IJMRSET

ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Impact Factor: 8.206

Volume 8, Issue 5, May 2025

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ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Fake News Detection using AI

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ABSTRACT*:* The increasing spread of misinformation across online platforms poses a ensuring the authenticity of digital content is increasingly challenging due to the rapid spread of misinformation, highlighting the need for advanced AI-driven fake news detection. As false information continues to circulate widely, distinguishing between factual and misleading news has become more complex. Intelligent computational techniques provide effective strategies for addressing this issue by leveraging advanced data-driven models. This study examines the application of artificial intelligence in identifying deceptive content, utilizing various predictive algorithms such as support vector machines (SVM), long short-term memory (LSTM), A publicly available dataset is employed to train and test these models, integrating natural language processing (NLP) methods such as text segmentation, redundant word elimination, root word extraction, and statistical weighting techniques. The models are evaluated using key performance indicators, including classification accuracy, predictive precision, retrieval capability, F1-score, and graphical assessment through ROC analysis. The results indicate that deep learning frameworks with BERT attaining a peak accuracy of 98% and LSTM following closely at 95%. This research highlights the effectiveness of AI-driven approaches in reducing misinformation and strengthening the credibility of digital narratives.

KEYWORDS: False Information Detection, Intelligent Systems, Computational Learning, Deep Neural Networks, NLP, Predictive Modeling, Digital Content Verification.

I. INTRODUCTION

The digital era has revolutionized how people access and consume information, with the internet and social media acting as primary sources for news dissemination. While these advancements have fostered global connectivity and knowledge exchange, they have also facilitated the rapid spread of misinformation. The intentional distribution of misleading or fabricated news has emerged as a critical global challenge, influencing public perception, political landscapes, and economic stability. The unchecked proliferation of deceptive content on digital platforms has intensified concerns, often leading to public unrest, financial instability, and distorted political discourse.

Traditional fact-checking methods and manual verification processes often fall short in handling the vast amount of misinformation spreading daily. Since these methods require significant time and manpower, they are not practical for large-scale use. To address this challenge, artificial intelligence (AI) has become a key solution for automating fake news detection. By utilizing machine learning (ML) and natural language processing (NLP), AI-driven systems can efficiently analyze text, identify deceptive patterns.

The role of AI in combating fake news, leveraging various models such as logistic regression, decision trees, Naïve Bayes, and support vector machines (SVM). Additionally, advanced deep learning architectures, are employed to enhance detection capabilities. Through AI-powered techniques, the fight against digital misinformation can become more effective and scalable, ensuring a more reliable flow of information.

The main contributions of this research include:

- The development of an AI-based automated system for detecting fake news using ML and NLP techniques.
- Multiple classification models, including traditional ML algorithms and advanced deep learning frameworks.

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- A comprehensive comparison of model performance based on key evaluation metrics such as accuracy, precision, recall, F1-score, and ROC analysis.

The remainder of this paper is structured as follows: Section III details the methodology and system framework, Section IV presents experimental results and performance evaluation, and Section V concludes the study with potential future improvements in AI-driven fake news detection.

II. RELATED WORKS

The challenge of detecting fabricated news content has led to significant research in artificial intelligence (AI)-powered solutions. Various studies have explored machine learning (ML) and deep learning (DL) frameworks to enhance the accuracy and efficiency of misinformation identification. Researchers have developed and tested multiple computational models to analyze text-based content and determine its authenticity.

One research effort introduced a hybrid deep learning model integrating Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks. The approach utilized structured datasets containing relationships between article claims and supporting evidence. The study incorporated text preprocessing techniques and dimensionality reduction methods, significantly improving classification accuracy and reducing computational complexity.
Another investigation assessed the limitations of conventional ML algorithms by applying multiple classification techniques on different datasets. A statistical evaluation method was used to compare performance across various models. The results demonstrated that deep learning-based solutions outperformed traditional classifiers, achieving near-perfect accuracy in some cases.

Further studies have focused on misinformation detection across social media platforms, emphasizing the role of textual and metadata-based features. One research initiative analyzed tweets and social media posts, using labeled datasets combined with natural language processing (NLP) techniques to improve classification precision. The findings highlighted the significance of integrating linguistic features with behavioral data to strengthen detection models.
In a separate study, researchers proposed an AI-driven system for identifying false news on digital media platforms. The system leveraged multiple ML techniques, including Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression, to classify news content. Among the tested methodologies, the SVM-based approach demonstrated the highest accuracy, reinforcing the effectiveness of feature-based learning models.

Additionally, ensemble learning techniques have been explored to refine misinformation classification. Researchers examined various dataset sources and applied preprocessing techniques to filter out low-quality content. Feature extraction tools were employed to convert textual information into numerical representations, allowing for more effective classification. The study compared different ML models, concluding that decision trees and boosting classifiers offered optimal accuracy when validated through cross-fold testing.

Overall, these studies highlight the rapid advancements in AI-driven misinformation detection. The increasing adoption of hybrid models, deep learning frameworks, and feature engineering techniques continues to enhance the effectiveness and scalability of automated detection systems. As research progresses, more sophisticated AI methodologies are expected to further improve the identification and mitigation of misleading content in digital environments.

III. METHOD

This section outlines the approach taken in this research, detailing the various artificial intelligence (AI), machine learning (ML), deep learning (DL), and natural language processing (NLP) techniques utilized to detect fabricated news content..

A. Dataset Selection

An online repository has been employed. The dataset comprises news articles gathered through automated web scraping from multiple digital platforms, including news websites and social media channels. Given the widespread dissemination of misinformation, this dataset plays a crucial role in building an effective detection system.
The dataset contains approximately 26,000 distinct news pieces, systematically categorized into authentic and misleading content. It features four core attributes: the headline of the article, details about the author, and the complete

text of the news content. Additionally, a label column is included in the training data to specify whether the article is factually accurate or deceptive.

B. Data Preprocessing

To enhance the reliability of the classification models, various preprocessing steps are applied before the data is fed into AI-based algorithms. These steps help eliminate irrelevant information, reduce redundancy of the model predictions.
The following preprocessing methods have been implemented:

1. **Regex Processing**: Regex, or regular expressions, help in cleaning text by eliminating unwanted symbols and punctuation marks
2. **Tokenization**: Tokenization is used to break down the news articles into individual words or tokens.
3. **Stopwords Removal**: Common words that do not contribute meaningfully to fake news detection (e.g., "the," "is," "and") are removed using stopword libraries.
4. **Lemmatization**: Lemmatization converts words to their root forms, reducing dimensionality and improving consistency.

C. Machine Learning Models

To classify news as fake or real, we implement several machine learning algorithms:

1. **Logistic Regression**: A statistical classification model that estimates the probability of news being fake or real using a sigmoid function.
2. **Naïve Bayes**: A Bayesian classifier that relies on the assumption that all features are independent of each other.
3. **Decision Tree**: A hierarchical model that makes classification decisions based on feature importance and information gain.
4. **Support Vector Machine (SVM)**: A supervised learning model that separates data into distinct classes using a hyperplane.

D. Deep Learning and NLP-Based Models

To improve accuracy, deep learning and advanced NLP models are applied:

1. **Long Short-Term Memory (LSTM)**: A type of capable of learning long-term dependencies, making it effective for textual data classification.

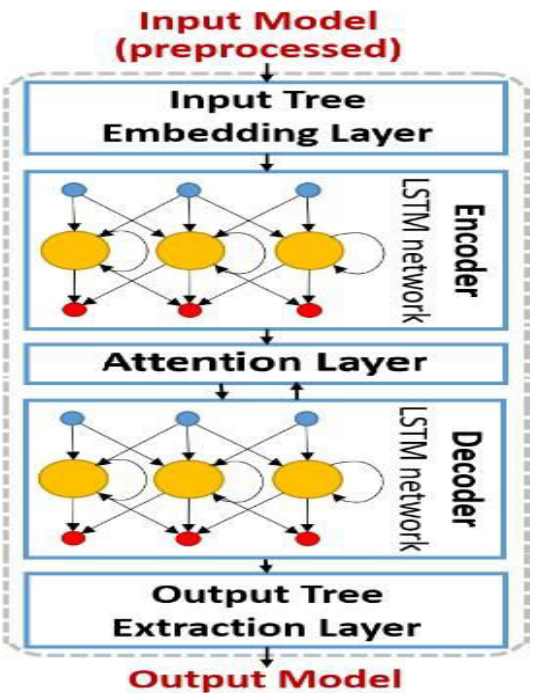

Figure 1. Structural Representation of LSTM.

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TABLE I. Architecture and Hyperparameters of the Proposed LSTM Model

Layer	Output Shape	Number of Parameters
Input	(None, 256)	0
Embedding	(None, 256, 300)	60,974,100
Spatial Dropout	(None, 256, 300)	0
Bidirectional	(None, 256)	439,296
Dense	(None, 64)	16,448
Dropout	(None, 64)	0
Total parameters: 61,429,909 Trainable parameters: 61,429,909 Non-trainable parameters: 0		

2. Bidirectional Contextual Understanding Using Transformer-Based Architecture (BERT): A transformer-based NLP model that considers both left and right contexts in text analysis. BERT is pre-trained on large datasets and fine-tuned for fake news detection.

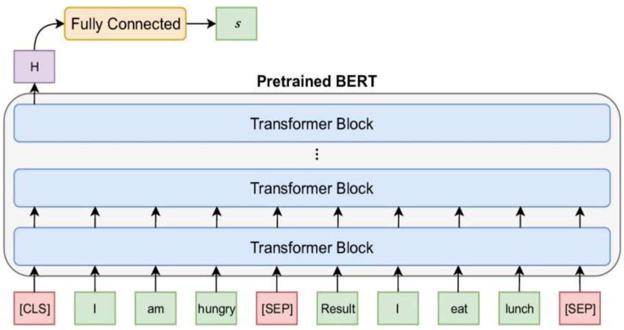

Figure 2. BERT Framework Architecture

The LSTM model is trained on tokenized word sequences, using an embedding layer to convert words into numerical vectors. The BERT model uses pre-trained embeddings and attention mechanisms to extract contextual features from news text. batch processing to optimize classification accuracy.

TABLE II Architecture and Specifications of the Proposed BERT-Based NLP Model

Layer	Number of Parameters	Connected to
Input	0	
Attention masks	0	
TF BERT model	109,482,240	Input [0][0] Attention masks [0][0]
Dense	24,608	TF BERT model [0][1]
Dropout	0	Dense [0][0]
Total parameters: 109,506,881 Trainable parameters: 109,506,881 Non-trainable parameters: 0		

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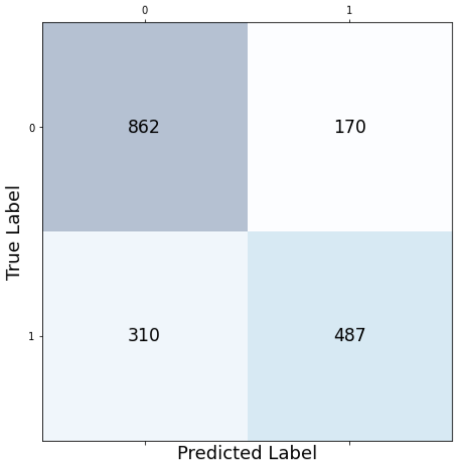
By combining traditional machine learning techniques with deep learning approaches, this methodology enhances the reliability of AI-based fake news detection.

IV. RESULTS AND DISCUSSIONS

This section presents a detailed evaluation of the AI-driven fake news detection system's performance. A range of machine learning (ML) and deep learning (DL) models were trained and assessed using natural language processing (NLP) techniques to differentiate between authentic and deceptive news content. To ensure a fair assessment, sets in an 80:20 ratio. Following comprehensive data preprocessing, each model's performance was analyzed using key metrics, including accuracy, precision, recall, F1-score, confusion matrix, into the effectiveness of AI-based approaches in identifying and mitigating misinformation.

A. Evaluation of Logistic Regression Model

A confusion matrix to determine its classification accuracy. The results indicated that out of 1,032 news samples labeled as authentic, the model correctly identified 862 instances, while 170 samples were misclassified as misleading. This outcome highlights the model's ability to differentiate between factual and deceptive content, with its overall performance further validated through precision, recall, and F1-score calculations.



2. Classification Matrix for logistic regression.
3.

The accuracy for detecting real news is 83.52%, whereas for fake news, 487 correct predictions and 310 misclassifications resulted in 61% accuracy. The overall model accuracy is 74%.

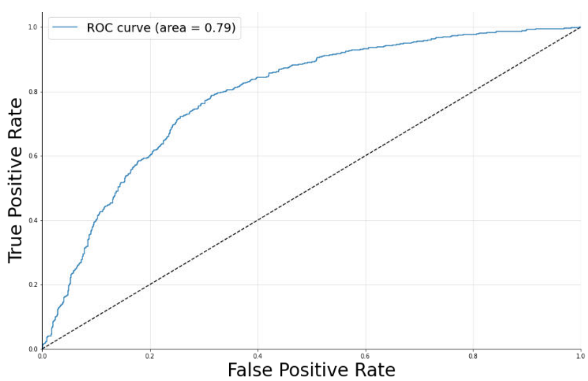


Figure 4. Performance Analysis: ROC Curve for Logistic Regression

The ROC curve (Fig. 4) demonstrates an AUC score of 0.79. The detailed evaluation metrics are shown in Table III.

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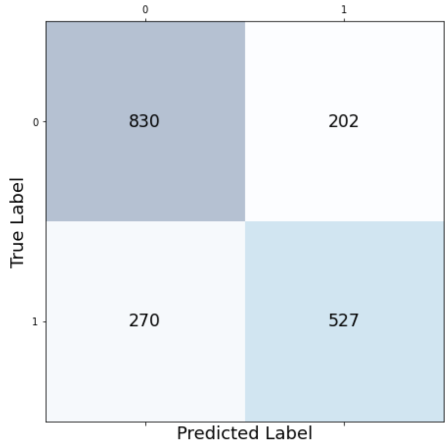
TABLE III. Performance Evaluation Metrics for Logistic Regression

Class	Precision	Recall	F1-score
Not Fake	0.74	0.84	0.78
Fake	0.74	0.61	0.67
Accuracy			0.74
Weighted Average	0.74	0.74	0.73

B. Evaluation of Naive Bayes Model
The naive bayes model's confusion matrix (Fig. 5) shows that 830 real news samples were correctly classified, achieving 80% accuracy, whereas 66% accuracy was achieved for fake news.



4. Classification Matrix for naive bayes.
5.

The overall accuracy of this model is 74%, with an AUC score of 0.79 (Fig. 6).

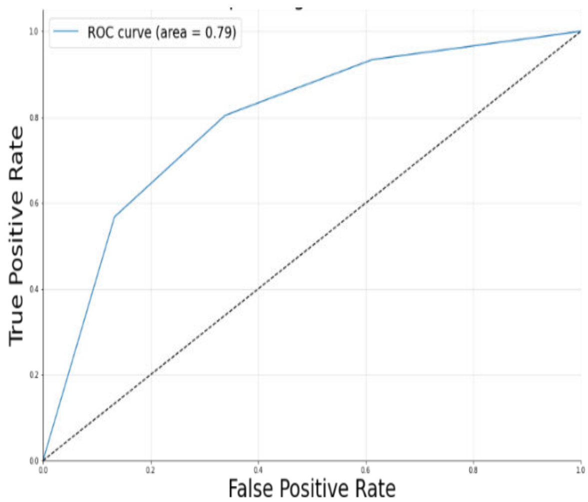


Figure 6. Performance Characteristic Curve for naive bayes.

TABLE IV. Evaluation Metrics for Naïve Bayes

Class	Precision	Recall	F1-score
Not Fake	0.75	0.80	0.78
Fake	0.72	0.66	0.69
Accuracy			0.74
Weighted Average	0.74	0.74	0.74

C. Evaluation of AI-Based Machine Learning Models
Long Short-Term Memory (LSTM) Model
The LSTM model significantly outperforms traditional ML models in fake news detection.

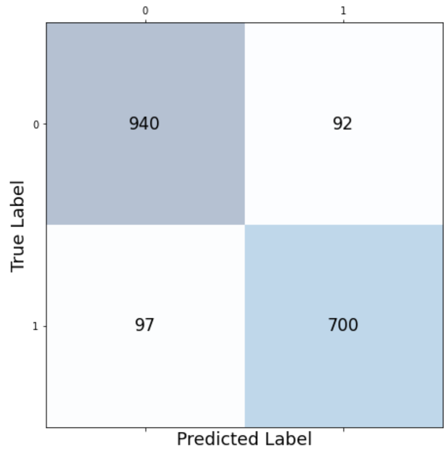


Figure 7. Classification matrix for decision tree.

The confusion matrix (Fig. 11) indicates an accuracy of 92% for real news and 95% for fake news, leading to an overall accuracy of 95%.

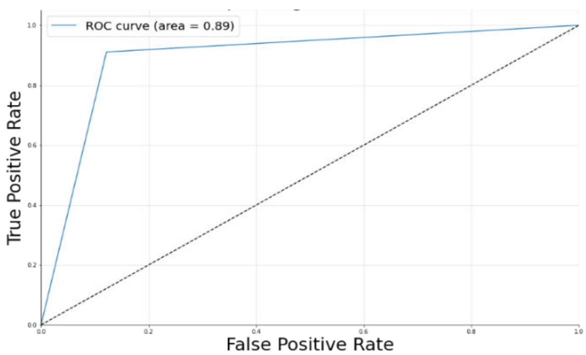


Figure 8. Performance Characteristic Curve for decision tree.

The accuracy and loss trends over epochs (Fig. 12) show stable model performance. Table VII presents the evaluation metrics.

© 2025 IJMRSET | Volume 8, Issue 5, May 2025| DOI:10.15680/IJMRSET.2025.0805064

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

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TABLE VII. Evaluation Metrics for LSTM Models

Class	Precision	Recall	F1-score
Not Fake	0.98	0.92	0.95
Fake	0.91	0.97	0.94
Accuracy			0.95
Weighted Average	0.95	0.95	0.95

Bidirectional Contextual Understanding Using Transformer-Based Architecture (BERT)

The BERT model achieves approaches. As depicted in Fig. 13, the initial validation accuracy of 97% increased to 98% after multiple training epochs. This performance surpasses conventional ML and LSTM models, making BERT the most effective AI-driven approach for detecting fake news.

D. Model Comparison

Table IX compares the accuracy of all models employed in this study. BERT outperforms other models, achieving the highest accuracy of 98%.

TABLE IX. Performance Evaluation of Various Models

Model	Precision	Recall	F1-Score	Accuracy
Logistic Regression	74%	72%	73%	74%
Naive Bayes	74%	73%	73%	74%
Decision Tree	90%	89%	89%	90%
SVM	76%	76%	76%	77%
LSTM	94%	95%	94%	95%
BERT				98%

E. Comparison with Other Studies

Table X provides a comparative evaluation of our BERT-based fake news detection model against previous research. The existing approaches, highlighting the superiority of AI-driven NLP techniques in detecting misinformation. This reinforces the potential of advanced deep learning models in enhancing the reliability of automated fake news classification.

TABLE X. ACCURACY COMPARISON WITH OTHER WORKS

Reference	Applied Method	Accuracy
[3]	Random forest	95%
[4]	Decision tree	96.8%
[5]	CNN+LSTM with PCA	96%
[8]	SVM	93.5%
[9]	Decision tree	94%
[25]	Deep neural network	94%
Our Study	BERT	98%

V. CONCLUSION

In an era where digital misinformation spreads rapidly, the integration of AI-driven solutions for fake news detection is crucial in maintaining the integrity of online information. This study has demonstrated the effectiveness of various machine learning and deep learning models, emphasizing the superiority of advanced neural networks such as LSTM and BERT in identifying fabricated content. By leveraging natural language processing and feature extraction techniques, the proposed system enhances accuracy in distinguishing genuine news from deceptive narratives.

Future enhancements can extend the system's capabilities by incorporating multimodal analysis, enabling the detection of fake content across text, images, and videos. Additionally, the integration of multilingual NLP models will ensure broader applicability across diverse linguistic landscapes. As AI technologies continue to advance, attention-based models and reinforcement learning can further refine classification accuracy, making fake news detection more robust and adaptable.

Ultimately, the development of AI-powered detection frameworks will serve as a cornerstone in combating misinformation, fostering a more reliable digital ecosystem, and empowering users with credible and fact-based information. AI methodologies will in shaping a media landscape where truth prevails over manipulation.

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