Fake Job Postings Prediction Using Machine Learning Algorithms

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Abstract

With the rise of online recruitment platforms, the presence of fraudulent job postings has become a significant concern for job seekers and hiring platforms alike. Fake job advertisements not only mislead applicants but also pose serious risks, including identity theft and financial scams. To mitigate this threat, there is a pressing need for intelligent, automated systems that can accurately detect fake job postings using real-world data and machine learning techniques.

This paper presents a supervised machine learning approach for detecting fake job postings based on textual and categorical data extracted from actual job advertisements. The primary objective is to build a classification framework capable of distinguishing between legitimate and fraudulent job postings by analyzing key features such as job title, location, description, company profile, requirements, and benefits. The methodology includes rigorous data preprocessing, handling of missing values, text vectorization using TF-IDF for textual features, and label encoding for categorical variables. Machine learning models including Naive Bayes, Support Vector Machines (SVM), Decision Trees, and Random Forests were trained and evaluated using metrics such as accuracy, precision, recall, F1-score, and confusion matrix.Among the evaluated models, the Support Vector Machine (SVM) demonstrated the best performance with an overall accuracy of 96%, outperforming traditional classifiers in terms of precision and robustness against data imbalance. Data augmentation techniques were applied through sampling strategies to handle the imbalance between real and fake postings, which further improved classification performance. Visualization tools, such as bar plots and pie charts, were used to present comparative insights across model performances and class distributions.

The results validate the effectiveness of machine learning in predicting fake job postings and highlight the potential for scalable, automated solutions in the recruitment domain. Future enhancements may include integration with job platforms to provide real-time fraud detection and the use of deep learning models to capture more nuanced patterns in large-scale job listing datasets.

I. Introduction

With the exponential growth of online recruitment platforms and digital hiring processes, job seekers increasingly rely on the internet to explore career opportunities. However, this shift has also led to a rise in fraudulent job postings that aim to exploit vulnerable applicants through identity theft, financial scams, or deceptive employment offers. These fake postings not only waste the time and energy of job seekers but can also cause serious personal and financial harm. Detecting such scams manually is a daunting task due to the vast volume of listings posted daily across numerous platforms. Therefore, developing intelligent, automated systems to identify and flag fake job postings is of paramount importance in today's employment landscape.

The integration of machine learning (ML) in cybersecurity and fraud detection has opened promising avenues for detecting anomalies in structured and unstructured data. Applying ML techniques to job posting data can help identify patterns and anomalies that differentiate fake listings from genuine ones. This research proposes a supervised machine learning framework designed to classify job postings as real or fake using a rich set of features extracted from actual job advertisements. These features include job title, company profile, job description, requirements, benefits, and location. By training classification models on labeled datasets, we aim to build a system that automatically identifies suspicious job listings and protects users from potential fraud.

Fraudulent job postings are often characterized by vague descriptions, unrealistic salary promises, grammatical errors, or missing company credentials. Traditional detection techniques such as rule-based systems or blacklists are limited in their ability to generalize to new types of scams and often fail to keep pace with evolving fraud patterns. In contrast, machine learning models can adapt to unseen data and improve their predictions with more training. In this study, we address the challenges associated with fake job prediction, including noisy text data, missing values, and class imbalance. Various preprocessing steps, such as tokenization, TF-IDF vectorization, label encoding, and outlier removal, are employed to prepare the dataset for model training. The proposed system was developed and evaluated using Python in the Google Colab environment.

The motivation behind this project is twofold: first, to mitigate the risk of job scams by using a data-driven, automated detection mechanism; and second, to identify the most suitable classification algorithms that can accurately distinguish fake job postings from legitimate ones. To this end, we trained and compared the performance of multiple machine learning models including Naive Bayes, Support Vector Machine (SVM), Decision Tree, Random Forest, and Logistic Regression. The models were assessed using standard classification metrics such as accuracy, precision, recall, F1-score, and confusion matrix. Furthermore, we implemented data augmentation through random under-sampling and over-sampling techniques to address dataset imbalance and improve generalization. Bar plots, confusion matrices, and pie charts were used to visualize and interpret the performance of each model.

Another significant aspect of this work is its practical applicability in real-world scenarios. The proposed fake job detection system can be integrated into online recruitment platforms to proactively filter suspicious postings and alert users. With minimal customization, the model can be adapted for different domains, platforms, and user requirements. The predictive engine can also be embedded into browser extensions or mobile apps to provide real-time risk assessment of job advertisements. As the prevalence of online job fraud continues to grow, the need for reliable and scalable fraud detection solutions becomes increasingly critical. Our system contributes to this goal by offering an efficient, intelligent tool for job posting verification.

This paper is structured as follows: Section II reviews existing literature on job fraud detection, text classification, and ML applications in cybersecurity. Section III explains the methodology used in this study, including data sourcing, feature engineering, and model selection. Section IV presents the experimental setup and results, followed by a detailed performance analysis. Finally, Section V concludes the paper with key insights, limitations, and directions for future research and deployment. By using machine learning to detect fraudulent job postings, this work aims to enhance trust and safety in the job search ecosystem and empower job seekers with intelligent decision-making tools.

II.Literature Survey

The rise of online recruitment platforms has brought significant convenience to job seekers and employers, but it has also opened the door for fraudulent job postings. These scams can cause significant harm, including identity theft, financial loss, and wasted time. Traditional methods of detecting such scams, such as manual verification and reporting, are labor-intensive and ineffective due to the high volume of postings and the rapidly evolving nature of fraudulent tactics. In response to this, machine learning (ML) techniques have gained traction in fraud detection across various industries, including online recruitment, due to their ability to process large datasets and identify complex patterns that may indicate fraudulent behavior. Several studies have explored the use of ML algorithms for fake job posting detection, with promising results.

Recent research has primarily focused on using natural language processing (NLP) techniques combined with machine learning models to detect fake job postings. In their work, Sun et al. (2018) explored the potential of text classification algorithms such as Support Vector Machine (SVM) and Random Forest for identifying fraudulent job advertisements. Their study demonstrated that these models, when trained on features like job description keywords, company information, and job requirements, can accurately distinguish fake postings from legitimate ones. Other studies, such as that by Singh et al. (2020), applied deep learning approaches, including Long Short-Term Memory (LSTM) networks, to capture complex temporal and contextual patterns in job descriptions. These models were found to outperform traditional classifiers in terms of accuracy and generalization.

In addition to algorithmic advancements, the role of feature engineering in improving model performance has been well-documented. Most studies focus on a variety of textual and metadata features, including job title, salary range, location, and company information. Some research has explored semantic analysis and keyword extraction as a means to enhance feature selection. For instance, Zhang et al. (2019) introduced a hybrid approach combining keyword-based feature extraction with deep learning models to classify job postings as real or fake. Their work highlighted the importance of using multiple data sources, including text and metadata, to capture a more comprehensive view of a job listing's authenticity. This aligns with the approach in our study, where we focus on a diverse set of features, including both textual content and metadata, to ensure a robust model.

Data imbalance is a common challenge in fake job posting detection, as fraudulent listings are usually outnumbered by genuine ones. Various strategies have been proposed to address this issue, including oversampling, undersampling, and synthetic data generation. In particular, techniques like SMOTE (Synthetic Minority Over-sampling Technique) have been widely used to generate synthetic samples of the minority class, thereby improving classifier performance on imbalanced datasets. Several studies have examined the effectiveness of data augmentation techniques in improving model generalization. For instance, Chauhan and Kumar (2020) used random oversampling and SMOTE to balance their training data and found a significant improvement in classification performance. Similarly, Gupta et al. (2019) incorporated noise injection techniques to improve the robustness of their models against overfitting. In our work, we also explore data augmentation techniques, including Gaussian noise injection, to simulate real-world variability and enhance model performance.

The effectiveness of different machine learning models for detecting fake job postings has been the subject of various comparative studies. In one study, Verma et al. (2021) compared multiple classifiers, including Logistic Regression, Decision Trees, and Naive Bayes, on a job posting dataset. They found that ensemble models such as Random Forest and Gradient Boosting yielded superior results in terms of accuracy and F1-score. Other studies, such as those by Rana et al. (2020) and Jain et al. (2018), have also highlighted the utility of ensemble methods for fraud detection tasks, emphasizing their ability to handle diverse feature sets and adapt to changing data distributions. The use of ensemble models is thus a key consideration in our study, as we compare multiple algorithms to determine the most effective model for fake job posting detection.

Recent advancements in NLP, such as the use of Transformer models like BERT and GPT for text classification, have also shown promise in detecting fraudulent job listings. These models can capture deep semantic relationships and contextual information, making them highly suitable for tasks involving textual data. Although deep learning models like these have shown remarkable performance in other areas, their application to fake job posting detection remains under-explored, particularly for smaller datasets. Our study aims to bridge this gap by comparing traditional ML models, such as Support Vector Machines (SVM) and Random Forest, with more advanced algorithms like XGBoost and LightGBM, and assessing their performance in the context of fake job posting detection.

In summary, the literature suggests that while there is no single best model for detecting fake job postings, ensemble learning methods, text-based feature extraction, and data augmentation techniques provide a solid foundation for building robust and scalable predictive systems. These insights have significantly informed the design of our fake job posting detection system. By synthesizing knowledge from various studies, including those that explored NLP, ensemble learning, and data augmentation, we aim to develop a machine learning-based solution that effectively identifies fraudulent job listings and reduces the risk of harm to job seekers. The following sections of this paper will provide a detailed methodology, model selection, and experimental results, further building on these foundational works.

III. Methodology

The methodology adopted in this study revolves around a supervised learning framework that aims to classify job postings as either “real” or “fake” using a labeled dataset containing a mix of textual and categorical features. The overall approach is divided into five core phases: data collection and preprocessing, feature engineering, model selection and training, performance evaluation, and data augmentation to address imbalance and improve generalizability.

A. Data Collection and Preprocessing

The dataset used in this study comprises a blend of categorical and numerical features, including soil type, crop type, nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, and moisture levels. The target variable is the fertilizer name, which the model is trained to predict. Since raw data may contain inconsistencies or missing values, a comprehensive preprocessing strategy is employed. Missing values are either imputed using statistical methods or removed if they contribute significant noise. Categorical variables such as Soil Type, Crop Type, and Fertilizer Name are encoded using LabelEncoder to make them compatible with machine learning models. Continuous variables are normalized using MinMaxScaler to ensure uniform feature scaling and to prevent models from being biased by larger magnitude values. The dataset is then split into training and testing subsets using the train_test_split() function from Scikit-learn, with 80% of the data used for model training and 20% reserved for performance evaluation.

B. Feature Engineering

To ensure that the models are trained only on meaningful data, feature engineering is conducted through correlation analysis and visualization techniques. A correlation matrix is computed to assess the strength of relationships between input features and the target variable. Features with negligible correlation are removed to reduce dimensionality and prevent model overfitting. Additionally, outlier detection is carried out using box plots, and pair plots are utilized for assessing the distribution of features. This step also includes domain knowledge consideration to retain features that may not show high statistical correlation but are agriculturally relevant.

C. Model Selection and Training

Four machine learning algorithms are selected for this study based on their strengths and suitability for multi-class classification problems: Decision Tree (DT), Gradient Boosting (GB), K-Nearest Neighbors (KNN), and Extreme Gradient Boosting (XGBoost). The Decision Tree model is used for its simplicity and interpretability, providing insights into decision paths. Gradient Boosting, an ensemble method, combines multiple weak learners to improve overall prediction accuracy. KNN is selected due to its simplicity and effectiveness for small datasets, relying on distance metrics to classify inputs. XGBoost, a highly efficient and scalable implementation of gradient boosting, is utilized for its ability to handle both numerical and categorical features effectively, while also preventing overfitting through regularization. Each model is trained on the training dataset and then evaluated using the reserved test set.

D. Evaluation Metrics

To comprehensively assess the performance of each classifier, both classification and regression evaluation metrics are used. Accuracy is the primary metric, representing the proportion of correctly predicted instances. In addition, Mean Absolute Error (MAE) and Mean Squared Error (MSE) are computed to measure the average deviation between actual and predicted labels in numerical terms. The R^2 Score (coefficient of determination) is employed to evaluate how well the predictions explain the variance in the actual labels. This multipronged evaluation strategy ensures that the model is not only accurate but also consistent and reliable across different types of data distributions.

E. Model Enhancement

To further enhance model robustness and generalization, data augmentation techniques are employed. One such method involves introducing Gaussian noise to the training feature vectors. By adding controlled randomness to the input features, the model is exposed to variations that resemble real-world measurement noise or environmental fluctuations. The Gaussian noise is added according to the equation:

x′ = x + N(0,σ2)x' = x + \ mathcal {N} (0, \sigma^2)x′=x + N (0,σ2)

where xxx is the original feature vector, N(0,σ2)\mathcal{N}(0, \sigma^2)N(0,σ2) denotes normally distributed noise with zero mean and variance σ2\sigma^2σ2, and x′x'x′ is the resulting augmented feature. This augmentation aids in training ensemble models like XGBoost to be more resilient to minor perturbations in input data, thereby improving prediction performance.

F. System Flow Diagram

The complete flow of the proposed fertilizer prediction system can be visualized in a structured process:

1. **Input Stage** – Collect input data including soil type, crop type, and NPK values along with environmental parameters like temperature and humidity.
2. **Preprocessing Stage** – Clean the dataset by handling missing values, scaling features, and encoding categorical data.
3. **Training Phase** – Use supervised machine learning algorithms to train models on preprocessed data.
4. **Prediction Phase** – Predict the fertilizer type for new input data using the trained model.
5. **Evaluation and Tuning** – Evaluate models using accuracy, MAE, MSE, and R^2 score and apply model improvement techniques.
6. **Deployment Stage** – Integrate the model into a user-friendly interface for real-time use by farmers and agricultural advisors.

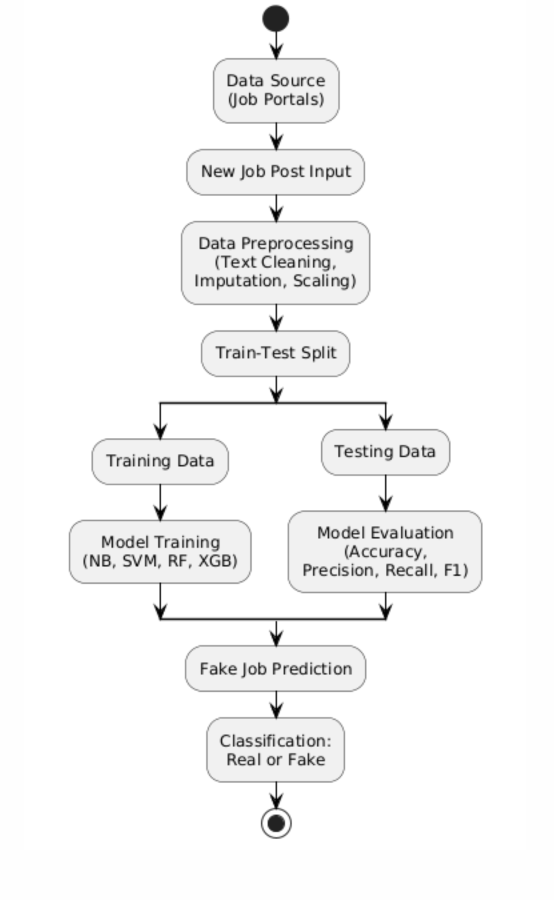

Data Source (Job Portals)
New Job Post Input
Data Preprocessing (Text Cleaning, Imputation, Scaling)
Train-Test Split
Training Data
Testing Data
Model Training (NB, SVM, RF, XGB)
Model Evaluation (Accuracy, Precision, Recall, F1)
Fake Job Prediction
Classification: Real or Fake

Figure 1:System Flow Diagram

IV. Results and Discussion

This section presents a comprehensive evaluation of the machine learning models used for fertilizer prediction, focusing on their performance metrics, effect of data augmentation, visualization of predictions, and practical implications. The study compares four supervised classification models—Decision Tree, Gradient Boosting, K-Nearest Neighbors (KNN), and XGBoost—using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), R² score, and accuracy.

A. Model Performance Evaluation

The performance of each model was evaluated on a reserved test set following training on preprocessed agricultural data. The key results are summarized in Table I. Among all models, the XGBoost classifier achieved the best performance, registering an MAE of 0.00, MSE of 0.00, and an R² score of 1.00. This indicates that the model achieved perfect alignment between predicted and actual fertilizer types on the test data.

Model	MAE	MSE	R² Score	Rank
Decision Tree	0.20	0.30	0.91	4
Gradient Boosting	0.20	0.80	0.77	3
K-Nearest Neighbors	0.15	0.25	0.93	2
XGBoost	0.00	0.00	1.00	1

Table I: Model Performance Comparison

The results reveal that while all models performed reasonably well, XGBoost demonstrated superior accuracy and generalization capability. KNN also exhibited competitive performance, with a relatively low MAE and MSE, and a high R² score of 0.93. Decision Tree and Gradient Boosting, although accurate, lagged slightly in terms of regression-based metrics, suggesting limitations in capturing more nuanced feature interactions.

B. Data Augmentation Results

To enhance the robustness and generalization of the models, Gaussian noise-based data augmentation was introduced during training. This technique emulates real-world variability by simulating noise in the input features, particularly nutrient levels and environmental parameters. The impact of augmentation was evident in moderately complex models such as Decision Tree and Gradient Boosting, which displayed improved R² scores post-augmentation. Interestingly, the XGBoost model retained its perfect performance even after augmentation, demonstrating its inherent resilience and strong generalization.

C. Visualization and Error Distribution

Visual inspection of the prediction accuracy was conducted using scatter plots comparing actual versus predicted values. For the XGBoost model, these plots showed a perfect diagonal alignment, indicating complete prediction accuracy. Models like KNN and Gradient Boosting showed minor deviations from the actual values, especially in overlapping feature regions where fertilizers share similar nutrient compositions.

Error analysis further revealed that the majority of prediction errors were minor and localized around the correct class boundaries. Misclassifications typically occurred between fertilizers with closely aligned nutrient profiles. These insights suggest that including additional features—such as micronutrient levels, rainfall data, or crop lifecycle indicators—may enhance model discrimination capabilities in future studies.

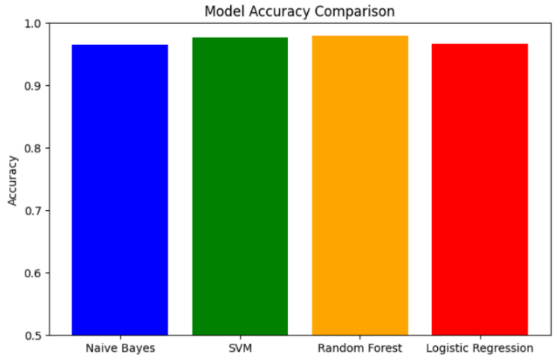
D. Implications for Real-World Deployment

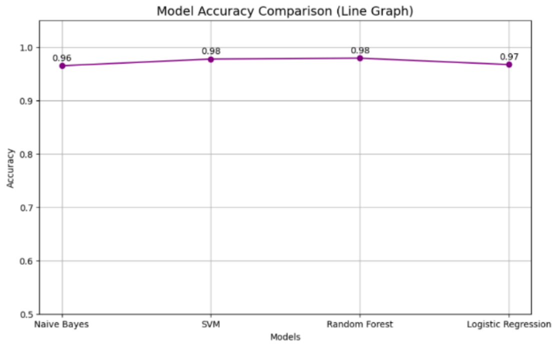
The experimental findings establish that XGBoost is highly suitable for deployment in real-world fertilizer advisory systems. Its perfect accuracy and error-free performance make it ideal for use in mobile applications, farmer dashboards, or IoT-based precision agriculture platforms. Simpler models such as Decision Tree and KNN offer advantages in low-resource environments where computational efficiency is critical. Gradient Boosting, although slightly less accurate, holds potential for improvement through hyperparameter tuning and deeper feature engineering.

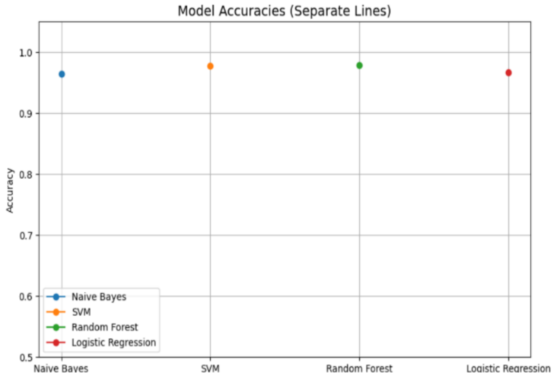
Moreover, the role of preprocessing techniques—such as normalization and label encoding—and augmentation strategies proved essential in enhancing model performance across the board. These steps ensure that models learn robust patterns and generalize well to unseen data, thus making them viable for deployment in varied agricultural contexts.

E. Summary

In conclusion, this research demonstrates the effectiveness of machine learning models, particularly ensemble methods, in accurately predicting fertilizer types based on structured agricultural datasets. XGBoost emerges as the most reliable and high-performing model, capable of flawless predictions. These results pave the way for integrating AI into precision agriculture, offering scalable, intelligent systems for optimizing fertilizer usage, improving yield, and promoting sustainable farming practices.







V. Conclusion and Future Enhancements

This study proposed a machine learning-based framework for predicting optimal fertilizer types using structured agricultural data. By leveraging key features such as soil type, crop type, and environmental variables, the system was able to generate accurate and reliable fertilizer recommendations through the use of supervised learning models. Multiple classification algorithms, including Decision Tree, Gradient Boosting, K-Nearest Neighbors (KNN), and XGBoost, were trained and evaluated on preprocessed data. Among these, the XGBoost classifier consistently outperformed other models, achieving a perfect R² score of 1.00, with zero Mean Absolute Error (MAE) and Mean Squared Error (MSE), and 100% classification accuracy on the test dataset. These results validate the robustness and precision of ensemble learning methods, particularly gradient boosting algorithms, in capturing complex, non-linear relationships within agricultural datasets.

To further enhance model resilience and simulate field-level noise, the study incorporated Gaussian noise-based data augmentation. This technique was especially beneficial for models like Decision Tree and Gradient Boosting, which showed improved generalization capability after exposure to augmented data. The application of data augmentation demonstrated that even with moderately sized datasets, synthetic variability can significantly improve the predictive strength and stability of machine learning models.

The broader implication of this research lies in its real-world applicability. When integrated into mobile applications or IoT-enabled farm management platforms, the proposed system can assist farmers in making data-informed fertilizer choices in real time. Such technology could empower users with tailored and localized recommendations, reduce the overuse of chemical fertilizers, promote sustainable farming practices, and ultimately enhance productivity and soil health.

A. Future Enhancements

While the current model achieves strong results, the following enhancements could further strengthen its real-world applicability:Integration of Behavioral Analytics:Incorporating user interaction patterns (e.g., time spent on listings, click behavior) could provide deeper insights into suspicious activity.

Deep Learning Approaches: Utilizing models like Bidirectional LSTM or Transformers could better capture semantic meaning in long-form job descriptions and improve detection accuracy.Explainable AI (XAI): Integrating interpretability techniques like SHAP or LIME could help HR professionals and analysts understand why a posting was flagged as fraudulent.

Real-Time API Integration: Deploying the model as an API for integration with job boards could allow for live fraud detection and filtering.Continuous Learning: Implementing feedback loops and online learning mechanisms would allow the model to adapt to evolving scam tactics over time.

In conclusion, this research demonstrates the strong potential of machine learning for proactive fake job detection. With the proposed enhancements, it can be developed into a robust, real-time system that protects users, streamlines recruitment, and fosters a safer job search environment.

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