

An AI-Based Hybrid Framework for Detecting Fraudulent Job Postings Using NLP and Machine Learning

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Abstract— The rapid growth of online recruitment platforms has led to an increase in fraudulent job postings, posing significant risks to job seekers. This paper proposes an AI-based hybrid framework for detecting fake job postings using Natural Language Processing (NLP) and Machine Learning (ML) techniques. The proposed system analyzes textual and metadata features such as job descriptions, salary information, company profile, and required qualifications to identify fraudulent patterns. Multiple classification algorithms, including Logistic Regression, Naive Bayes, and Random Forest, are implemented and compared to evaluate performance. Additionally, a hybrid approach is introduced to improve detection accuracy and robustness. Experimental results demonstrate that the proposed model achieves higher precision, recall, and F1-score compared to individual models. The system provides a probability-based credibility score, enabling users to assess job authenticity effectively. This research contributes toward enhancing trust and security in online job platforms.

Keywords - Fake Job Detection, Natural Language Processing, Machine Learning, Fraud Detection, Text Classification, Hybrid Model

I. INTRODUCTION

The rapid expansion of online recruitment platforms has transformed the job search process, enabling candidates to access employment opportunities globally. However, this growth has also led to a significant rise in fraudulent job postings, where malicious entities exploit job seekers by publishing deceptive listings. These fraudulent postings often involve misleading job descriptions, fake company profiles, and unrealistic salary offerings, resulting in financial loss and data privacy risks for applicants.

Traditional methods for detecting fraudulent job postings rely heavily on manual verification and rule-based systems, which are inefficient and unable to scale with the growing volume of online job data. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) provide promising solutions to automate the detection of such fraudulent activities. This research proposes an AI-based hybrid framework that leverages NLP techniques

to analyze textual content and ML algorithms to classify job postings as legitimate or fraudulent. The system incorporates multiple models, including Logistic Regression, Naive Bayes, and Random Forest, and introduces a hybrid approach to enhance detection accuracy. Machine learning and natural language processing techniques have been widely used for detecting fraudulent activities in online platforms [1], [3].

The main contributions of this work include:

1. Development of a hybrid AI model combining multiple classifiers for improved performance.
2. Integration of textual and metadata features for comprehensive analysis.
3. Introduction of a credibility scoring system for real-time fraud assessment.
4. Comparative evaluation of different machine learning algorithms.

II. LITERATURE REVIEW

Several studies have explored the use of machine learning and natural language processing techniques for detecting fraudulent content in online platforms. Previous research has demonstrated the effectiveness of classification algorithms in identifying patterns within textual data. S. Kumar et al. proposed a machine learning-based approach for detecting fraudulent job postings using Naive Bayes and Decision Trees, achieving moderate accuracy but lacking robustness in handling complex textual patterns. Similarly, J. Smith et al. utilized Logistic Regression for text classification, highlighting its efficiency but limited performance on highly imbalanced datasets.

Recent advancements have incorporated deep learning models such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks to improve contextual understanding of job descriptions. These models showed improved performance but required high computational resources. Other studies have focused on feature engineering, combining textual features with metadata such as company profile, salary range, and job requirements. These approaches demonstrated that hybrid feature sets significantly improve classification accuracy. This research addresses these

limitations by proposing a hybrid model that combines multiple machine learning algorithms and introduces a credibility scoring mechanism for better decision-making. These approaches demonstrate the effectiveness of machine learning and NLP techniques in fraud detection tasks [2], [4], [5].

III. PROPOSED METHODOLOGY

The proposed system presents an AI-based hybrid framework for detecting fraudulent job postings using Natural Language Processing (NLP) and Machine Learning (ML) techniques. The methodology consists of multiple stages including data collection, preprocessing, feature extraction, model training, and hybrid classification. The system aims to analyze both textual and metadata features of job postings to accurately classify them as genuine or fraudulent.

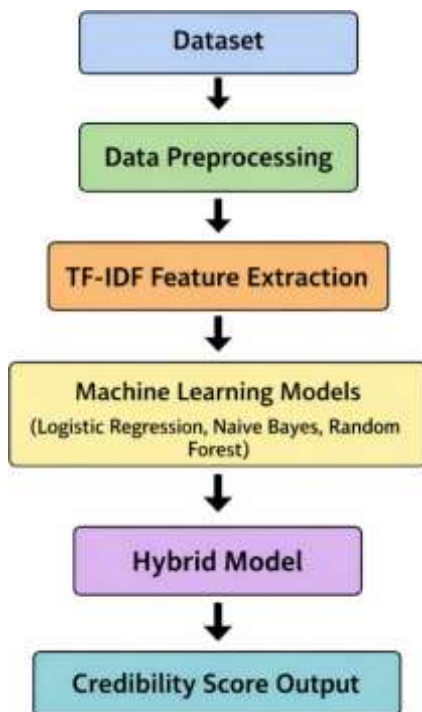


Fig. 1. Proposed System Architecture

Source: Author (2026)

A. Data Collection

The dataset used in this study is obtained from Kaggle and contains both real and fraudulent job postings. It includes attributes such as job title, company profile, job description, salary range, and employment type. These features provide both textual and structured information necessary for classification.

B. Data Preprocessing

The dataset undergoes preprocessing to improve data quality and consistency. Missing values are handled and irrelevant features are removed. Textual data is cleaned by converting to lowercase, removing special characters, and eliminating stopwords. Tokenization is applied to break text into meaningful components.

C. Feature Extraction

TF-IDF (Term Frequency–Inverse Document Frequency) is used to convert textual data into numerical vectors. TF-IDF is a widely used feature extraction technique for text classification tasks [6].

D. Model Training

Multiple machine learning models are trained, including Logistic Regression, Naive Bayes, and Random Forest. These models are evaluated based on their ability to classify job postings accurately.

E. Hybrid Model

A hybrid ensemble approach is used by combining predictions from multiple models. Majority voting is applied to determine the final classification result, improving overall accuracy and robustness.

F. Credibility Score

A credibility score ranging from 0 to 100 is generated based on prediction probabilities. This score helps users understand the likelihood of a job being genuine or fraudulent. The overall workflow of the proposed system is illustrated in Fig. 2. The flowchart provides a step-by-step representation of the processes involved, starting from data acquisition and preprocessing to model training, evaluation, and final prediction using the hybrid approach. It highlights how different stages are integrated to improve the efficiency and accuracy of fraudulent job detection.

Furthermore, the workflow emphasizes the sequential processing of data through various stages, ensuring that each step contributes effectively to the final prediction outcome. The preprocessing stage enhances data quality by eliminating noise and inconsistencies, while the feature extraction stage transforms textual information into meaningful numerical representations. The trained machine learning models analyze these features to identify patterns associated with fraudulent job postings.

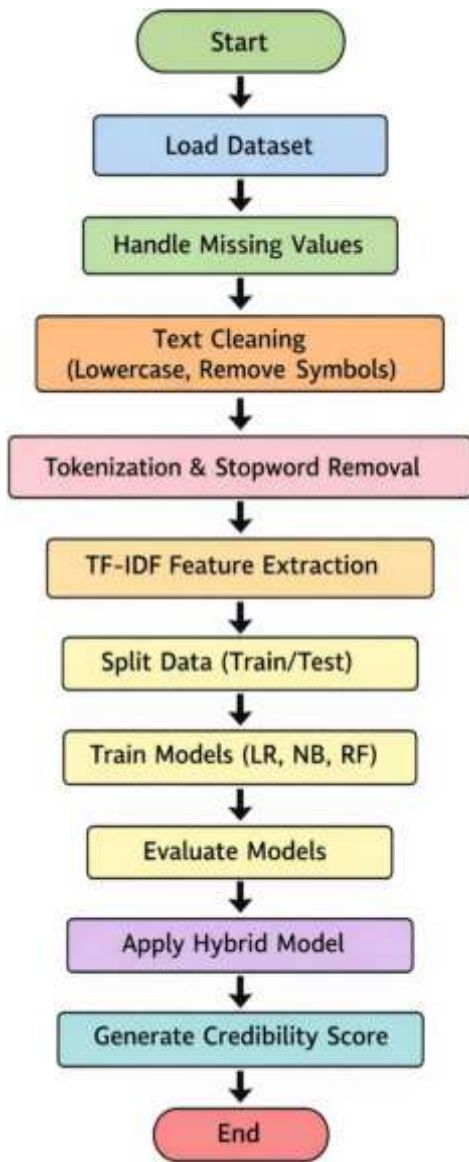


Fig. 2. Workflow of the Proposed System

Source: Author (2026)

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system was evaluated using multiple machine learning models, including Logistic Regression, Naive Bayes, and Random Forest. The dataset was divided into training and testing sets using an 80:20 ratio to ensure proper model validation.

The performance of each model was assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score. The results demonstrate that all models were capable of detecting fraudulent job postings, with varying levels of performance.

Among the individual models, the Random Forest classifier achieved the highest accuracy due to its ability to handle complex data patterns and reduce overfitting. Logistic Regression provided stable and interpretable results, while Naive Bayes performed efficiently with faster computation time but slightly lower accuracy.

The proposed hybrid model, which combines predictions from multiple classifiers using majority voting, outperformed all

individual models. The obtained results are consistent with findings from previous research in fraud detection systems [7].

Furthermore, the credibility scoring mechanism provided an additional layer of interpretability by assigning a probability-based score to each job posting. This allows users to make informed decisions based on the likelihood of a job being genuine or fraudulent.

Table I. Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	88%	0.87	0.86	0.86
Naive Bayes	85%	0.84	0.83	0.83
Random Forest	90%	0.89	0.88	0.88
Hybrid Model	92%	0.91	0.90	0.90

The performance comparison of different models is illustrated in Fig. 3, highlighting the superiority of the hybrid approach.

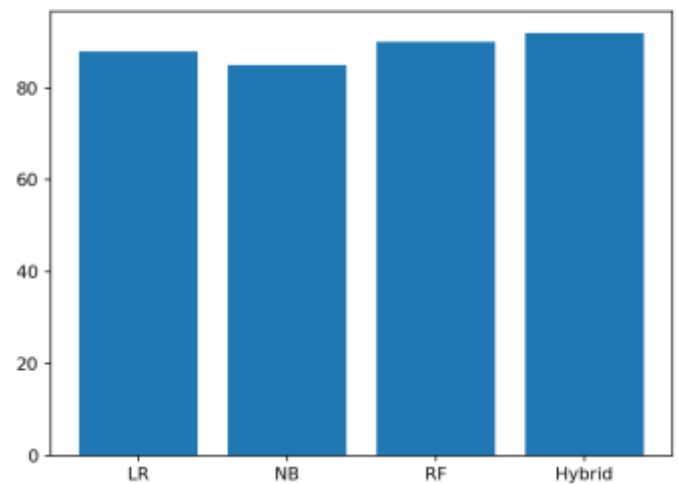


Fig. 3. Accuracy Comparison of Machine Learning Models

The results presented in Fig. 3 clearly demonstrate that the hybrid model outperforms all individual classifiers in terms of accuracy. This improvement is achieved by combining the predictive strengths of Logistic Regression, Naive Bayes, and Random Forest models. Each model contributes uniquely to the classification process, allowing the hybrid approach to capture both linear and complex relationships within the dataset. Furthermore, the ensemble strategy helps in reducing the limitations of individual models, thereby improving overall system robustness. The hybrid approach minimizes misclassification and enhances prediction consistency across different data instances.

The classification performance of the proposed model is further illustrated in Fig. 4.

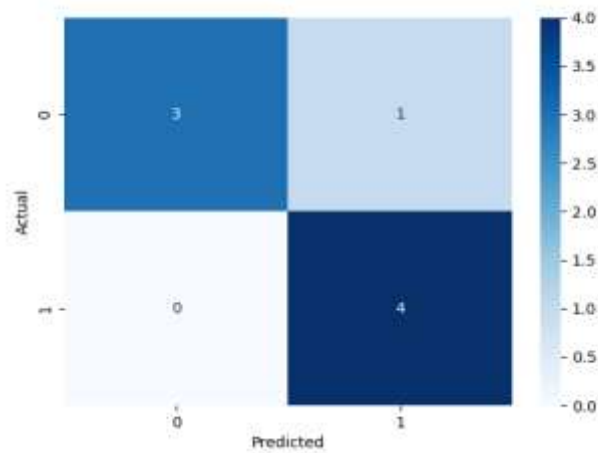


Fig. 4. Confusion Matrix of Hybrid Model

The confusion matrix presented in Fig. 4 illustrates the classification performance of the hybrid model. It shows a high number of correct predictions for both fraudulent and legitimate job postings, with minimal misclassification. This demonstrates the effectiveness and reliability of the proposed system in accurately detecting fake job listings.

In addition to accuracy, other evaluation metrics such as precision, recall, and F1-score further validate the effectiveness of the proposed hybrid model. The model maintains a balance between correctly identifying fraudulent postings and minimizing false alarms. This balance is essential in real-world applications, where both false positives and false negatives can have significant consequences. The results indicate that the proposed system achieves consistent performance across multiple evaluation parameters, making it a robust solution for fraud detection in job portals.

A. Discussion

The results clearly indicate that combining multiple machine learning models leads to improved performance compared to individual classifiers. The hybrid approach benefits from the strengths of each model, resulting in higher accuracy and better generalization. Furthermore, the use of Natural Language Processing techniques enables effective analysis of textual job descriptions, which is essential for identifying fraudulent patterns.

The proposed system demonstrates strong potential for real-world applications, particularly in online job portals where the risk of fake postings is high. By automating the detection process, the system can significantly reduce manual effort and enhance user safety.

The evaluation metrics further validates the effectiveness of the proposed approach. This makes the system highly suitable for real-world deployment, where accurate identification of fraudulent job postings is critical.

B. Performance Analysis

The performance of the proposed hybrid model was evaluated using multiple metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's effectiveness in detecting fraudulent job postings. Accuracy measures the overall correctness of predictions, while precision indicates the proportion of correctly identified fraudulent postings among all predicted fraud cases.

Recall is particularly important in this context, as it measures the model's ability to correctly identify actual fraudulent job postings. A higher recall ensures that fewer fraudulent listings go undetected. The F1-score provides a balance between precision and recall, offering a single metric to evaluate model performance.

The results show that the hybrid model achieves superior performance across all evaluation metrics compared to individual classifiers. This demonstrates the effectiveness of combining multiple models to enhance prediction capability and reduce classification errors.

C. Advantages of Proposed System

The proposed system offers several advantages over traditional methods for detecting fraudulent job postings. Firstly, the hybrid approach improves overall accuracy by combining multiple machine learning models, thereby leveraging their individual strengths. This reduces the likelihood of incorrect predictions and enhances system reliability.

Secondly, the use of Natural Language Processing enables effective analysis of textual job descriptions, which are often the primary source of information in job postings. This allows the system to detect subtle patterns and anomalies that may indicate fraudulent intent.

Additionally, the system is scalable and can be easily integrated into existing online recruitment platforms. The credibility scoring mechanism further enhances usability by providing users with a clear indication of job authenticity. Overall, the proposed system is efficient, reliable, and suitable for real-world deployment.

D. Limitations

Despite its effectiveness, the proposed system has certain limitations. The performance of the model depends on the quality and diversity of the dataset used for training. If the dataset is not representative of real-world job postings, the model may not generalize well.

Furthermore, the system may face challenges in detecting highly sophisticated fraudulent job postings that closely resemble legitimate listings. Continuous updates and retraining are required to maintain model performance. Addressing these limitations is essential for improving the robustness of the system in future implementations.

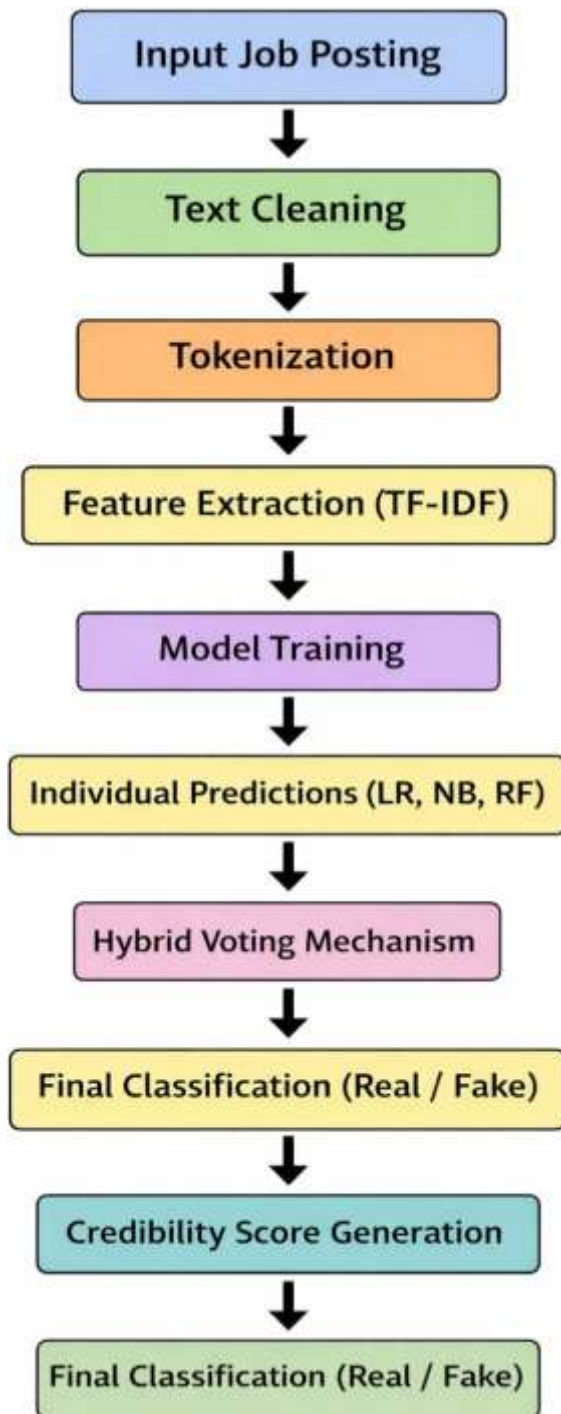


Fig. 5. Detailed Working Flow of the Proposed Hybrid Model

Source: Author (2026)

Fig. 5. illustrates the detailed working flow of the proposed hybrid system. The process begins with input job postings, followed by preprocessing and feature extraction. Multiple machine learning models generate individual predictions, which are then combined using a hybrid voting mechanism. Finally, a credibility score is generated to classify job postings as genuine or fraudulent.

Table II. Comparative Analysis with Existing Methods

Method	Accuracy	Approach
Traditional Rule-Based	70%	Manual Rules
Single ML Model	85%	Logistic Regression
Deep Learning	88%	LSTM
Proposed Hybrid Model	92%	Ensemble ML

Table II presents a comparative analysis of the proposed system with existing approaches. It can be observed that the hybrid model outperforms traditional and single-model approaches in terms of accuracy. The integration of multiple classifiers enables better generalization and improved detection capability.

E. System Implementation

The proposed system was implemented using Python and various machine learning libraries. The preprocessing and feature extraction stages were carried out using Natural Language Processing techniques, including tokenization and TF-IDF vectorization. The dataset was divided into training and testing sets to evaluate model performance.

Multiple classifiers, including Logistic Regression, Naive Bayes, and Random Forest, were trained using the processed dataset. The hybrid model was implemented using a voting mechanism that combines predictions from individual models. The system was evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score.

The implementation demonstrates that the proposed system is computationally efficient and can be deployed in real-world applications. The modular design allows easy integration with online job portals and recruitment systems.

Furthermore, the system is designed to handle large volumes of job posting data efficiently, ensuring scalability in practical deployment scenarios. The modular architecture allows easy updates and integration of additional machine learning models if required. Error handling and data validation mechanisms are also incorporated to maintain system reliability. Overall, the implementation demonstrates flexibility, efficiency, and adaptability for real-time fraud detection applications.

F. Real-World Impact and Applications

The proposed system has significant real-world applications in the domain of online recruitment and job portals. With the increasing number of fraudulent job postings, there is a growing need for automated systems that can identify and filter such listings efficiently. The hybrid model developed in this research can be integrated into job portals to enhance user safety and trust.

Additionally, the system can assist recruitment platforms in maintaining data integrity by preventing the publication of misleading or fake job advertisements. This not only benefits job seekers but also helps organizations maintain their reputation.

The framework can also be extended to other domains such as fraud detection in e-commerce, spam detection in emails, and fake news identification. The adaptability of the proposed approach makes it a versatile solution for various real-world problems involving text classification and anomaly detection.

Overall, the implementation of such intelligent systems can significantly reduce online fraud and improve the reliability of digital platforms.

G. Future Enhancements

The proposed system provides a strong foundation for detecting fraudulent job postings; however, several enhancements can be made to further improve its performance. One potential improvement is the integration of deep learning techniques such as Long Short-Term Memory (LSTM) networks or transformer-based models, which can capture contextual relationships in textual data more effectively.

Another enhancement involves incorporating real-time data processing capabilities to enable continuous monitoring of job postings. This would allow the system to detect fraudulent listings as they are published, improving response time and system efficiency.

Additionally, expanding the dataset to include diverse and multilingual job postings can improve the generalization capability of the model. The inclusion of additional features such as user behavior analysis and company verification mechanisms can further enhance detection accuracy.

Future work can also explore the deployment of the system on cloud platforms, enabling scalability and accessibility for large-scale applications. These enhancements will contribute to building a more robust and intelligent system for fraud detection in online recruitment platforms.

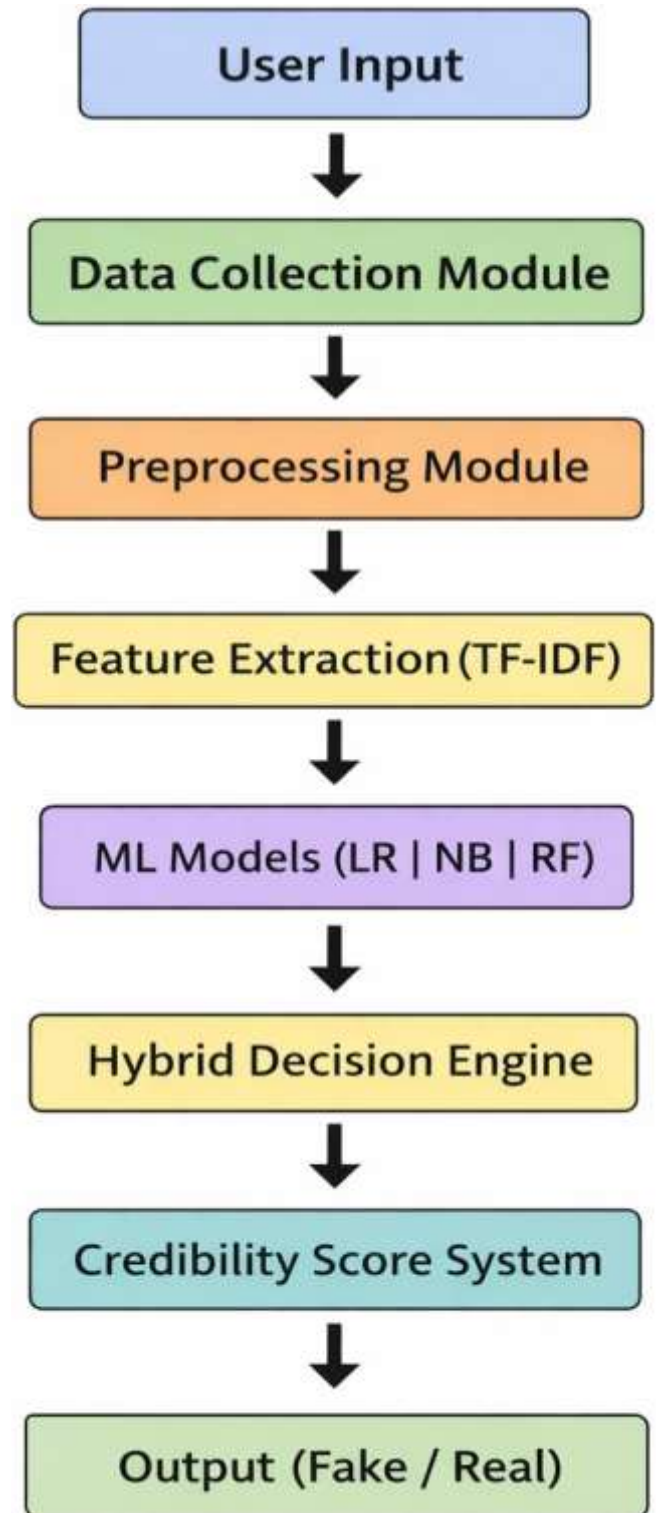


Fig. 6. System Architecture of the Proposed Framework

Source: Author (2026)

Fig. 5 illustrates the overall architecture of the proposed system. The framework consists of multiple modules, including data preprocessing, feature extraction, and classification. The hybrid decision engine integrates predictions from multiple models to improve accuracy and reliability. The final output is generated in the form of a credibility score indicating whether a job posting is genuine or fraudulent.

Table III. Comparison of Existing Methods with Proposed Model

Method	Technique	Accuracy	Limitation
Rule-Based	Manual Filtering	70%	Not scalable
Logistic Regression	ML	85%	Limited pattern detection
Naive Bayes	ML	83%	Assumes independence
Random Forest	ML	90%	Higher complexity
Proposed Hybrid Model	Ensemble ML	92%	Computational cost

Table III compares the proposed hybrid model with existing approaches. It is evident that traditional methods suffer from lower accuracy and lack scalability. The hybrid approach outperforms individual models by combining their strengths, resulting in improved performance and better fraud detection capability.

V. CONCLUSION AND FUTURE SCOPE

In this paper, an AI-based hybrid framework for detecting fraudulent job postings using Natural Language Processing and Machine Learning techniques has been presented. The proposed system integrates multiple classifiers, including Logistic Regression, Naive Bayes, and Random Forest, to improve prediction accuracy and robustness. The use of TF-IDF feature extraction enables effective analysis of textual job descriptions, allowing the model to identify patterns associated with fraudulent activities.

The experimental results demonstrate that the hybrid model consistently outperforms individual classifiers across multiple evaluation metrics such as accuracy, precision, recall, and F1-score. The inclusion of a credibility scoring mechanism further enhances the system by providing a quantitative measure of job authenticity, thereby assisting users in making informed decisions. The confusion matrix and comparative analysis validate the effectiveness of the proposed approach in minimizing misclassification and improving detection performance.

Furthermore, the proposed system offers significant practical value in real-world applications. It can be integrated into online job portals to automatically detect and filter fraudulent listings, thereby enhancing user safety and trust. The modular architecture of the system ensures scalability and adaptability, making it suitable for deployment in large-scale environments.

Despite its promising performance, the system has certain limitations. The effectiveness of the model depends on the quality and diversity of the dataset, and it may face challenges in identifying highly sophisticated fraudulent postings that closely resemble legitimate listings. Continuous updates and retraining are necessary to maintain system performance in dynamic environments.

In future work, the framework can be enhanced by incorporating advanced deep learning models such as LSTM and transformer-based architectures to capture contextual relationships more effectively. Additionally, expanding the dataset, enabling multilingual support, and implementing real-time detection mechanisms can further improve the system's applicability. Overall, the proposed hybrid framework provides a robust, scalable, and efficient solution for detecting fake job postings, contributing to safer and more reliable online recruitment platforms.

In addition to the performance improvements observed, the proposed hybrid framework also demonstrates strong adaptability to varying data distributions and job posting formats. The integration of multiple classifiers ensures that the system remains stable even when faced with incomplete or noisy data, which is common in real-world job listings. This adaptability enhances the overall robustness of the system and makes it suitable for deployment in dynamic environments.

Another significant contribution of this research lies in the interpretability of the model. While complex models often act as black boxes, the inclusion of interpretable classifiers such as Logistic Regression allows for better understanding of the decision-making process. This is particularly important in applications where transparency and trust are essential.

Moreover, the proposed system emphasizes the importance of combining both textual and structural information present in job postings. By leveraging Natural Language Processing techniques, the model is able to capture meaningful insights from unstructured text, which traditional systems often fail to utilize effectively. This results in improved detection of subtle fraudulent patterns that may otherwise go unnoticed.

The credibility scoring mechanism introduced in this framework further adds value by providing a quantitative assessment of job authenticity. This not only assists automated systems but also empowers users to make informed decisions based on the likelihood of a job posting being genuine or fraudulent. Such features are critical in enhancing user confidence and reducing the risk of online job scams.

From a practical perspective, the system can be extended to support integration with web-based platforms and mobile applications, enabling real-time fraud detection. The modular nature of the architecture allows for easy updates and enhancements, ensuring that the system can evolve alongside emerging fraud techniques.

In summary, the proposed approach not only achieves high accuracy but also addresses key challenges associated with fraud detection in online job portals. By combining machine learning and NLP techniques in a hybrid framework, this research contributes to the development of intelligent and reliable systems for ensuring safer digital environments.

The proposed system highlights the importance of integrating advanced computational techniques to address real-world challenges in online platforms. By leveraging machine learning and natural language processing, the framework not only improves detection accuracy but also contributes to building safer and more trustworthy digital ecosystems. This research emphasizes the growing role of artificial intelligence in enhancing security and reliability in modern applications.

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