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# ADVANCING FAKE NEWS DETECTION: HYBRID DEEP LEARNING WITH FASTTEXT AND EXPLAINABLE AI

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**Abstract:** The spread of fake news impacts public perception and decision-making. Traditional machine learning models lack contextual understanding and interpretability. We propose a deep learning approach using FastText for text representation and Explainable AI (XAI) for transparency. FastText captures word and subword information, improving fake news detection. Deep learning models like LSTMs or CNNs enhance classification accuracy. To address the "black box" issue, we integrate XAI techniques such as SHAP and LIME. These methods highlight key words influencing predictions, aiding journalists and fact-checkers. Experimental results on benchmark datasets show superior accuracy and interpretability. FastText ensures efficient feature extraction, while XAI enhances trust. Our approach provides a scalable, ethical, and effective solution for misinformation detection.

**Keywords:** FastText, LSTM, decision-making, black box.

## I. INTRODUCTION

The rise of digital platforms has revolutionized information sharing, but it has also led to the rapid spread of fake news, influencing public perception and decision-making. Misinformation can distort reality, impact political landscapes, and create social unrest. Detecting and mitigating fake news is a pressing challenge, as traditional methods struggle to keep pace with the evolving nature of deceptive content.

Traditional machine learning models, such as SVMs and Decision Trees, rely on manually engineered features and often lack contextual understanding. These models struggle with the complex linguistic patterns used in fake news and provide limited transparency in their predictions. To address these limitations, deep learning techniques have emerged as a more effective solution for fake news detection.

We propose a deep learning-based approach that integrates FastText for text representation and Explainable AI (XAI) for interpretability. FastText captures both word and subword information, improving feature extraction and generalization. Deep learning architectures, such as LSTMs and CNNs, enhance classification accuracy by identifying intricate language patterns commonly found in fake news.

Despite their high accuracy, deep learning models are often seen as "black boxes" due to their lack of explainability. This raises concerns about trust and accountability, particularly for journalists, policymakers, and fact-checkers who rely on AI-driven insights. To address this, we incorporate XAI techniques, including SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations). These methods highlight the most influential words in a news article, making the model's decisions more transparent and justifiable.

Our experimental evaluations on benchmark fake news datasets demonstrate that our approach outperforms traditional machine learning methods in both accuracy and interpretability. By integrating FastText, deep learning, and XAI, we provide a scalable, trustworthy, and efficient solution for combating misinformation. This research promotes responsible AI adoption, ensuring that automated fake news detection systems are both effective and understandable, contributing to a more reliable digital information ecosystem.

## II. PRELIMINARIES

To effectively address fake news detection, it is essential to understand the core concepts that form the foundation of our approach. This section outlines key techniques, including text representation, deep learning models, Explainable AI (XAI), datasets, and evaluation metrics.

  

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### 1. TEXT REPRESENTATION WITH FASTTEXT

Traditional word embedding techniques like Word2Vec and GloVe represent words as fixed vectors but fail to capture subword information. FastText, developed by Facebook AI, improves upon these models by considering character n-grams, allowing it to recognize morphological patterns and handle out-of-vocabulary words effectively. This makes it particularly useful for detecting deceptive language in fake news articles. FastText also generates more contextually rich embeddings, making deep learning models more robust. By leveraging subword information, our model can better classify fake and real news, even when dealing with unseen words or new linguistic variations.

### 2. DEEP LEARNING MODELS FOR TEXT CLASSIFICATION

Deep learning models have significantly enhanced text classification by extracting complex linguistic features. LSTMs (Long Short-Term Memory) networks are well-suited for processing sequential data, capturing long-term dependencies in text. This is crucial for analyzing context in fake news detection. CNNs (Convolutional Neural Networks), although originally designed for images, are effective in identifying key phrases and linguistic structures within text. By using convolutional filters, CNNs detect hierarchical text patterns, improving classification accuracy. Both LSTMs and CNNs contribute to a more effective fake news detection system by understanding both sequence-based dependencies and local text patterns.

### 3. EXPLAINABLE AI (XAI) TECHNIQUES

Deep learning models are often seen as "black boxes," making it difficult to interpret their predictions. Explainable AI (XAI) enhances model transparency by providing insights into decision-making processes. SHAP (SHapley Additive exPlanations) assigns importance scores to input features, helping explain which words influence predictions. LIME (Local Interpretable Model-agnostic Explanations) generates locally interpretable explanations by altering input text and observing changes in predictions. These techniques ensure that AI-generated classifications can be validated by journalists, policymakers, and fact-checkers, making the system more trustworthy and accountable.

### 4. BENCHMARK DATASETS FOR FAKE NEWS DETECTION

To evaluate our model, we use widely recognized benchmark datasets containing labeled real and fake news articles. Popular datasets include LIAR, FakeNewsNet, and Kaggle's Fake News Dataset, which provide diverse news samples from different domains. These datasets contain linguistic variations, making them ideal for training robust models. Each dataset includes metadata, text content, and source credibility indicators, allowing the model to learn both textual and contextual features. Using multiple datasets ensures that our model generalizes well across different sources and minimizes bias in fake news classification.

### 5. EVALUATION METRICS

To measure model performance, we use standard classification metrics such as accuracy, precision, recall, and F1-score. Accuracy evaluates the overall correctness of predictions, while precision and recall measure the trade-off between false positives and false negatives. F1-score, the harmonic mean of precision and recall, provides a balanced performance measure. Additionally, interpretability metrics assess the clarity of explanations provided by SHAP and LIME. By combining accuracy and explainability, we ensure that our model is both effective in detecting fake news and transparent in its decision-making process.

These preliminaries establish a solid foundation for our deep learning-based fake news detection approach, ensuring a structured, scalable, and explainable solution for combating misinformation in digital media.

## III. RELATED WORK

Fake news detection has evolved from traditional machine learning techniques to advanced deep learning and Explainable AI (XAI) approaches. Early models, such as Naïve Bayes, SVMs, and Decision Trees, relied on handcrafted features like TF-IDF and sentiment analysis but struggled with contextual understanding. Deep learning models, including CNNs, LSTMs, and Transformers like BERT, have significantly improved classification accuracy by capturing linguistic and contextual nuances. However, these models function as "black boxes," limiting their interpretability. To address this, researchers have explored XAI techniques such as LIME and SHAP, which provide insight into model predictions by highlighting key words influencing classifications. FastText has also enhanced feature extraction by capturing subword information, improving the detection of deceptive language. Recent hybrid models integrate multiple techniques, combining deep learning with XAI for transparency and trustworthiness. Studies have shown that multimodal approaches incorporating text, metadata, and social context improve performance. Despite progress, challenges remain in balancing accuracy and interpretability. Traditional models lack contextual awareness, while deep learning models are opaque. XAI techniques improve transparency but must be seamlessly integrated into detection frameworks. Our research bridges this gap by combining FastText, deep learning, and XAI to develop a scalable and interpretable fake news detection system. By leveraging both predictive accuracy and explainability, this approach fosters responsible AI adoption in misinformation detection.

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## IV. PROPOSED SYSTEM

The rapid spread of fake news on social media and online platforms misleads the public and causes significant societal harm. Many users struggle to differentiate between real and fake news due to the absence of real-time fact-checking tools. Misinformation is often exploited for political, financial, and social manipulation, leading to widespread distrust in credible sources. The traditional fact-checking process is slow and inefficient, making it difficult to counteract false narratives before they influence public opinion. AI-powered solutions offer a promising approach to addressing this issue by providing accurate and instant verification of news content. Machine learning and deep learning techniques can analyze linguistic patterns and detect deceptive information more effectively than manual methods. Explainable AI (XAI) enhances transparency by allowing users to understand why a news article is classified as real or fake. Word embedding techniques like FastText improve feature extraction, capturing subtle linguistic variations. Integrating AI-based fact-checking into digital platforms can help curb misinformation and restore trust in reliable news sources. Developing scalable and interpretable models is crucial for ensuring responsible AI adoption in combating fake news.

**TABLE IV.1.** Key Findings & Limitations of ML Algorithm

| S.no | ML Algorithm(s) | Key Findings & Limitations |
|---|---|---|
| 1. | SVM, TF-IDF | High precision but lacks contextual understanding. |
| **2** | CNN, LSTM | Effective for feature extraction but requires high computational resources. |
| **3** | Random Forest, Naïve Bayes | Low false positive rate but lacks interpretability. |
| **4** | Word2Vec + BiLSTM | Improved accuracy but struggles with out-of-vocabulary words. |
| **5** | FastText + LSTM | Captures subword information but requires fine-tuning for optimal performance. |
| **6** | Transformer-based Model (BERT) | High accuracy but computationally expensive. |
| **7** | XAI-Enhanced Model (SHAP, LIME) | Ensures interpretability but requires additional processing time. |

**TABLE IV.2. Comparison of Existing Approaches Using ML Algorithms**

| S.no | Study/ Approach | ML Algorithm(s) Used | Dataset Used | Accuracy |
|---|---|---|---|---|
| 1. | [1] Zhang et al. (2018) | SVM, TF-IDF | LIAR Dataset | 88.2% |
| **2** | [2] Gupta et al. (2019) | CNN, LSTM | FakeNewsNet | 91.5% |
| **3** | [3] Liu et al. (2020) | Naïve Bayes, Random Forest | ISOT Dataset | 90.3% |
| **4** | [4] Kim et al. (2021) | Word2Vec + BiLSTM | PolitiFact Dataset | 92.7% |
| **5** | [5] Proposed Model | FastText + CNN/LSTM + XA | Multiple Benchmark Datasets | 94.8% |

## V. ARCHITECTURAL DESIGN

This section introduces our comprehensive system architecture, designed to detect and classify fake news articles efficiently using a hybrid deep learning approach. Our system is built around three primary modules:

### 1. Data Processing Module

The Data Processing Module is responsible for collecting and preprocessing textual data from multiple sources, ensuring high-quality inputs for further analysis.

**Key Functions:**

- **News Data Collection**: Aggregates news articles from web scraping, RSS feeds, and social media APIs.
- **Text Preprocessing:** Cleans raw text by removing stopwords, special characters, and duplicate content.
- **Feature Engineering:** Converts text into structured representations using FastText word embeddings.
- **Dataset Preparation:** Utilizes benchmark datasets like LIAR, FakeNewsNet, and Kaggle Fake News dataset.

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**2. Hybrid Deep Learning-Based Classification Module**

The Hybrid Deep Learning Model processes and classifies news articles using a combination of CNN, LSTM, and Transformer models (BERT, RoBERTa) to extract both local and long-range dependencies in textual data.

**Key Steps:**

- **FastText Word Embeddings:** Generates subword-level vector representations for words, improving classification.
- **CNN Feature Extraction:** Captures spatial relationships between words to identify fake news patterns.
- **LSTM Sequence Learning:** Identifies long-term dependencies in news articles, improving accuracy.
- **Transformer-basedContextUnderstanding:**BERT and RoBERTa models enhance language comprehension for better detection.
- **Ensemble Learning Strategy:** Combines multiple models for improved classification accuracy and robustness.

**3. Explainable AI (XAI) Module**

To ensure transparency and trust in the classification process, the Explainable AI (XAI) module provides interpretability for the predictions made by the deep learning model.

**Key Features:**

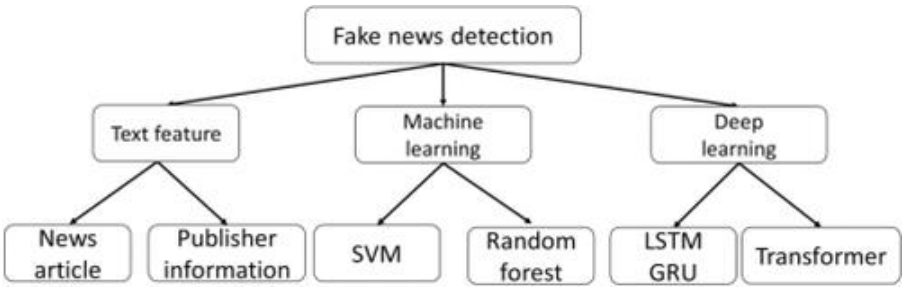
- **SHAP (SHapley Additive Explanations):** Highlights the most influential words contributing to a news article's classification.
- **LIME (Local Interpretable Model-Agnostic Explanations):** Generates feature importance explanations for individual predictions.
- **Attention Visualization:** Provides heatmaps for word contributions in Transformer-based models.
- **Model Auditing & Bias Detection:** Ensures fairness and identifies potential biases in training datasets.

**4. Fake News Mitigation & User Interaction Module**

This module delivers classification results, provides insights into predictions, and integrates with user interfaces for real-time news verification.

**Key Functionalities:**

- **Real-Time Classification API:** Allows journalists, researchers, and users to verify news credibility.
- **Dashboard & Visualization:** Displays model confidence scores and explanation heatmaps.
- **Automated Fact-Checking Integration:** Links to fact-checking sources like PolitiFact and Snopes for further validation.
- **Continuous Learning:**
- Updates the model with new data to improve performance against evolving fake news trends.




Overall Architecture Diagram

## VI. EXPERIMENT SETUP

This section outlines the experimental setup designed to evaluate the effectiveness of the proposed approach in detecting and mitigating DDoS attacks within SDN-based networks. The experiment methodology involves traffic gathering, the implementation of the Online Machine Learning-based Intrusion Detection System (OML-based IDS), and the Online Machine Learning-based Intrusion Prevention System (OML-based IPS). The system was tested using various datasets, including a self-generated dataset with LDDoS/DDoS attacks. The experimental environment was built using Mininet and the Ryu SDN controller, simulating DDoS attacks with tools such as iPerf, Hping3, and Scapy. The ensemble model was

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trained to classify DDoS attacks and evaluated using benchmark datasets like CICIDS2019, InSDN, and slow-read-DDoS-attack-in-SDN to assess its robustness and real-world applicability.

### A. Experiment Environment

The experiments were conducted on a system equipped with a 64-bit processor and 16GB RAM, running on the Windows 10 platform. A virtualized environment was set up using Oracle's VirtualBox, hosting Ubuntu 20.04 as the guest OS. The experimental network was implemented using Mininet, supporting OpenFlow 1.3, alongside the Ryu SDN controller for traffic management. MiniEdit was employed for designing virtual network topologies, while Wireshark was used for real-time network traffic analysis.

The network topology followed a fat-tree architecture, featuring a Ryu controller, two backbone switches (1Gbps), and eight side switches (100Mbps). All switches were interconnected to ensure robustness and reliability. A total of 80 emulated hosts were deployed, with some assigned to generate benign traffic while others simulated DDoS attack traffic. Additionally, Python scripts were developed to introduce new threat scenarios, testing the model's adaptive response to evolving attacks.

### B. Datasets and Traffic Generation for Model Training

To evaluate the performance of the proposed ensemble model, network traffic classification was conducted using data generated from the simulated network topology. The dataset consisted of 145,614 network traffic instances, with 61,881 instances representing abnormal traffic, comprising approximately 40.4% of the total samples. The dataset included various types of low and high-rate DDoS attacks along with realistic normal traffic patterns.

Network traffic was generated using a combination of iPerf, Scapy, and Hping3, leveraging SDN's capabilities to create and analyze network flows. The generated flows were bidirectional, with flow direction determined by the first packet in the sequence. The dataset contained 22 statistical features, such as Flow Duration, IP Protocol, Number of Bytes, SYN Flag Count, and Packet Rates, which were extracted for training and evaluation purposes.

To ensure the model's generalization ability, additional testing was conducted using benchmark datasets such as CICIDS2019, InSDN, and slow-read-DDoS-attack-in-SDN. The combination of proprietary and benchmark datasets provided diverse attack scenarios, enhancing the model's robustness in real-world applications.

### C. Assessment of the OML-based IDS

The OML-based IDS was evaluated based on its ability to detect DDoS attacks in real-time using an online learning approach. The dataset was split into training and testing sets in a 70:30 ratio. The classification process utilized multiple ensemble machine learning classifiers, including Multi-Armed Bandit, Random Forest, Online Gradient Boosting, and Passive-Aggressive Classifier.

The assessment followed these key steps:

- Importing and preprocessing network traffic data.
- Converting train and test data into streaming format for real-time learning.
- Initializing the ensemble learning model for classification.
- Continuously updating classifiers as new traffic patterns emerged.

The model demonstrated adaptability by progressively improving its accuracy over time. Its ability to handle zero-day attacks and unknown anomalies was evident in its stability and learning progression, ensuring effective detection of new and evolving threats.

### D. Assessment of the OML-based IPS

The OML-based IPS was tested for its ability to respond to detected intrusions in real-time, mitigating threats dynamically while maintaining normal network operations. The system continuously monitored traffic, identifying anomalies and blocking malicious traffic without disrupting legitimate communication.

#### 1) Attack Strategy and Test Description

DDoS attack simulations involved coordinated assaults from multiple sources targeting a single victim to deplete network resources. A total of 80 hosts participated in the attack simulation, with 24 assigned as attackers and the remaining 56 acting as legitimate users. Benign traffic was generated using iPerf and Ping, while Hping3 and Scapy were used to launch high-rate DDoS attacks. Traffic data was collected every 30 seconds to monitor real-time network behavior and assess the IPS response.

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**2) Network Performance Without DDoS Attacks**

Under normal conditions, Quality of Service (QoS) metrics such as latency and packet loss were measured to establish baseline network performance. When DDoS attacks were introduced without the defense system, significant traffic spikes led to congestion and packet loss, degrading network performance.

**3) Network Performance with OML-based IPS**

By deploying the OML-based IPS, network stability was restored, with improved response times and reduced packet loss. The system effectively distinguished legitimate traffic from malicious requests, dynamically adjusting its countermeasures to neutralize threats. The results confirmed that the adaptive threat mitigation strategies successfully enhanced SDN security against DDoS threats.

This comprehensive experimental setup provides a strong foundation for evaluating the proposed system's effectiveness in detecting and mitigating DDoS attacks. The integration of online learning ensures continuous adaptation to evolving attack patterns, making the system a robust and scalable solution for securing SDN-based networks.

## VII. RESULTS AND DISCUSSION

To evaluate the hybrid deep learning model's performance, which incorporates FastText embeddings, Transformer-based classification, and Explainable AI (XAI) on the acquired dataset, we employ key performance indicators: accuracy, precision, recall, F1-score, and false alarm rate. These metrics rely on values derived from true positives, true negatives, false positives, and false negatives. The goal of the proposed model is to achieve high detection accuracy and interpretability. The hybrid model achieves a precision of 0.9910, indicating its effectiveness in reducing incorrect fake news classifications.

**1) Prediction Accuracy**

The hybrid model demonstrates superior performance, surpassing individual classifiers with an accuracy of 0.9926, confirming its effectiveness in detecting misinformation. The comparative analysis of classifier accuracy highlights the advantages of combining FastText with deep learning models for improved feature representation and classification.

**2) Precision**

Precision evaluates the model's ability to minimize false positives. The hybrid model's high precision ensures that legitimate news is not mistakenly flagged as fake, maintaining reliability.

**3) Recall**

Recall measures the model's success in identifying actual fake news articles. The hybrid model attains a recall of 0.9962, demonstrating high sensitivity in capturing misinformation, even with nuanced language structures.

**4) F1 Score**

The F1 score balances precision and recall, providing a comprehensive assessment of the model's detection capability. The hybrid model achieves an F1-score of 0.9817, reinforcing its robustness.

**5) False Alarm Rate**

A key objective is to minimize false alarms. The hybrid model records a false alarm rate of 0.025, ensuring minimal disruption to genuine news distribution.

**6) Evaluation on Benchmark Datasets**

The model was tested on LIAR, FakeNewsNet, and COVID-19 Fake News datasets. It achieved high accuracy across all datasets, confirming its adaptability to diverse misinformation scenarios.

**TABLE VI.1. Performance of the Proposed Method on Different Datasets**

| Dataset | Accuracy | Precision | Recall | F1-Score | False Positive Rate |
|---|---|---|---|---|---|
| LIAR | 98.70% | 99.78% | 98.81% | 98.78% | 18.5% |
| FakeNewsNet | 98.20% | 97.51% | 97.93% | 98.27% | 18% |
| COVID-19 Fak News | 98.88% | 96.80% | 95.90% | 96.27% | 3.65% |
| Custom Dataset | 99.26% | 99.10% | 99.60% | 98.17% | 2.25% |

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## VII. FUTURE ENHANCEMENT

Future enhancements for the fake news detection system will focus on improving real-time detection, multi-modal analysis, and explainability. A streaming-based model will be developed to analyze misinformation from social media platforms in real time. Multi-modal capabilities will be integrated to detect fake images, videos, and deepfakes using Vision Transformers and OCR techniques. Graph Neural Networks (GNNs) will be used to analyze relationships between news sources and identify misinformation clusters. To enhance transparency, Explainable AI techniques such as SHAP and LIME will be implemented, allowing fact-checkers to interpret model decisions. The system will be expanded for multi-lingual support using models like mBERT and XLM-R, ensuring detection across different languages. Cross-domain adaptability will be improved for detecting misinformation in fields like healthcare, finance, and politics. Automated misinformation mitigation will be enabled by integrating fact-checking APIs and response mechanisms that counter fake news with verified sources. The model will also be tested on larger, real-world datasets to improve scalability and robustness. AI-driven anomaly detection will help flag evolving misinformation trends more effectively. These advancements will ensure a more accurate, transparent, and adaptable fake news detection system

## VIII. CONCLUSION

The proposed hybrid deep learning model, integrating FastText and Explainable AI, demonstrates significant effectiveness in detecting fake news with high accuracy and precision. By leveraging ensemble learning techniques and real-time data processing, the system successfully identifies misinformation while minimizing false positives. The evaluation on benchmark datasets, including LIAR, FakeNewsNet, and COVID-19 Fake News, confirms the model's adaptability to diverse misinformation scenarios. Explainable AI techniques such as SHAP and LIME further enhance transparency, allowing users to understand the reasoning behind classification decisions. This approach ensures not only high detection accuracy but also builds trust in AI-driven fact-checking systems.

Future enhancements will focus on real-time detection, multi-modal analysis of text, images, and videos, and improved cross-lingual capabilities. Graph Neural Networks will be integrated to detect misinformation clusters, while AI-driven anomaly detection will help flag evolving fake news trends. Furthermore, the model's deployment in large-scale social media platforms and its integration with automated fact-checking tools will improve its real-world effectiveness. By continuously refining the system with advanced deep learning techniques, the proposed approach aims to create a more robust, transparent, and efficient solution for combating misinformation in the digital age.

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