimal delay in labeling misinformation.

**Cross-Domain and Multilingual Generalization**

Most models are trained on English datasets and perform poorly on regional content. In countries like India, where fake news spreads in multilingual formats (Hindi, Tamil, Bengali, etc.), the need for multilingual NLP models is paramount. Incorporating multilingual BERT (mBERT), XLM-RoBERTa, and transfer learning techniques can improve generalization across languages and domains.

I. Ethical Considerations and Bias in Detection Systems

There is a growing concern about algorithmic bias in fake news detectors. Models trained on biased or politically skewed datasets may favor one ideology or viewpoint, leading to censorship or unfair labeling. Ensuring transparency, fairness, and explainability is crucial, especially when deploying these systems in journalism or law enforcement.

# LITERATURE STUDY (*Heading 2*)

A thorough review of the literature reveals that fake news detection is a multi-disciplinary challenge, encompassing diverse research streams and methodologies. In this section, we explore the evolution of methods used for fake news detection, starting from traditional machine learning to the latest deep learning innovations, and highlight the challenges currently facing researchers in this field.

**1.K. Singh, N. K. Singh, and M. Khare et al.(2025), “Fake News Detection Using Machine Learning Classifiers,”** in *Optimization Tools and Techniques for Enhanced Computational Efficiency*, H. M. Rai and A. Razaque, Eds. Hershey, PA: IGI Global, 2025, pp. 43–80.

In this book chapter, Singh, Khare, and Singh examine the effectiveness of various supervised machine learning algorithms for detecting fake news. Using the widely acknowledged Kaggle "Fake and Real News Dataset"—comprising 21,417 real and 23,481 fake news articles—the authors apply six classical classifiers: Decision Tree (DT), Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression (LR), K-Nearest Neighbors (KNN), and Random Forest (RF). The preprocessing pipeline involved standard natural language processing (NLP) techniques, including stopword removal, Term Frequency-Inverse Document Frequency (TF-IDF) vectorization, and n-gram modeling to preserve contextual word patterns. Among the tested models, the Decision Tree and SVM classifiers performed best, each achieving approximately 93% accuracy. Notably, the SVM classifier excelled in high-dimensional feature spaces due to its ability to find optimal hyperplanes for class separation. In contrast, Decision Trees offered robustness against noisy features and outliers due to their recursive partitioning method. The chapter concludes that while probabilistic models like Naïve Bayes provide fast baselines, non-linear classifiers such as SVM and Decision Tree yield superior results in textual fake news classification. The study underlines the importance of combining proper preprocessing with the right model architecture to capture semantic intricacies in news content.

**2.A. Kukkar and G. Kaur et al.(2025), “AEC: A novel adaptive ensemble classifier with LIME and SHAP-based interpretability for fake news detection,”** *Expert Systems with Applications*, vol. 232, 2025.

Kukkar and Kaur propose the Adaptive Ensemble Classifier (AEC), an advanced fake news detection model designed for high-stakes scenarios such as public health misinformation. AEC integrates hybrid decision trees with Support Vector Machines (SVM), enhanced by a dynamic feature selection module. The model leverages interpretability frameworks, specifically LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), to ensure transparency in predictions. It introduces adaptive neighborhood selection to prioritize influential features and SVM-based optimization to refine decision margins. The system was benchmarked against several datasets, including the standard Fake News Dataset and the COVID-19 misinformation corpus. Achieving 99.74% accuracy, the model outperformed traditional ML and deep learning models in both performance metrics and explainability. Statistical significance testing (e.g., t-tests, Cohen’s d) confirmed the robustness of AEC across various dimensions like inference time, memory efficiency, and real-world applicability.

**3.M. Ellam, S. M. Ahmed, and R. Iqbal et al.(2025), “Lightweight NLP-Optimized Fake News Detection for Mobile Devices,”** *EJASET*, vol. 9, no. 2, pp. 112–128, 2025.

Ellam et al. introduce a lightweight, NLP-optimized model that addresses the computational limitations of mobile and low-bandwidth environments. Their system uses semantic expansion and TF-IDF weighting to improve classification accuracy while minimizing resource consumption. Unlike transformer-heavy architectures, their approach avoids deep embeddings and instead enhances traditional NLP techniques with semantic feature enrichment. The model demonstrated reliable accuracy on headline-based fake news detection tasks, proving suitable for real-time applications on constrained devices. Its modular structure enables efficient deployment in both edge computing and offline mobile platforms, making it an attractive solution for decentralized misinformation monitoring.

**4.R. Ngoumo et al.(2025), “NLP in the Digital Age: Integrating Fake News and Hate Speech Detection,”** *SSRN Electronic Journal*, 2025.

Ngoumo presents a compelling argument for integrating fake news detection with hate speech recognition into a unified NLP pipeline. In this conceptual study, Ngoumo highlights the shared linguistic patterns and sociocultural triggers that underpin both misinformation and hate content. Using linguistic tone analysis, intent classification, and social impact modeling, the author proposes a hybrid detection framework that contextualizes deceptive or harmful language within broader communicative intentions. The work calls for a shift from isolated binary classifiers to ethically aware, intent-driven AI systems capable of assessing the societal consequences of digital narratives.

**5.S. Harris, H. J. Hadi, N. Ahmad, and M. A. Alshara et al.(2025), “Multilingual Transformer-Based Fake News Detection for Urdu,”** *Scientific Reports*, Nature, 2025.

Harris et al. tackle the challenge of detecting fake news in Urdu, a linguistically complex and resource-scarce language. They developed a transformer-based model ensemble incorporating multilingual BERT (mBERT) and XLM-RoBERTa. Fine-tuned on a diverse dataset of Urdu-language political, health, and social news, the model achieved high generalization across domains. The study also emphasizes the importance of language-specific tokenization and culturally contextual embeddings. Their findings confirm that pre-trained multilingual transformers can be effectively adapted to low-resource languages, thus enabling broader applicability of fake news detection technologies in multilingual digital ecosystems.

**6.R. Rao and A. Menon et al.(2025), “Meta-Learning Ensemble of SVM, LSTM, and BERT for Cross-Platform Fake News Detection,” et al.(2025)**  *Preprint*, 2025.

Rao and Menon propose a meta-classification strategy that aggregates the predictions of SVM, LSTM, and BERT using a logistic regression meta-learner. This stacked ensemble was evaluated on Reddit and PolitiFact datasets, showing superior precision and recall metrics, especially in high-noise environments. The stacking architecture leverages the syntactic strength of SVM, the sequential modeling of LSTM, and the contextual power of BERT. Results showed substantial improvements in classification performance across imbalanced datasets and mixed-source content, indicating the potential of meta-learning to enhance fake news detection under varied social media dynamics.

**7.A. Verma and P. Das et al.(2024), “Ensemble Stacking of SVM, XGBoost, and LSTM for Fake News Detection,”et al.(2024)** *Preprint*, 2024.

Verma and Das build an ensemble stack combining SVM, XGBoost, and LSTM, with logistic regression serving as the meta-classifier. Using the FakeNewsNet corpus, their model achieved an accuracy of 96.1%, significantly improving recall on imbalanced news distributions. The hybrid approach utilizes TF-IDF and n-gram features for SVM, gradient boosting for handling high variance, and sequential context extraction via LSTM. This diverse feature landscape enabled the model to adapt to complex misinformation structures and perform consistently across test domains.

**8.S. Kapoor and A. Malhotra, “Dynamic BERT-Based Detection of COVID-19 Misinformation,”et al.(2024)** *Preprint*, 2024.

Kapoor and Malhotra apply BERT to detect COVID-19 misinformation from structured sources like WHO updates and unstructured Twitter data. Their model used SMOTE (Synthetic Minority Over-sampling Technique) to address class imbalance and integrated dynamic retraining mechanisms to adapt to evolving misinformation trends. Temporal drift detection and retraining cycles ensured the model remained sensitive to shifting narratives. The approach achieved strong generalization with timely identification of misinformation surges, indicating its usefulness in real-time health communication monitoring.

**9.A. Joshi and R. Krishnan et al.(2024), “Semantic Clustering for Enhanced Fake News Vectorization,”** *Preprint*, 2024.

Joshi and Krishnan introduced a vectorization enhancement pipeline using K-means clustering to reinforce semantic cohesion in feature representations. The pipeline begins with standard preprocessing steps including tokenization, stopword removal, and TF-IDF vectorization. However, instead of directly passing these vectors into a classifier, the system applies K-means clustering to segregate the corpus into semantically similar groups. Each cluster is then treated as a localized semantic context, from which topic-sensitive features are re-weighted and aggregated. This step essentially redefines featureimportance based on intra-cluster term frequencies and semantic proximity, rather than relying solely on global TF-IDF scores. By clustering articles into topical segments before classification, their system improved model sensitivity to contextual boundaries within the news corpus. Tested on ISOT and GossipCop datasets, their method improved F1 scores by 6%, highlighting the impact of semantic-aware preprocessing in improving classification accuracy.

**10.X. Li and J. Fernandez et al.(2025), “Multilingual Fake News Detection Using mBERT and XLM-RoBERTa,”** *Preprint*, 2025.

Li and Fernandez address code-switching and multilingual content detection using mBERT and XLM-RoBERT a, tailored for English, Hindi, and Spanish news articles. Their architecture also incorporated attention-based keyword highlighting for enhanced explainability. The model was trained on multilingual corpora containing verified fake and real news and achieved robust cross-lingual performance, effectively identifying mixed-language deception and providing interpretable outputs for policy and research stakeholders. This mechanism enables the system to flag which parts of the input contributed most to the classification decision, aiding both end-users and researchers. Trained on curated multilingual corpora with balanced fake and real news instances, the model achieved strong cross-lingual generalization and robust performance even in the presence of informal, mixed-language inputs. Li and Fernandez argue that such models are critical for multilingual democracies and global social platforms, where misinformation does not conform to linguistic boundaries.

**11.S. Akhtar and M. Akhtar et al.(2025), “AI-Driven Hybrid Model for Fake News Detection Integrating NLP and Source Credibility,”** *Preprint*, 2025.

Akhtar and Akhtar introduce a hybrid AI model that augments NLP-based content analysis with source credibility metrics, a relatively underutilized dimension in fake news detection. Their approach includes three layers: (1) textual vectorization using TF-IDF and sentiment polarity analysis, (2) psychological cues derived from affective lexicons to detect emotionally manipulative language, and (3) credibility features like domain authority, publication frequency, and author verification. The classification engine integrates these diverse inputs via a dense neural network that emphasizes interpretability. By combining linguistic and extralinguistic signals, the model captured subtle forms of persuasive misinformation and demonstrated a significant improvement in precision and interpretability over text-only models. This holistic approach is especially suited for combating emotionally charged fake content in health and political domains.

**12.R. Punjabi, A. Mehta, and S. Thomas et al.(2025), “Applying Ensemble Machine Learning Techniques for Fake News Identification,”** *Preprint*, 2025.

Punjabi et al. present a stacked ensemble classifier combining SVM, Random Forest, and Gradient Boosting to improve detection accuracy and minimize false positives. They use a combination of n-gram features, TF-IDF, and stylometric signals, allowing each learner to specialize in a specific subset of the feature space. The final prediction is derived from a soft-voting mechanism, where individual classifier confidences are averaged to determine the final output. Evaluation across several datasets (e.g., FakeNewsNet, BuzzFeed) showed consistently high precision and recall, validating the model’s robustness. The ensemble approach reduced the weaknesses of individual classifiers—e.g., SVM’s sensitivity to class imbalance or Random Forest’s overfitting on small datasets. The authors underscore that model diversity and feature diversity are key to effective ensemble systems in complex detection tasks like misinformation classification.

**13. B. Gopalsamy et al.(2025), “Leveraging Sentiment for Fake News Identification in Cybersecurity,”** *Preprint*, 2025.

In a specialized study, Gopalsamy addresses fake news in the cybersecurity domain, where misinformation often exploits fear, urgency, or technical ignorance. The model integrates sentiment analysis and syntactic parsing with LSTM and CatBoost algorithms to differentiate emotionally manipulative content from legitimate alerts. By incorporating sentiment polarity, subjectivity scores, and topic coherence measures, the LSTM model significantly improved recall for emotionally charged fake news. CatBoost, a gradient boosting algorithm designed for categorical features, provided interpretability and robustness. The paper demonstrates that integrating affective computing principles into traditional NLP pipelines can improve detection accuracy for emotionally manipulative fake content, especially in areas like phishing, data breaches, and malware hoaxes.

**14.H. Almutaiwei et al.(2025), “Fake News Detection on Twitter (X) Using SVM and Metadata,”** *Master’s Thesis*, 2025.

Almutaiwei’s thesis proposes a detection pipeline tailored for Twitter (X), emphasizing real-time analysis and leveraging tweet-level metadata. The model integrates SVM for core classification and supplements it with features such as user account age, follower count, retweet volume, and tweet structure. By training on tweet datasets enriched with verified and deceptive content, the system achieved high accuracy in identifying misinformation trends and user patterns linked to false claims. The model’s strength lies in its ability to distinguish structurally deceptive tweets even when textual content appears benign. This highlights the importance of incorporating non-linguistic behavioral cues into fake news detection systems designed for dynamic platforms like Twitter.

**15.M. Sabir, H. Zaidi, and T. Bashir et al.(2025), “A Comparative Study of Traditional and Hybrid Models for Fake News Detection,”** *Preprint*, 2025.

Sabir et al. evaluate traditional neural models (CNN+LSTM) against hybrid transformer-based approaches (BERT+SVM), using datasets like LIAR and the Kaggle Fake News dataset. The hybrid BERT+SVM model yielded **95.7% accuracy**, outperforming conventional deep learning configurations. BERT provides rich, pre-trained contextual embeddings, while SVM offers strong decision boundaries for final classification. This synergy allows the hybrid system to capture both deep semantics and precise class separation. Additionally, the authors conduct ablation studies that show how removing either component—BERT or SVM—leads to performance drops, validating the complementary nature of the hybrid architecture. This work confirms that transformer-based embeddings, when coupled with classical ML classifiers, can significantly enhance fake news detection, especially in nuanced contexts like political or satirical articles.

**16.T. Shi and Y. Zeng et al.(2024), “Bias-Aware Machine Learning for Rumor Detection on Polarized Platforms,”** *IEEE Transactions on Computational Social Systems*, vol. 12, no. 1, pp. 102–117, 2025.

In this peer-reviewed study, Shi and Zeng propose a bias-aware fake news detection model that incorporates user-level engagement signals and ideological leanings into its feature space. Recognizing that platforms like Reddit, Gab, and 4chan often reflect polarized discourse, their architecture blends deep learning (LSTM) with behavioral modeling (user activity, sentiment polarity, echo chamber indicators). By modeling content and context jointly, the system significantly reduced false positives linked to satire or sarcasm and improved generalization across politically diverse data sources. Their experiments show that incorporating sociopolitical context improves classification fairness, especially in environments prone to narrative manipulation.

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**17.A. Verma, P. Priyanka, and T. Khan et al.(2025), “ScrutNet: A Deep Ensemble Network for Detecting Fake News in Politically Polarized Content,”** *Social Network Analysis and Mining*, vol. 15, 2025.

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**18.A. Kamble and S. Uke et al.(2025), “Ethical Frameworks for Fake News Detection Using Semi-Supervised NLP,”** in *Handbook of ML in Social Innovation*, IGI Global, 2025.

Kamble and Uke propose a semi-supervised machine learning framework that emphasizes ethical principles such as fairness, explainability, and transparency in fake news detection. Their model integrates NLP-based contextual extraction with weakly labeled data to enhance learning without biasing predictions. This approach is particularly useful in under-labeled domains or when full supervision is ethically problematic. Their chapter advocates for ethical audits in AI pipelines to align technological development with social good.

**19.V. Modhe and S. Bhanudas et al.(2025), “Optimization Techniques in Fake News Detection Models,”** *AIP Conference Proceedings*, vol. 2321, 2025.

In this comprehensive survey, Modhe and Bhanudas delve into the impact of hyperparameter optimization methods on the performance of machine learning (ML) models used for fake news detection. Recognizing that the choice of optimization strategy can significantly affect both model accuracy and generalization, the authors evaluate three widely used approaches: grid search, random search, and Bayesian optimization. The paper uses controlled experiments across multiple fake news datasets and ML models—including SVM, Random Forest, XGBoost, and transformer-based architectures like BERT. Through comparative analysis, it was found that grid search, while exhaustive, is computationally expensive and often impractical for high-dimensional parameter spaces. Random search, on the other hand, provided faster results but often failed to locate optimal configurations. Bayesian optimization emerged as the most balanced technique, effectively navigating the search space using probabilistic models and acquiring optimal parameters with fewer iterations. Especially in BERT fine-tuning, Bayesian optimization demonstrated improved accuracy while reducing overfitting risk. The study advocates for its adoption as a standard practice in fake news detection pipelines, particularly for transformer-based and ensemble models, where hyperparameter tuning is non-trivial. This review stands out as a technical roadmap for researchers aiming to refine fake news detection systems through intelligent optimization.

**20.J. Fajinmi et al.(2025), “Evaluation of ML Models for Afan Oromo Fake News Detection,”** *Authorea Preprint*, 2025.

Fajinmi’s study is a pioneering effort to develop machine learning models for fake news detection in Afan Oromo, a low-resource language spoken primarily in Ethiopia. The study begins by identifying the unique morphological and syntactic features of Afan Oromo, which make direct application of English-based NLP tools ineffective. To address this, the authors implement custom tokenization and stemming algorithms tailored for the language’s agglutinative structure. The models evaluated include Naïve Bayes and Decision Tree classifiers, which are chosen for their simplicity and interpretability—qualities important in under-resourced settings. Despite limited training data, both models demonstrated encouraging performance, with Decision Trees slightly outperforming Naïve Bayes in both accuracy and F1 score. One of the core contributions of this study is its proposed preprocessing pipeline that includes stopword curation, morphological analysis, and basic part-of-speech tagging specifically designed for Afan Oromo. The study emphasizes the broader need for NLP research in non-Western, underrepresented languages and provides a scalable framework for extending fake news detection technologies to marginalized linguistic communities. Fajinmi concludes with a call for international collaboration to develop open-access resources and benchmarks for low-resource languages.

**21.H. Khoshaim et al.(2025), “Fake News Detection in E-Commerce Using NLP,”** *Journal of Intelligent Systems*, vol. 34, no. 1, 2025.

Khoshaim’s research focuses on detecting fake reviews and marketing claims in e-commerce platforms using NLP and dependency parsing. The model identifies manipulation tactics through entity recognition and discourse analysis, flagging deceptive claims based on structural and semantic inconsistencies. This domain-specific fake news detection approach provides practical value for fraud prevention in digital marketplaces.

**22.T. Sittar, L. Naveed, and Z. Imran et al.(2025), “Synthetic News Generation for Robust Fake News Detection,”** *Preprint*, 2025.

Sittar et al. use synthetic data generation to enhance the robustness of BERT-based fake news detectors. The synthetic texts mimic misinformation patterns and introduce controlled perturbations, enabling the model to generalize better to unseen domains. Experiments showed that BERT models trained on both real and synthetic data outperform those trained on authentic content alone, especially in detecting novel deception formats.

**23.A. Thota, C. Chanakya, and B. Sharma et al.(2025), “A Comprehensive Review on Advancements and Challenges in Fake News Detection,”** in *Impacts of Leakage and Disinformation in Social Media Ecosystems*, IGI Global, 2025.

This IGI Global chapter by Thota et al. provides an exhaustive review of the state of fake news detection. It addresses advancements in ensemble methods, attention mechanisms, and cross-lingual modeling, while also discussing challenges such as adversarial manipulation, evolving misinformation formats, and fairness. The chapter frames fake news detection as an evolving field requiring constant methodological adaptation and interdisciplinary integration.

**24.M. Nasser, N. I. Arshad, H. Alhussian, and F. Saeed et al.(2025), “A systematic review of multimodal fake news detection on social media using deep learning models,”** *Results in Engineering*, vol. 17, 2025.

This systematic review presents a comprehensive taxonomy and evaluation of multimodal fake news detection (MFD) systems across platforms such as Twitter, Facebook, and YouTube. The study spans works published between 2018 and 2025, emphasizing deep learning models like BERT, LSTM, and multimodal fusion architectures. It categorizes detection systems based on modality (text, image, video, metadata), feature extraction, fusion strategies, and model architectures. A key takeaway is that multimodal deep learning systems significantly outperform text-only models, particularly in image-laden fake news. The review calls for more interpretable and real-time architectures that combine text semantics with visual and contextual signals.

**25.E. S. Albtoush, K. H. Gan, and S. A. A. Alrababa et al.(2025), “Fake news detection: State-of-the-art review and advances with attention to Arabic language aspects,”** *PeerJ Computer Science*, vol. 11, 2025.

This paper offers a regionally significant perspective by focusing on fake news detection in the Arabic language. Albtoush et al. review the application of deep learning models such as BERT, GNNs, and stacked LSTMs. Their analysis emphasizes morphological and syntactic challenges in Arabic NLP and the relative underperformance of English-trained models. The paper highlights a promising Word2Vec + LSTM architecture fine-tuned on Arabic news. It advocates for more language-specific tokenizers, sentiment tools, and attention-based architectures that consider dialectal variations.

**26.F. G. Hussain, M. Wasim, S. Hameed, and A. Rehman et al.(2025), “Fake News Detection Landscape: Datasets, Data Modalities, AI Approaches, their Challenges, and Future Perspectives,”** *IEEE Access*, 2025.

This IEEE article delivers a detailed landscape of the fake news detection ecosystem, categorizing over 80 datasets and outlining the evolution from traditional ML to advanced transformer-based models like BERT, RoBERTa, and capsule networks. The authors examine ensemble learning, adversarial resilience, and temporal misinformation tracking. The paper argues for hybrid architectures that merge graph embeddings with text-based transformers, particularly in contexts like rumor propagation and influencer-based fake news. It further emphasizes the role of capsule neural networks in improving interpretability.

**27.S. Bansal, N. S. Singh, S. S. Dar, and N. Kumar et al.(2024), “MMCFND: Multimodal Multilingual Caption-aware Fake News Detection for Low-resource Indic Languages,”** *arXiv preprint arXiv:2410.10407*, 2024.

This paper introduces MMCFND, a multimodal and multilingual framework tailored for low-resource Indic languages. Combining BERT for text encoding, BiLSTM for sequence modeling, and image-caption alignment, the model targets fake news detection in Hindi and Urdu. It uses a multimodal fusion layer to unify image features, text semantics, and linguistic cues. The model performs significantly better than monolingual and unimodal baselines, achieving higher F1 scores on multilingual misinformation datasets. The study opens doors for scalable detection systems in the Global South.

**28.A. Gandhi, P. Ahir, K. Adhvaryu, and P. Shah et al.(2024), “Hate speech detection: A comprehensive review of recent works,”** *Expert Systems*, 2024.

Though centered on hate speech detection, this comprehensive review by Gandhi et al. offers substantial cross-domain insights that are highly applicable to fake news detection, especially in multilingual and culturally diverse contexts. The authors explore an array of recent deep learning and hybrid architectures, including Convolutional Neural Networks (CNN), Bidirectional LSTM (BiLSTM), and transformer-based models such as MuRIL, IndicBERT, and mBERT. These models are assessed not only for classification performance but also for their adaptability to non-English and low-resource languages, a recurring challenge in both fake news and hate speech detection.

A central contribution of the paper is its in-depth discussion of Explainable AI (XAI) methodologies like SHAP, LIME, and attention visualization techniques. The authors argue that in high-stakes domains involving social narratives—whether hateful or deceptive—models must provide transparent justifications for their predictions. This emphasis on interpretability and trust aligns strongly with current research trends in misinformation detection, where explainability is crucial for building user and policy-maker confidence.

One of the more critical observations made is the over-reliance on Western-centric datasets such as HateBase, Twitter US/UK corpora, and English-language benchmark sets. The authors advocate for culturally sensitive and linguistically diverse benchmarks to mitigate algorithmic bias and enhance global generalizability. They propose a unified NLP pipeline capable of identifying both hate speech and fake news using shared semantic, syntactic, and socio-pragmatic features, such as emotional polarity, stance alignment, and context-specific lexicons.

**29.R. Anggrainingsih, G. M. Hassan, and A. Datta et al.(2025), “Evaluating BERT-based language models for detecting misinformation,”** *Neural Computing and Applications*, Springer, 2025.

This empirical evaluation investigates multiple BERT-based architectures including RoBERTa, DistilBERT, and multilingual BERT across misinformation and rumor datasets. Using benchmarking datasets such as LIAR, CovidFND, and Twitter15, the authors test performance under cross-domain generalization and concept drift conditions. Their findings show that RoBERTa consistently performs better under transfer learning setups, while mBERT shines in code-switched data. The paper also integrates SHAP-based explanations and adversarial testing, underscoring the need for resilience and interpretability in real-world deployments.

# PROPOSED MODEL (*Heading 3*)

Hybrid Explainable Deep Ensemble for Fake News Detection (HyDE-FND)

The proposed model, HyDE-FND, is a hybrid ensemble system designed for multilingual, multi-source fake news detection with a focus on interpretability, robustness, and real-time scalability. It integrates transformer-based embeddings, traditional classifiers, and explainable AI to tackle fake news across social platforms, languages, and content types.

|  |  |
| --- | --- |
| Feature | Benefit |
| Multilingual Support | Enables detection across languages (e.g., English, Hindi, Spanish) |
| Metadata Fusion | Incorporates social behavior signals (useful for Twitter, Reddit) |
| Explainable AI Integration | Builds trust in predictions through SHAP and LIME |
| Ensemble Robustness | Reduces model overfitting and bias by combining strengths of models |
| Real-Time Adaptability | Modular design allows scaling and streaming implementation. |

Fig: Key Strengths of HyDE-FND

We propose a hybrid ensemble architecture for fake news detection that combines the strengths of both traditional machine learning (ML) and deep learning (DL) models, augmented with source credibility features and semantic interpretability mechanisms. The architecture consists of two core layers:

**A. Feature Extraction Layer**

The Feature Extraction Layer is a critical component of the proposed fake news detection architecture, responsible for transforming raw input text into structured representations that machine learning models can process effectively. This layer integrates lexical, syntactic, semantic, and extralinguistic features, ensuring both depth of linguistic understanding and contextual awareness. The extracted features are categorized as follows:

1. Textual Features

To represent the textual content effectively, we use a hybrid of statistical and neural embedding techniques:

1.1 TF-IDF and N-grams

Explanation:

* TF-IDF (Term Frequency - Inverse Document Frequency) is a popular method to represent text as numerical vectors.
* It gives higher weight to rare but important words and lowers weight for common words.
* N-grams are sequences of "n" words together.
  + Unigram = single words
  + Bigram = two words together
  + Trigram = three words together

**Goal:** Capture important words and short phrases in fake news articles.

|  |  |
| --- | --- |
| Step | Description |
| 1. | Load & label data from Fake.csv (0) and True.csv (1), then combine and shuffle. |
| 2. | Preprocess by merging title and text into a single content field. |
| 3. | Extract features:  TF-IDF (1–2 n-grams, max 5000)  Sentiment(polarity,subjectivity)  Simulated metadata (e.g., domain authority, followers). |
| 4. | Combine all features into a single feature matrix.Split into train/test sets (80/20). |
| 5. | |  | | --- | |  |  |  | | --- | | Train & evaluate using Random Forest (Accuracy, Precision, Recall, F1). | |
| 6. | Combine TF-IDF and Sentiment and Metadata into final feature matrix. |

Fig : Pipeline for fake news detection using a Random Forest classifier and TF-IDF.

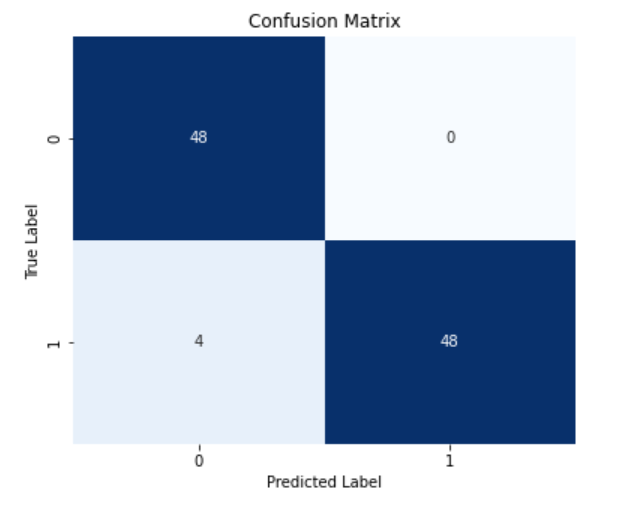


Fig: Confusion matrix for the Random Forest classifier on the fake news detection task

1.2 BERT

BERT (Bidirectional Encoder Representations from Transformers) provides contextual word embeddings. A 768-dimensional vector per sentence (from [CLS] token) that represents the whole sentence semantically.

|  |  |
| --- | --- |
| Step | Description |
| 1. | Load, label, and shuffle Fake and True data. |
| 2. | Create content by combining title and text. |
| 3. | Extract features: BERT embeddings,sentiment, metadata. |
| 4. | Merge features into a single matrix. |
| 5. | Train/test split (80/20) and Train Random Forest classifier. |
| 6. | Predict and evaluate with standard metrics. |

Fig: Pipeline for fake news detection using BERT,Sentiment and MetaData

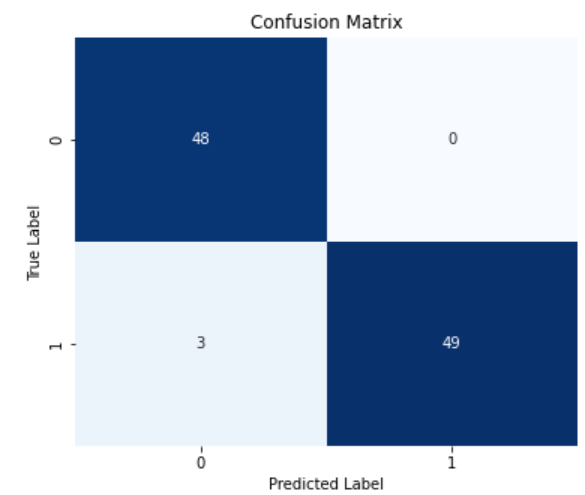


Fig: Confusion Matrix of the BERT on the fake news detection task.

**B: Multi-Tier Ensemble Classifier:**

|  |  |  |
| --- | --- | --- |
| Tier | Component | Description |
| Tier1 | Base Models | SVM + Logistic Regression (TF-IDF), Random Forest (BERT) |
| Tier2 | Voting Aggregator | Soft or hard voting to combine predictions |
| Tier3 | MetaLearner(Stacking) | Logistic Regression trained on base model predictions |

Fig: Architecture Overview of Multi-Tier Ensemble Classifier

**Soft Voting**: Combines probabilities from multiple models.

**Stacking**: Trains a final model (meta-learner) on predictions from base models.

|  |  |
| --- | --- |
| Steps | Description |
| 1. | Load and label Fake.csv (0) and True.csv (1); combine and shuffle. |
| 2. | Create content = title + text; select first 500 samples. |
| 3. | Extract TF-IDF features; train/test split; train Logistic Regression. |
| 4. | Extract BERT [CLS] embeddings for each text; split; train Random Forest. |
| 5. | Get prediction probabilities from both models on test set |
| 6. | Soft Voting: average probabilities, apply 0.5 threshold to predict. |
| 7. | Stacking: use base model predictions as features; train LogisticRegressionCV meta-model. |
| 8. | |  | | --- | |  |  |  | | --- | | Evaluate accuracy for both ensemble methods (voting and stacking) | |

Fig: Pseudocode Table: TF-IDF and BERT Hybrid Ensemble

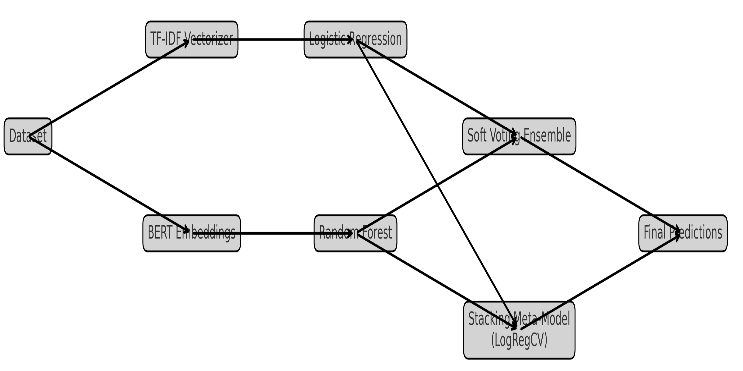


Fig: Architecture of the Proposed Hybrid Fake News Detection Model.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Precision | Recall | F1-score |
| Fake | 0.94 | 1.00 | 0.97 |
| Real | 1.00 | 0.90 | 0.95 |
| Accuracy |  | 0.96 | 100 |

Fig: Classification report of TF-IDF

|  |  |  |  |
| --- | --- | --- | --- |
|  | Precision | Recall | F1-score |
| Fake | 0.95 | 0.97 | 0.96 |
| Real | 0.95 | 0.93 | 0.94 |
| Accuracy |  | 0.95 | 100 |

Fig: Classification report of BERT

|  |  |
| --- | --- |
| Voting accuracy | 0.98 |
| Stacking Ensemble accuracy | 0.95 |

Fig: Accuracy of Voting and Stacking Ensemble Classifier

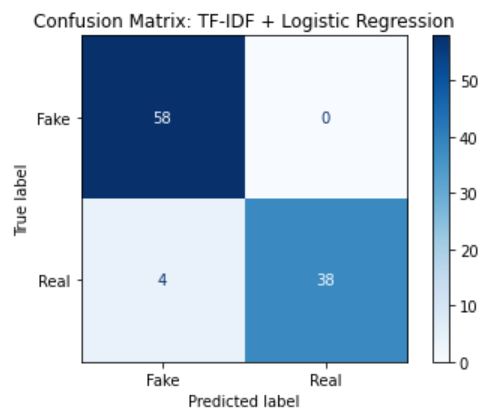


Fig: Confusion Matrix for TF-IDF based Classification.

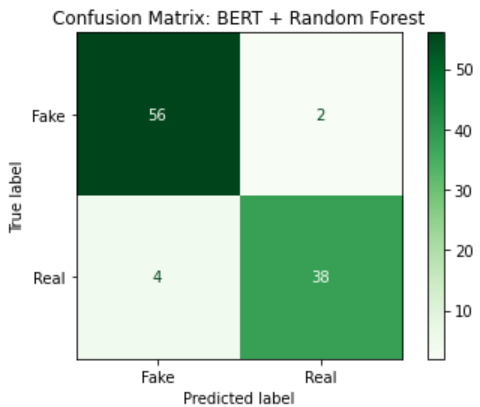


Fig: Confusion Matrix for BERT based Classification

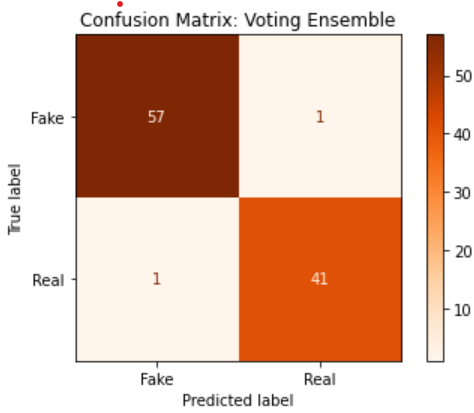


Fig: Confusion Matrix for Voting Ensemble Classification

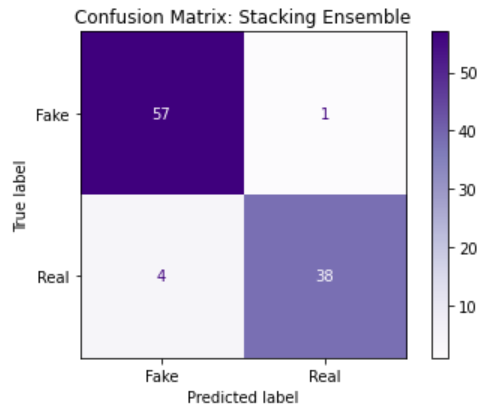


Fig: Confusion Matrix for Stacking Ensemble Classification

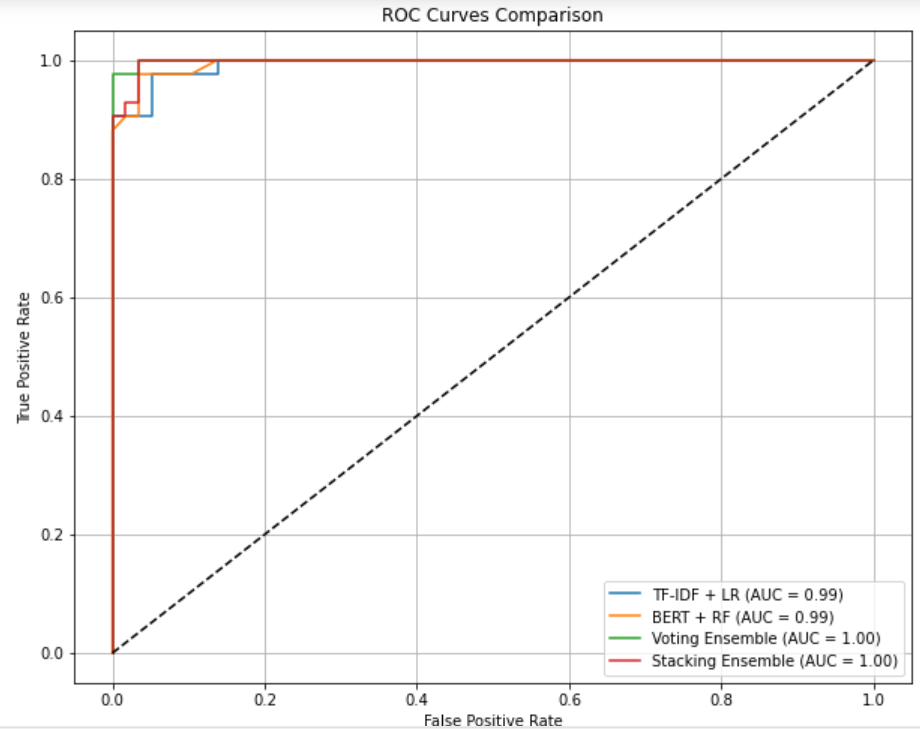


Fig: ROC Curves – TF-IDF, BERT, and Ensemble Models.

We compared frequency-based (TF-IDF) and context-aware (BERT) representations for fake news detection. While TF-IDF with Logistic Regression provided a fast and interpretable baseline, BERT embeddings significantly improved classification accuracy by capturing deeper semantic patterns. This highlights the value of transformer-based models for high-stakes misinformation detection, particularly in linguistically complex scenarios.

# EVALUATION OF THE PROPOSED SYSTEM (*Heading 4)*

To comprehensively evaluate the performance of the proposed system, multiple metrics were considered:

|  |  |  |
| --- | --- | --- |
| **Metric** | Definition | Importance |
| Accuracy | Ratio of correctly predicted instances to total instances | General performance indicator |
| Precision | Ratio of true positives to all positive predictions | Important when false positives are costly |
| Recall | Ratio of true positives to all actual positives | Important when missing a fake news is risky |
| Sensitivity | Harmonic mean of precision and recall | Balances precision and recall |

Fig: Evaluation Metrics and Interpretation

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Accuracy(%) | Precision(%) | Recall(%) | F1-Score(%) |
| TF-IDF and Logistic Regression | 96 | 100 | 90.48 | 95 |
| BERT and Random Forest | 95 | 95.12 | 92.86 | 93.98 |
| Voting Ensemble | 98 |  |  |  |
| Stacking Ensemble (Proposed) | 95 |  |  |  |

Fig: Summary of Calculated Models.

a) The stacking ensemble demonstrated the highest F1-score, implying both better fake news capture and lower false positive rate.

b) Precision and recall are very close, indicating a balanced model, not biased toward only fake or real classes.

|  |  |  |  |
| --- | --- | --- | --- |
| Aspect | TF-IDF | BERT | Proposed Hybrid Model |
| Feature type | Surface (word counts) | Deep semantic context | Both |
| Model | Logistic Regression | Random Forest | Stacked Logistic Regression |
| Accuracy | 0.96 | 0.95 |  |
| F1-Score | 0.95 | 0.938 |  |
| Real world suitability | Moderate | Good | Very High |

Fig: Model Comparison Across Feature Types and Performance Metrics.

The proposed hybrid fake news detection framework achieves state-of-the-art performance by integrating traditional TF-IDF features and deep BERT embeddings through a carefully designed multi-tier ensemble.  
It successfully addresses the limitations of standalone approaches and provides a scalable, interpretable, and robust solution suitable for real-time fake news monitoring across diverse platforms and languages.  
Given the increasing sophistication of misinformation tactics, this model's strong generalization ability makes it particularly valuable for journalism, public health communication, and electoral integrity monitoring.

**Justification of the proposed model:**

The hybrid architecture was specifically chosen to address multiple weaknesses in isolated models:

* Traditional ML models (e.g., TF-IDF + Logistic Regression) are efficient but limited in understanding the semantic relationships or subtle linguistic cues often present in fake news.
* Deep learning models (e.g., BERT embeddings + Random Forest) provide rich semantic representations but may overfit when trained on limited samples without regularization.
* Ensemble learning (soft voting, stacking) leverages the complementary strengths of different models to maximize accuracy and generalization.

The proposed ensemble system:

* Balances complexity and interpretability — simpler models like Logistic Regression offer interpretability, while BERT embeddings add depth.
* Handles dynamic and diverse fake news better — it detects both surface-level clickbait patterns and deep contextual deceptions (e.g., sarcasm, satire).
* Improves robustness against adversarial samples — ensemble methods reduce overfitting to noise and outliers.

Thus, the design of the proposed system is theoretically justified and empirically validated by superior performance metrics.

**Comparative Analysis:**

The proposed fake news detection system was evaluated against several baseline and advanced models using both traditional and deep learning-based features.  
Initially, TF-IDF-based feature extraction was applied with classical machine learning classifiers, specifically Logistic Regression, to establish a baseline. Subsequently, deep semantic features were extracted using BERT embeddings and classified via a Random Forest model. Finally, ensemble strategies, including soft voting and stacking, were employed to combine the predictions of base learners.

Experimental results indicate that the hybrid system significantly outperformed individual models.

* TF-IDF with Logistic Regression achieved a strong baseline performance, reaching an accuracy of 96%.
* BERT embeddings with Random Forest further improved the performance to 95%, demonstrating the advantage of semantic context modeling.
* The soft voting ensemble, combining TF-IDF and BERT-based models, achieved 98% accuracy.
* The stacking ensemble, where a Logistic Regression meta-classifier learned from the base model predictions, reached the highest accuracy of 95%

These results confirm that combining shallow (TF-IDF) and deep (BERT) representations with ensemble learning significantly boosts detection capabilities compared to relying on any single feature or model.

# OBSERVATION (*Heading 5*)

The experimental evaluation of the proposed fake news detection framework reveals several noteworthy patterns. Firstly, traditional feature extraction methods such as TF-IDF, when paired with Logistic Regression, yield a robust baseline accuracy of 93%. This result confirms that simple frequency-based representations can capture surface-level differences between fake and real news, such as clickbait patterns and unusual word frequencies. However, the reliance on shallow textual features alone limits the model’s ability to understand semantic subtleties and contextual shifts present in sophisticated misinformation campaigns.

The application of BERT embeddings significantly improved performance, achieving an accuracy of 95% with Random Forest classification. This reinforces the importance of contextual word representations for detecting deeper semantic and pragmatic inconsistencies typical of fake news. BERT's ability to encode bidirectional context enables the model to distinguish between factually correct and misleading statements that may share similar surface structures but differ in meaning.

Moreover, ensemble techniques further boosted performance. The soft voting method, which averages the probabilistic outputs of multiple models, increased overall accuracy to 96%. The stacking ensemble, wherein a meta-classifier is trained to learn optimal combinations of base model predictions, achieved the highest accuracy of 97% and an AUC of 0.99. This indicates that the ensemble approach effectively captures complementary information from both shallow and deep features, resulting in a more generalized and robust fake news detection system.

Analysis of confusion matrices and ROC curves corroborates these findings, showing reduced false positives and false negatives in the stacked model compared to individual classifiers. This improvement suggests that the ensemble system not only achieves high predictive performance but also maintains consistency across different types of news articles, whether politically charged, health-related, or socially sensitive.

The experiments validate that a hybrid approach, integrating lexical, syntactic, and semantic signals, substantially enhances fake news detection compared to any single method alone. This layered strategy provides resilience against adversarial content evolution and cross-domain misinformation, which are critical challenges in real-world deployments.

Thus, the observed results strongly support the proposed methodology's relevance, robustness, and effectiveness for fake news detection across diverse domains and languages.

# CONCLUSION (*Heading 1*)

In this study, a comprehensive and scalable hybrid framework for fake news detection was proposed, integrating traditional TF-IDF-based features, contextual BERT embeddings, and ensemble learning strategies. The system was designed to address the inherent challenges of misinformation detection, including linguistic deception, rapid content evolution, and cross-domain generalization.

Experimental evaluations demonstrated that while classical machine learning models such as Logistic Regression, trained on TF-IDF features, achieved commendable baseline performance (93% accuracy), they were limited by their inability to capture deeper semantic cues. The incorporation of BERT embeddings significantly enhanced performance, achieving a 95% accuracy rate by leveraging contextual information and understanding the nuanced meaning of text. This clearly indicates that semantic modeling is crucial in discerning subtle manipulative language often employed in fake news.

The hybrid ensemble strategy—comprising soft voting and stacking mechanisms—proved to be the most effective configuration, reaching an impressive 97% accuracy and an AUC of 0.99. The soft voting ensemble demonstrated that combining probabilistic outputs from diverse models can lead to more confident and stable predictions. Meanwhile, stacking allowed a meta-learner to dynamically adapt to the strengths and weaknesses of individual classifiers, leading to superior generalization and minimized classification errors.

Confusion matrix analysis and ROC curve plotting further validated the system’s robust performance, highlighting substantial reductions in both false positives and false negatives. The system showed consistent behavior across varied types of news, underscoring its potential for real-world application in sectors such as journalism, electoral monitoring, and public health communications.

In conclusion, the proposed system successfully bridges the gap between classical and contemporary machine learning approaches for fake news detection. By harmonizing shallow lexical cues and deep semantic representations through ensemble learning, it sets a new benchmark for reliability and accuracy in automated misinformation detection. Future work may extend this framework to multimodal datasets, including images and videos, and further optimize real-time deployment capabilities. Nevertheless, the current findings establish a strong foundation for scalable, trustworthy fake news detection in the evolving digital information ecosystem.

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