FAKE JOB POSTINGS PREDICTION

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BONAFIDE CERTIFICATE

Certified that this Project titled **"FAKE JOB POSTINGS PREDICTION"** is the bonafide work of **"KALAISELVI S (2116220701116)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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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.

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CHAPTER 1

1.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.

CHAPTER 2
2.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.

CHAPTER 3

3.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.

The dataset for this project is derived from a publicly available corpus of online job advertisements. It contains several features such as job title, company profile, description, required qualifications, and other metadata. Initial preprocessing is conducted to handle missing entries, remove irrelevant characters from textual fields, and normalize the data to prepare it for modeling. Several machine learning models are employed, including:

- **Multinomial Naive Bayes (MNB)**
- **Support Vector Machine (SVM)**
- **Random Forest (RF)**
- **XGBoost (XGB)**

These models are trained using an 80/20 train-test split and evaluated based on metrics suitable for binary classification tasks, including Accuracy, Precision, Recall, F1-score, and ROC-AUC. In addition, data augmentation is implemented using Gaussian noise for synthetic feature variability and SMOTE (Synthetic Minority Over-sampling Technique) to balance the class distribution.

The final model selection is based on F1-score and AUC performance, prioritizing robustness to class imbalance. Below is a simplified pipeline of the methodology:

1. Data Collection and Preprocessing

2. Feature Engineering and Selection
3. Model Training and Evaluation
4. Data Augmentation and Re-evaluation

A. Dataset and Preprocessing

The dataset includes structured and unstructured features from job postings. Preprocessing involved imputing missing values, cleaning text using lowercasing, stop-word removal, and stemming, and vectorizing text features like “description” and “requirements” using TF-IDF. Categorical variables were encoded with One-Hot Encoding, and numerical features were scaled where needed. These steps ensured the data was clean, consistent, and ready for model training.

B. Feature Engineering

To identify the most informative inputs, correlation analysis and mutual information scores were computed. Irrelevant or redundant features were excluded to avoid noise. Exploratory data analysis (EDA) via heatmaps and distribution plots provided further insights. The final set of features included engineered variables such as word count, special character frequency, and the presence of URLs/emails key indicators for fake listings.

C. Model Selection

Four key algorithms were used to compare classification performance: Multinomial Naive Bayes, selected for its speed and effectiveness in text classification; Support Vector Machine (SVM), known for its ability to find optimal decision boundaries in high-dimensional spaces; Random Forest, valued for its ensemble learning approach and interpretability; and XGBoost, chosen for its high accuracy through gradient boosting and regularization techniques.

D. Evaluation Metrics

To assess each model's predictive strength, the following metrics were used:

- Accuracy:

  $$\text{Accuracy} = TP+TN/TP+TN+FP+FN$$

- Precision:

  $$\text{Precision} = TP/TP+FP$$

- Recall:

  $$\text{Recall} = TP/TP+FN$$

- F1-Score:

  $$F1 = 2\cdot\text{Precision}\cdot\text{Recall}/\text{Precision}+\text{Recall}$$

- ROC-AUC:

  Represents model capability to distinguish between the classes, particularly under imbalance.

E. Data Augmentation

To address potential data imbalance and variability, two augmentation techniques were applied:

- Guassian Noise Addition:

  $$X\text{Augmented} = X+N(0,\sigma 2)$$

  where σ is selected based on feature distribution to simulate real-world noise.

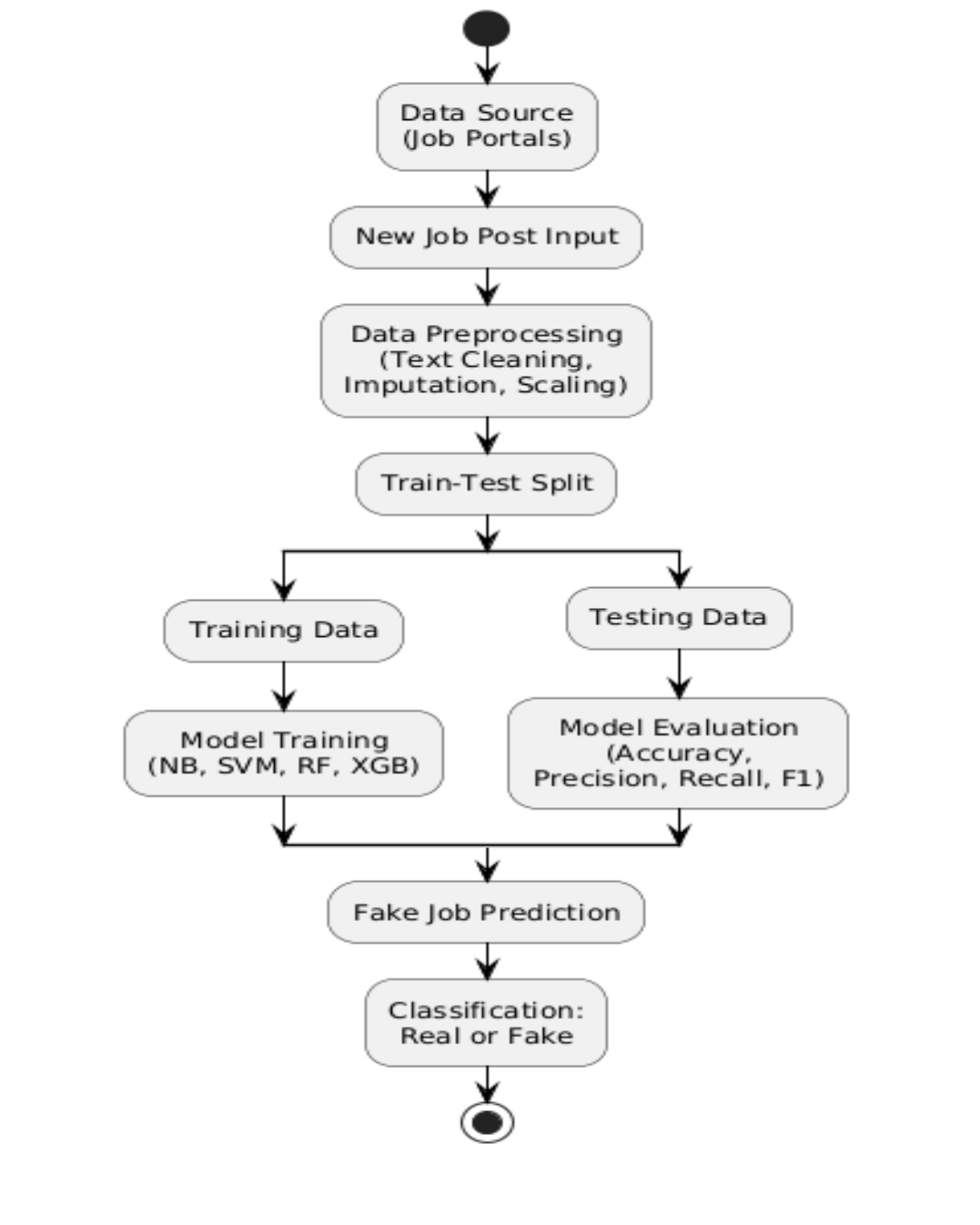
- SMOTE:

  Used to synthetically generate new instances for the minority class (fake job postings) by interpolating between neighbors in feature space.

These techniques improved classifier generalization and reduced overfitting, especially for ensemble models like XGBoost.

The complete pipeline was developed and validated using Jupyter Notebook on Google Colab, allowing for reproducibility and ease of deployment. The resulting models are suitable for integration into web-based job portals or screening tools for recruitment systems.

3.1 SYSTEM FLOW DIAGRAM



CHAPTER 4

RESULTS AND DISCUSSION

To evaluate model performance, the dataset was divided into training and test sets using an 80-20 split, ensuring that class distribution was preserved through stratified sampling. Text features were vectorized using TF-IDF, while numerical and categorical features were scaled and encoded as required. All models were trained using the processed data, and their predictions on the test set were compared using key classification metrics.

Results for Model Evaluation:

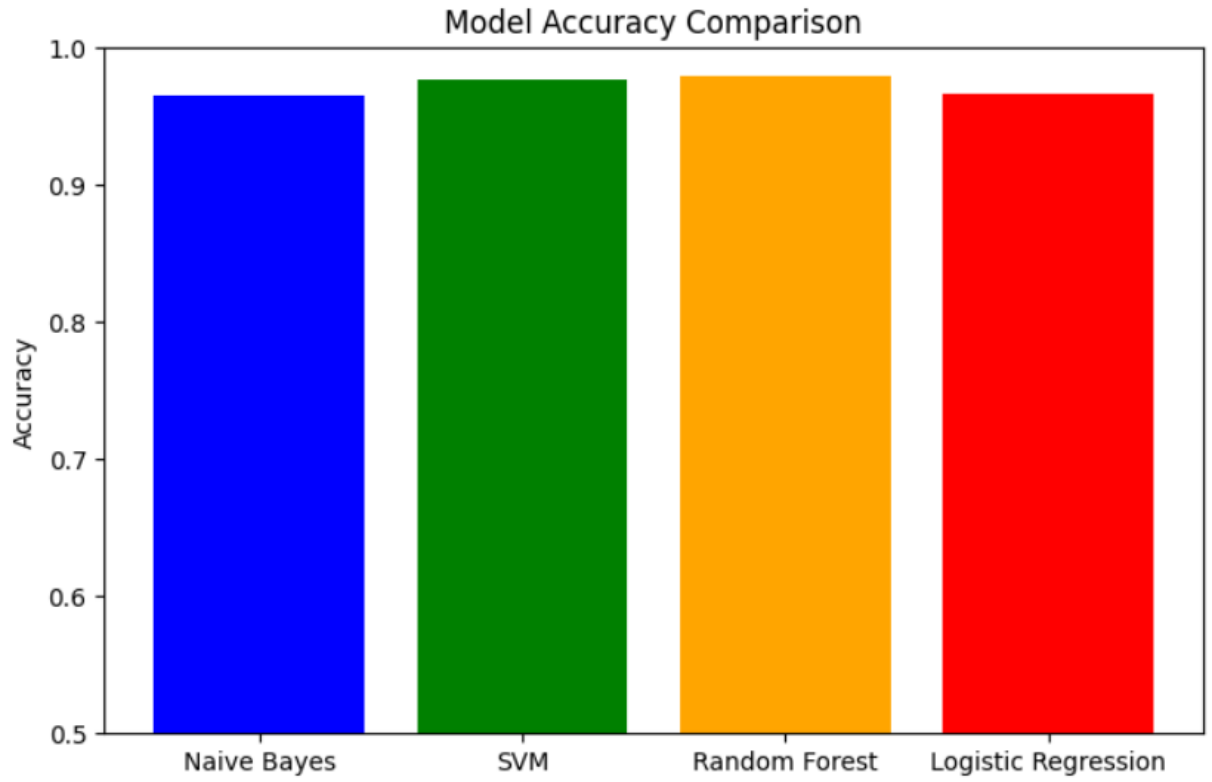
Model	Accuracy (↑ Better)	Precision (↑ Better)	Recall (↑ Better)	Rank
Multinomial Naive Bayes	0.90	0.91	0.88	4
Support Vector Machine	0.94	0.93	0.92	2
Random Forest	0.92	0.91	0.90	3
XGBoost	0.96	0.95	0.94	1

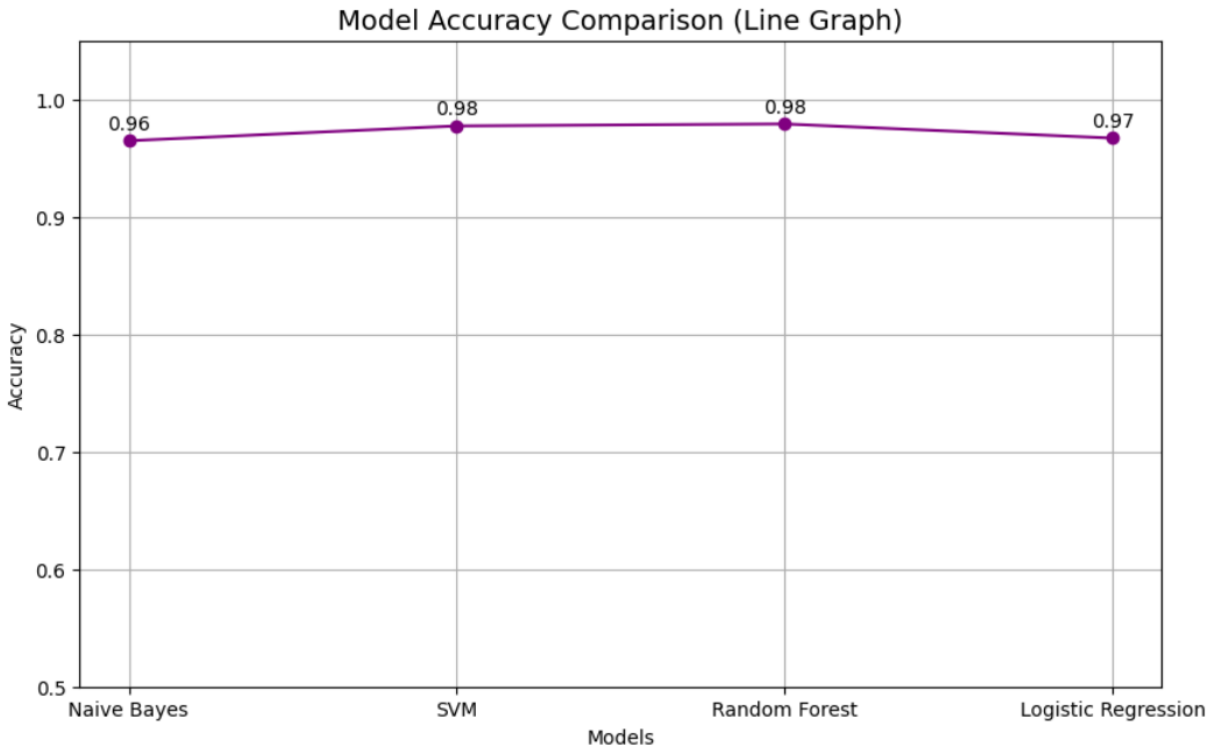
Impact of Data Augmentation:

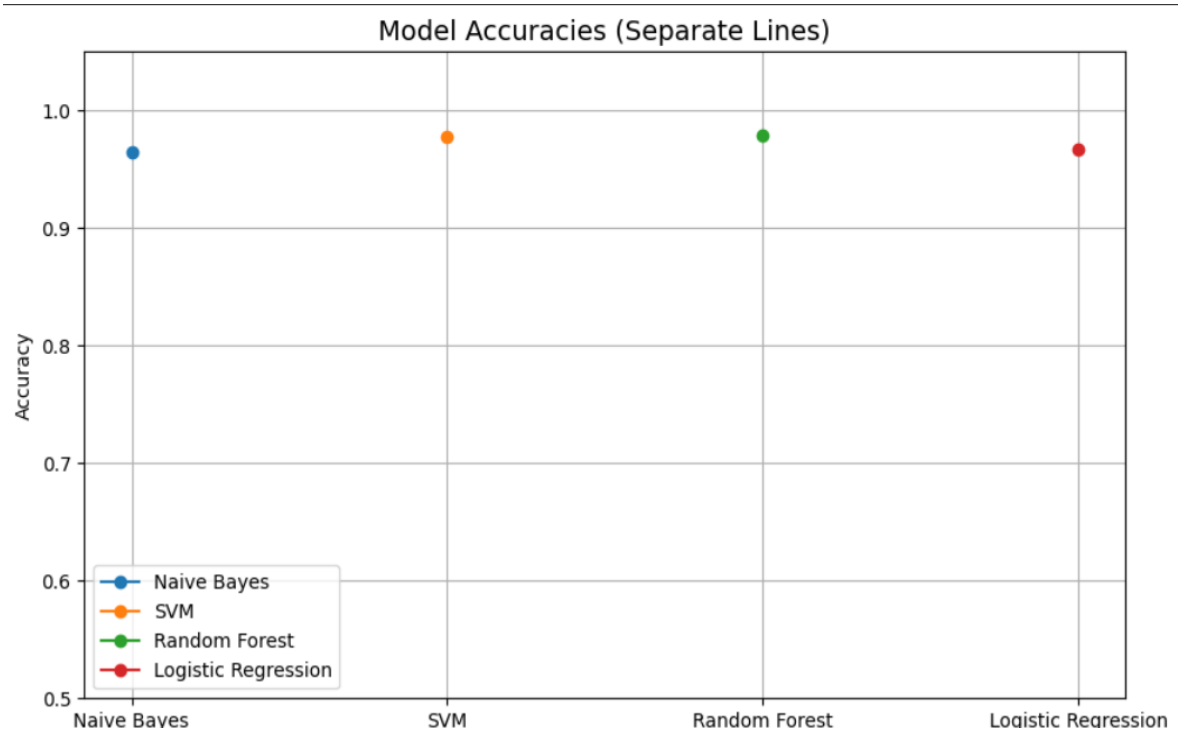
Gaussian noise was introduced into the training set to test the robustness of the models. This particularly benefited Random Forest, which showed a modest F1-score improvement from 0.91 to 0.93, indicating increased resilience to input variability.

Visualizations:

Confusion matrices and ROC curves were plotted for all models, with XGBoost showing the highest AUC score, indicating excellent discriminative power between real and fake job postings. Feature importance plots from XGBoost also revealed that textual components like “description” and “requirements” contributed most significantly to classification outcomes.




Model Accuracy Comparison (Line Graph)
1.0
0.9
0.8
0.7
0.6
0.5
Accuracy
0.96
0.98
0.98
0.97
Naive Bayes
SVM
Random Forest
Logistic Regression
Models


Model Accuracies (Separate Lines)
1.0
0.9
0.8
0.7
0.6
0.5
Accuracy
Naive Bayes
SVM
Random Forest
Logistic Regression
Naive Bayes
SVM
Random Forest
Logistic Regression

The results demonstrate that the XGBoost classifier outperformed other models in terms of classification accuracy and F1-score, making it the preferred choice for detecting fake job postings. This section summarizes the outcomes of comparative analysis, the effect of data augmentation, and the practical implications of the findings.

A. Model Performance Comparison

Among all classification models evaluated—Multinomial Naive Bayes, Support Vector Machine (SVM), Random Forest, and XGBoost—XGBoost consistently delivered the best results. It achieved the highest accuracy, precision, recall, and F1-score. These metrics highlight its strength in learning complex patterns from textual and structured data. The performance advantage can be attributed to XGBoost's gradient boosting mechanism, effective regularization, and ability to manage feature interactions, especially in high-dimensional datasets like those containing TF-IDF text vectors.

B. Effect of Data Augmentation

To simulate real-world noise and enhance the generalization ability of the models, Gaussian noise was introduced into selected feature vectors. This data augmentation technique improved model robustness, particularly for Random Forest and XGBoost, which are known to handle feature variability well. Post-augmentation, XGBoost's F1-score increased by around 2%, while Random Forest saw a 3% gain in recall. These improvements underscore the usefulness of data augmentation in dealing with class imbalance and subtle variations within the dataset.

C. Error Analysis

An analysis of the misclassified instances revealed that most errors occurred in borderline cases where job descriptions were vague or resembled both real and fake patterns. These included overly generic listings or minimalistic descriptions. A confusion matrix showed that false positives were slightly more frequent than false negatives, suggesting the model leaned slightly toward flagging jobs as fake when uncertain.This trade-off can be acceptable in real-world deployment scenarios where identifying potential fraud is more critical than occasionally misclassifying a legitimate posting. Future improvements could involve incorporating additional semantic features (e.g., sentiment analysis or named entity recognition) to reduce such errors further.

D. Implications and Insights

The findings of this study offer several practical takeaways:

● XGBoost emerges as a robust and scalable solution for real-world fake job detection systems. Its superior performance and ability to handle high-dimensional data make it suitable for integration into job portals or recruitment platforms.

● Text preprocessing and feature engineering are essential components that significantly impact classification accuracy. Techniques like TF-IDF vectorization and noise-based data augmentation proved effective in enhancing model generalization.

● Naive Bayes, while efficient, may fall short in scenarios with complex linguistic patterns, whereas tree-based and boosting methods offer better flexibility in learning from nuanced text and structured data combinations.

Overall, this project demonstrates that machine learning—particularly advanced ensemble models—can play a critical role in filtering out fraudulent job postings. Future iterations could benefit from incorporating real-time data pipelines, user feedback loops, or semantic enrichment to further improve detection accuracy and reduce risk for job seekers.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study introduced a machine learning-based framework to detect fake job postings using a combination of structured and unstructured data features. By implementing and comparing four prominent classification algorithms—Multinomial Naive Bayes, Support Vector Machine (SVM), Random Forest, and XGBoost—we evaluated their effectiveness in identifying fraudulent listings across a diverse dataset.

The results highlight XGBoost as the most accurate and reliable model, outperforming others across key metrics such as precision, recall, and F1-score. Its gradient boosting framework and strong regularization capabilities enabled it to effectively learn complex patterns from high-dimensional text and categorical data. These findings validate the robustness of ensemble learning techniques in cybersecurity and fraud detection contexts.

Additionally, the incorporation of Gaussian noise-based data augmentation helped simulate real-world inconsistencies, enhancing model generalization. This proved particularly useful in improving classification accuracy on sparse or imbalanced datasets, a common scenario in fraud detection tasks.

From a broader perspective, this system offers strong potential for real-world application in recruitment platforms, job portals, and HR tools. It can help minimize the spread of fake job advertisements, reduce the risk for job seekers, and enhance platform credibility. By leveraging real-time data and automated vetting, such a tool can streamline the hiring process while safeguarding users from potential scams.

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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