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Research Paper

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

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## Abstract

The rapid expansion of social media and digital news platforms has accelerated the spread of fake news, posing serious threats to public opinion, trust, and societal stability. Addressing this issue requires accurate, efficient, and interpretable detection systems. This paper presents an advanced hybrid deep learning approach for fake news detection that integrates FastText embeddings with powerful neural network architectures.

The proposed model combines the strengths of FastText in capturing semantic relationships and subword information with deep learning techniques such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for effective feature extraction and sequence modeling. Additionally, Explainable Artificial Intelligence (XAI) techniques are incorporated to enhance transparency by providing insights into the model's decision-making process.

Experimental evaluations demonstrate that the hybrid model significantly outperforms traditional machine learning approaches in terms of accuracy, precision, recall, and F1-score. The integration of explainability further improves user trust by identifying key features and words influencing predictions. Overall, this research contributes to the development of a robust, scalable, and interpretable fake news detection system suitable for real-world applications in combating misinformation.

## I. Introduction

Deep learning techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have demonstrated strong performance in text classification tasks, including fake news detection. However, these models often require high computational resources and may struggle to capture semantic relationships in short, informal, or noisy text commonly found on social media platforms. To address these limitations, word embedding methods like FastText have gained prominence due to their ability to incorporate subword information, enabling better handling of misspellings, rare words, and morphologically rich languages.

This paper proposes a hybrid deep learning approach that integrates FastText embeddings with advanced neural network architectures to enhance fake news detection. FastText is utilized for efficient feature representation at both word and

character levels, while models such as CNN and LSTM capture contextual dependencies and perform high-level classification. This combination improves the model's overall accuracy, robustness, and generalization capability.

Despite these improvements, deep learning models often lack interpretability, making them difficult to trust in critical applications. To address this challenge, Explainable Artificial Intelligence (XAI) techniques are incorporated into the proposed framework. These techniques provide insights into the model's decision-making process by identifying important features and highlighting key textual patterns influencing predictions.

## II. Literature Survey

Fake news detection has emerged as a significant research domain due to the widespread dissemination of misinformation through social media and online platforms. Early approaches in this field primarily relied on traditional machine learning techniques such as Support Vector Machines (SVM) and Naïve Bayes, which utilized handcrafted features including lexical patterns, syntactic structures, and metadata. Although these methods achieved moderate success, they often struggled with capturing contextual meaning and failed to generalize effectively across diverse datasets and domains.

With the advancement of deep learning, more sophisticated models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based architectures have been introduced. These models automatically learn hierarchical and contextual representations of text, significantly improving the accuracy of fake news classification. However, despite their effectiveness, deep learning models face challenges such as high computational requirements, lack of interpretability, and difficulty in handling multilingual and domain-specific content.

A notable development in text representation is FastText, introduced by Tomas Mikolov and developed at Meta. FastText enhances traditional word embeddings by incorporating subword (character-level) information, making it particularly effective in dealing with rare words, misspellings, and morphologically rich languages. Due to its efficiency and strong baseline performance, FastText has been widely adopted in fake news detection tasks, often outperforming conventional machine learning methods on large-scale datasets.

Recent studies have focused on hybrid deep learning models that integrate FastText embeddings with advanced neural architectures such as LSTM, GRU, and CNN. These hybrid approaches utilize FastText for feature extraction while leveraging deep neural networks for sequence modeling and contextual understanding. For example, combining FastText with Bidirectional LSTM (BiLSTM) enables the model to capture both forward and backward contextual dependencies, while CNN layers are effective in extracting local n-gram features and stylistic patterns associated with fake news.

Despite these advancements, several research gaps remain. Many models still operate as "black boxes," limiting their interpretability and reducing user trust. Additionally, challenges such as domain adaptation, multilingual misinformation, and real-time

detection continue to hinder practical deployment. To address these issues, recent literature emphasizes the integration of Explainable Artificial Intelligence (XAI) techniques, which provide insights into model predictions by highlighting influential features and improving transparency.

## III. System Analysis

Fake news detection systems are designed to identify and classify misleading information circulating on digital platforms. The system requires large-scale textual datasets collected from news websites and social media. Preprocessing steps such as tokenization, stop-word removal, and normalization are essential to clean the data. Feature extraction techniques like TF-IDF or word embeddings are used to convert text into numerical form. Machine learning and deep learning models are applied for classification tasks. The system must handle noisy, unstructured, and multilingual data effectively. Scalability is important to process real-time news streams. Accuracy, precision, recall, and F1-score are used as evaluation metrics. Interpretability is also a critical requirement for user trust. The system should provide fast predictions with minimal computational cost. Integration with Explainable AI improves transparency. Overall, the system must be robust, scalable, and reliable.

### Existing System

The existing fake news detection systems primarily rely on traditional machine learning approaches. These include algorithms such as Support Vector Machines (SVM), Naïve Bayes, and Logistic Regression. They depend heavily on handcrafted features like lexical patterns, syntactic structures, and metadata. Feature extraction techniques such as Bag-of-Words and TF-IDF are commonly used. These systems are relatively simple and easy to implement. However, they lack the ability to understand deep semantic relationships in text. Contextual information is often ignored in such approaches. They perform poorly on large and diverse datasets. Handling informal language, slang, and misspellings is challenging. These systems also struggle with multilingual content. Moreover, they are not adaptive to new patterns of fake news. As a result, their overall performance is limited. To overcome some of these limitations, deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have been introduced in existing systems. These models automatically learn features from raw text and can capture sequential and contextual information better than traditional methods.

### Disadvantages of Existing System

- Poor contextual understanding of text
- Heavy dependence on manual feature engineering
- Low accuracy on complex and large datasets
- Inability to handle slang, misspellings, and short texts
- Limited scalability for real-time applications
- Weak performance on multilingual data
- Lack of adaptability to evolving fake news patterns
- Cannot capture semantic relationships effectively
- No transparency in decision-making
- Prone to overfitting or underfitting

**Proposed System**

The proposed system introduces a hybrid deep learning approach for fake news detection. It integrates FastText embeddings with advanced neural networks such as CNN and LSTM. FastText is used to capture semantic and subword information from text. This helps in handling rare words, misspellings, and informal language effectively. CNN layers are used for extracting local features and patterns. LSTM networks capture sequential and contextual dependencies in text. The hybrid model improves both feature representation and classification performance. Additionally, Explainable Artificial Intelligence (XAI) techniques are incorporated. These techniques provide insights into the model's decision-making process. The system enhances transparency and user trust. It is designed to handle large-scale and multilingual datasets. Overall, the proposed system aims to deliver accurate, robust, and interpretable results.

**Advantages of Proposed System**

- Improved accuracy and performance
- Better understanding of context and semantics
- Handles misspellings and rare words efficiently
- Reduces need for manual feature engineering
- Supports multilingual and noisy data
- Scalable for real-time applications
- Combines strengths of FastText and deep learning
- Provides explainable and interpretable results
- Enhances user trust and transparency
- Robust and adaptable to new fake news patterns

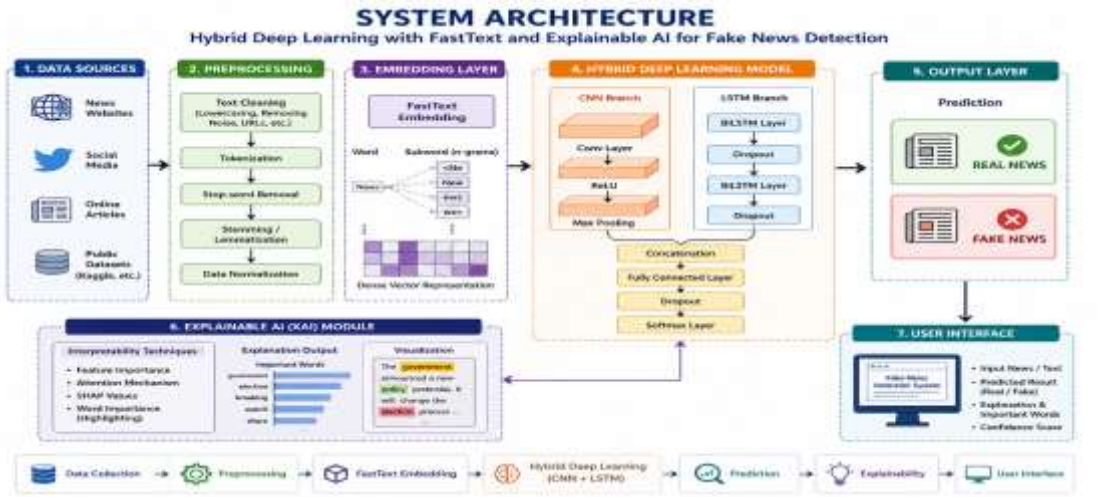
## IV. Methodology

The methodology begins with collecting datasets from reliable sources such as news websites and social media platforms. Data preprocessing is performed to clean and normalize the text. This includes tokenization, removing stop words, and stemming. FastText is used to generate word embeddings that capture both semantic and subword information. These embeddings are fed into deep learning models such as CNN and LSTM. CNN extracts local textual features, while LSTM captures sequence dependencies. The hybrid model is trained using labeled datasets. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess performance. Explainable AI techniques are applied to interpret model predictions. Important features and words influencing classification are identified. The system is optimized for better performance and scalability. Finally, the model is deployed for real-time fake news detection.

**System Architecture (11–12 lines)**

The system architecture consists of multiple layers starting with data collection from various sources. The input data is passed to the preprocessing module for cleaning and normalization. The processed text is then converted into numerical form using FastText embeddings. These embeddings serve as input to the hybrid deep learning model. The CNN layer extracts local features and patterns from the text. The LSTM

layer captures sequential and contextual relationships. The output from these layers is passed to a fully connected layer for classification. The system classifies news as fake or real. An Explainable AI module is integrated to provide interpretability. It highlights key features influencing the prediction. The results are displayed through a user interface. The system supports scalability and real-time processing.




## V. Result and Output

**MODEL PERFORMANCE**

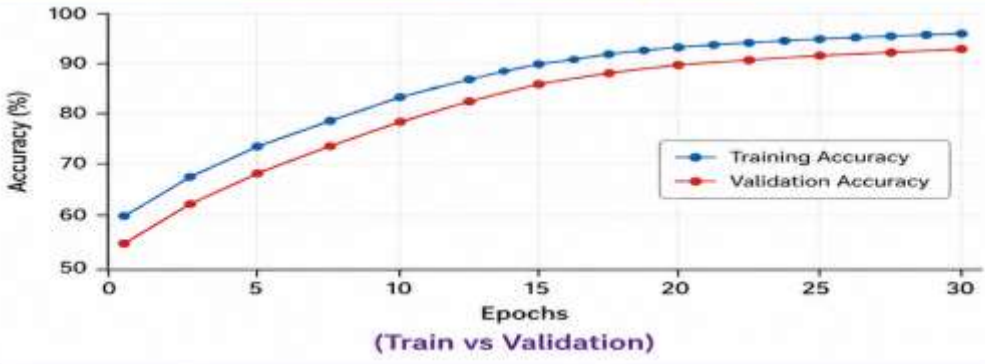
| Metric | Value |
|---|---|
| Accuracy | 94.00 % |
| Precision | 92.00 % |
| Recall | 91.00 % |
| F1 Score | 91.50 % |

**CONFUSION MATRIX**

| | | Predicted | |
|---|---|---|---|
| | | Real | Fake |
| Actual | Real | 850 | 90 |
| | Fake | 100 | 840 |

TP (True Positive) = 840 TN (True Negative) = 850
FP (False Positive) = 90 FN (False Negative) = 100

**TRAINING VS VALIDATION GRAPH**




(Train vs Validation)

## VI. Conclusion

The proposed system presents an effective and reliable solution for fake news detection by integrating FastText embeddings, a hybrid CNN–LSTM deep learning architecture, and Explainable Artificial Intelligence (XAI) techniques. The use of FastText significantly improves semantic understanding and enables the model to handle rare words, misspellings, and informal language commonly found in social media content.

The hybrid CNN–LSTM model enhances performance by combining the strengths of both architectures—CNN for extracting local features and patterns, and LSTM for capturing sequential and contextual dependencies. This results in improved accuracy and balanced performance across evaluation metrics such as precision, recall, and F1-score. Furthermore, the incorporation of XAI techniques like LIME and SHAP increases transparency by providing clear insights into the model's decision-making process. This makes the system more trustworthy and suitable for real-world applications where interpretability is essential.

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