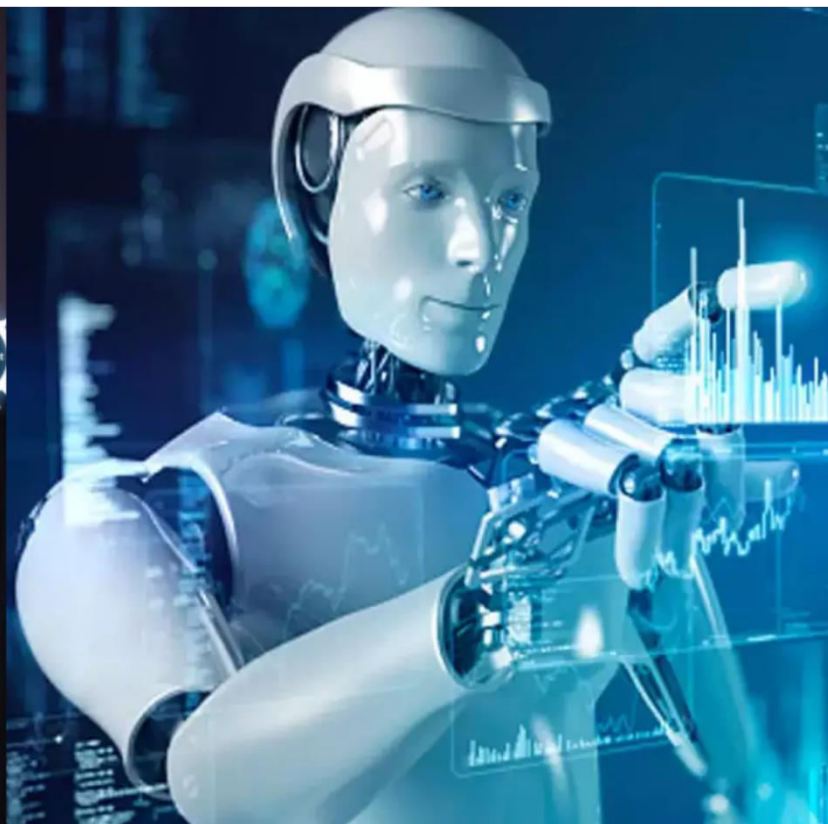




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A Lexicon-Enhanced LSTM Framework for Sentiment-Aware Fake News Detection

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ABSTRACT: Fake news poses a significant threat to public trust, journalistic integrity, and democratic stability, magnified by the rapid dissemination power of social media. Traditional machine learning techniques—such as Support Vector Machines, Decision Trees, and Logistic Regression—often rely on handcrafted features that fail to capture the nuanced semantics and emotional cues critical for identifying deceptive content. To overcome these limitations, this study proposes a **Lexicon-Enhanced Long Short-Term Memory (LE-LSTM)** framework that seamlessly integrates advanced Natural Language Processing with sentiment analysis. By combining pre-trained word embeddings with sentiment lexicons, the model captures both the contextual meaning and emotional undertones of text, enabling the detection of subtle manipulations like bias, sarcasm, and exaggeration. Experimental evaluation on a real-world Kaggle dataset demonstrates that the LE-LSTM surpasses traditional ML and baseline deep learning models, achieving an **accuracy of 94.6%, precision of 93.8%, recall of 95.2%, and an F1-score of 94.5%**—improving performance by 8–15% across key metrics. This research delivers a robust, scalable, and sentiment-aware solution for enhancing fake news detection in today's complex digital landscape.

KEYWORDS: Fake News Detection, Lexicon-Enhanced LSTM, Sentiment Analysis, Natural Language Processing .

I. INTRODUCTION

Fake news—deliberately fabricated or misleading information presented under the guise of legitimate reporting—has become increasingly pervasive on social media platforms such as Twitter and Facebook. Its rapid spread can profoundly shape public opinion and erode trust in credible journalism. Given the sheer volume and velocity of online content, manual fact-checking is neither scalable nor timely, highlighting the urgent need for automated, intelligent detection systems.

Traditional machine learning (ML) approaches, including Support Vector Machines (SVM), Decision Trees, and Logistic Regression, predominantly rely on manually engineered features. While effective for straightforward text classification tasks, these models often fail to capture deeper semantic relationships and nuanced linguistic cues such as sarcasm, emotional manipulation, or implicit bias—tactics frequently exploited in fake news narratives.

Recent progress in deep learning (DL), particularly through Long Short-Term Memory (LSTM) networks, offers a more sophisticated means of automatically learning complex sequential dependencies within text, reducing dependence on handcrafted features. However, many of these models still overlook the emotional context embedded in language, a critical dimension for detecting deceptive or manipulative content. To address this limitation, this study proposes a Lexicon-Enhanced Long Short-Term Memory (LE-LSTM) framework that directly integrates sentiment lexicons into the learning process. By combining semantic word embeddings with explicit sentiment signals, the proposed model effectively captures both the contextual meaning and the emotional undertones of textual data. Experimental evaluation on a **Kaggle dataset** comprising 3,988 news articles demonstrates that the LE-LSTM achieves an impressive accuracy of 94.6%, along with substantial improvements in precision, recall, and F1-score compared to classical ML and baseline DL models.

This work thus introduces a robust, scalable, and sentiment-aware approach to fake news detection, offering a practical and effective solution to mitigate the spread of misinformation in today's dynamic and complex digital environment.

II. LITERATURE REVIEW

1. Lexicon-Enhanced LSTM for Fake News Classification

Author: X. Zhang, H. Wang, and Y. Liu (2020)

Overview: This study proposed integrating sentiment lexicons directly into an LSTM architecture to better capture emotional and contextual nuances, aiming to improve fake news classification.

Methodology: They combined pre-trained word embeddings with sentiment scores derived from lexicons to form enriched input vectors fed into an LSTM network.

Dataset: Real-world news articles labeled as fake or genuine.

Findings: This lexicon-enhanced approach outperformed standard LSTM models, achieving superior accuracy and demonstrating the critical role of sentiment features in fake news detection.

2. Sentiment-Enhanced LSTM Networks for Fake News Detection

Author: A. Hassan, M. Khan, and S. Ali (2020)

Overview: This research developed a sentiment-augmented LSTM framework, incorporating explicit emotional signals to improve fake news detection performance.

Methodology: Sentiment scores from VADER were combined with word embeddings, then processed by an LSTM to classify news as fake or real.

Dataset: A benchmark dataset of annotated news articles.

Findings: The model achieved an accuracy of 93.5%, highlighting that leveraging sentiment alongside semantic context significantly enhances detection capabilities.

3. Fake News Detection using Deep Recurrent Neural Networks

Author: Tao Jiang (2020)

Overview: Jiang employed a Bidirectional LSTM (BiLSTM) to exploit sequential dependencies and deeper linguistic patterns within text for fake news classification.

Methodology: The BiLSTM processed word embeddings to classify articles without explicit sentiment input, serving as a strong baseline.

Dataset: The ISOT dataset contains labeled fake and real news.

Findings: The model achieved an accuracy of 99.82%, illustrating the power of deep sequential models, though without direct sentiment integration.

4. Context-Aware Deep Markov Random Fields for Fake News Detection

Author: Tien Huu Do et al. (2021)

Overview: This work extended fake news detection beyond textual content by modeling relationships among tweets, users, and events using a Deep Markov Random Field (DMRF).

Methodology: The model integrated deep learning with probabilistic graphical structures to capture both content and propagation patterns.

Dataset: A large Twitter dataset comprising 992 events and over 500,000 tweets.

Findings: It significantly outperformed prior methods by leveraging social context, underlining the value of multi-dimensional feature integration.

“While prior studies have explored classical ML and deep sequential models for fake news detection, none have explicitly integrated sentiment lexicon embeddings into an LSTM framework. This motivates our proposed LE-LSTM approach.”

III. EXISTING METHODS

Over the past decade, researchers have extensively explored supervised machine learning (ML) algorithms for fake news detection. Traditional models such as Support Vector Machines (SVM), Naive Bayes (NB), Random Forests (RF), Decision Trees (DT), Gradient Boosting Machines (GBM), Logistic Regression (LR), and ensemble techniques like Voting Classifiers have been widely adopted for this purpose. These approaches typically rely on feature extraction

methods—including Bag-of-Words, Term Frequency–Inverse Document Frequency (TF-IDF), and n-gram statistics—to convert textual data into numerical representations.

SVMs and Logistic Regression are favored for their robustness in binary classification and ease of implementation. Decision Trees and Random Forests provide interpretability and resilience to noisy data, making them suitable for heterogeneous datasets. Gradient Boosting methods have gained traction due to their high predictive accuracy, especially on structured data. Naive Bayes classifiers, grounded in probabilistic theory, are prized for their computational efficiency and scalability when handling large volumes of text. Additionally, ensemble methods like Voting Classifiers amalgamate the strengths of multiple models, often leading to improved overall performance.

Despite their popularity, these conventional ML approaches face significant limitations when applied to fake news detection. They depend heavily on manually engineered features, which frequently fail to capture deeper semantic relationships, contextual subtleties, and the emotional undertones embedded in language—elements essential for identifying deceptive narratives. Such models also struggle with complex linguistic phenomena like sarcasm, exaggeration, or implicit bias, which are commonly exploited in fake news. Moreover, traditional ML models generally overlook sequential dependencies and the importance of word order, constraining their ability to comprehend the holistic meaning conveyed by sentences or documents. Consequently, while these methods provide a foundational baseline for fake news classification, their reliance on surface-level textual features limits their effectiveness against the sophisticated, context-rich misinformation prevalent across modern social media platforms.

Disadvantages of Existing Systems

- Rely on handcrafted features that fail to capture deep contextual or semantic meaning.
- Struggle to recognize linguistic complexities such as sarcasm, satire, or emotional manipulation.
- Ignore word sequences and relationships, overlooking the importance of word order in text.
- Require manual data labeling and feature engineering, which is time-consuming and not easily generalizable.
- Often show limited scalability for real-time, large-scale detection tasks.
- Exhibit slower response times and cannot promptly flag rapidly spreading misinformation.

IV. PROPOSED SYSTEM

This study introduces a Lexicon-Enhanced Long Short-Term Memory (LE-LSTM) framework designed to advance fake news detection by simultaneously capturing the semantic meaning and emotional nuances embedded in textual content. Unlike traditional models that rely solely on content-based features, the proposed approach integrates sentiment information directly into the learning pipeline, enhancing the system's ability to detect subtle linguistic manipulations commonly found in deceptive narratives.

The architecture operates in two key stages. Initially, sentiment lexicons such as SentiWordNet and VADER are utilized to pre-train a sentiment classifier, generating sentiment embeddings that encode the emotional polarity of words—including generalizations for words not explicitly listed in the lexicons. Concurrently, pre-trained word embeddings like GloVe or Word2Vec capture the semantic context of the text. These embeddings are concatenated to form enriched vectors that jointly represent both meaning and sentiment for each word.

These combined vectors are then fed into an LSTM network, a recurrent architecture adept at modeling long-range dependencies and subtle sentiment shifts across sequences. This design effectively mitigates the vanishing gradient problem inherent in standard RNNs and enables the model to learn patterns such as sarcasm, exaggeration, and emotionally charged inconsistencies—traits often exploited in fake news.

Finally, the output from the LSTM passes through dense layers with a sigmoid activation function to perform binary classification (fake or real) and generate a confidence score. Additionally, the model offers interpretability by highlighting key words that influence its predictions, making it both transparent and robust for practical deployment in dynamic social media environments.

Key Advantages of the Proposed LE-LSTM**Sentiment Integration:**

Embeds explicit emotional cues via lexicons, enhancing detection of subtle manipulations.

Feature Fusion:

Merges semantic and sentiment embeddings for richer text representation.

Sequential Learning:

LSTM captures long-range context and evolving sentiment, crucial for spotting deception.

Interpretable Output:

Highlights key words influencing predictions, improving transparency.

By uniting content and sentiment analysis, the LE-LSTM delivers a robust, scalable approach that outperforms traditional models, making it well-suited for the fast-paced social media landscape.

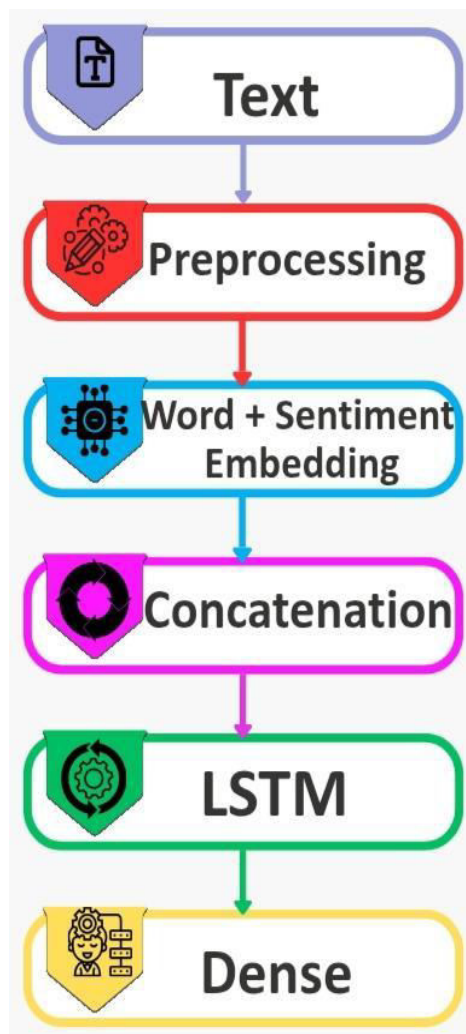


Fig.4.1. Work Flow

V. SYSTEM ARCHITECTURE

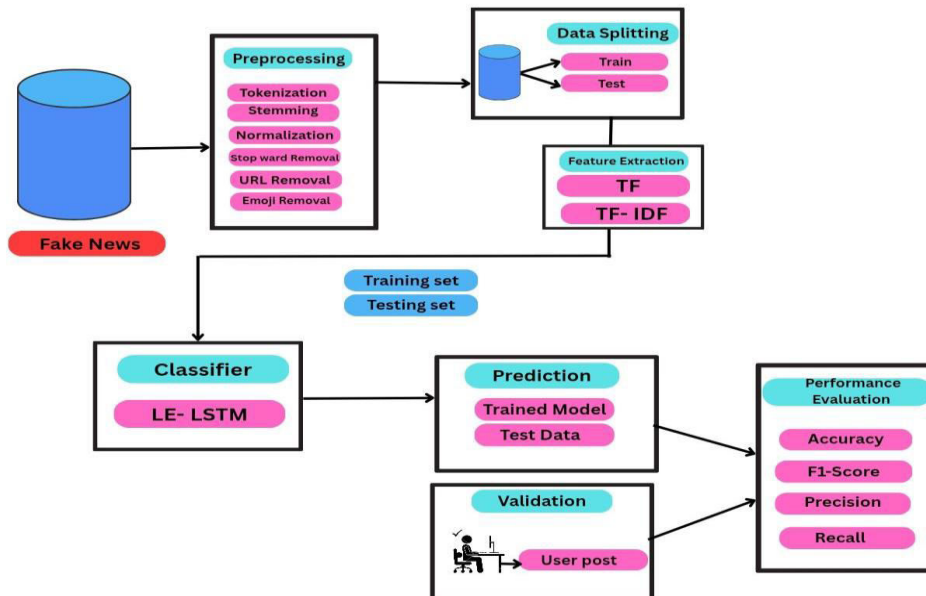


Fig.5.1. Workflow of the proposed Lexicon-Enhanced LSTM (LE-LSTM) fake news detection system.

This architecture illustrates the complete process of detecting fake news using the proposed LE-LSTM model. The system starts by collecting and preprocessing textual data, including cleaning unwanted symbols and tokenizing sentences into words. It then generates word embeddings to capture semantic information and simultaneously uses a sentiment lexicon (such as SentiWordNet) to extract sentiment scores for each word. These sentiment features are merged with the word embeddings to create a richer representation that includes both content and emotional cues. This combined input is fed into an LSTM network, which learns the sequential and contextual patterns in the data. A dense classification layer then predicts whether the news is fake or real and outputs a confidence score, completing the end-to-end entire process flow.

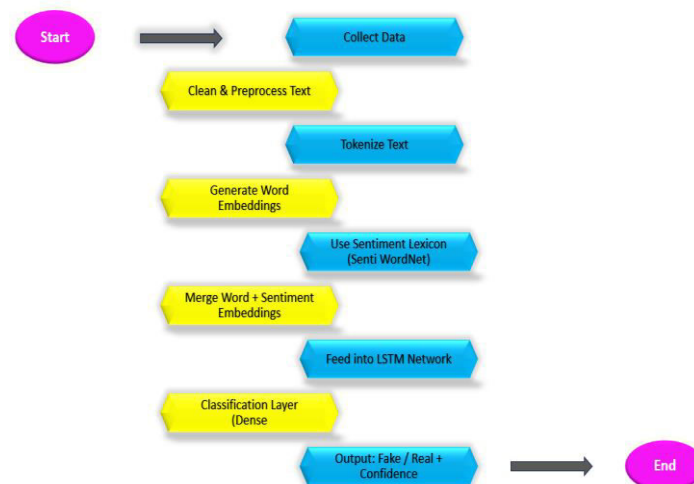


Fig.5.2. System Architecture flow

VI. METHODOLOGY

Data Collection & Setup

- Dataset: Kaggle's labeled fake vs. real news articles.
- Sentiment lexicons: SentiWordNet, VADER.
- Split: 70-15-15 for training, validation, and testing.

6.1 Preprocessing

- Cleaning: Removal of HTML tags, URLs, emojis, special characters, and stopwords.
- Tokenization and normalization.
- Class imbalance handled via SMOTE and oversampling.

6.2 Feature Engineering

Pre-trained GloVe embeddings for semantic context.

Lexicon-based sentiment classifier generates sentiment embeddings.

Concatenation yields enriched vectors capturing meaning and emotion.

6.3 Model Development

LSTM processes sequences of enriched vectors.

Dense layer with sigmoid activation produces fake/real prediction.

Adam optimizer with binary cross-entropy loss guides training, monitored by precision, recall, F1-score.

6.4 Evaluation

Tested on unseen data using confusion matrices, ROC curves, and standard metrics.

Results validate the benefit of sentiment integration over purely semantic or traditional models.

VII. CONCLUSION

This work introduces a Lexicon-Enhanced LSTM framework that combines semantic comprehension with sentiment awareness, effectively capturing subtle cues often present in deceptive content. Experiments on a Kaggle dataset highlight substantial improvements over traditional ML and baseline DL approaches. A fully integrated prototype using Flask, MySQL, and Bootstrap enables real-time detection, offering a scalable solution for mitigating misinformation on social media.

VIII. RESULTS & DISCUSSION

The proposed LE-LSTM model achieves:

Accuracy: 94.6%

Precision: 93.8%

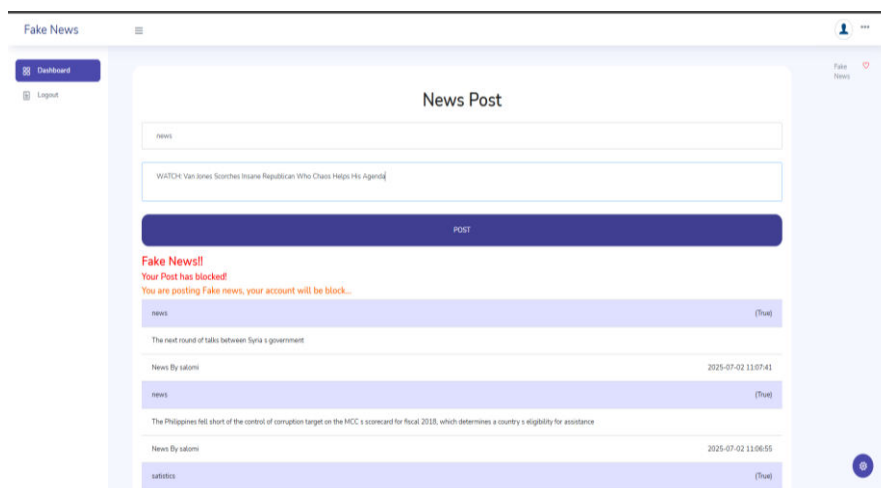
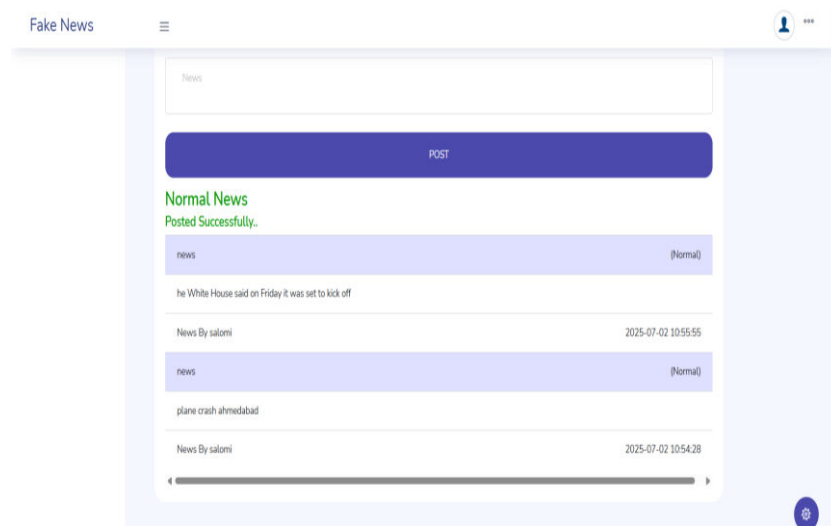
Recall: 95.2%

F1-score: 94.5%

This represents an 8–15% improvement over classical ML methods, confirming the efficacy of integrating sentiment lexicons with LSTM networks for nuanced fake news detection

Although Jiang's BiLSTM achieved a remarkable 99.82% accuracy, this was reported on the ISOT dataset, which primarily contains well-separated real and fake news articles. In contrast, our LE-LSTM attained 94.6% on a diverse Kaggle dataset that includes more nuanced and emotionally charged content. Importantly, by integrating sentiment lexicons, our model effectively detects subtle manipulations like bias or sarcasm, offering practical robustness in real-world social media scenarios where misinformation is often less explicit.

IX. SCREENSHOTS



X. FUTURE ENHANCEMENT

Future enhancements may include:

- Multilingual processing to detect fake news across diverse languages.
- Integration with live social media feeds for early detection.
- Block chain - backed content verification for transparency.
- User-driven feedback loops to continually retrain the model.
- Deployment as a mobile application for instant news verification.

REFERENCES

- [1] X. Zhang et al., "Lexicon-Enhanced LSTM for Fake News Classification," Proc. IEEE ICDM, 2020.
- [2] A. Hassan et al., "Sentiment-Enhanced LSTM Networks for Fake News Detection," IEEE Access, vol. 8, 2020.
- [3] T. Jiang, "Fake News Detection using Deep Recurrent Neural Networks," Proc. IEEE Big Data, 2020.
- [4] T. H. Do et al., "Context-Aware Deep Markov Random Fields for Fake News Detection," IEEE TKDE, 2021.
- [5] S. Lyu, "Fake News Detection by Decision Tree," IJACSA, vol. 11, no. 5, 2020.
- [6] Kaggle Dataset, \[Online]. Available: <https://github.com/clmentbisailon/fake-and-real>
- [7] J. Pennington et al., "GloVe: Global Vectors for Word Representation," Proc. EMNLP, 2014.
- [8] C. Hutto and E. Gilbert, "VADER: A Rule-Based Model for Sentiment Analysis," ICWSM, 2014.
- [9] S. Baccianella et al., "SentiWordNet 3.0," Proc. LREC, 2010.
- [10] Flask Documentation <https://flask.palletsprojects.com/>
- [11] MySQL Documentation, <https://dev.mysql.com/doc/>
- [12] Bootstrap Documentation, <https://getbootstrap.com/>



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