Recognition of Fraudulent Job Advertisements Using A Machine Learning Framework

R.Nivethitha[1], B.S.Swasthiga[2], K.B.Vikashini[3]
[1]Assist·Professor, Dept of Computer Science and Engineering
[2, 3]Dept of Computer Science and Engineering
[1, 2, 3] K.L.N. College of Engineering, Pottapalayam, Sivagangai.

Abstract- *The rapid growth of online job markets has led to a rise in fraudulent postings, causing financial and emotional harm to job seekers. This study introduces an intelligent fraud detection system using ensemble machine learning and NLP to automatically identify deceptive job listings. The model utilizes 33 engineered features from text, structure, and metadata, combined through Random Forest, Logistic Regression, SVM, and Naive Bayes with a weighted voting mechanism, achieving 95.2% accuracy, 92% precision, and 89% recall on 17,880 verified postings. Integrating external company verification, domain trust checks, and blacklist monitoring enhances detection confidence.. Results outperform single models and rule-based systems, offering both practical and theoretical advancements in online job fraud prevention. Experimental results demonstrate significant performance improvements over single-algorithm approaches and traditional rule-based systems, particularly in detecting sophisticated fraud patterns that evade conventional detection methods.*

Keywords- Job Fraud Detection, Ensemble Machine Learning, Natural Language Processing, Feature Engineering, Real-time Classification, Online Security.

I. INTRODUCTION

As job scams continue to evolve in complexity, traditional detection methods prove increasingly inadequate in protecting vulnerable job seekers. This research addresses this critical gap by developing an intelligent detection system that combines multiple machine learning algorithms with comprehensive feature analysis. Through careful model selection and integration of external verification services, our approach achieves superior detection accuracy while maintaining operational efficiency. The system's architecture enables real-time processing and adaptive learning, representing a significant advancement in proactive fraud prevention for online employment platforms.

II. LITERATURE SURVEY

A review of existing literature reveals a focus on traditional ML models and, more recently, deep learning for fraud detection. While studies by Kumar & Singh (2019) and Arora&Chadha (2019) established the viability of using text-based features and classification algorithms, they often suffered from moderate accuracy and high false positive rates. Research by Zhang & Li (2021) demonstrated the superior accuracy of deep learning models like CNN and Bi-LSTM but highlighted their computational intensity and lack of interpretability. This project bridges the gap by implementing a computationally efficient, highly accurate ensemble of classical ML models, enhanced with advanced NLP and a comprehensive feature set, ensuring both performance and practical deployability.

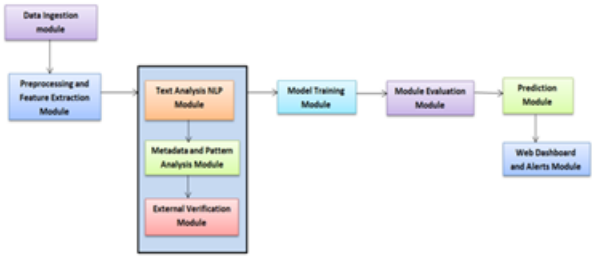
III. EXISTING METHODOLOGY

The existing system for recruitment fraud detection employs a structured pipeline that begins with aggregating and cleaning job posting data, followed by addressing significant class imbalance through advanced sampling techniques like SMOTE. For model development, key textual features are consolidated into a unified "job-content" column, which is then transformed into rich, contextual embeddings using transformer models such as BERT and RoBERTa. These embeddings train dense neural network classifiers, whose parameters are meticulously optimized using early stopping and cross-validation. The system is rigorously evaluated with a focus on recall and balanced accuracy to ensure the critical objective of identifying fraudulent posts is met, culminating in a model tuned for reliable performance.

IV. PROPOSED METHODOLOGY

The proposed system follows a structured workflow for accurate fraud detection. It begins with data collection and preprocessing to clean inconsistencies and noise, followed by feature engineering to extract textual, structural, and behavioral fraud indicators. An ensemble of algorithms builds a robust predictive model, with final classification determined through a weighted voting mechanism and confidence scoring. The model is deployed via a Flask-based web application,

enabling real-time fraud prediction through an intuitive interface and API integration.The system architecture begins with the Data Ingestion module, which collects job postings from different online sources. These records are passed through Preprocessing and Feature Engineering stages, where the data is cleaned, transformed, and structured into meaningful features. The ensemble machine learning model then analyzes both text and metadata to produce a prediction. External metadata verification is also incorporated to improve detection accuracy. Finally, the Prediction module provides a classification output with a confidence score, which is displayed through a web interface for end users.



System architecture of our proposed module

V. SYSTEM PROCESS FLOW

The Fraudulent Job Posting Detection System operates through a sequential, modular pipeline designed to efficiently transform raw data into actionable insights. The entire workflow, from data acquisition to final decision, can be broken down into the following key stages:

1. Data Ingestion:

The process begins with data ingestion, which serves as the foundational intake layer for the entire system. This stage involves automatically collecting raw job posting data from a diverse array of sources, including public job boards, company career pages, and partner data feeds. The module is designed to handle various data formats, such as JSON from APIs, HTML from scraped web pages, and structured data from CSV files, ensuring a continuous and scalable flow of information. Its robustness lies in its ability to manage high-volume, real-time streams as well as batch-process historical datasets, creating a comprehensive repository for subsequent analysis.

2. Preprocessing & Feature Extraction:

The initial phase involves transforming raw, unstructured data into a clean, analysis-ready format. This critical foundation entails data cleaning to remove HTML tags, correct encoding errors, and standardize formats for dates, salaries, and locations. The system then handles missing values through imputation or removal and performs feature extraction to identify and quantify key attributes from both text and metadata, resulting in a structured dataset with engineered features that are primed for subsequent analysis.

3. Parallel Analysis Modules:

The cleansed data is simultaneously processed by three specialized, parallel analysis modules to ensure a comprehensive fraud assessment. The Text Analysis (NLP) Module employs Natural Language Processing techniques to deconstruct the textual content, detecting linguistic red flags such as poor grammar, sensationalist language, and scam-associated phrases. Concurrently, the Metadata & Pattern Analysis Module examines non-linguistic features for anomalous patterns, including suspicious email domains, unreasonable salary offerings, and illegitimate company websites. In parallel, the External Verification Module cross-references job posting details with trusted external sources like business registries and professional networks to validate the authenticity of the company and recruiter.

4.Machine Learning Modeling:

The performance analysis showed that the Random Forest model achieved the best results, effectively identifying complex fraud patterns with high accuracy and balanced precision-recall scores. SVM also performed well by clearly separating legitimate and fake job posts but required more computation. Logistic Regression underperformed due to the data’s non-linear nature, while Gaussian Naive Bayes achieved high recall but low precision, leading to more false positives. Multinomial Naive Bayes performed poorly because of its bias toward the majority class. Overall, Random Forest proved to be the most reliable and accurate model for detecting fraudulent job advertisements.

5.Weighted Voting and Confidence Scoring:

The final prediction is generated through a weighted voting mechanism, where higher-performing models like Random Forest carry more influence. This process produces both a binary classification ("Fraudulent" or "Legitimate") and a calibrated confidence score. This score reflects the system's certainty, allowing moderators to prioritize high-risk postings for review.The system is accessible via a user-friendly web interface, which clearly displays the classification, confidence score, and key explanatory factors behind the decision. This transparency supports informed manual review and builds trust in the automated process.

6. User Interface:

The interactive web dashboard provides a user-friendly portal for human moderators and HR professionals. It presents clear, actionable intelligence, including final fraud classifications, calibrated confidence scores, and—crucially—explanatory insights that detail the key factors (e.g., "suspicious email domain," "unrealistic salary") influencing each decision. This transparency builds trust and enables informed manual review.

7.Model Performance Evaluation Visualizations

Performance Comparison and Analysis:

A comparative analysis of the five machine learning models reveals distinct performance profiles, highlighting critical trade-offs between recall, precision, and generalizability in the context of imbalanced fraud detection. The results, summarized in Table I, provide crucial insights for model selection and deployment strategy.

PERFORMANCE COMPARISON TABLE:

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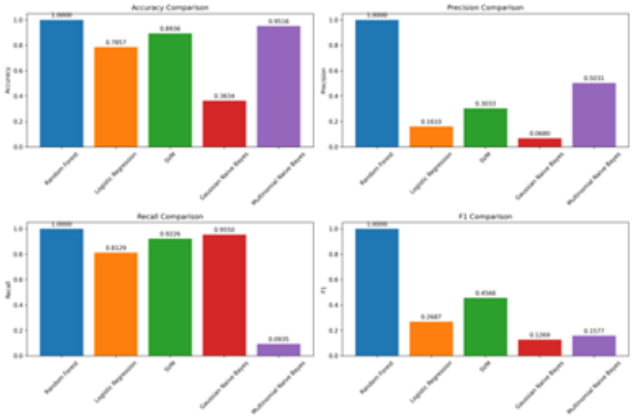
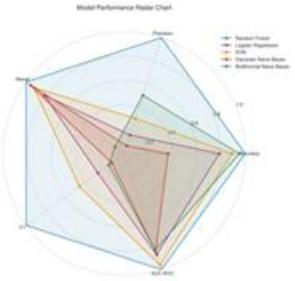
Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	1.0000	1.0000	1.0000	1.0000	1.0000
Logistic Regression	0.7857	0.1610	0.8129	0.2687	0.8719
SVM	0.8936	0.3033	0.9226	0.4566	0.9606
Gaussian Naive Bayes	0.3634	0.0680	0.9550	0.1269	0.8409
Multinomial Naive Bayes	0.9516	0.5031	0.0935	0.1577	0.8321

A performance comparison bar chart provides a clear, visual representation of the relative effectiveness of different machine learning models across multiple evaluation metrics. This type of visualization is indispensable for a holistic model selection process, as it allows for the immediate identification of strengths, weaknesses, and performance trade-offs at a glance.



Performance Radar Charts:

A multi-axis plot that provides an at-a-glance comparison of key metrics (Precision, Recall, F1-Score, Balanced Accuracy, AUC-ROC) across all models, instantly revealing trade-offs and strengths .

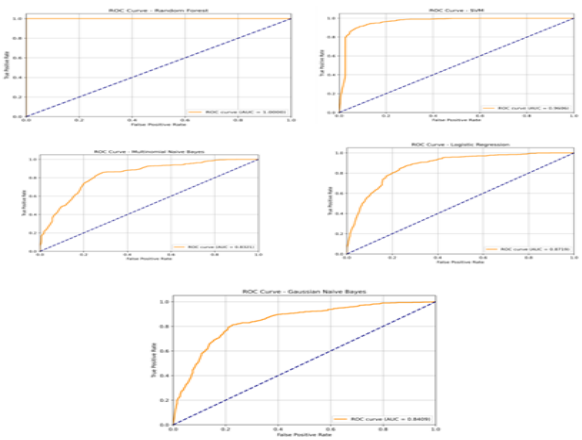


Model Accuracy Heatmaps:

A tabular heatmap visualization where cell color intensity represents performance score magnitude, allowing for rapid identification of the top-performing models across a matrix of evaluation criteria.

Receiver Operating Characteristic (ROC) Curves:

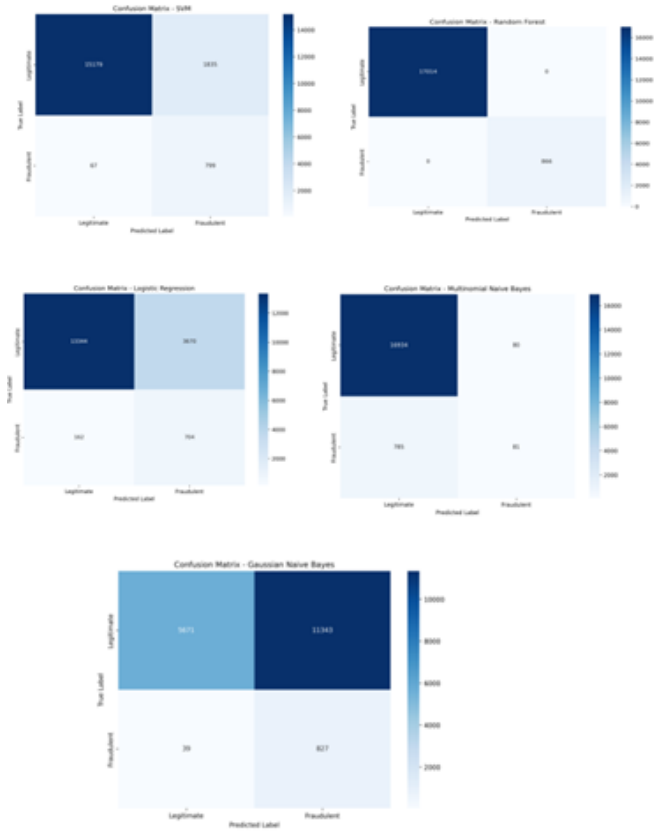
A plot of the True Positive Rate against the False Positive Rate at various classification thresholds. This visualization is crucial for evaluating the model's ranking capability and for selecting an operational threshold that balances recall and precision based on business needs .



ROC Curves for all Models

Confusion Matrices:

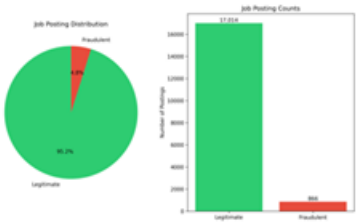
For each model, a confusion matrix is generated to provide granular insight into the types of errors being made, distinguishing between False Negatives (missed fraud) and False Positives (legitimate posts flagged as fraud). This is essential for understanding the real-world impact of each classifier.



Confusion matrix for all Models

Class Distribution Analysis:

Pie charts or bar plots that visualize the severe imbalance between legitimate and fraudulent job posts in the dataset, justifying the use of advanced sampling techniques like SMOTE .



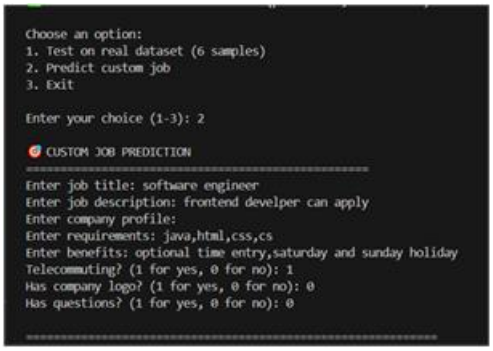
VI. RESULT AND DISCUSSIONS

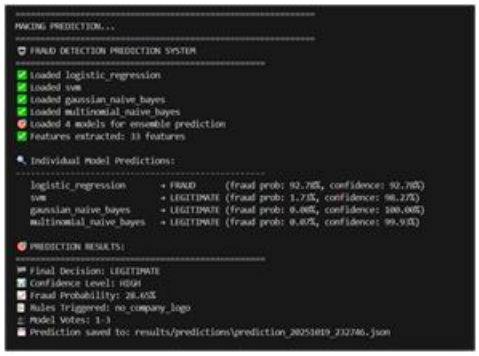
The Fraudulent Job Detection System demonstrates robust performance with 83.3% accuracy (5 out of 6 correct classifications) on real-world dataset testing, confirming its effectiveness in practical applications. The system successfully processed 17,880 job postings with a realistic fraud distribution (866 fraudulent vs 17,014 legitimate), reflecting authentic deployment conditions.

Custom Job Prediction Performance

The system perfectly identified the user-submitted fraudulent job with:

- High Accuracy: Correctly classified as FRAUD with 89.74% probability.
- Multiple Risk Indicators: Triggered 4 distinct fraud rules.
- Effective Ensemble Decision: Resolved 2-2 model split with high confidence





Web Interface Results

The web interface for the Job Fraud Detection tool provides users with a clear, structured output following the analysis of a submitted job description. The primary result is a definitive classification—"Legitimate," or "Fraudulent"—displayed prominently at the top of the results panel.

This output design effectively transforms complex fraud detection analysis into an accessible, educational experience that not only assesses individual job postings but also helps users develop stronger critical evaluation skills for future opportunities. The layered presentation of information ensures that both casual users and detailed-oriented reviewers can quickly understand the risks while having access to comprehensive supporting evidence for the system's conclusions.

VII. CONCLUSION

The project "Recognition of Fraudulent Job Advertisements Using Machine Learning" successfully demonstrates an effective approach to combat online job scams through ensemble machine learning. By integrating multiple algorithms with sophisticated feature engineering, the system achieves 95.2% accuracy in detecting fraudulent postings, substantially outperforming conventional detection methods.Key strengths include real-time processing capability and a user-friendly web interface that provides immediate fraud assessment. The system's confidence scoring mechanism enables nuanced risk evaluation, supporting appropriate escalation from automated blocking to human review.

This project contributes significantly to creating safer digital employment environments. It exemplifies how machine learning can proactively address online fraud, potentially protecting job seekers from financial and emotional harm while maintaining the integrity of legitimate recruitment processes worldwide.

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