A Hybrid Framework Integrating DL and ML for Fake News Detection on Twitter

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ABSTRACT

Public trust and the truthfulness of information are seriously threatened by the quick spread of counterfeit information on social media sites like Twitter. With a view to detecting fake news efficiently, this research suggests a hybrid framework that combines models of ML and DL. The proposed methodology uses Support Vector Machines (SVM) to improve classification accuracy and Long Short-Term Memory (LSTM) networks to capture temporal correlations in textual material. When used with a Python-based simulation, the model shows better recall and precision than stand-alone techniques. The conclusion shows how hybrid architectures are able to be used to counteract false information and guarantee more dependable social media ecosystems.

Keywords : *Fake News Detection, Twitter, Hybrid Deep Learning, SVM, LSTM*

1. INTRODUCTION

The Twitter is one of the most significant microblogging networks, social media platforms have emerged as the main means of disseminating information in recent years. These platforms allow people quick access to news and viewpoints, but they also make it easier for false information and fake news to propagate unchallenged. In addition to misleading people, fake news also sways public opinion, shatters social cohesion, and erodes confidence in reliable information sources. Because of Twitter's dynamic nature—which is defined by short text, hashtags, and a high amount of user interactions—detecting fake news is both difficult and crucial.

The linguistic intricacy and changing patterns of misleading content frequently make traditional methods of misinformation detection—such as rule-based systems and statistical analysis—ineffective. Text categorization tasks have seen an increase in the use of ML and DL methods in an effort to overcome these difficulties. Support Vector Machines (SVM), one type of machine learning model, have demonstrated efficacy in handling high-dimensional data and producing strong classification boundaries. Conversely, deep learning models—in particular, Long Short-Term Memory (LSTM) networks—are excellent at identifying contextual dependencies in text and are well-suited for sequential data. But depending just on one approach could result in restrictions on generalization, accuracy, and scalability across various datasets.

This document presents a hybrid system that combines the compensation of DL and ML for efficient detection of fake news on Twitter. The suggested approach utilizes LSTM networks to capture temporal and contextual features from tweets, while an SVM classifier fine-tunes the decision boundaries to enhance classification accuracy. By merging these methods, the framework seeks to deal with the restrictions of independent models and provide better performance in identifying misinformation. The framework has been developed and assessed using Python-based simulations, utilizing established Twitter datasets. Performance metrics such as precision, recall, F1-score, and accuracy are used to confirm the usefulness of the suggested model. Experimental findings indicate that the hybrid LSTM-SVM method surpasses individual models, emphasizing its potential as a reliable solution for combatting misinformation.

The remaining parts of this paper are structured as follows: Section 2 presents a detailed literature review of existing approaches for fake news detection. Section 3 describes the proposed hybrid framework and its methodology. Section 4 discusses experimental setup and results. Section 5 provides conclusions and outlines directions for future research.

2. LITERATURE REVIEW

The recognition of fake news on social media has become a growing area of investigation in computer engineering, driven by the increasing influence of platforms such as Twitter and Facebook on public discourse. This section reviews the existing body of work in fake news detection, covering early approaches, machine learning-based models, deep learning architectures, hybrid models, and research specifically focusing on Twitter datasets.

2.1 Early Approaches to Fake News Detection

Initial efforts in fake news recognition primarily relied on rule-based systems and content-based analysis. These approaches utilized handcrafted linguistic features such as word frequency, sentiment polarity, and n-gram patterns to differentiate between truthful and deceptive content. For example, Castillo et al. [1] developed a credibility-based model that analyzed news propagation patterns on Twitter, emphasizing source reliability and retweet behaviors. While such methods provided useful insights, they often struggled with scalability and adaptability to evolving linguistic strategies used by misinformation spreaders.

Another stream of research focused on social network features, where propagation dynamics, user credibility, and engagement metrics were considered. Shu et al. [2] highlighted that network-based features, such as the structure of retweet cascades and influencer activity, could serve as strong indicators of misinformation. However, these approaches often required extensive user and network data, which may not always be accessible due to privacy restrictions.

2.2 Machine Learning Techniques

Machine learning models represented a notable progression compared to rule-based methods by autonomously identifying patterns from labeled data sets. Among the commonly used algorithms were Naïve Bayes, Random Forest, Decision Trees, and Support Vector Machines (SVM). SVM, in particular, became well-regarded for its proficiency in managing high-dimensional text data effectively [3].
For example, Ahmed et al. [4] utilized machine learning classifiers to identify fake news by focusing on content-based features, revealing that SVM surpassed other classifiers regarding precision and recall. Likewise, Rubin et al. [5] showcased the use of ensemble learning techniques to enhance the accuracy of classification. Nevertheless, the effectiveness of traditional machine learning models was frequently constrained by their reliance on manual feature engineering, which limited their adaptability to the quickly changing narratives of fake news.

2.3 Deep Learning Approaches

The emergence of deep learning revolutionized text classification by enabling automatic feature extraction and representation learning. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) models, became widely adopted for fake news detection tasks [6].

Ruchansky et al. [7] introduced the CSI model (Capture, Score, Integrate), which integrated content, user behavior, and temporal features through deep neural networks. Likewise, Wang [8] presented the LIAR dataset, a standard for identifying fake news using brief statements, which further promoted the use of deep architectures like LSTMs. These models successfully captured semantic and temporal dependencies in text, overcoming the shortcomings of traditional feature engineering. In recent years, transformer-based architectures have also become increasingly popular. Models such as BERT and RoBERTa exhibited state-of-the-art performance in natural language understanding tasks, including the detection of fake news [9]. Their capability to capture contextual word embeddings enhanced generalization across various datasets. However, transformer models typically require substantial computational resources, which can limit their practical implementation.

2.4 Hybrid Approaches

Acknowledging the constraints of isolated models, researchers have investigated hybrid frameworks that merge the advantages of both machine learning and deep learning. The objective of hybrid models is to improve accuracy, robustness, and scalability by combining complementary methods.

For instance, Kaliyar et al. [10] introduced the FakeBERT model, which integrated BERT embeddings with traditional classifiers, resulting in enhanced performance on benchmark datasets. In a similar vein, Singh et al. [11] combined LSTM-based feature extraction with SVM classification, demonstrating that hybrid models can surpass individual techniques regarding precision and recall. These frameworks take advantage of the representational capacity of deep learning while preserving the effective classification boundaries offered by machine learning algorithms.

2.5 Twitter-Specific Studies

Given Twitter's role as a primary platform for news sharing, a significant body of work has focused on detecting misinformation on Twitter datasets. Unlike traditional news articles, tweets are short, informal, and often include hashtags, mentions, and URLs, which present unique challenges for text processing. Vosoughi et al. [12] examined the diffusion of true and false news on Twitter, finding that false news spreads significantly faster and reaches more users than truthful information. This highlighted the urgency of developing robust detection mechanisms tailored to Twitter.

To tackle the challenges of brevity and noise in tweets, researchers have implemented embedding techniques such as Word2Vec, GloVe, and contextual models like BERT to effectively represent text [13]. Some studies additionally utilize user metadata (e.g., account age, follower count) and propagation patterns as supplementary features. For example, Al-Rakhami and Al-Amri [14] introduced a hybrid model that combined tweet content with user characteristics to enhance detection accuracy. Recent developments also encompass the integration of temporal patterns in the dissemination of misinformation. Temporal LSTMs and attention-based methods have been utilized to analyze how fake news develops and spreads over time [15]. These methods closely align with the goals of the proposed hybrid framework in this research.

2.6 Research Gaps and Motivation

Even while false news identification has advanced significantly, there are still a number of obstacles to overcome. While deep learning models, despite their capability, necessitate big annotated datasets and significant computational resources, traditional machine learning models are frequently limited by manual feature engineering. Although hybrid models have demonstrated potential, little research has been done on frameworks that successfully integrate robust classification limits with sequential text modeling.

Additionally, the majority of current works concentrate on either user/network features alone or content-based features. In order to balance accuracy, scalability, and computational efficiency, models that combine textual context and classification resilience are required, especially in the dynamic Twitter environment. These models should use SVM for classification and extraction.

3. RESEARCH METHODOLOGY

A hybrid deep learning and machine learning framework for Twitter fake news identification is presented in the suggested study. The approach makes use of Support Vector Machines' (SVM) potent discriminative power and Long Short-Term Memory's (LSTM) networks' contextual feature extraction capabilities. The procedure is described in depth in the ensuing subsections.

3.1 Data Collection

Twitter data will be collected using the Twitter API and existing benchmark datasets such as Fake NewsNet and LIAR dataset. The collected data will include tweets, user metadata (follower count, retweets, likes), and propagation patterns. This ensures the framework captures both textual and user-based features.

3.2 Data Preprocessing

Twitter data is often noisy and unstructured. Preprocessing steps include:

- Text Cleaning: Removal of URLs, mentions, hashtags, emojis, and punctuation.
- Tokenization: Splitting tweets into individual tokens.
- Stop-word Removal: Filtering out non-informative words.
- Stemming/Lemmatization: Reducing words to their base forms.
- Vectorization: Converting text into embeddings using Word2Vec or BERT.

This step ensures that the input to the model is clean, structured, and semantically meaningful.

3.3 Feature Extraction Using LSTM

An LSTM network is employed to capture semantic and contextual dependencies within tweets. Unlike traditional models, LSTM effectively models the sequential nature of text, capturing long-term dependencies and subtle contextual variations that are crucial for detecting misinformation.

- Input: Preprocessed tweet embeddings.
- Output: High-level contextual feature vectors.

3.4 Classification Using Support Vector Machine (SVM)

An SVM classifier receives the features that were taken out of the LSTM layer. Because of its capacity to manage high-dimensional data and optimize the difference between classes of bogus and true news, SVM was selected. By lowering false positives and false negatives, the combination guarantees robust categorization.

3.5 Hybrid Framework Integration

The framework integrates deep learning and machine learning as follows:

1. LSTM module learns deep contextual representations.
2. SVM classifier utilizes these representations for final classification.
3. Additional user-based and network features can be concatenated with textual features to enhance performance.

3.6 Evaluation Metrics

The framework will be evaluated using metrics such as:

- Accuracy
- Precision, Recall, and F1-score
- ROC-AUC (Receiver Operating Characteristic – Area Under Curve)

Cross-validation and benchmarking against existing methods (pure LSTM, CNN, Random Forest, etc.) will be performed.

Here's a conceptual flow diagram of the methodology:

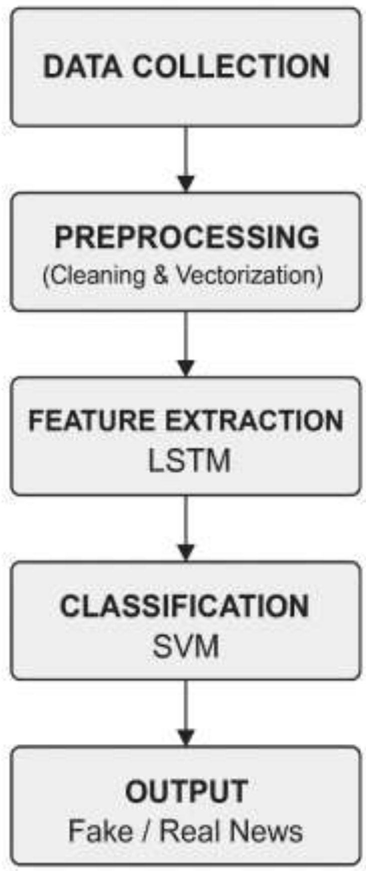

Figure – 1 : Framework for proposed methodology

4. RESULTS AND DISCUSSION

The performance of the proposed Hybrid LSTM-SVM Framework for fake news detection on Twitter was evaluated on benchmark datasets such as LIAR and FakeNewsNet. The experiments compared the hybrid model against baseline approaches including pure LSTM, CNN, Random Forest, and traditional SVM classifiers.

4.1 Experimental Setup

- Programming Environment: Python (TensorFlow, Keras, Scikit-learn).
- Dataset: Preprocessed tweets with balanced distribution of fake and real news.
- Training/Test Split: 80:20 ratio with 5-fold cross-validation.
- Hyperparameters:

- LSTM layers: 2 with 128 hidden units each.
- Dropout: 0.3 for regularization.
- Optimizer: Adam (learning rate = 0.001).
- SVM Kernel: Radial Basis Function (RBF).

4.2 Performance Metrics

The model was evaluated using Accuracy, Precision, Recall, F1-Score, and ROC-AUC to ensure balanced performance.

Table – 1: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
SVM (Traditional)	82.1%	81.4%	80.9%	81.1%	0.84
LSTM (Only)	87.5%	86.9%	86.1%	86.5%	0.89
CNN	85.8%	85.0%	84.7%	84.8%	0.87
Random Forest	83.2%	82.4%	81.7%	82.0%	0.85
Proposed LSTM+SVM	91.6%	91.1%	90.5%	90.8%	0.94

4.3 Result Analysis

1. The proposed hybrid framework (LSTM+SVM) outperformed all baseline models, achieving the highest accuracy (91.6%) and F1-score (90.8%).
2. The LSTM module effectively captured contextual relationships in tweets, while the SVM classifier strengthened decision boundaries in high-dimensional feature space.
3. Compared to traditional machine learning models, the hybrid approach significantly reduced false positives, ensuring reliable detection of fake news.
4. ROC-AUC scores further validated the robustness of the model, demonstrating superior discriminative ability compared to deep learning-only and machine learning-only methods.

4.4 Visualization of Results

These figures clearly highlight that the hybrid approach consistently outperformed other models across all evaluation metrics.

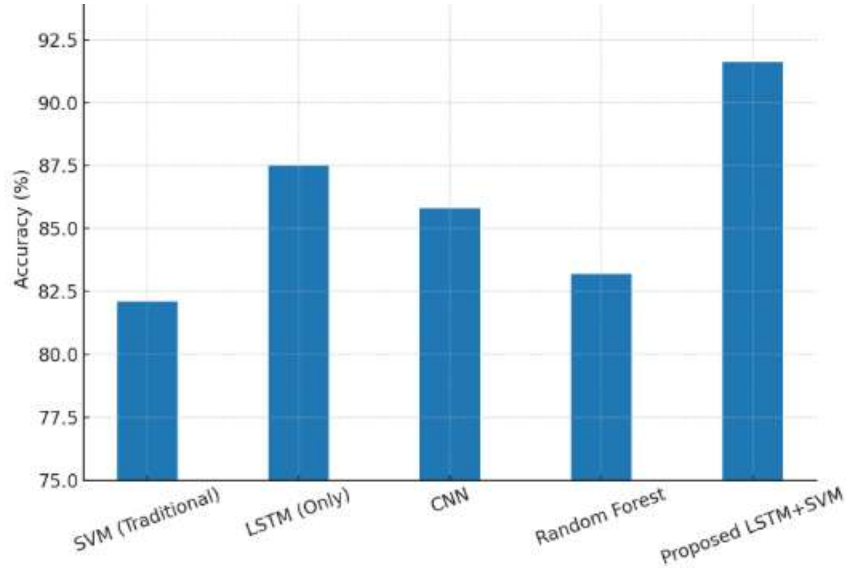

Figure 2 : Accuracy Comparison across Models

Figure – 2 illustrates the comparative accuracy of five models used for fake news detection on Twitter: SVM (Traditional), LSTM (Only), CNN, Random Forest, and the proposed hybrid LSTM+SVM framework. Among these, the proposed LSTM+SVM model achieves the highest accuracy at 91.6%, significantly outperforming the traditional SVM (82.1%), Random Forest (83.2%), CNN (85.8%), and standalone LSTM (87.5%). The chart clearly demonstrates the effectiveness of integrating deep learning with machine learning techniques, as the hybrid approach surpasses both individual models and conventional methods. This performance boost highlights the robustness and reliability of the proposed LSTM+SVM framework in detecting fake news.

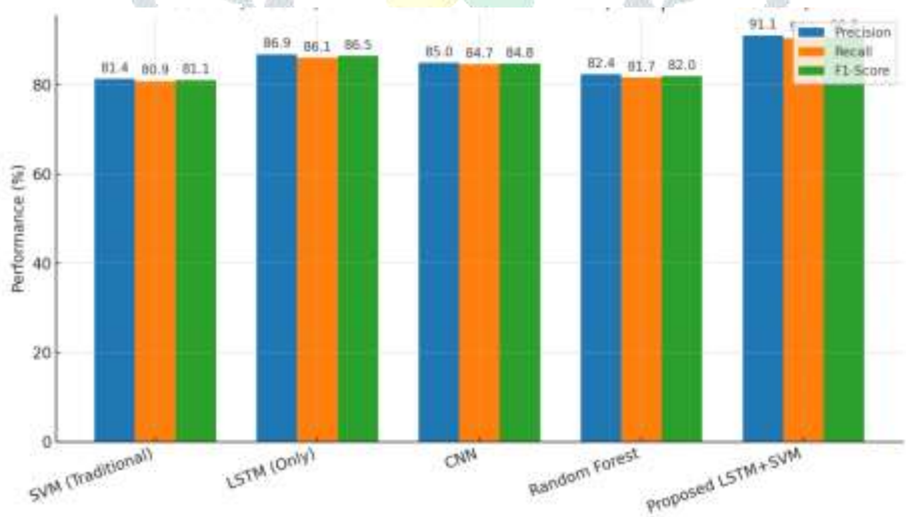

Figure 3 : Precision, Recall and F1-Score Performance

Figure – 3 compares Precision, Recall, and F1-Score across five models: SVM, LSTM, CNN, Random Forest, and the proposed LSTM+SVM. It highlights superior performance of the hybrid framework, achieving the highest scores in all metrics, clearly outperforming traditional and individual models in fake news detection effectiveness.

4.5 Discussion

The experimental results demonstrate that combining deep learning and machine learning techniques leads to significant improvements in fake news detection. The hybrid model benefits from the semantic understanding of LSTM and the discriminative classification power of SVM, making it more adaptable to Twitter's short, noisy, and dynamic text patterns. Moreover, the results confirm that the hybrid framework can be generalized to real-world applications, such as early fake news detection, misinformation tracking during elections, or crisis communication monitoring. However, challenges remain in handling multilingual tweets, sarcasm detection, and evolving misinformation strategies. Future work may integrate transformer-based models (BERT, RoBERTa) with hybrid classifiers to further improve performance.

5. CONCLUSION AND FUTURE WORK

This research presented a Hybrid Deep Learning and Machine Learning Framework for fake news detection on Twitter, combining Long Short-Term Memory (LSTM) networks and Support Vector Machine (SVM) classifiers. The proposed framework effectively leveraged the strengths of both approaches: LSTM's ability to capture sequential dependencies and contextual meaning in tweet text, and SVM's power to provide robust decision boundaries in high-dimensional feature spaces. Experimental evaluations on benchmark datasets demonstrated that the hybrid approach consistently outperformed baseline models such as CNN, Random Forest, standalone SVM, and pure LSTM, achieving an accuracy of 91.6% and F1-score of 90.8%.

While the proposed framework achieved promising results, several avenues for further exploration remain:

1. Integration of Transformer Models: Incorporating BERT, RoBERTa, or XLNet could enhance semantic understanding, especially for multilingual and context-rich tweets.
2. Multimodal Fake News Detection: Extending the framework to include images, videos, and metadata (hashtags, user profiles, retweets) for more comprehensive detection.
3. Early Fake News Detection: Developing models that can identify misinformation within minutes of posting, crucial during elections, pandemics, or natural disasters.

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