

Misinformation Detection and Analysis of Social Media Platforms Using Machine Learning and Deep Learning

Arun Chorge^{1,*}, Prajwal Dahane², Sonu Gupta³

Abstract

Social media platforms have become deeply embedded in everyday life, reshaping how people produce, distribute, and engage with information. Although these platforms facilitate quick communication, they have also developed into important avenues for the spread of false information and fake news. The increasing volume of online content makes manual verification impractical, creating a need for reliable automated detection systems. The effectiveness of deep learning and machine learning models in spotting fraudulent content in online news articles is examined in this study. It compares the performance of a conventional logistic regression model with that of a combined convolutional neural network–long short-term memory (CNN–LSTM) deep learning framework. The models are trained and tested using the Information Security and Object Technology (ISOT) Fake News Dataset for experimentation. Before model development, the textual data is carefully preprocessed through several steps, including cleaning unnecessary content, breaking text into tokens, removing common stop words, and applying lemmatization to normalize word forms. For the baseline model, TF–IDF vectorization is used to represent textual features, while the proposed deep learning model learns contextual and sequential patterns directly from text sequences. Experimental results indicate that both approaches achieve strong classification performance; however, the CNN–LSTM model consistently produces superior results across all evaluation metrics. The suggested model outperforms the logistic regression baseline with an accuracy of 99.30% and an F1-score of 99.29%. The findings demonstrate that combining local feature extraction with long-range contextual learning significantly improves misinformation detection. The proposed approach offers an effective and scalable solution for identifying deceptive content and can support efforts to reduce the spread of misinformation across social media and online news platforms.

Keywords: Misinformation detection, fake news detection, machine learning, deep learning, CNN–LSTM, natural language processing, social media analytics

*Author for Correspondence

Arun Chorge

E-mail: arunchorge2405@gmail.com

^{1,2}Research Scholar, Department of MCA, Thakur Institute of Management Studies, Career Development & Research (TIMSCDR), Mumbai, Maharashtra, India

³Assistant Professor & Deputy Director, Department of MCA, Thakur Institute of Management Studies, Career Development & Research (TIMSCDR), Mumbai, Maharashtra, India

Received Date: March 10, 2026

Accepted Date: July 13, 2026

Published Date: August 15, 2026

Citation: Arun Chorge, Prajwal Dahane, Sonu Gupta. Misinformation Detection and Analysis of Social Media Platforms Using Machine Learning and Deep Learning. International Journal of Algorithms Design and Analysis Review. 2026; 4(2): 22–34p.

INTRODUCTION

Social media platforms have expanded rapidly, reshaping how people produce, exchange, and access information. Platforms such as Facebook, X (formerly Twitter), Instagram, and online news portals allow information to reach millions of users within a short period. While this accessibility has improved communication and information exchange, it has also increased the circulation of misinformation, fake news, and misleading content on social media. The widespread availability of unverified information can influence public opinion, affect decision-making processes, create social unrest, and negatively impact public trust in digital media [1].

Detecting misinformation has become a significant challenge because of the large volume of content generated daily. Manual verification of online information is time-consuming and often impractical, particularly during rapidly evolving events. Consequently, automated misinformation detection systems based on machine learning and artificial intelligence have gained considerable attention in recent years. These systems aim to analyze textual content and identify patterns that differentiate genuine information from deceptive or manipulated content.

Classical machine learning methods like logistic regression, support vector machines (SVM), and random forest classifiers have long been applied to a wide range of text classification problems. Although these methods produce satisfactory results when combined with feature extraction techniques such as TF-IDF, they primarily rely on the lexical and statistical characteristics of the text. Consequently, their ability to capture semantic relationships, contextual meanings, and long-range dependencies remains limited [2].

Recent developments in deep learning have enabled more advanced natural language processing approaches. Models that integrate convolutional neural networks (CNNs) with long short-term memory (LSTM) networks have shown impressive results in text classification tasks. CNN layers are effective in identifying local linguistic patterns, whereas LSTM layers model sequential and contextual relationships across text sequences [3]. The integration of these complementary capabilities makes hybrid CNN-LSTM architectures suitable for detecting misinformation.

This study contributes to the field of misinformation detection through the following objectives:

1. To compare the performance of a traditional TF-IDF-based logistic regression classifier with a deep learning approach.
2. A Hybrid CNN-LSTM model that can effectively learn both fine-grained local patterns and broader contextual relationships in text data is created and implemented.
3. To evaluate model performance using the ISOT Fake News Dataset and standard classification metrics.
4. To analyze the effectiveness of contextual and sequential learning for automated misinformation detection.

BACKGROUND AND THEORETICAL FRAMEWORK

Text Classification for Misinformation Detection

Feature extraction plays a crucial role in misinformation detection because textual information must be transformed into numerical representations before it can be processed by classification models. Traditional approaches frequently employ statistical techniques such as TF-IDF, whereas modern deep learning methods automatically learn semantic representations from text sequences [4]. The accuracy of the classification process largely depends on the quality of these representations.

Baseline Model: Logistic Regression

Logistic Regression remains one of the most widely adopted baseline algorithms because of its computational efficiency, ease of implementation, and interpretability. Despite its advantages, the model relies heavily on feature engineering and may struggle to capture the complex contextual relationships present in misleading narratives.

Proposed CNN-LSTM Hybrid Architecture

A hybrid architecture integrates the advantages of both CNNs and recurrent neural networks, allowing the model to capture spatial patterns as well as sequential dependencies more effectively [5]. While CNN layers focus on extracting informative local patterns from textual sequences, LSTM layers preserve contextual information over longer text spans. This setup allows the model to capture more meaningful patterns in the data, leading to better representation learning and stronger classification results [6]. The overall architecture of the proposed misinformation detection framework is illustrated in Figure 1.

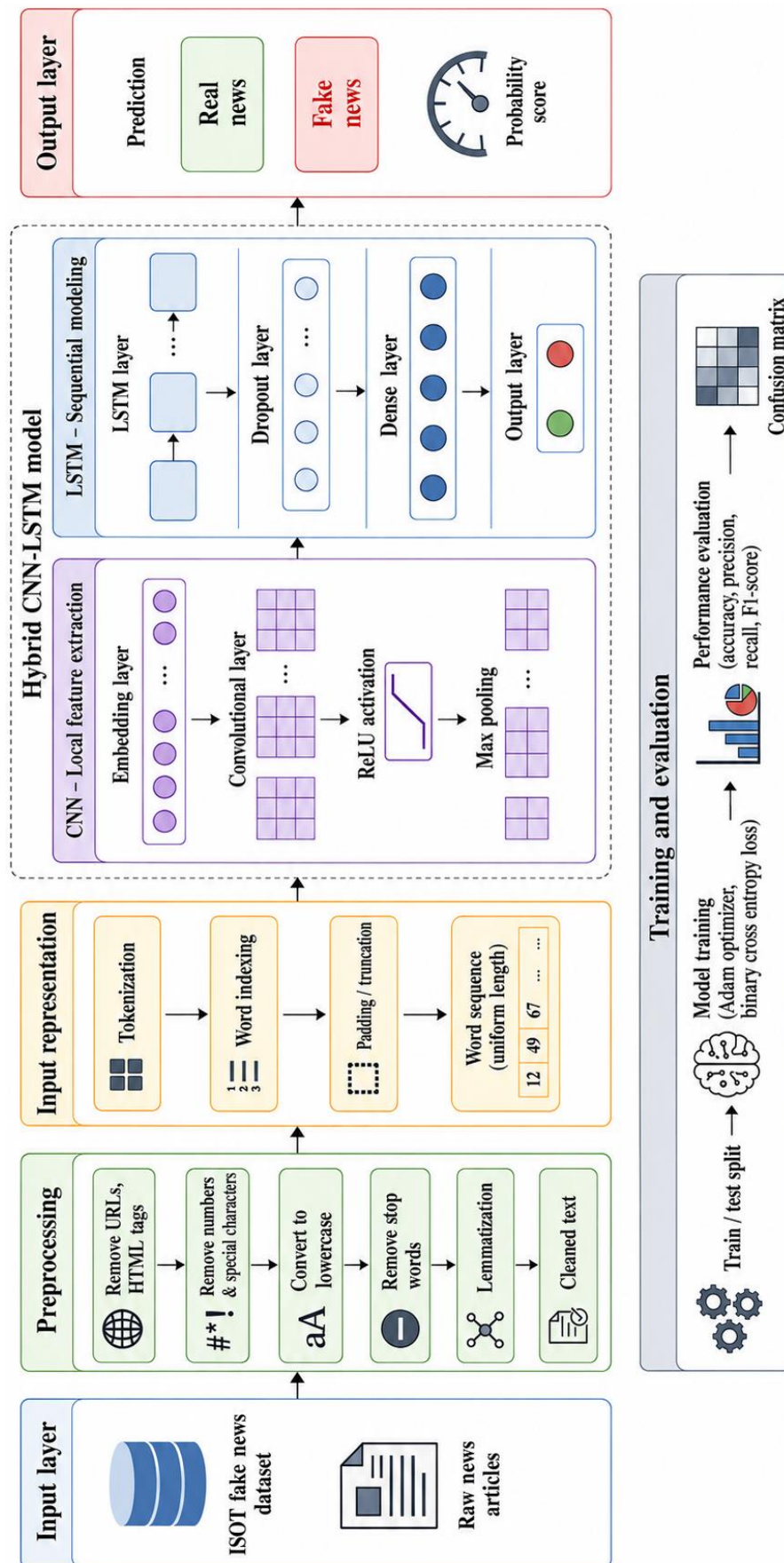


Figure 1. Proposed CNN-LSTM based misinformation detection architecture.

REVIEW OF LITERATURE

Background and Context

The widespread growth of social media has led to a sharp rise in the circulation of unverified content, making manual fact-checking nearly impossible. This has amplified the harmful effects of misinformation in areas such as healthcare, politics, and public confidence [7]. Consequently, the development of automated methods for detecting false or misleading content has emerged as an important area of research.

Existing studies broadly classify misinformation detection techniques based on the type of features they exploit, including content-based textual analysis, social context signals, and external knowledge. Among these, content-based approaches remain the most widely adopted due to their independence from user metadata and network structures, making them suitable for large-scale deployment [8].

The increasing complexity of misinformation has encouraged researchers to explore intelligent detection mechanisms capable of analyzing textual content on a large scale. Recent advancements in natural language processing and deep learning have significantly improved the ability of automated systems to identify deceptive patterns, semantic inconsistencies, and contextual irregularities within online content. Consequently, misinformation detection has emerged as an active research area that combines machine learning, linguistic analysis, and data mining techniques [9].

Review of Related Work

Traditional Machine Learning Techniques

Early research on misinformation detection primarily relied on traditional machine learning classifiers that used manually engineered textual features to distinguish between real and fake news. Because they are easy to interpret and require comparatively less computational power, these models are often used as baseline approaches in studies.

The major traditional machine learning approaches used for misinformation detection are summarized in Table 1.

Prior studies have demonstrated that traditional machine learning models can achieve competitive performance when paired with effective textual features such as TF-IDF. However, these approaches assume independence between words, limiting their ability to capture contextual relationships and the narrative structure. As misinformation increasingly mimics legitimate news writing, this limitation reduces their effectiveness. Table 2 presents the contributions of the deep learning architectures reported in previous studies.

Table 1. Role of different machine learning (ML) models in related work.

Reference	Algorithm	Techniques	Key finding
[1]	Logistic regression, random forest, SVM	TF-IDF (Text-based)	Demonstrated strong baselines, but performance is limited by models' inability to capture semantic context.
[3]	Random forest, Naïve Bayes, passive aggressive	Exploratory data analysis (EDA) on features	It showed that ML classifiers have advantageous discriminative potential, but the focus remained on lexical cues.
[4]	Support vector machine (SVM)	TF-IDF (text-based)	Emphasized that simple algorithms with proper TF-IDF vectorization can still achieve effective prediction rates
[5]	Various ML classifiers	Text-based content analysis	Highlighted the foundational role of ML in early fake news detection systems on social media.

Table 2. Role of different deep learning (DL) models in related work.

Reference	Architecture	Key capability	Role in detection
[2]	LSTM, RNN	Sequence Modeling	Utilized LSTMs to capture long- range dependencies in news tweets, proving DL superior for handling linguistic variations.
[7]	Machine Learning & Deep Learning	Contextual Modeling	Emphasized the necessity of sequential models (like LSTMs) to track the flow of information for misinformation related to pandemic diseases.
[10]	Deep Neural Networks (DNN)	Feature Hierarchy Learning	Applied DNNs to identify hostile disinformation, showcasing the ability of deep models to find subtle patterns.
[9]	Deep Learning with Semantic Knowledge	Semantic Understanding	Argued that enhancing DL models with external semantic knowledge improves detection accuracy.

Table 3. Advantages of different neural network components.

Approach type	Component role	Rationale in context of fake news
CNN layer (1D)	Local feature Extraction	Extracts N-grams/Phrases: Automatically detects short, discriminative local patterns (like clickbait or sensationalist phrases) without requiring manual feature engineering.
LSTM layer	Global context modeling	Captures Sequential Flow: Models the long-term dependencies across Sentences to understand the narrative structure, tone consistency, and semantic coherence of the entire article.

Deep Learning Architectures

To overcome the contextual limitations of traditional classifiers, recent research has explored deep learning architectures capable of learning semantic and sequential representations directly from text data.

Deep learning models, particularly those based on recurrent and convolutional architectures, have demonstrated improved performance by processing texts sequentially and preserving contextual coherence. These models are better suited for identifying subtle linguistic cues and long-range dependencies that are often present in deceptive narratives [10].

Hybrid and Proposed Model Rationale

Recent trends in misinformation detection research have emphasized hybrid architectures that combine multiple neural network components to leverage their complementary strengths.

The functional roles of the different neural network components used for misinformation detection are summarized in Table 3.

Hybrid models that integrate convolutional and recurrent layers have shown consistent improvements in classification accuracy by capturing both local linguistic patterns and global narrative consistencies. This motivated the architectural design adopted in the present study.

Research Gaps and Problems

Limited Context Awareness in Traditional Models

Traditional machine learning approaches primarily rely on frequency-based textual representations, which restrict their ability to model word order and contextual dependencies. Consequently, these models struggle to distinguish sophisticated misinformation that closely resembles authentic news content.

Incomplete Integration of Local and Global Features

Although deep learning models, such as CNNs and LSTMs, are effective individually, many existing studies focus on either local phrase detection or global context modeling. Although several

studies have investigated hybrid approaches, there remains a need for architectures that effectively integrate both local and global textual features for comprehensive misinformation analysis.

Trade-off Between Accuracy and Practical Deployment

Highly complex models often achieve strong performance but require substantial computational resources and lack interpretability. This creates challenges for real-time or large-scale deployment, highlighting the need for efficient, scalable, and interpretable hybrid solutions suitable for practical applications.

Limited Generalization Across Datasets

Many misinformation detection studies have evaluated model performance using a single benchmark dataset. Consequently, the ability of these models to generalize across different domains, topics, and writing styles remains unclear. Developing models that maintain consistent performance across diverse datasets remains an important research challenge.

RESEARCH METHODOLOGY

This study followed a systematic experimental framework to assess how effectively both traditional machine learning methods and deep learning models can identify misinformation. The methodology includes dataset selection, text preprocessing, feature representation, model construction, and performance evaluation.

The overall research workflow followed in this study is presented in Figure 2.

Data Acquisition and Preprocessing

Dataset

The ISOT Fake News Dataset is used in this work as it provides a large collection of labeled news articles categorized as real or fake, making it suitable for supervised learning experiments. Prior to model training, the raw text data were processed to ensure uniformity and reduce noise.

Text Preprocessing

The preprocessing steps included the removal of irrelevant elements, such as URLs, HTML tags, numerical values, and special characters. To ensure uniformity, all the text was first converted to lowercase. Frequently occurring stop words are then removed, and lemmatization is performed to return words to their root form. After preprocessing, the dataset was split into training and testing sets in a way that preserved the balance between classes.

Vectorization and Feature Engineering

To make the data suitable for training, the text was converted into numerical form using different approaches depending on the type of model being used.

1. For the baseline machine learning model, TF-IDF vectorization was applied to capture the relative importance of words and short phrases within the corpus. Unigrams and bigrams were used to retain a small amount of contextual meaning without making the feature set too large or complex.
2. For the deep learning model, text sequences were generated using tokenization, followed by sequence padding to ensure a consistent input length. This representation allows the neural network to process the word order and contextual dependencies more effectively.

Model Implementation and Training

1. Logistic Regression was used as the baseline classifier because it is straightforward to implement and easy to interpret. It operates on TF-IDF feature vectors and serves as a benchmark for assessing the performance improvements achieved by the deep learning approach.
2. The suggested model uses a hybrid CNN-LSTM framework that is built to learn both fine-grained local patterns and broader contextual features from the text. The convolutional layer

identifies informative local patterns, such as short phrases, whereas the LSTM layer models long- term dependencies across sentences.

3. The model was trained using supervised learning. The deep learning model was trained using the Adam optimization algorithm and employed Binary Cross-Entropy as its loss function. A validation split was used during training to monitor the performance and reduce the risk of overfitting.

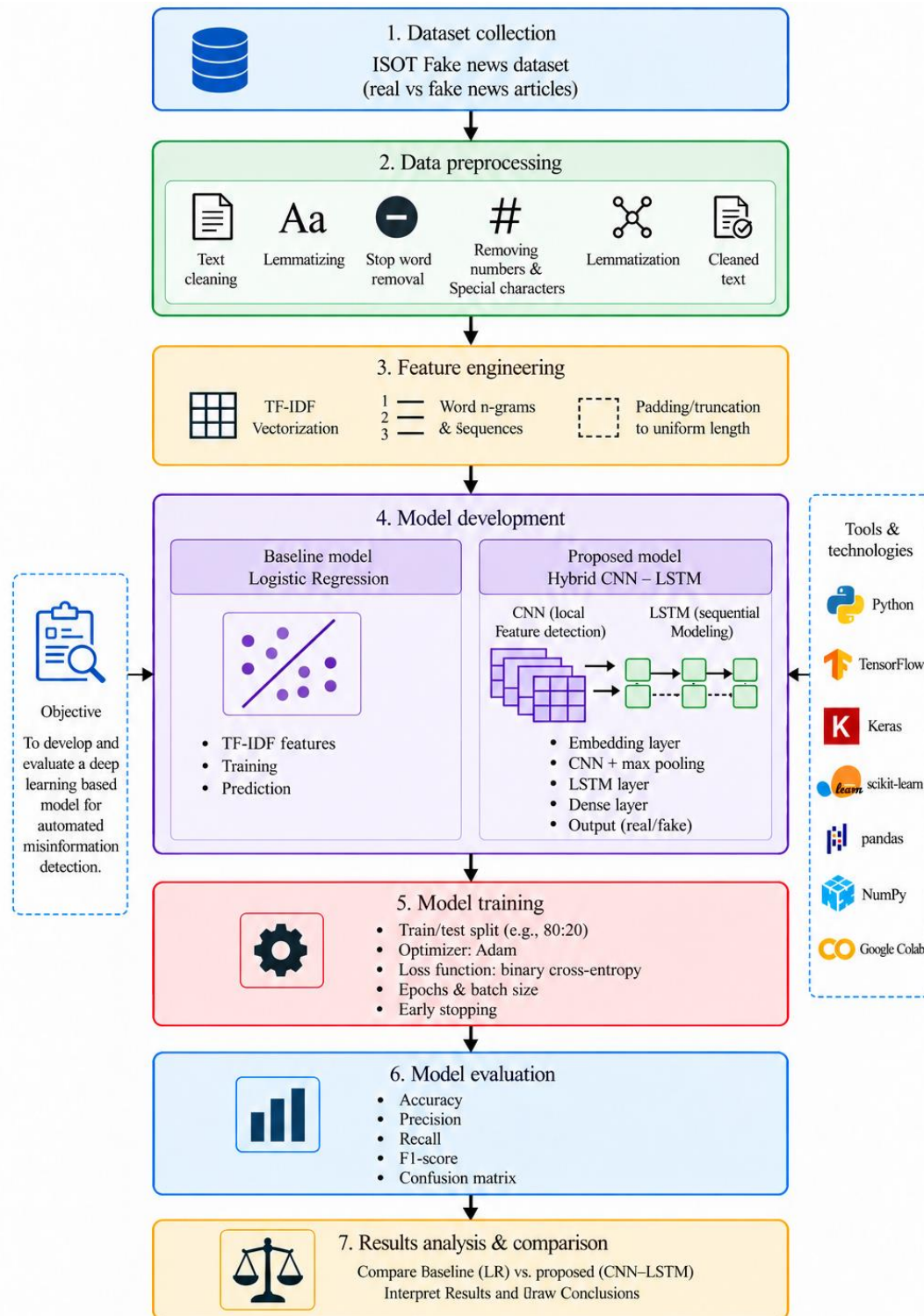


Figure 2. Research methodology workflow.

Evaluation Metrics

The model performance was rigorously evaluated on the held-out test set using metrics suitable for binary classification, as shown in Table 4.

The model's effectiveness was assessed using widely used binary classification metrics. Accuracy measures the overall correctness of predictions, whereas Precision and Recall were used to evaluate how well the model could correctly detect fake news cases. The F1-score offers a balanced evaluation by considering both Precision and Recall, particularly in situations where class imbalance may exist. In addition, a confusion matrix analysis was used to examine the classification errors and gain deeper insight into the model behavior.

EXPERIMENTAL RESULTS AND ANALYSIS

This section reports the experimental outcomes obtained by evaluating a traditional logistic regression baseline and the proposed Hybrid CNN-LSTM model on the ISOT Fake News Dataset. The objective was to assess whether incorporating deep sequential learning leads to measurable performance improvements over lexical-based methods.

Performance of Baseline Model

The logistic regression model demonstrated strong baseline performance on the ISOT dataset, indicating that TF-IDF features effectively captured prominent lexical indicators of misinformation. The results confirm the suitability of the proposed model as a reference for evaluating more complex architectures. The results are shown in Table 5.

The logistic regression classifier demonstrated strong baseline performance, indicating that TF-IDF features effectively captured prominent lexical cues commonly present in fake news articles. The achieved F1-score confirms its suitability as a reference model for comparison with deep learning architectures.

Confusion Matrix Analysis for LR

The confusion matrix analysis indicated that the baseline model produced a low number of misclassifications. Both false positives and false negatives remain limited, suggesting that the model is effective in identifying surface-level misinformation patterns while missing deeper contextual inconsistencies. The confusion matrix for the logistic regression model is shown in Figure 3.

Table 4. Evaluation of metrics used in the study.

Metric	Formula/description	Rationale
Accuracy	Overall proportion of correctly classified news articles.	Measures overall classification performance
Precision	Proportion of correctly identified fake news articles among all articles predicted as fake.	Reduces false positive predictions
Recall	Proportion of actual fake news articles correctly identified by the model.	Reduces false negative predictions
F1-Score	Harmonic mean of Precision and Recall.	Provides a balanced performance measure
Confusion Matrix	Tabular representation of prediction outcomes including true positives, true negatives, false positives, and false negatives.	Supports detailed error analysis and model interpretation

Table 5. Overall correct classification rate.

Metric	Value	Interpretation
Accuracy	95.82	Overall correct classification rate.
Precision	96.15	Of all articles predicted as <i>Fake</i> , 96.15% were actually fake.
Recall	95.34	Of all actual <i>Fake</i> articles, 95.34% were correctly identified.
F1 Score	95.74	Harmonic mean of Precision and Recall, representing a measure of Performance.

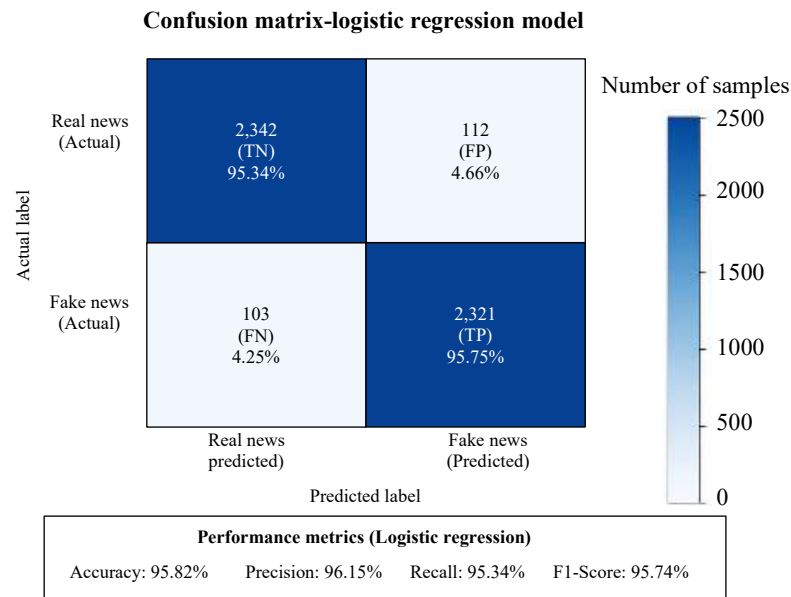


Figure 3. Confusion matrix of the logistic regression model.

Table 6. Performance metrics of the proposed model (hybrid CNN–LSTM).

Metric	Value	Interpretation
Accuracy	99.30	Superior overall correct classification rate.
Precision	99.51	Achieves near- perfect identification of <i>fake</i> news predictions.
Recall	99.08	Nearly all Actual <i>Fake</i> Articles were successfully identified.
F1 Score	99.29	Demonstrates the highest balanced performance across all models.

Performance of Proposed Model

The Hybrid CNN–LSTM architecture, designed to capture both local phrase patterns (CNN) and global context (LSTM), was trained and evaluated.

The results are presented in Table 6

The proposed Hybrid CNN–LSTM model achieved superior performance across all evaluation metrics. The combination of convolutional feature extraction and sequential context modeling enables the system to accurately distinguish between real and fake news, resulting in a notably higher F1-score compared to the baseline.

Learning Curve Analysis

The training and validation curves indicate the stable convergence of the Hybrid CNN–LSTM model. The validation accuracy closely follows the training accuracy, while the validation loss remains controlled, suggesting that the selected training configuration effectively mitigates overfitting and ensures generalization.

The classification performance of the proposed Hybrid CNN–LSTM model is shown in Figure 4.

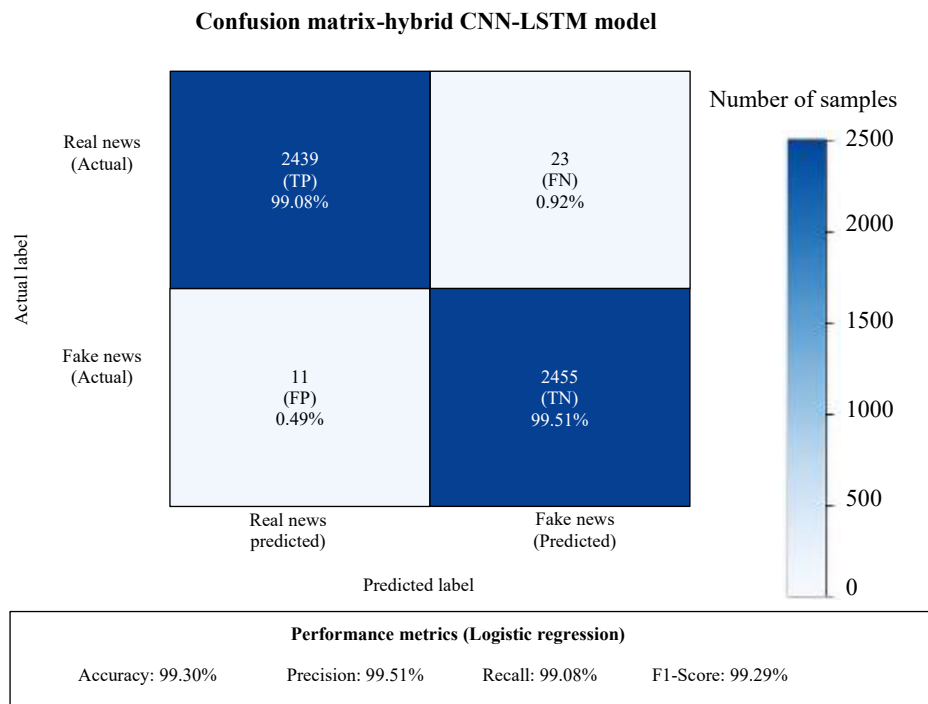
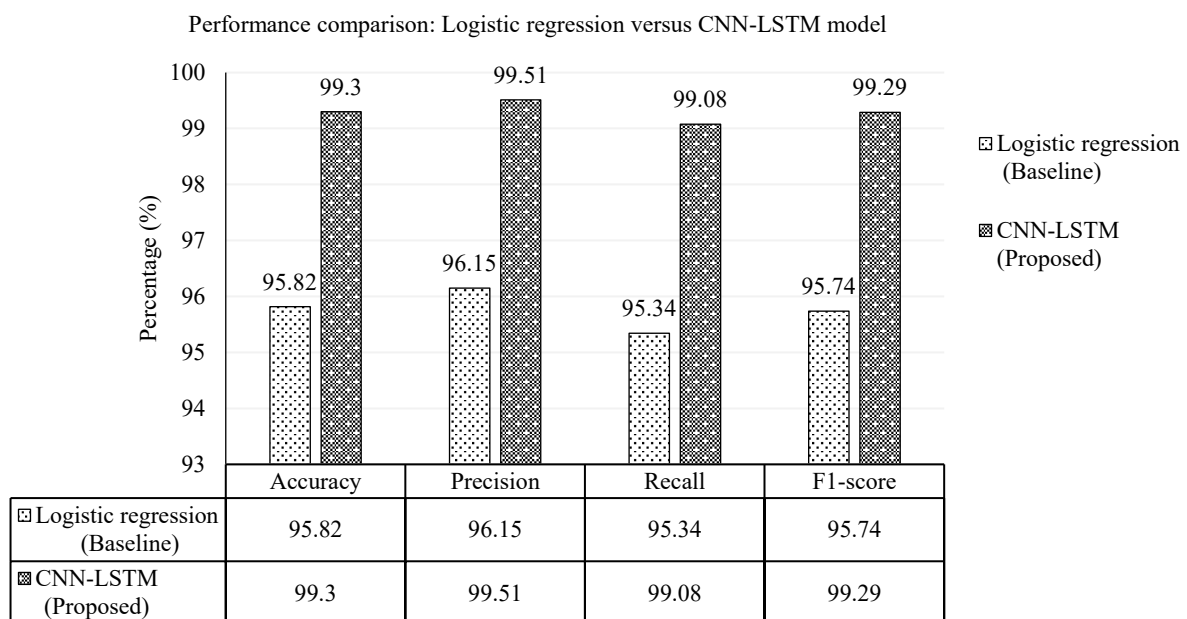
Comparative Analysis and Discussion

Head-to-Head Model Comparison

A direct comparison of the baseline and proposed models highlighted the impact of contextual learning. The observed performance gains demonstrate that integrating deep sequential architectures substantially enhances classification effectiveness beyond traditional lexical methods (Table 7).

Table 7. Comparative performance of baseline versus proposed model.

Metric	Logistic regression	Hybrid CNN–LSTM	Performance gain
Accuracy	95.82	99.30	+3.48
Precision	96.15	99.51	+3.36
Recall	95.34	99.08	+3.74
F1 Score	95.74	99.29	+3.55

**Figure 4.** Confusion matrix of the hybrid CNN–LSTM model.**Figure 5.** Comparison of accuracy, precision, recall, and F1-score.

A graphical comparison of model performance is presented in Figure 5.

Discussion of Performance Gains

The improvement in the F1-score achieved by the Hybrid CNN–LSTM model reflects its ability to capture nuanced linguistic patterns that are overlooked by feature-based classifiers. This performance gain validates the architectural design that combines local phrase detection with a long-range contextual understanding.

The observed improvement in performance highlights the importance of contextual understanding in misinformation detection tasks. While traditional machine learning models rely primarily on lexical indicators, the proposed hybrid architecture effectively captures both local linguistic patterns and long-range semantic relationships. This capability enables a more accurate differentiation between authentic and misleading news content, particularly in cases where deceptive articles closely resemble legitimate reporting styles.

Significance of Metrics:

High Precision achieved by the proposed model is particularly significant for real-world fake news detection, as it minimizes the risk of incorrectly labeling legitimate news as false. This quality is crucial for preserving confidence in automated misinformation detection.

DISCUSSION

This section explains the experimental results by relating them to misinformation detection. The results demonstrate that while traditional machine learning models perform adequately using lexical features, deep learning approaches provide a more comprehensive understanding of textual structure and context. The observed improvements highlight the importance of modeling both local linguistic cues and long-range narrative dependencies in fake news classification.

Interpretation of Key Findings

The experimental evaluation revealed a consistent hierarchy in the model performance, with the Hybrid CNN–LSTM model achieving the highest effectiveness across all metrics. This outcome confirms the study's central assumption that sequential deep learning models are better suited for capturing the contextual and semantic characteristics of misinformation compared to feature-based classifiers.

Validation of Contextual Modeling

The improvement in the F1-score observed for the Hybrid CNN–LSTM model underscores the value of contextual learning in misinformation detection. By integrating convolutional feature extraction with sequential modeling, the proposed architecture successfully moves beyond surface-level lexical analysis and captures deeper narrative inconsistencies present in deceptive content.

Significance of Metrics: The high precision value achieved by the proposed CNN–LSTM model (99.51%) has significant practical implications. In real-world misinformation detection systems, precision is a critical metric because it minimizes the likelihood of incorrectly classifying legitimate news articles as false ones. Excessive false positive predictions may reduce user trust and raise concerns regarding content censorship. Therefore, the strong precision performance of the proposed model supports its suitability for practical misinformation detection applications.

Comparison with Related Work

The findings of this study are consistent with recent advancements in the fake news detection literature. Previous studies have demonstrated the limitations of traditional classifiers that rely solely on TF–IDF features, particularly in handling complex linguistic structures. The strong performance of the Hybrid CNN–LSTM model reinforces the view that combining deep learning architectures can improve detection effectiveness.

Confirming the ML Performance Limit

The baseline logistic regression model achieved performance levels comparable to those reported in prior research using traditional machine learning techniques. This observation reinforces the notion that such models reach a performance ceiling when they are restricted to lexical feature representations.

Validating Hybrid Models.

The improved results obtained using the Hybrid CNN–LSTM architecture align with existing research advocating the fusion of convolutional and recurrent networks. This combination enables the simultaneous extraction of localized patterns and long-term dependencies, resulting in superior classification performance.

Limitations and Future Scope

Although the proposed model demonstrates a strong overall performance, it is important to recognize that it still has certain limitations. The current study relies primarily on content-based textual features and does not incorporate social interaction patterns, user behavior, or network propagation characteristics that may contribute to misinformation spread. Additionally, the experimental evaluation relied on only one benchmark dataset, which could restrict how well the results apply to other domains and languages, thereby limiting their overall generalizability. Future research should focus on integrating social context information, transformer-based language models, multilingual datasets, and real-time misinformation monitoring frameworks. Additional investigations into explainable artificial intelligence techniques may also improve model transparency and user trust.

CONCLUSION

The rapid spread of misinformation through social media and digital news platforms has created significant challenges for individuals, organizations, and policymakers. Therefore, the accurate identification of misleading information is essential for maintaining the reliability of online information ecosystems. This study examined the efficacy of machine learning and deep learning methods in automatically identifying misinformation by applying them to the ISOT Fake News Dataset. A comparative analysis was conducted between a traditional logistic regression classifier based on TF–IDF features and a Hybrid CNN–LSTM architecture designed to capture both local linguistic patterns and long-range contextual relationships within textual content.

The experimental results demonstrate that both approaches are capable of distinguishing between real and fake news articles; however, the proposed Hybrid CNN–LSTM model consistently achieved superior performance. The model achieved an accuracy of 99.30% and an F1-score of 99.29%, demonstrating superior performance compared to the logistic regression baseline across all evaluated metrics. These findings indicate that contextual and sequential learning play a crucial role in identifying complex misinformation patterns that may not be detected through lexical analysis alone.

This study confirms that combining convolutional feature extraction with sequential context modeling provides a reliable framework for misinformation classification. This approach can help reduce the spread of deceptive content and support more trustworthy information sharing on digital platforms. Future work may focus on incorporating social context features, transformer-based language models, multilingual datasets, and real-time detection mechanisms to further improve model robustness and applicability in practical environments.

Acknowledgement

The authors express their sincere gratitude to Prof. Sonu Gupta for her valuable guidance, continuous encouragement, and constructive suggestions during this research. The authors also thank the faculty members and administration of Thakur Institute of Management Studies, Career Development & Research (TIMSCDR) for providing the academic resources and support necessary for the successful completion of this work. We also extend our appreciation to all contributors and participants whose cooperation and feedback assisted in the development of this study.

REFERENCES

1. Ahmad I, Yousaf M, Yousaf S, Ahmad MO. Fake news detection using machine learning ensemble methods. *Complexity*. 2020;2020:1-11. doi:10.1155/2020/8885861.
2. Güler G, Gündüz S. Deep learning based fake news detection on social media. *Int J Inf Secur Sci*. 2023;12:1-21. doi:10.55859/ijiss.1231423.
3. Sharma A, Sharma MK, Dwivedi RK. Exploratory data analysis and deception detection in news articles on social media using machine learning classifiers. *Ain Shams Eng J*. 2023;14:102166. doi:10.1016/j.asej.2023.102166.
4. Sudhakar M, Kaliyamurthi KP. Detection of fake news from social media using support vector machine learning algorithms. *Meas Sens*. 2024;32:101028. doi:10.1016/j.measen.2024.101028.
5. Santhosh Kumar A, Kalpana P, Sharan Athithya K, Sri Ajay Sundar V. Fake news detection on social media using machine learning. *J Phys Conf Ser*. 2021;1916(1):012235. doi:10.1088/1742-6596/1916/1/012235.
6. Alenezi MN, Alqenaei ZM. Machine learning in detecting COVID-19 misinformation on Twitter. *Future Internet*. 2021;13:244. doi:10.3390/fi13100244.
7. Naeem J, Gül ÖM, Parlak IB, Karpouzis K, Kadry SN, Salman YB. Detection of misinformation related to pandemic diseases using machine learning. In: *International Conference on Robotics and Networks*. Cham: Springer Nature Switzerland; 2023. p.147-159.
8. Mishra S, Shukla P, Agarwal R. Analyzing machine learning enabled fake news detection techniques for diversified datasets. *Wirel Commun Mob Comput*. 2022;2022:1575365. doi:10.1155/2022/1575365.
9. Sabeeh V, Zohdy M, Mollah A, Al Bashairah R. Fake news detection on social media using deep learning and semantic knowledge sources. *Int J Comput Sci Inf Secur*. 2020;18:45-68.
10. Cartwright B, Frank R, Weir G, Padda K. Detecting and responding to hostile disinformation activities on social media using machine learning and deep neural networks. *Neural Comput Appl*. 2022;34:15141-15163. doi:10.1007/s00521-022-07296-0.