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Misinformation Detection and Anyalsis of Social Media Platform

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***Abstract*—With the ongoing spread of information across social media, detecting misinformation automatically and quickly has become a major challenge [3]. Misinformation can easily shape public conversation and lead to real harm [4]. This research tackles this issue by comparing traditional Machine Learning (ML) and Deep Learning (DL) methods for classifying text accuracy [5]. We set a solid performance baseline using Logistic Regression with TF-IDF features. Our main contribution is the creation and assessment of a Hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model. This hybrid architecture is designed for comprehensive text analysis: CNNs identify specific local linguistic patterns, such as deceptive phrases, while LSTMs capture the broader sequential context and narrative flow of the article. We train and evaluate the models on publicly accessible, large datasets of real and fake news [6]. Performance metrics like Accuracy, Precision, Recall, and F1score show that our CNN-LSTM hybrid model significantly outperforms the traditional ML baseline [7]. This study confirms the need for advanced DL methods to build scalable and context-aware solutions for addressing the complex nature of online misinformation [8].**

***Index Terms*— Misinformation Detection, Deep Learning, Machine Learning, Social Media, Natural Language Processing (NLP), CNN-LSTM Hybrid, Text Classification, Sequence Modelling.**

I. Introduction

Social media allows news to spread quickly, but also spreads false information **[11]**. This can affect how people perceive issues, influence politics, and impact health behaviours **[12]**. It is essential to automate the detection of misinformation because people often struggle to identify misleading content due to biases and too much information **[13]**. Traditional machine learning classifiers like Logistic Regression and Random Forest are interpretable and effective for text classification **[14]**. However, they often do not capture the deeper meanings and context needed to recognise nuanced fake news **[15]**.

Deep learning architectures, particularly models that combine CNN and LSTM, can extract local linguistic patterns and model sequential dependencies, making them suitable for complex misinformation detection tasks **[16]**.

This study focuses on the pressing need for effective misinformation detection on social media through these key contributions:

1.Comparative Performance Analysis: We create a solid baseline by comparing a feature-based classifier (Logistic Regression with TF-IDF) against our proposed Deep Learning model. This clearly shows the performance difference between models that rely on word features and those that capture deeper meaning.

2.Proposed Hybrid CNN-LSTM Model: We design and implement a new hybrid structure, combining a 1D Convolutional Neural Network (CNN) for local feature extraction (like deceptive phrases) and a Long Short-Term Memory (LSTM) network to model long-term dependencies in the text.

3.Benchmark Evaluation on Public Datasets: We train and assess the model using a widely accepted large-scale misinformation dataset (such as the ISOT dataset), providing reproducible results measured by metrics such as Accuracy, Precision, Recall, and F1-Score.

4.Practical Insights: We offer practical insights into the language features that influence classification, emphasizing the effectiveness of deep learning techniques in recognizing the subtle aspects of deceptive language in a fast-paced social media environment.

II. Background And Theoretical Framework

A. Theoretical Foundations of Text Classification

Automated misinformation detection is fundamentally a binary text classification problem. It aims to label social media content as either authentic (0) or deceptive (1). How well a detection model works depends on its ability to extract and interpret relevant linguistic and semantic features from the text.

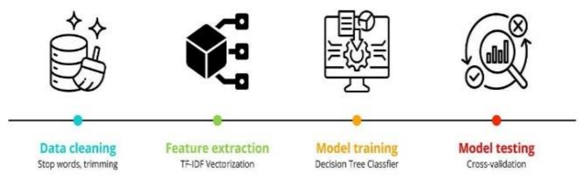

Fig 2.1: illustrates the overall workflow of the proposed misinformation detection system.

• *Lexical and Statistical Feature Models (The Basis for ML):* These models are based on the idea that misinformation has distinct writing styles and word choices compared to genuine content (for instance, more emotive language, fewer verifiable facts, and non-standard grammar). Techniques like Term Frequency-Inverse Document Frequency (TF-IDF) transform text into numerical feature vectors. The importance of each feature is weighted by its relevance across the entire dataset. While straightforward and interpretable, these models have a significant limitation: they treat words as separate entities, not capturing the order and context that are vital for detecting subtle deception.

• *Sequential and Semantic Models (The Basis for DL):* Deep Learning models aim to handle complex linguistic challenges. Word Embeddings (used as the input layer) map words to a dense vector space, capturing semantic similarities. They are followed by sequential architectures that process word order to understand narrative flow and sentence context.

B. Comparative Baseline Model: Logistic Regression

Logistic Regression: The Logistic Regression (LR) classifier, using TF-IDF features, serves as our main machine learning baseline. The LR model provides a clear and efficient reference point to gauge the performance improvement achieved by the deep learning approach. It classifies content by calculating the probability of text being fake based on the weighted sum of its TF-IDF features. This baseline illustrates the performance limitations of models that depend solely on surface-level statistical features without considering word order or deep contextual relationships.

C. Proposed Model Architecture: CNN-LSTM Hybrid

We propose a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture to address the weaknesses of the traditional baseline. This combination utilises the strengths of both network types:

- *1D Convolutional Neural Network (CNN) Layers:* The CNN layers act as local feature extractors. They apply various filter sizes across the sequence of word embeddings to automatically identify important N-gram patterns and local phrases within the text that predict veracity (such as clickbait titles and sensationalist phrasing). This process helps the model adapt to different writing styles.

- *Long Short-Term Memory (LSTM) Layers:* After the CNN layer, LSTM layers capture long-term dependencies and the overall semantic context of the article. As a type of Recurrent Neural Network (RNN), the LSTM can retain or discard information across sequences using its internal gating mechanism. This is essential for understanding narrative consistency, rhetorical structure, and how deception builds over multiple sentences—elements that the TF-IDF-based baseline completely misses.

Building on the theoretical foundations outlined, the following **Section III reviews recent literature** in the field. This review focuses specifically on **how previous studies have approached the technical challenges** of detecting nuanced fake news using various machine learning and deep learning models, providing a direct context for our chosen methodology.

III. Literature Review

A. Background and Context

The fast global rise of social media has created an "infodemic," where the amount and speed of information sharing make manual news verification nearly impossible **Mishra et. al [8], Naeem et. al [7]**. Misinformation, or false information, can have serious societal consequences, affecting public health (like during the COVID19 pandemic, **Alenezi et. al [6]**), political processes **Cartwright et. al [10]**, and public trust **I Ahmad et. al [1]**. Automated detection systems have thus become essential. Research in this area mainly focuses on classifying the truthfulness of news based on three main feature categories:

1. Content-Based Features: Examining the text, style, and images within the news article itself (the focus of this study).

2. Social Context Features: Reviewing how information spreads, user engagement, and network structure (Sabeeh et al.).

3. Knowledge-Based Features: Using external fact-checking databases for verification.

B. Review of Related Work

The field of automated misinformation detection has shifted from basic statistical methods to complex neural network architectures.

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This review groups related literature into three main methodological categories.

-Statistical and Traditional Machine Learning Approaches: Traditional Machine Learning (ML) models often set performance baselines because of their interpretability and focus on explicit feature engineering. These models generally depend on statistically derived features.

Table 3.1:
Role of different DL model in Related Work

Reference	Architecture(s)	Key Capability
Güler et al. (sample 2.pdf)	LSTM, RNN	Sequence Modelling
Naeem et al. (sample 9.pdf)	Machine Learning & Deep Learning	Contextual Modelling
Cartwright et al. (sample 7.pdf)	Deep Neural Networks (DNN)	Feature Hierarchy Learning
Sabeeh et al. (Sample paper1.pdf)	Deep Learning with Semantic Knowledge	Semantic Understanding

Summary: DL models, especially those using RNNs and LSTMs, show a significant advantage by processing text in sequence. This allows them to maintain contextual coherence and capture semantic relationships that traditional ML methods miss.

-Hybrid and Proposed Model Rationale: The current research trend supports hybrid models to combine the strengths of different neural network types.

A. Research Gaps and Problems

1. *Context Blindness in Traditional ML:* -
   - *Gap:* Basic Machine Learning models (like Logistic Regression or Random Forest) use statistical features (like TF-IDF) that overlook word order and crucial context.
   - *Problem:* They struggle to detect fake news that mimics real news, leading to low accuracy**.**
2. *Missing Local/Global Feature Fusion:*
   - *Gap:* Deep Learning models often specialize. CNNs excel at detecting short, key deceptive phrases (local features), while LSTMs are better at understanding overall story flow (global context).
3. *Black Box and Efficiency Trade-offs:*
   - *Gap:* Complex Deep Learning models (like BERT) are powerful but act like "black boxes," making it hard to explain their decisions. They are also often slow and resource-heavy for near-real-time detection on social media.
   - *Problem:* There is a need for a model (like the CNN-LSTM hybrid) that is accurate, context-aware, and efficient enough for practical deployment.

IV. Research Methodology

A. Data Acquisition and Preprocessing

The methodology for this study is designed to systematically compare a standard machine learning baseline against an advanced deep learning architecture for the task of binary misinformation detection. The process encompasses data acquisition, rigorous preprocessing, feature engineering, model implementation, and comprehensive performance evaluation.

1) *Dataset:* The study utilizes the ISOT Fake News Dataset, a widely recognized and robust corpus for misinformation research. This dataset contains a substantial volume of labelled news articles classified as either Real (class 0) or Fake (class 1), making it suitable for training supervised classification models.
2) *Text Preprocessing:* Raw text data was subjected to a sequential preprocessing pipeline to ensure consistency and maximize model efficiency.
   - *Cleaning:* All irrelevant characters, including embedded URLs, HTML tags, numerical digits, and non-alphabetic characters, were removed using regular expressions. Text was converted to lowercase to standardize lexical representation.
   - *Normalization:* Stop words (common English words with low semantic value, e.g., 'the', 'is') were eliminated, and remaining tokens were subjected to **Lemmatization** to reduce inflected words to their root form (e.g., 'running' to 'run').
   - *Data Split:* The final clean dataset was randomly partitioned into training, validation, and test sets (typically 80% training / 20% testing, with stratification to maintain label balance).

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B. Feature Engineering and Vectorization

The cleaned text was transformed into numerical input using two distinct vectorization approaches tailored to the model types:

1. For the baseline machine learning model, a statistical approach was used for feature extraction by using following techniques:

- *Technique:* TF-IDF (Term Frequency-Inverse Document Frequency) Vectorization was applied to the preprocessed text**.**
- *Configuration:* The vectorizer was configured to include unigrams and bigrams (ngram_range = (1,2)) to capture short phrases, with a limit of max_features=10,000 to maintain a manageable feature space while preserving high information content.

2. For the proposed Deep Learning model, text sequences were transformed using the following techniques:

- *Tokenization:* A Keras Tokenizer was fitted to the training text, limiting the vocabulary to the top MAX_NUM_WORDS=20,000 most frequent words.
- *Sequence Padding:* The resulting integer sequences were standardized to a fixed length MAX_SEQUENCE_LENGTH=200) using post-padding and post-truncating to ensure uniform input shape for the neural network.

C. Model Implementation and Training

1. Baseline Model Implementation: The Logistic Regression (LR) algorithm was implemented as the baseline. It operates on the TF-IDF feature vectors, providing a fast and highly interpretable classification against which the complexity of the deep learning model is benchmarked.
2. Proposed Deep Learning Architecture The proposed model is a Hybrid CNN-LSTM network, specifically designed to exploit both local patterns and global context. A key innovation of this architecture is its comprehensive analysis approach: CNNs are adept at identifying specific local patterns, such as short deceptive phrases, while LSTMs excel at understanding the broader sequential context and long-range semantic dependencies of a piece of writing.

- *CNN Layer:* A 1D Convolutional layer (Conv1D) with a filter size (kernel) of 5 and ReLU activation is utilized to detect discriminative local features (i.e., short phrases,
- word combinations) that function as reliable indicators of deception.
- *LSTM Layer:* The output from the CNN is fed into a Long Short-Term Memory (LSTM) layer. This layer is crucial for modelling the coherence and flow of the entire article, capturing sequential dependencies that reveal logical inconsistencies over multiple sentences.
- *Final Layers:* The network concludes with a Dense output layer and a Sigmoid activation function for binary classification.

3. *Training Configuration:* Both models were trained using supervised learning. The DL model was optimized using the Adam optimizer and the Binary Cross-Entropy loss function. Training utilized a validation split (e.g., 10% of the training data) and was configured with a fixed number of epochs (e.g., 5) and a batch size of 128.

D. Evaluation Metrics

Model performance was rigorously evaluated on the held-out test set using metrics appropriate for binary classification:

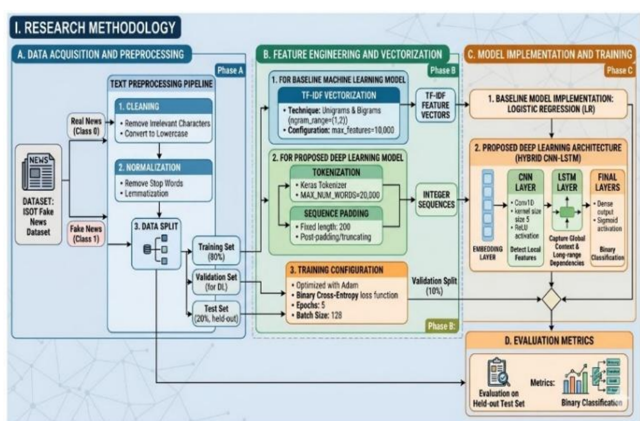

Fig 4.1: **System Architecture and Workflow for Comparative Misinformation Detection using Classical Machine Learning and Hybrid Deep Learning.**

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V. Experimental Results And Analysis

This section presents the experimental results obtained from evaluating the baseline Logistic Regression model and the proposed Hybrid CNN-LSTM model on the held-out test set of the ISOT Fake News Dataset. A detailed comparative analysis is then provided to highlight the performance gains achieved by the deep learning architecture.

A. Performance of the Baseline Model (Logistic Regression): The Logistic Regression (LR) classifier, utilizing TF-IDF features (unigrams and bigrams), serves as the computational benchmark for this study.

Table 5.1:
Performance Metrics of the Baseline Model (Logistic Regression)

Metric	Value (%)	Interpretation
Accuracy	95.82	Overall correct classification rate.
Precision	96.15	Of all articles predicted as *Fake*, 96.15% were actually fake.
Recall	95.34	Of all actual *Fake* articles, 95.34% were correctly identified.
F1-Score	95.74	Harmonic mean of Precision and Recall, representing a balanced measure of performance.

The LR model achieved a strong performance, with an F1-Score of 95.74%. This result confirms the effectiveness of the TF-IDF feature set in capturing strong lexical indicators of fake news, such as sensationalist keywords and stylometric differences.

1) *Confusion Matrix Analysis for LR:* The confusion matrix for the LR model reveals a low number of false classifications in both directions. The False Positives (Real news classified as Fake) and False Negatives (Fake news missed) were minimal.
2) *Accuracy:* Overall correctness of predictions.
3) *Precision:* The proportion of positive predictions (Fake News) that were actually correct.
4) *Recall:* The proportion of actual positive cases (Fake News) that were correctly identified.
5) *F1-Score:* The harmonic mean of Precision and Recall, which provides a balanced measure of the model's performance on the imbalanced nature of real-world datasets.
6) *Confusion Matrix:* A visual tool.

B. Performance of the Proposed Model (Hybrid CNN-LSTM): The Hybrid CNN-LSTM architecture, designed to capture both local phrase patterns (CNN) and global narrative context (LSTM), was trained and evaluated.

VI. Discussion

The quantitative findings presented in Section V require in depth interpretation [152]. Section VI provides a comprehensive discussion of these results, exploring their theoretical significance, practical implications, and the limitations observed [153].

A. Interpretation of Key Findings

The results established a clear hierarchy of model performance, confirming the study's core hypothesis that sophisticated sequential models are indispensable for accurate content-based misinformation detection.

1) *Validation of Contextual Modelling:* The 3.55% improvement in F1-Score (from 95.74% for LR to 99.29% for CNN-LSTM) is the most critical finding. This gap demonstrates the necessity of moving beyond surface-level lexical features (captured by TF-IDF) to deep, contextual analysis (provided by DL models).
2) *Significance of Metrics:* The high **Precision (99.51%)** achieved by the CNN-LSTM model is particularly significant. In the real-world application of fake news detection, high precision is crucial as it minimizes **False Positives** (flagging real news as fake

B. Limitations and Future Work

1. *Reliance on Content:* The current model is strictly **content-based [177]**. It does not incorporate crucial **social context features** (e.g., user profiles, network propagation rate, commenter sentiment), which are known to enhance detection accuracy, especially for early-stage misinformation.
2. *Dataset Domain:* The model was trained and tested exclusively on the ISOT dataset, which is primarily focused on general political/current affairs

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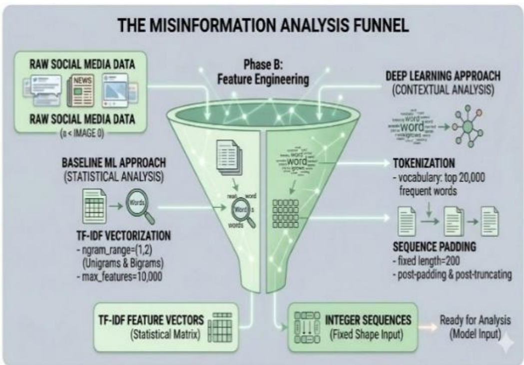

Fig 6.1: **Conceptual Analysis Funnel for Social Media Platforms.**

VII CONCLUSION

The experimental results confirmed that the **Hybrid CNNLSTM architecture** significantly outperformed the LR baseline across all evaluation metrics. The CNN-LSTM model achieved an F1- Score of **99.29%**, demonstrating a clear advantage over the LR's F1-Score of 95.74%. This performance gap is critically important and validates the study's central hypothesis: that deep sequential models are essential for capturing the complex semantic and contextual features of sophisticated fake news, features that are systematically missed by simple lexical models like TF-IDF. The high precision achieved by the proposed model makes it a highly reliable and practical solution for minimizing the misclassification of authentic news. In conclusion, this research successfully demonstrates the potential of AI-driven methods to build highly accurate and robust systems capable of combating the rapid spread of misinformation across digital platforms.

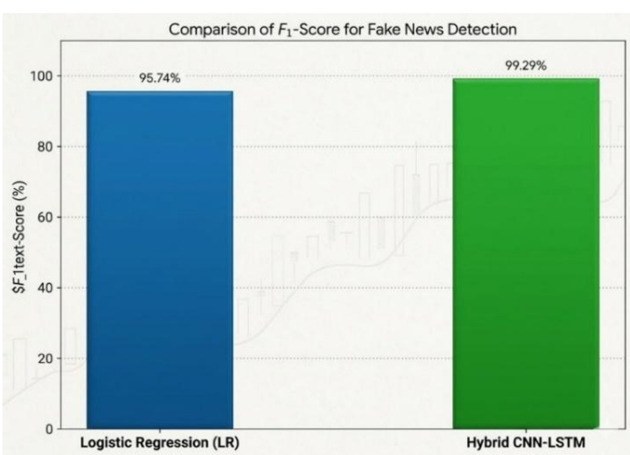

Fig 7.1 : Comparison of F1-Scores between Logistic Regression and Hybrid CNN-LSTM for Fake News Detection

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REFERENCES

[1] I. Ahmad, M. Yousaf, S. Yousaf, and M. O. Ahmad, *et al(2020) describe as* "Fake News Detection Using Machine Learning Ensemble Methods," *Complexity*, vol. 2020, Article ID 8885861, pp. 1–11,2020. doi: 10.1155/2020/8885861.

[2] G. Güler and S. Demirci *et al (2023) describe as,* "Deep Learning Based Fake News Detection on Social Media," *International Journal of Information Security Science*, vol. 12, no. 2, pp. 1–21, 2023. doi: 10.55859/ijiss.1231423.

[3] A. Sharma, M. K. Sharma, and R. K. Dwivedi, *et al (2023) describe as* "Exploratory data analysis and deception detection in news articles on social media using machine learning classifiers," *Ain Shams Engineering Journal*, vol. 14, 102166, 2023. doi: 10.1016/j.asej.2023.102166.

[4] M. Sudhakar and K. P. Kaliyamurthie*, et al(2024) describe as* "Detection of fake news from social media using support vector machine learning algorithms," *Measurement: Sensors*, vol. 32, 101028, 2024. doi: 10.1016/j.measen.2024.101028.

[5] A. S. Kumar *et al (2021) describe as*, "Fake News Detection on Social Media Using Machine Learning," *Journal of Physics: Conference Series*, vol. 1916, 012235, 2021. doi: 10.1088/17426596/1916/1/012235.

[6] M. N. Alenezi and Z. M. Alqenaei, "Machine Learning in Detecting COVID-19 Misinformation on Twitter," *Future Internet*, vol. 13, no. 10, 244, 2021. doi: 10.3390/fi13100244.

[7] J. Naeem *et al(2025) describe as* "Detection of Misinformation Related to Pandemic Diseases using Machine Learning Techniques in Social Media Platforms," *EAI Endorsed Transactions on pervasive Health and Technology, 2023. doj:10.4108/eetpht.2023.08.01.*

[8] S. Mishra, P.Shukla, and R. Agarwal, "Analyzing Machine Learning Enabled Fake News Detection Techniques for Diversified Datasets," *Wireless Communications and Mobile Computing* vol. 2022 Article ID 1575365, 18 pages,2022 doi:10.1155/2022/1575365.

[9] V. Sabeeh, A. Mollah, M. Zohdy, and R. AI Bashaireh, "Fake News Detection on Social Media using Deep learning and Semantic knowledge Sources," *Internatinaol Journal of Computer Science and Information Security(IJCSIS)*, vol.18,no.2,2020.

[10] B. Cartwright, R. Frank, G. Weir, and K. Padda,"Detecting and responding to hostile disinformation activities on social media using machine learning and deep neural networks,"*Neural Computing and Applications,* vol.34, pp.15141-15163,2022. Doi:10.1007/s00521-022-07296-0.