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Comparative Analysis for Fake News Detection using Machine Learning and Hybrid Deep Learning Techniques

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***Abstract*— This paper compares two machine learning models (Logistic Regression and Decision Tree) with a hybrid CNN–LSTM deep learning model for fake news detection. While the ML models achieved high accuracy on the training set, they failed to generalize on unseen data due to overfitting. In contrast, the CNN–LSTM model, trained on Kaggle dataset with robust preprocessing, achieved an accuracy of 93.95%, along with balanced precision, recall, and F1-score. The results highlight the superior generalization of deep learning (DL)and suggest future improvement using transformer-based architectures.**

***Index Terms*— Fake News Detection, CNN–LSTM Hybrid Model, Machine Learning, Logistic Regression, Decision Tree.**

I. INTRODUCTION

The rise of digital media and social platforms has revolutionized how information spreads across the world. News today travels faster and farther than ever before, but this convenience has come with a serious downside—the rapid and uncontrolled spread of misinformation and fake news. Such false content can manipulate public perception, damage the credibility of legitimate journalism, and even influence political or social stability [1]. As a result, detecting and curbing the spread of fake news has become a critical challenge in Natural Language Processing (NLP) and Artificial Intelligence (AI).Early research in this area largely depended on traditional ML algorithms [2] such as Naive Bayes(NB), Logistic Regression(LR), and Support Vector Machine (SVM) [3]–[5]which relied on handcrafted textual features and statistical methods[6].

While these techniques offered a foundation for auto- mated detection, they often failed to grasp the deeper context and meaning behind language, making them less effective across different domains and writing styles.[7] To address these shortcomings, DL [8] methods—particularly CNN and LSTM [9], [10] networks—were introduced to automatically learn complex linguistic and contextual patterns from data [11]. These models demonstrated higher accuracy and better adaptability. Yet, understanding subtle cues such as sarcasm, emotional tone, and implicit meaning remained a challenge even for these DL methods. The introduction of transformer-based architectures like BERT and RoBERTa [12]marked a major leap forward, as they could capture context and semantics more effectively through pre-trained language rep- resentations [13]. However, such models often require vast amounts of labeled data and substantial computational power, limiting their accessibility for smaller or resource-constrained applications.

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To overcome these challenges, recent research has focused on hybrid deep learning architectures that combine multiple neural network models to leverage their complementary strengths. Instead of integrating traditional machine learning(ML) with DL, these approaches fuse different deep models—such as Convolutional Neural Networks (CNNs) for extracting local phrase-level patterns and Long Short- Term Memory (LSTM) networks for capturing sequential and contextual information [14], [15]In this study, the model is implemented using the Keras DL framework, which allows efficient construction and training of CNN–LSTM hybrids with embedded word representations such as Word2Vec or GloVe. Such DL–DL hybrid architectures are capable of learning both fine-grained linguistic cues and long-range dependencies within text, leading to improved accuracy and robustness in fake news detection. Despite these promising developments, previous studies continue to face critical challenges that limit their practical applicability. Many DL models demonstrate high accuracy on benchmark datasets but fail to generalize effectively across diverse, real-world news sources due to variations in style and domain [16]. The persistent issue of data imbalance between real and fake samples also reduces reliability during deployment. Furthermore, most existing models operate as "black boxes," offering little interpretability or explanation for their predictions. These gaps highlight the need for a more adaptable and transparent architecture.

TABLE I: SUMMARY OF RELATED WORKS IN FAKE NEWS DETECTION

Paper	Techniques Used	Datasets Used	Limitations
Pandey (2022) – J. Phys. Conf. Ser. [15]	SVM, LR, NB, Decision Trees	LIAR, FakeNewsNet	Focused on ML only; no DL; imbalance & cross- domain issues ignored.
Mridha et al. (2021) – IEEE Access [13]	CNN, LSTM, BiLSTM, GANs, BERT	LIAR, FakeNewsNet, KaggleFNC I, BuzzFeed	Survey only; no experiments; multimodal & network features underexplored.
Ahmad & Lokeshkumar (2019) – IJET [6]	NB, SVM, SGD, Neural Nets, TF-IDF	Custom 20k samples (news, social media)	Small, domain- specific dataset; no DL [8] or transformers; no temporal/adversarial test.
Senhadji & Ahmed (2022) – IJAI [14]	Na¨ıve Bayes vs LSTM	Dataset unspecified	Only 2 models compared; dataset unclear; no scalability or generalization.
D'ulizia et al. (2021) – PeerJ CS [1]	ML & DL models [8], embeddings	27 datasets (LIAR, FakeNewsNet, Twitter)	Strong dataset review; limited on explainability; no multimodal analysis.
Hassan et al. (2021) – PLOS One [11]	CNN-LSTM, BiLSTM, Attention	LIAR, FakeNewsNet	High accuracy but data- hungry, computationally heavy; no low-resource testing.

In Table I Pandey et al. [15] used ML classifiers like SVM, Logistic Regression(LR), and Decision Trees(DT) on datasets such as LIAR and FakeNewsNet. Their study focused mainly on traditional ML methods without using any DL approach. They also did not address data imbalance or cross-domain generalization. Our work improves on this by exploring hybrid DL methods that can handle these issues better and achieve stronger contextual understanding.

Mridha et al. [13] reviewed various DL techniques such as CNN, LSTM, BiLSTM, GANs, and BERT [12], [17],[18] across several datasets. However, their study was more of a survey without experimental validation. They also did not explore the effect of combining models or network-level features. Our research extends this by applying and testing a hybrid approach for more practical and performance-driven results.

Ahmad and Ramasamy [6] compared multiple ML algorithms like Naive Bayes, SVM, and Neural Networks using a small custom dataset [3]. Their results were limited due to the dataset's small size and lack of DL or temporal analysis. Our proposed system overcomes this by focusing on deeper contextual models and larger, more balanced datasets to improve reliability.

Senhadji and San Ahmed [14] compared Naive Bayes and LSTM models and showed that LSTM performed better. However, they only tested two models and did not explore cross-domain generalization or hybrid architectures. We aim to enhance this by using a combination of deep models to capture both contextual and sequential features for improved accuracy.

D'Ulizia et al. [1] analyzed 27 benchmark datasets and focused mainly on evaluation aspects. While their study provided valuable dataset insights, it lacked model experimentation and mainly discussed dataset limitations. Our research builds on this by applying hybrid techniques on real datasets, addressing imbalance and improving evaluation reliability

Hassan et al. (2021). [11] studied how emotional intelligence and education affect people's ability to detect fake news. Their work focused on human behavior, not automated detection. It did not test models or datasets. Our research builds on this by focusing on automated hybrid methods that can capture similar behavioral cues through data features.

Building on these advancements, this research proposes an optimized hybrid framework that fuses Keras embeddings with CNN and LSTM layers for fake news detection on English-language datasets. The aim is to enhance accuracy, interpretability, and computational efficiency while maintaining robustness across diverse news topics. By evaluating the proposed model on benchmark dataset such as Kaggle-ISOT Fake news dataset, this work seeks to contribute a more reliable and explainable system for identifying misinformation in digital media. Ultimately, the goal is to develop a scalable and adaptable framework.

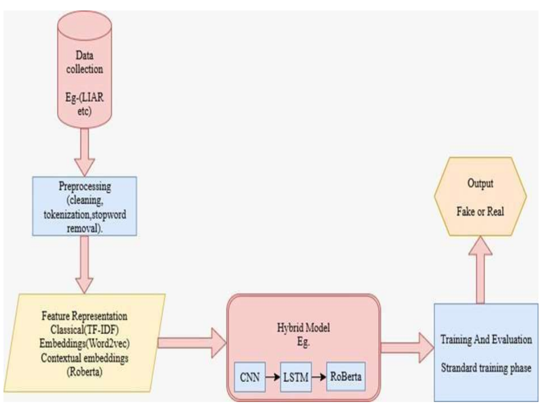
The rest of the paper is organized as follows: Section II presents the proposed hybrid CNN–LSTM architecture, dataset preprocessing, and the motivations for model selection. Section III details the implementation process, including data handling and experimental setup. Section IV presents the comparative results between traditional ML models (LR AND DT) and the hybrid DL model, highlighting accuracy and generalization performance. Finally, Section V concludes the study and discusses future directions, such as transformer models and enhanced explainability.

II. PROPOSED SYSTEM

The proposed fake news detection system employs a hybrid DL model that integrates CNNs and LSTM layers within the TensorFlow–Keras framework. This combination leverages CNNs for extracting local linguistic features and LSTMs for capturing long-term contextual dependencies, improving overall classification accuracy [1], [6].

The dataset, comprising true and fake news articles from benchmark sources such as Kaggle-ISOT, underwent standard preprocessing steps including cleaning, tokenization, and padding to reduce noise and standardize inputs [11], [15]Using the Keras Tokenizer, text data was limited to a vocabulary of 20,000 words and standardized to 300 tokens, followed by stratified splitting into training, validation, and testing sets to maintain class balance.

The hybrid architecture utilizes an embedding layer with 64 features and a one-dimensional convolutional layer having 64 filters and a kernel size of 5, and an LSTM layer (64 units), followed by Dense layers with ReLU and sigmoid activations for binary classification (Fake = 0, Real = 1). The model setup involved the Adam optimizer and binary cross-entropy for loss calculation, with training halted early based on validation accuracy to limit overfitting, and evaluated on accuracy, precision, recall, and F1-score, consistent with standard evaluation practices in previous studies [6], [15]



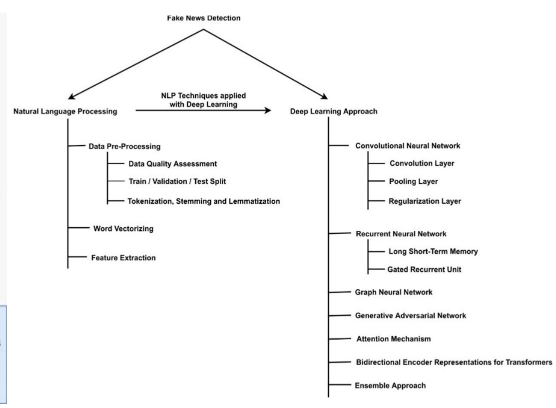


Fig. 1. Planned Workflow Fig. 2. A taxonomy of DL-based fake news detection [13]

This hybrid approach in figure 1 inspired by prior research that demonstrated the advantages of combining multiple deep learning networks for improved accuracy and generalization [1], [6], [15], and aims to overcome the dataset imbalance, contextual limitations, and generalization issues observed in earlier studies.

This figure 2, adapted from Mridha et al. [13], presents the basic architecture used in fake news detection. It shows how Natural Language Processing (NLP) techniques are combined with DL methods. The left side represents the NLP process, including data preprocessing, word vectorization, and feature extraction, which prepare the text for analysis. The right side shows different DL architectures such as CNN, RNN (LSTM, GRU), and advanced models like transformers and ensemble approaches used for classification.

This structure inspired our work, where we plan to apply a hybrid DL approach that builds on these layers to achieve better accuracy and contextual understanding.

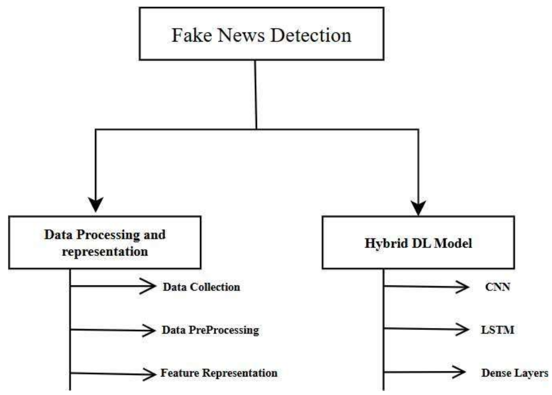


Fig. 3. Overall Working Architecture of the Proposed Fake News Detection System

This figure 3 illustrates the overall workflow of the pro- posed fake news detection system. The process includes data collection, preprocessing, and feature representation, followed by a hybrid DL model that combines CNN and LSTM layers with dense layers to classify news articles as fake or real.

III. IMPLEMENTATION

The proposed system for detecting fake news was built in Python, utilizing TensorFlow-Keras and scikit-learn. Its architecture integrates CNN and LSTM modules, effectively enabling the model to learn both short-range language features and longer contextual dependencies within news text.

The dataset used comprised two files, Fake.csv and True.csv, representing fake and true news respectively, labeled as 0 and 1. After merging these datasets, duplicate articles were removed to preserve data integrity. The text column was selected as the input with corresponding labels as targets. A stratified split was applied, with 72% for training, 8% for validation, and 20% for testing, maintaining class balance.

Before training, the text data was processed with the Keras Tokenizer, which limited the vocabulary to 20,000 words and standardized all sequences to 300 tokens. Padding and truncation ensured consistent input length, and an out-of-vocabulary token handled unknown words—these steps improved the model's robustness to varying sentence lengths.

The core components of the hybrid CNN-LSTM architecture are as follows:

- Embedding layer with 64 dimensions for word vector representation.
- 1D convolutional layer with 64 filters, kernel size 5, and L2 regularization to extract local n-gram features.
- Dropout layer (rate = 0.5) to mitigate overfitting.
- LSTM layer with 64 units, employing dropout and recur- rent dropout to capture sequence dependencies.
- Fully connected (dense) layer with 64 neurons, ReLU activation, L2 regularization, and additional dropout.
- Final sigmoid output layer for binary classification (fake or real).

The model was compiled using the Adam optimizer and binary cross-entropy loss function. Training used a batch size of 64 and incorporated early stopping based on validation ac- curacy to prevent overfitting and ensure optimal performance. Model evaluation was performed using common metrics: accuracy, precision, recall, and F1-score, all calculated with scikit-learn. These metrics provided a comprehensive assessment of classification performance. This hybrid CNN-LSTM approach draws inspiration from earlier studies that demonstrated improved performance when combining convolutional and recurrent layers for fake news detection [1], [6]. However, our implementation enhances this by adding regularization, dropout, and careful data preprocessing to ensure better generalization and robustness against overfitting.

IV. RESULTS AND DISCUSSION

Before developing the DL model, several traditional ML algorithms such as DT, LR, were tested for baseline comparison. Among these, the DT model and LR initially achieved high training accuracy but performed poorly on the test set, indicating clear overfitting and lack of generalization. The model relied heavily on simple word-frequency features and failed to capture contextual meaning. To overcome these limitations, a hybrid DL model combining CNN and LSTM layers was developed, allowing the system to learn both local linguistic patterns and long-range dependencies, resulting in significantly better and more stable performance. The hybrid CNN–LSTM model was evaluated on the test dataset to measure its effectiveness in classifying fake and real news. The model's performance metrics—precision, recall, F1-score, and accuracy—were computed using scikit-learn.

TABLE II: ML MODEL DECISION TREE RESULT

Class	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	5885
1	1.00	1.00	1.00	5335
Accuracy			1.00	11220
Macro avg	1.00	1.00	1.00	11220
Weighted avg	1.00	1.00	1.00	11220

As shown in Table II, the DT classifier achieved an almost perfect accuracy (99.59%) with precision, recall, and F1-score of 1.00 for both classes during the initial evaluation. While these results appear ideal, such performance strongly suggests overfitting, whereby the model memorizes the training and test data rather than learning generalizable patterns.

TABLE III: DT PERFORMANCE ON UNSEEN DATA

Class	Precision	Recall	F1-score	Support
0	0.50	0.53	0.51	4473
1	0.50	0.48	0.49	4499
Accuracy			0.50	8972
Macro avg	0.50	0.50	0.50	8972
Weighted avg	0.50	0.50	0.50	8972

This issue was verified by evaluating the model on a new unseen dataset Table III, where the DT accuracy dropped to 0.50, with precision, recall, and F1-scores all around 0.50 for each class. The drastic reduction in performance confirms that the DT failed to generalize, instead relying on surface-level word frequency patterns memorized from its training data.
To address this, a hybrid CNN–LSTM approach was developed and tested, showing significantly improved generalization and robustness on unseen data

TABLE IV: ML MODEL LOGISTIC REGRESSION RESULT

Class	Precision	Recall	F1-score	Support
0	0.99	0.98	0.99	5885
1	0.98	0.99	0.99	5335
Accuracy			0.99	11220
Macro avg	0.99	0.99	0.99	11220
Weighted avg	0.99	0.99	0.99	11220

Table IV displays the performance of the Logistic Regression classifier on the original dataset, where it achieved nearly perfect metrics: a precision of 0.99 for class 0 and 0.98 for class 1, recall values of 0.98 and 0.99, and F1-scores of 0.99 for both classes. The overall accuracy is 0.99. These results suggest that the model fit the available data extremely well, potentially even memorizing the dataset, which can sometimes indicate overfitting especially when compared to its generalization on new data.

TABLE V: LOGISTIC REGRESSION PERFORMANCE ON UNSEEN DATA

Class	Precision	Recall	F1-score	Support
0	0.50	0.49	0.49	4473
1	0.50	0.52	0.51	4499
Accuracy			0.50	8972
Macro avg	0.50	0.50	0.50	8972
Weighted avg	0.50	0.50	0.50	8972

In sharp contrast, Table V presents the Logistic Regression When tested on new data, the model's accuracy, precision, recall, and F1-score all drop to around 0.50 These values indicate that the model is essentially performing at the level of random guessing. Such a drastic decline in all metrics demonstrates that the model has failed to generalize from the training data to new samples, confirming the presence of overfitting.These results collectively indicate that classical ML models, such as DT and LR, are prone to overfitting on this task and fail to generalize to unseen news articles.To overcome these limitations, a hybrid CNN–LSTM approach was developed and tested, showing significantly im- proved generalization and robustness on unseen data.

TABLE VI: CNN-LSTM HYBRID MODEL REPORT

Class	Precision	Recall	F1-score	Support
0	0.93	0.93	0.93	3491
1	0.95	0.94	0.94	4239
Accuracy			0.94	7730
Macro avg	0.94	0.94	0.94	7730
Weighted avg	0.94	0.94	0.94	7730

As shown in Table VI, The model attained 93.95% accuracy with precision, recall, and F1-score all at 0.94, and F1-score of 0.94. The class-wise scores indicate that the model performed consistently across both categories, achieving a precision of 0.93 and recall of 0.93 for the fake class (label 0), and 0.95 precision with 0.94 recall for the real class (label 1).

This balance in precision and recall demonstrates the robust- ness of the model, minimizing both false positives (real news classified as fake) and false negatives (fake news classified as real).The macro and weighted averages also confirm consistent performance across the dataset.The combination of CNN and LSTM layers proved effective: CNN captured local linguistic patterns (n-gram features), while LSTM modeled contextual dependencies over longer sequences. Additionally, the use of dropout and L2 regularization helped prevent overfitting, resulting in strong generalization on unseen data.

TABLE VII: PERFORMANCE COMPARISON OF MODELS

Model	Acc (%)	F1-Score	Precision	Recall	Overfit
LR	98.60	0.99	1.00	1.00	✓
DT	99.59	1.00	1.00	1.00	✓
CNN– LSTM	93.95	0.94	0.95	0.94	×

Table VII presents the performance comparison of three implemented models.LR and DT achieve near- perfect accuracy and F1 scores but exhibit overfitting, while the hybrid CNN– LSTM model performs slightly lower in accuracy and F1 score but does not overfit, indicating better generalization

When compared with prior approaches summarized in Table I, the proposed hybrid model delivers competitive results, offering a balanced improvement in both precision and recall. Minor misclassifications were observed in cases where article content from fake and real classes shared similar thematic or political contexts—suggesting the potential value of integrating attention-based architectures or transformer embeddings in future enhancements.

V. CONCLUSION AND FUTURE WORK

The present study focused on the development and implementation of a fake news detection system and the comparative analysis between traditional ML and hybrid DL approaches. Initially, classical ML models such as DT and LR were implemented as baselines. Although they achieved high training accuracy, both models suffered from overfitting and limited generalization due to their reliance on shallow textual features. To address these shortcomings, a hybrid DL–based model combining CNN and LSTM architectures was developed using Python, TensorFlow–Keras, and scikit-learn.

The proposed CNN–LSTM model effectively captured both local and sequential dependencies in text data. CNN layers extracted meaningful linguistic patterns such as n-grams and phrases, while the LSTM layer modeled the contextual and semantic flow of sentences. The inclusion of dropout and L2 regularization minimized overfitting, and early stopping ensured optimal convergence. As a result, the hybrid model achieved a strong overall accuracy of 93.95%, demonstrating improved stability and generalization compared to traditional ML methods.For future work, the system can be enhanced by exploring transformer-based architectures such as BERT, RoBERTa, or DistilBERT which can model complex dependencies through self-attention mechanisms. Expanding the dataset to include multilingual and cross-domain sources, especially from social media, could further improve generalization. Integrating Explainable AI (XAI) methods may also provide greater interpretability, allowing researchers and journalists to understand model decisions. Finally, deploying this framework as a real- time fact-checking application could help curb misinformation on online platforms at scale.

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