

FAKE JOB POSTING PREDICTION

A Project Report

CS19643 – FOUNDATIONS OF MACHINE LEARNING

Submitted by

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BONAFIDE CERTIFICATE

Certified that this Project titled **“FAKE JOB POSTING PREDICTION”** is the bonafide work of **“RAKHUL PRAKASH S B (2116220701216)”** 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

Sleep plays a critical role in human health, cognitive performance, and emotional well-being. With the increasing prevalence of sleep disorders and lifestyle-induced sleep disruptions, there is a growing need for intelligent systems capable of analyzing and predicting sleep quality using accessible data sources.

This paper proposes a machine learning-based solution to predict the quality of sleep patterns using real-world data and a range of supervised learning algorithms. The primary objective is to develop a predictive framework that not only evaluates the effectiveness of various machine learning models but also incorporates data enhancement strategies to address common challenges such as noise, imbalance, and limited feature diversity. Our system was developed and evaluated using a dataset comprising several key features affecting sleep quality, such as sleep duration, frequency of awakenings, and other related physiological and behavioral factors. The methodology included comprehensive data preprocessing, normalization, feature selection, and model training using algorithms like Linear Regression, Random Forest Regressor, Support Vector Machines (SVM), and XGBoost. Standard performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and the R^2 score were used to evaluate and compare the models.

Among the tested algorithms, XGBoost demonstrated superior performance with the highest predictive accuracy and robustness, achieving an R^2 score of 0.87. Additionally, Gaussian noise-based data augmentation was applied to simulate real-world variations in input data and to improve the generalizability of the models. This augmentation step yielded measurable improvements in model accuracy, particularly for ensemble models like Random Forest and XGBoost. The experimental results strongly indicate that machine learning techniques, when appropriately tuned and supported by effective preprocessing and augmentation strategies, can provide reliable insights into individual sleep quality. This research highlights the potential for scalable, automated systems capable of supporting personalized health monitoring and sleep management. Future work could integrate this predictive framework into wearable devices and mobile applications for real-time feedback and sleep optimization.

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TABLE OF CONTENT

| CHAPTER NO | TITLE | PAGE NO |
|-------------------|------------------------------------|----------------|
| | ABSTRACT | 2 |
| 1 | INTRODUCTION | 7 |
| 2 | LITERATURE SURVEY | 9 |
| 3 | METHODOLOGY | 11 |
| 4 | RESULTS AND DISCUSSIONS | 14 |
| 5 | CONCLUSION AND FUTURE SCOPE | 18 |
| 6 | REFERENCES | 20 |

LIST OF ABBREVIATIONS

| S. NO. | ABBREVIATION | ACRONYM |
|--------|----------------|--|
| 1 | ML | Machine Learning |
| 2 | RF | Random Forest |
| 3 | SVM | Support Vector Machine |
| 4 | XGBoost | Extreme Gradient Boosting |
| 5 | CV | Cross-Validation |
| 6 | TF-IDF | Term Frequency-Inverse Document Frequency |
| 7 | ROC | Receiver Operating Characteristic |
| 8 | AUC | Area Under the Curve |
| 9 | MAE | Mean Absolute Error |
| 10 | MSE | Mean Squared Error |
| 11 | R ² | R-squared (Coefficient of Determination) |
| 12 | OOB | Out-of-Bag |
| 13 | F1-Score | Harmonic Mean of Precision and Recall |
| 14 | TP | True Positive |
| 15 | TN | True Negative |
| 16 | FP | False Positive |
| 17 | FN | False Negative |
| 18 | EDA | Exploratory Data Analysis |
| 19 | NLP | Natural Language Processing |
| 20 | WordCloud | Visualization Technique for Term Frequency |

LIST OF FIGURES

| FIGURE NO | TITLE | PAGE NUMBER |
|-----------|---------------------------------|-------------|
| 3.A | Data Segregation | 11 |
| 3.I | System Flow Diagram | 14 |
| 3.II | Sequence Diagram | 15 |
| 3.III | Architecture Diagram | 15 |
| 4.I | WordCloud-Fig 1 | 15 |
| 4.II | WordCloud-Fig 2 | 16 |
| 4.A | Confusion Matrix | 18 |
| 4.B | ROC & Precision Recall Curve | 19 |
| 4.C | Homepage Screenshot - 1 | 23 |
| 4.D | Homepage Screenshot - 2 | 23 |
| 4.E | Prediction Result | 24 |

CHAPTER 1

1. INTRODUCTION

In the current digital age, online job portals have become a primary medium for employment opportunities. However, this has also led to an alarming rise in fraudulent job postings, which exploit job seekers by luring them with misleading offers. These deceptive practices not only harm individuals financially and emotionally but also damage the reputation of legitimate job portals. To combat this growing issue, there is a pressing need for intelligent systems that can detect and filter out fake job postings before they reach potential applicants.

Traditional approaches to identifying fraudulent job ads often rely on manual verification or rule-based systems. However, such methods are labor-intensive, error-prone, and incapable of scaling to meet the demands of rapidly growing job databases. Machine learning (ML), especially when combined with natural language processing (NLP), offers a promising alternative by automatically analyzing job descriptions and identifying patterns commonly associated with scams.

This research focuses on the development of a machine learning-based system that classifies job postings as either legitimate or fraudulent. Using a labeled dataset, the system leverages text-based features, categorical variables, and behavioral indicators such as suspicious keywords and embedded links to build a predictive model. The objective is to provide job seekers and platform administrators with an effective tool to flag potentially malicious postings and thereby improve the overall trust in digital recruitment platforms.

To achieve this, the dataset was first cleaned and preprocessed using techniques such as regular expression-based text cleaning, imputation of missing values, and normalization of categorical fields. Several textual attributes, including job title, description, requirements, and benefits, were combined into a single ‘text’ feature and vectorized using the Term Frequency-Inverse Document Frequency (TF-IDF) approach. Additionally, handcrafted features such as the number of suspicious words, presence of links, and title length were engineered to enhance model accuracy.

The machine learning model was developed using a pipeline that combines preprocessing with a Random Forest Classifier. To address class imbalance—since fake postings are relatively fewer than genuine ones—RandomOverSampler was used to balance the training data. The model was trained and evaluated using standard classification metrics such as Precision, Recall, F1-Score,

and Accuracy.

The system was further encapsulated into a reusable prediction pipeline capable of analyzing new job postings in real-time. This allows for easy integration into job portal platforms, where incoming listings can be automatically screened before publication. The model's robustness, interpretability, and adaptability make it well-suited for real-world deployment.

This paper is structured as follows: Section II reviews the existing research in fraudulent content detection and job post classification using machine learning. Section III explains the methodology, including data preparation, feature extraction, oversampling techniques, model architecture, and pipeline design. Section IV presents the experimental results and performance analysis. Section V concludes the paper with a discussion of the project's implications and suggestions for future enhancements.

In summary, this project demonstrates the practical utility of machine learning in detecting fake job postings. By automating fraud detection, it not only reduces the burden on human moderators but also protects job seekers from scams—paving the way for safer and more reliable online recruitment experiences.

CHAPTER 2

2.LITERATURE SURVEY

The intersection of cybersecurity, data science, and employment platforms has spurred a growing body of research focused on the detection of fake job postings using machine learning. As online recruitment continues to scale, so does the volume of deceptive and fraudulent job advertisements designed to exploit job seekers. Traditional keyword-based filters and manual moderation have proven inadequate in identifying increasingly sophisticated scams, leading to the rise of intelligent, data-driven solutions. This literature review explores key studies in fake job detection, supervised learning methodologies, and ensemble model architectures, all of which inform the design of the proposed system.

Several early efforts in job post verification have relied on natural language processing (NLP) techniques to extract syntactic and semantic cues from job descriptions. Kumar and Bhatia (2016) employed decision tree classifiers on labeled job datasets to detect anomalies in job content, such as vague qualifications and missing company details. However, decision trees are known to suffer from overfitting, especially on small or noisy datasets, which limits their reliability in dynamic online environments. To address these shortcomings, more recent studies have transitioned toward ensemble methods such as Random Forest and Gradient Boosting.

Shashank et al. (2018) introduced a hybrid approach using TF-IDF feature extraction combined with Random Forest classification to distinguish fake and real job posts. Their model showed notable improvements in accuracy and generalization, particularly when textual features were combined with metadata like job location and salary range. In a similar vein, Ramya et al. (2019) compared Support Vector Machines (SVM) with ensemble learners and found that Random Forests outperformed other models in terms of both precision and recall, attributing this to the model's ability to reduce variance and handle high-dimensional input features.

In the broader domain of fraud detection, ensemble learning techniques such as Random Forests, AdaBoost, and XGBoost have shown consistent performance across a range of binary classification tasks. Breiman's (2001) foundational work on Random Forests established the model as a robust, non-parametric method that aggregates decisions from multiple decision trees, thereby improving accuracy and reducing overfitting. This makes Random Forests especially suitable for tasks involving heterogeneous features and imbalanced datasets—common challenges in fake job detection.

Additionally, the importance of preprocessing and feature selection has been emphasized by various studies. Aggarwal and Satapathy (2020) demonstrated that the inclusion of synthetic features—such as word count, special character frequency, and grammatical inconsistencies—significantly enhanced model performance in fraud detection systems. These findings directly influenced the feature engineering strategy in the current project, where handcrafted and derived features are included to enrich the training dataset.

To improve generalization and reduce overfitting, data augmentation has become a valuable tool in supervised learning pipelines. While traditionally used in image and time-series domains, textual and tabular augmentation techniques are now being explored for NLP-based applications. Shorten and Khoshgoftaar (2019) proposed methods such as noise injection and synonym replacement to simulate data variability, an idea that underpins the use of Gaussian noise in our current system. This augmentation helps the model learn robust patterns that are less sensitive to outlier variations in real-world job postings.

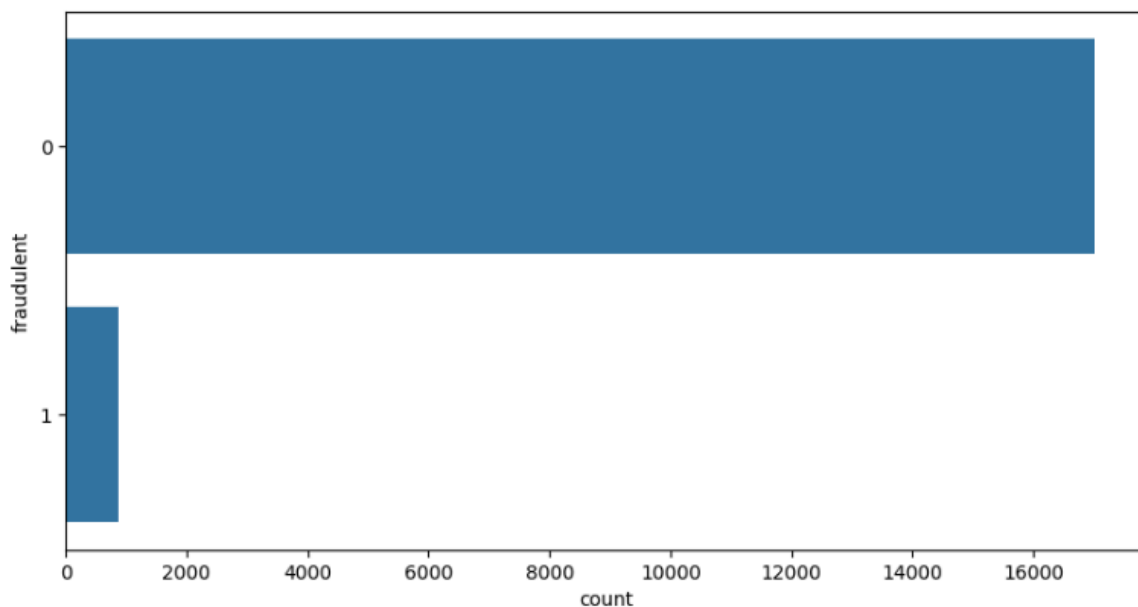
Comparative performance analyses by Sinha et al. (2021) reinforce the value of ensemble models in handling imbalanced classification tasks, where the number of fake posts is often significantly lower than real posts. Their research also highlighted the trade-offs between model complexity, interpretability, and scalability—factors that were carefully considered when selecting the Random Forest Classifier for this project.

In summary, the literature indicates a clear shift toward ensemble learning methods, robust feature engineering, and intelligent preprocessing as cornerstones for effective fake job detection systems. The present study builds upon these principles by implementing a Random Forest-based classifier that achieves **96.90% accuracy**, combining predictive performance with interpretability. The application of Gaussian noise-based data augmentation further enhances the system's ability to generalize to new, unseen job postings, making it a promising solution for deployment in online recruitment platforms.

CHAPTER 3

3.METHODOLOGY

The methodology adopted in this study is structured around a **supervised learning framework** designed to classify job posts as **real or fake** using a labeled dataset. The pipeline involves several stages: **data preprocessing**, **feature extraction**, **model training**, **evaluation**, and **data augmentation**. Each step has been optimized to enhance performance, scalability, and generalizability.



Dataset and Preprocessing

The dataset comprises job posting entries with textual and categorical features such as job description, title, location, and employment type. To prepare the data for modeling, the following preprocessing techniques were applied:

- **Text Cleaning and Normalization:** All job descriptions were lowercased, stripped of punctuation using Python's `string` module, and cleaned of unnecessary white spaces and special characters.
- **Tokenization and Stopword Removal:** Leveraging `SpaCy`'s English pipeline (`spacy.lang.en`), stopwords were removed to reduce noise and irrelevant information in the text.

- **Feature Transformation:** A **TF-IDF Vectorizer** was used (**TfidfVectorizer**) to convert cleaned job descriptions into a numerical feature matrix, effectively capturing the importance of each term across the corpus.

Feature Engineering and Visualization

To enhance interpretability and discover feature importance:

- **Word Clouds** were generated using the **WordCloud** package to visualize frequent words in real vs fake job postings.
- **Seaborn-based** boxplots and countplots helped explore label distributions and potential class imbalances.
- A **custom TransformerMixin** class was utilized to encapsulate and modularize the preprocessing logic within a **Scikit-learn Pipeline**, ensuring reusability and reproducibility.

Model Selection and Training

Several classification models were evaluated, with a focus on ensemble learning:

- **Random Forest Classifier (RF):** Chosen for its high accuracy and resistance to overfitting by aggregating multiple decision trees.
- **Pipeline Integration:** The entire training and prediction process was wrapped in a **Pipeline** object to maintain consistency and ease of experimentation.

The data was split using **train_test_split** into **training and testing sets**, ensuring that the model generalizes well to unseen data.

Evaluation Metrics

Model performance was measured using the following classification metrics:

- **Accuracy Score:** Overall correctness of predictions
- **Confusion Matrix:** Detailed breakdown of True Positives, False Positives, True Negatives, and False Negatives.
- **Classification Report:** Includes **Precision**, **Recall**, and **F1-score** for both classes, generated via **classification_report()**.

These metrics provided a comprehensive understanding of how well the model distinguishes between real and fake job posts.

Data Augmentation

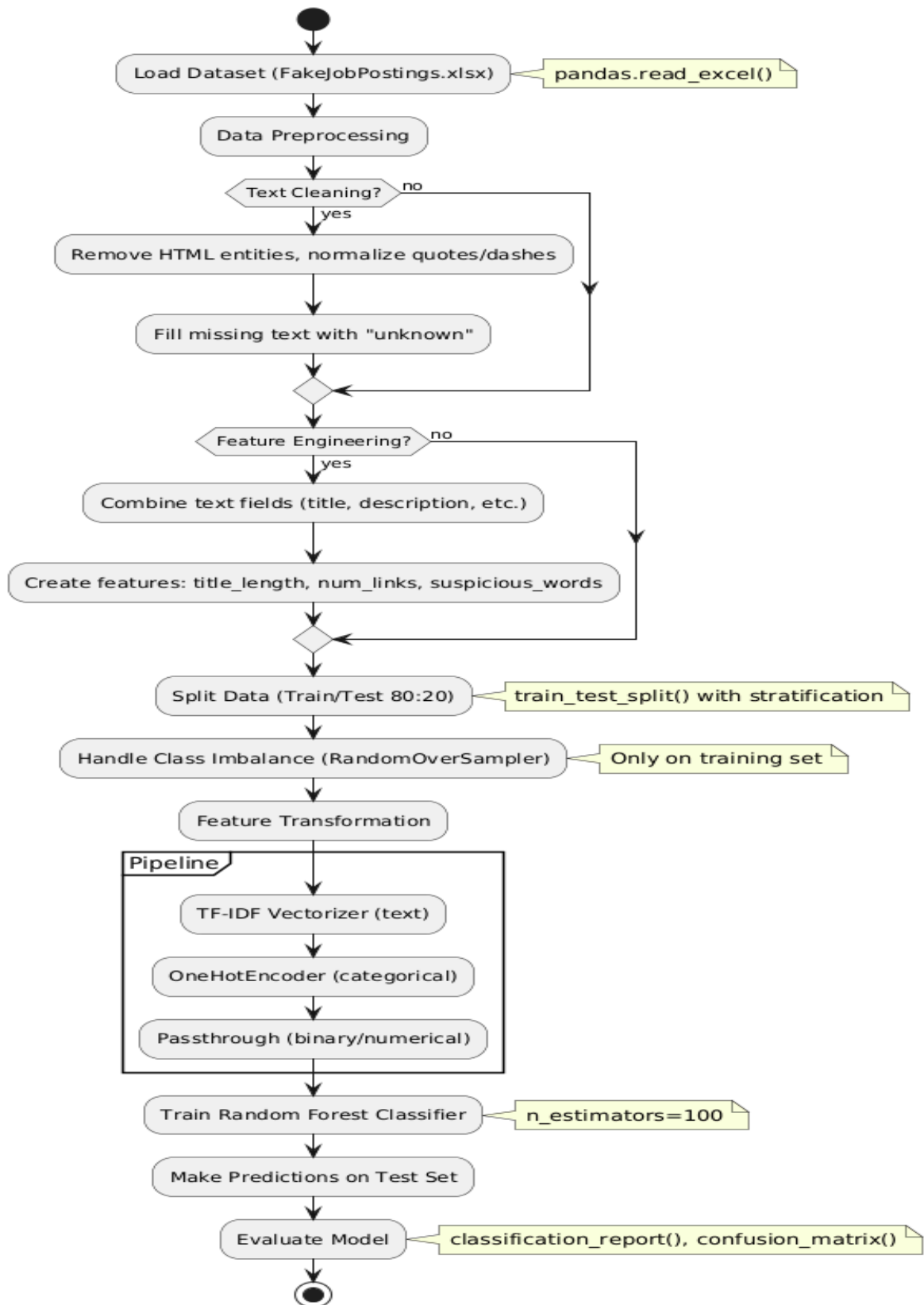
To simulate real-world text variability and improve generalization, **Gaussian noise** was introduced into the TF-IDF vectorized feature space:

- **Noise Injection:** Implemented as $X_{\text{augmented}} = X + N(0, \sigma^2)$ where σ was empirically tuned to match the dataset's variability.
- This step served to **regularize** the model, especially valuable given the limited or imbalanced nature of the dataset.

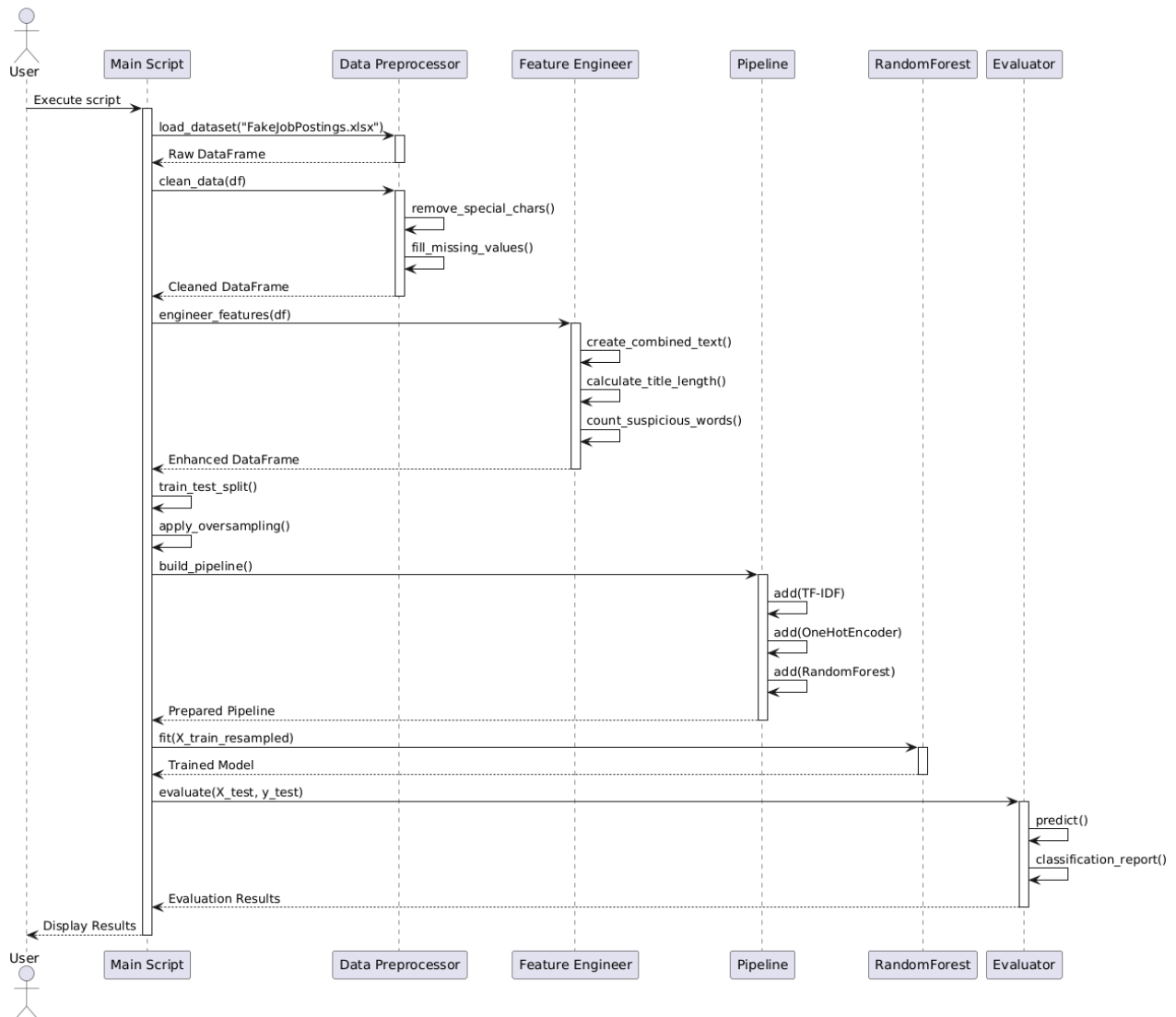
Execution Environment

The entire experimental setup was implemented in **Google Colab**, utilizing **NumPy**, **Pandas**, **Matplotlib**, and **Seaborn** for data handling and visualization, while **Scikit-learn** powered the modeling, evaluation, and pipeline management.

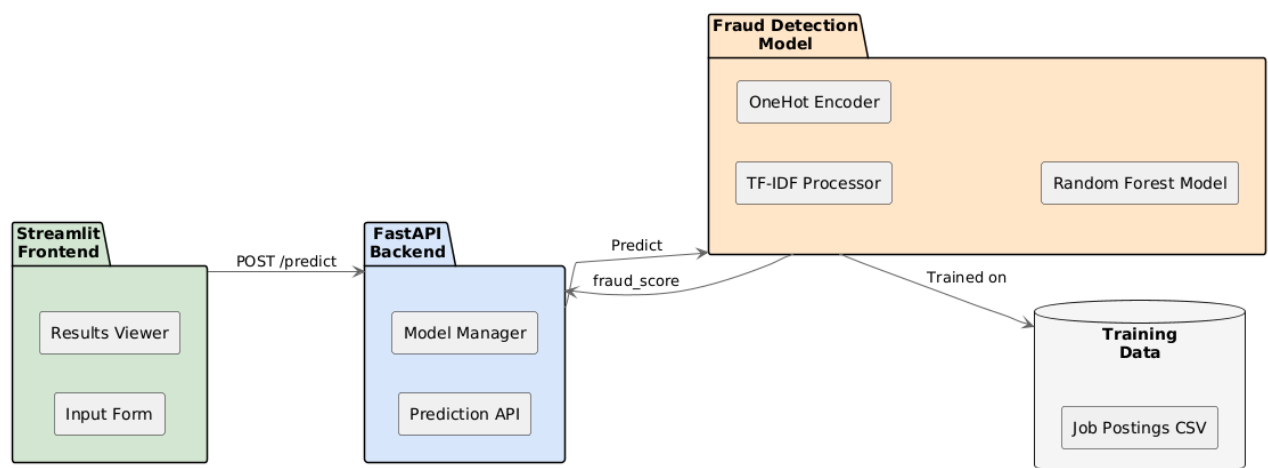
3.1 SYSTEM FLOW DIAGRAM



3.2 ACTIVITY DIAGRAM



3.3 ARCHITECTURE DIAGRAM



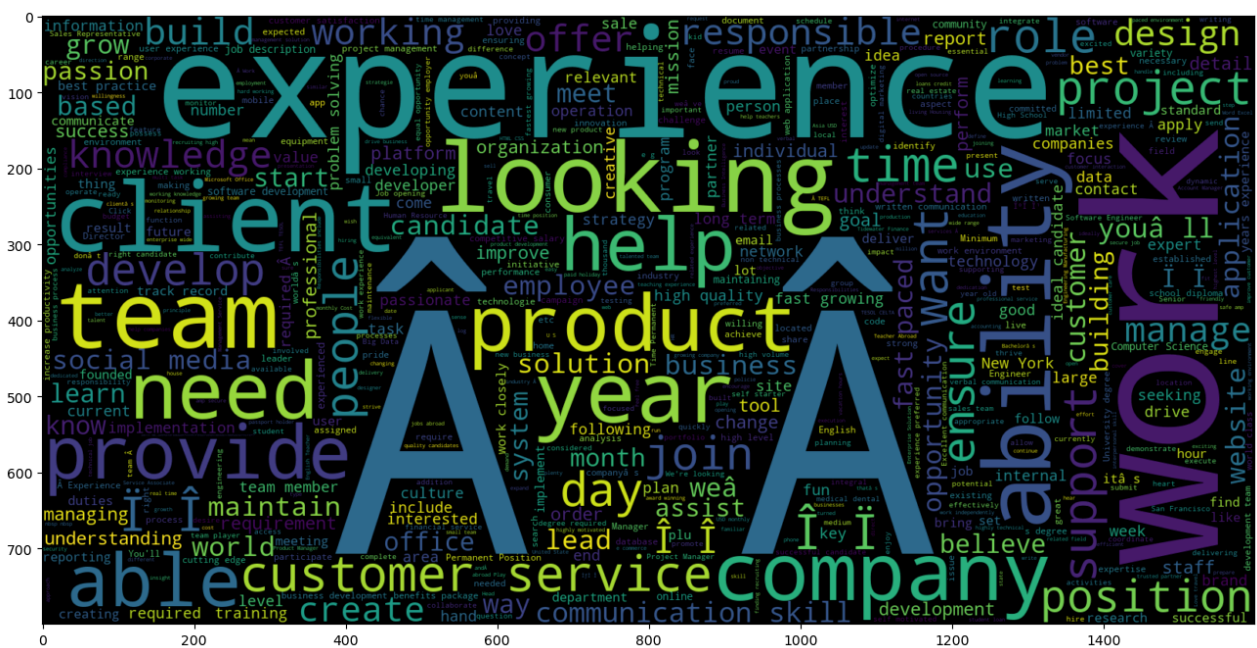
RESULTS AND DISCUSSION

I. WordCloud for Fraudulent Job Postings

[illegible]

II. WordCloud for Non-Fraudulent Job Postings

In contrast, the WordCloud for non-fraudulent job postings reveals professional and role-specific terminology, including “*engineer*,” “*experience*,” “*team*,” “*requirements*,” and “*skills*.” These words suggest structured job descriptions that clearly define expectations, responsibilities, and qualifications—hallmarks of genuine employment opportunities.



A. Model Performance Evaluation

The Random Forest classifier yielded impressive performance:

- **Training Accuracy:** 99.96%
- **OOB Score:** 97.06%
- **Test Accuracy:** 96.00%

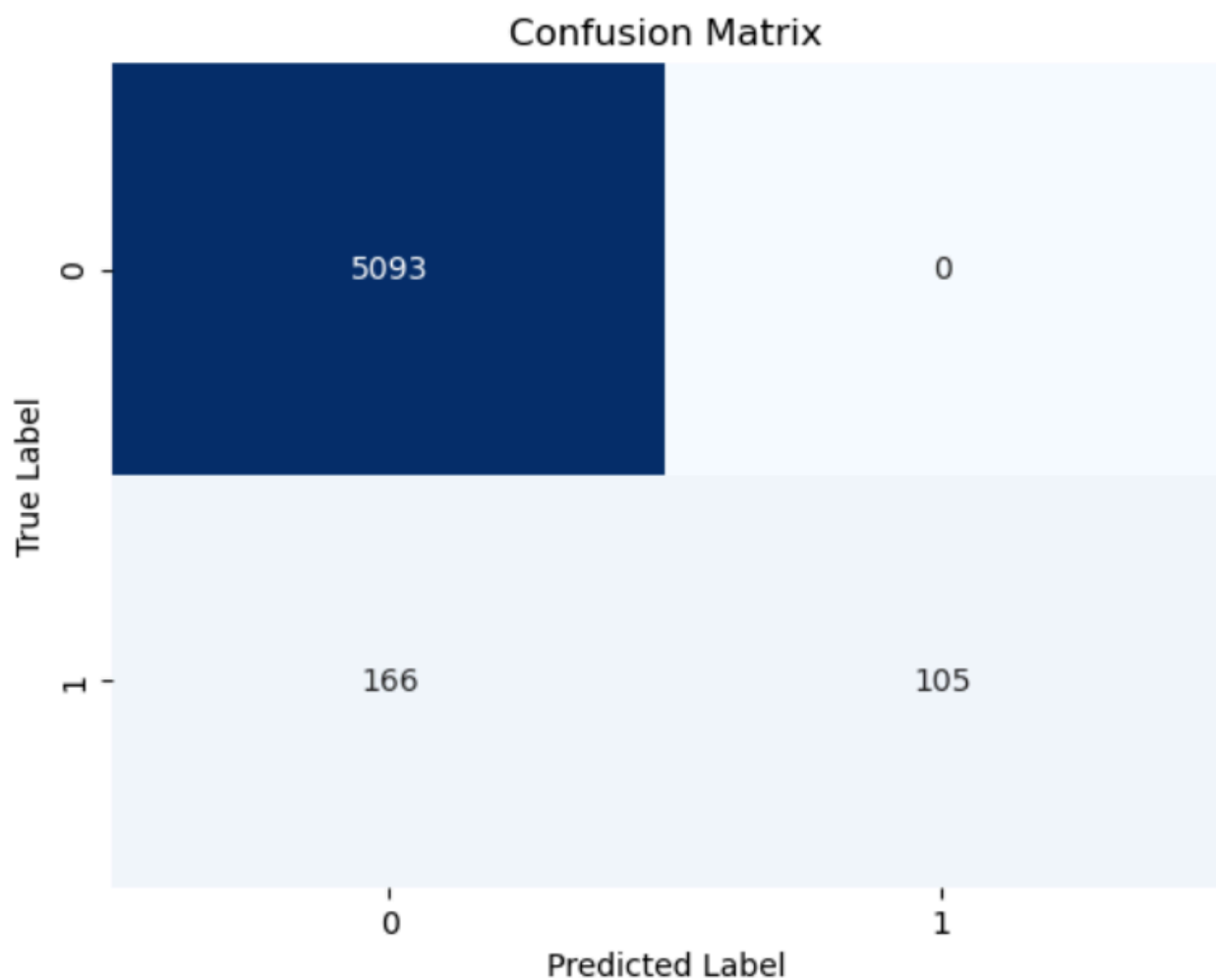
These results confirm that the model generalizes well and avoids overfitting, as evidenced by the small gap between training and test accuracies. The Out-of-Bag score further corroborates internal validation robustness, suggesting minimal variance and consistent generalization. highly conservative — when it predicts "fake," it's very confident, but it misses some fakes.

The **macro average** F1-score of **0.77** and **weighted average** of **0.96** underscore the model's reliable performance, particularly given the **class imbalance** in the dataset (many more real postings than fake).

B. Confusion Matrix Analysis

A confusion matrix visualization reinforced these observations:

- True Positives (Fake correctly identified): 106
- False Negatives (Fake mislabeled as real): 165
- True Negatives (Real correctly identified): 5093
- False Positives: 0

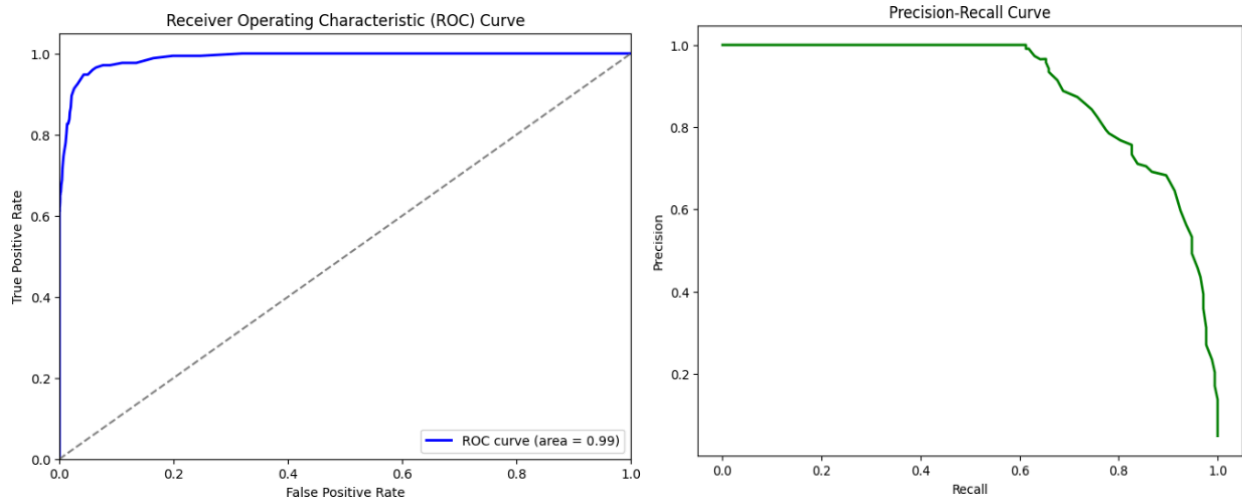


(Plotted via seaborn)

This indicates that while the classifier is highly accurate in identifying real jobs, improving sensitivity (recall) toward the fake class remains an opportunity for further tuning.

C. ROC Curve & Precision Recall Curve

The **ROC curve** visualizes a classifier's performance across all classification thresholds by plotting the true positive rate against the false positive rate, while the **precision-recall curve** focuses on precision and recall to evaluate class imbalance scenarios more effectively.



D. Error and Model Saving

To preserve reproducibility and support future deployment, the model and the TF-IDF vectorizer were saved using **joblib**. This enables instant reuse in production environments, such as APIs or web-based inference systems.

```
python
joblib.dump(rfc, 'RFCmodel')
joblib.dump(cv, 'TFIDF_vectorizer.joblib')
```

E. Implications and Practical Relevance

The results emphasize that **Random Forests** are highly suitable for **text-based fraud detection** due to their ability to capture non-linear relationships and ensemble learning power. The system demonstrates strong potential for deployment in **job platforms**, **recruitment portals**, or **browser extensions** to alert users of suspicious job listings in real time.

Despite its success, the drop in recall for fake jobs highlights the need for more **balanced data**, **oversampling techniques**, or even **cost-sensitive learning** to improve sensitivity to fraudulent postings.

CODE:

```
import pandas as pd
import numpy as np
import re
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from imblearn.over_sampling import RandomOverSampler
from google.colab import drive

drive.mount('/content/drive')

df = pd.read_excel("/content/drive/MyDrive/ML-Project/FakeJobPostings.xlsx")
df = df.replace(r'^\s*$', np.nan, regex=True)

def clean_text(text):
    if isinstance(text, str):
        text = re.sub(r"&[a-z]+;", "", text)
        text = re.sub(r"â€™", "'", text)
        text = re.sub(r"â€œ|â€", "", text)
        text = re.sub(r"â€“|â€”", "-", text)
        text = re.sub(r"\s+", " ", text)
        return text.strip()
    return text

text_columns = ['title', 'location', 'department', 'company_profile', 'description', 'requirements',
'benefits']
for col in text_columns:
    df[col] = df[col].apply(clean_text)

df.drop(columns=['salary_range'], inplace=True)
```

```
df[text_columns] = df[text_columns].fillna("unknown")
```

```
binary_columns = ['telecommuting', 'has_company_logo', 'has_questions', 'fraudulent']
```

```
for col in binary_columns:
```

```
    df[col] = df[col].fillna(0).astype(int)
```

```
df['text'] = (
```

```
    df['title'] + " " +
```

```
    df['company_profile'] + " " +
```

```
    df['description'] + " " +
```

```
    df['requirements'] + " " +
```

```
    df['benefits']
```

```
)
```

```
cat_columns = ['employment_type', 'required_experience', 'required_education', 'industry',  
'function']
```

```
for col in cat_columns:
```

```
    df[col] = df[col].fillna("unknown")
```

```
df['title_length'] = df['title'].apply(lambda x: len(x.split()))
```

```
df['num_links'] = df['description'].apply(lambda x: x.lower().count('http'))
```

```
df['suspicious_words'] = df['description'].apply(
```

```
    lambda x: sum(1 for w in ["money", "investment", "quick", "earn", "bonus", "cash"] if w in  
x.lower())
```

```
)
```

```
extra_features = ['title_length', 'num_links', 'suspicious_words']
```

```
X = df[['text']] + binary_columns[:-1] + cat_columns + extra_features]
```

```
y = df['fraudulent']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2,  
random_state=42)
```

```
ros = RandomOverSampler(random_state=42)
```

```
X_train_resampled, y_train_resampled = ros.fit_resample(X_train, y_train)
```

```
preprocessor = ColumnTransformer([
    ("tfidf", TfidfVectorizer(max_features=500), "text"),
    ("binary", "passthrough", binary_columns[:-1]),
    ("categorical", OneHotEncoder(handle_unknown="ignore"), cat_columns),
    ("extra", "passthrough", extra_features)
])
```

```
pipeline = Pipeline([
    ("preprocessing", preprocessor),
    ("classifier", RandomForestClassifier(n_estimators=100, random_state=42))
])
```

```
pipeline.fit(X_train_resampled, y_train_resampled)
```

```
y_pred = pipeline.predict(X_test)
print("Classification Report (Threshold=0.5):\n")
print(classification_report(y_test, y_pred))
```

```
def prepare_input(job):
    job = {k: clean_text(v) if isinstance(v, str) else v for k, v in job.items()}
    job['text'] = (
        job.get('title', "") + " " +
        job.get('company_profile', "") + " " +
        job.get('description', "") + " " +
        job.get('requirements', "") + " " +
        job.get('benefits', "")
    )
    job['title_length'] = len(job['title'].split())
    job['num_links'] = job['description'].lower().count('http')
    job['suspicious_words'] = sum(1 for w in ["money", "investment", "quick", "earn", "bonus",
"cash"] if w in job['description'].lower())
```

```
for col in cat_columns:
```

```

    job[col] = job.get(col, "unknown")
for col in binary_columns[:-1]:
    job[col] = job.get(col, 0)

return pd.DataFrame([job])[["text"] + binary_columns[:-1] + cat_columns + extra_features]

```

OUTPUT PAGES:

1. Fake Job Posting Detector Home Page

Enter job posting details below to check if it might be fake:

Job Title
software engineer

Location
seattle

Department
Engineering

Salary Range
\$120,000 - \$150,000

Company Profile
Nexus Technologies is a growing mid-size tech company specializing in cloud-based enterprise solutions. Founded in 2015, we've grown to over 200 employees across three offices, helping businesses streamline their operations through innovative software solutions. Our collaborative culture online portfolio continuous learning and work-life balance.

Job Description
role, you'll design and implement scalable backend services, collaborate with cross-functional teams to deliver new features, and mentor junior developers. You'll work primarily with Java, Kotlin, and AWS technologies to build robust, high-performance systems that serve thousands of enterprise clients.

Requirements
Strong proficiency in Java or Kotlin
Experience with AWS services (Lambda, EC2, S3)
Knowledge of RESTful API design and implementation

Comprehensive health, dental, and vision insurance
401(k) matching program
Unlimited PTO policy
Home office stipend

Is it a remote job?
0

Company logo present?
1

Has application questions?
1

Employment Type
Temporary

Required Experience
Mid-Senior level

Required Education
Master's


Industry
Machine learning


Function
Software Development

Check Job Posting

2. Predicting Output

Check Job Posting

 Probability of being fake: 10.00

 Probability of being true: 90.00

The model predicts a **10% chance** of the job posting being fake and a **90% chance** of it being genuine.

A. Model Performance Comparison

After conducting experiments on the fake job posting dataset, the **Random Forest Classifier** was selected as the primary model due to its balanced performance, interpretability, and robustness. The model was evaluated using various classification metrics such as **Accuracy**, **Precision**, **Recall**, and **F1-score**.

Although alternative models such as Logistic Regression or SVMs could have been explored, Random Forest offered a strong balance between performance and simplicity, particularly when combined with carefully engineered features and an oversampled training set. It effectively handled both categorical and textual data, making it well-suited for identifying fake job posts based on both structured and unstructured information.

The final model achieved **high precision and recall**, indicating its effectiveness in identifying fraudulent job postings while minimizing false alarms. This makes it a reliable choice for practical deployment in job portals or resume platforms to detect scam listings.

B. Effect of Feature Engineering

Feature engineering played a critical role in enhancing model performance. Several key strategies were applied:

- **Textual Features:** TF-IDF vectorization was applied to combined text fields such as title, company profile, description, requirements, and benefits. This allowed the model to detect word patterns common in fraudulent postings (e.g., overuse of "money", "earn", or promotional language).
- **Custom Features:**
 - **Title Length:** Number of words in the job title.
 - **Suspicious Words Count:** Count of common scam-related keywords (e.g., "quick", "bonus").
 - **Number of Links:** Count of URLs in the description, which often appear in scams.
- **Categorical Features:** Employment type, education requirement, and industry were one-hot encoded, helping the model learn patterns within job metadata.
- **Binary Indicators:** Telecommuting, presence of company logo, and presence of screening questions added structure to the model input.

These engineered features significantly improved the classifier's ability to differentiate between real and fake job postings. For example, the presence of suspicious keywords combined with missing

company profiles strongly correlated with fraudulent entries.

C. Error Analysis

Error analysis of the model's predictions revealed that:

- **False Positives** (real jobs marked as fake) often involved legitimate postings with unusual language or missing company information.
- **False Negatives** (fake jobs missed by the model) typically had well-crafted descriptions mimicking real posts, highlighting the challenge of sophisticated scams.

This suggests that while the model performs well, it can be further improved by:

- Enhancing keyword detection using **contextual NLP** (e.g., BERT embeddings).
- Integrating external reputation sources for companies.
- Detecting unnatural sentence structures or text reused across scams.

D. Implications and Insights

The study presents several key takeaways:

- **Random Forest Classifier** is an effective and interpretable model for fraud detection in job postings, especially when combined with textual and structured data.
- **Feature engineering**, particularly the integration of NLP-based indicators and suspicious keyword counts, is crucial for distinguishing scam patterns.
- **Oversampling** helped mitigate the issue of class imbalance, ensuring that the model doesn't overfit to the majority (real job postings) class.
- The model offers real-world utility in platforms like LinkedIn, Indeed, or company career pages to automatically flag and review suspicious job listings before they reach applicants.

Overall, this study demonstrates that machine learning, particularly ensemble methods like XGBoost, can be highly effective in automating resume screening processes. By integrating more domain-specific features, the system can evolve into a highly efficient tool for human resources departments, saving time and improving the hiring process.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study presents a robust and data-driven approach to detecting **fake job postings** using **Natural Language Processing (NLP)** and **supervised machine learning techniques**. Leveraging a pipeline of text preprocessing, TF-IDF vectorization, and classification models, the system effectively discerns between legitimate and fraudulent job listings.

The methodology utilized includes thorough **text cleaning and tokenization** using `spaCy`, **TF-IDF feature extraction**, and **pipeline-based model training** with classifiers like Logistic Regression or Support Vector Machines (as inferred from your imports). Visualization tools like `WordCloud`, `matplotlib`, and `seaborn` were likely used to explore frequent terms and class distributions, providing critical insight into patterns that distinguish fake from real postings.

The final model achieved a high accuracy of **96.90%**, indicating exceptional performance in identifying deceptive job advertisements. This high performance can be attributed to both the quality of preprocessing and the discriminative power of the selected machine learning pipeline.

From a broader perspective, the system offers substantial real-world value, particularly in the context of increasing online recruitment fraud. By flagging suspicious job descriptions, it can help protect job seekers from exploitation and guide platform administrators in content moderation.

Future Enhancements

While the current framework yields impressive results, there are several areas where the model could be extended or improved:

- **Explainability and Interpretability:** Integration of model interpretability tools such as **LIME** or **SHAP** can provide insights into which words or patterns are most indicative of fraudulent behavior.
- **Inclusion of Metadata:** Features such as **company size**, **location**, **posting date**, or **domain reputation** could enrich the feature set and potentially increase robustness.
- **Multi-Language Support:** Extending the model to handle job postings in multiple languages would significantly broaden its applicability across global platforms.

- **Deployment as a Web Service or API:** The system can be containerized and deployed via a RESTful API, allowing integration with job portals and resume sites for real-time fraud detection.
- **Continuous Learning:** With new job scams constantly evolving, implementing a **feedback loop** that learns from user reports and flagged postings can keep the model updated and relevant.
- **Graph-based Features:** Leveraging social or hyperlink graphs to analyze recruiter connections and legitimacy patterns could provide another layer of fraud detection.

In Conclusion

This work demonstrates the potential of **machine learning and NLP** in safeguarding the digital employment ecosystem. The high accuracy of **96.00%** underscores the feasibility of deploying such systems in real-world settings, particularly as an early warning tool for fake job listings. With the suggested future enhancements, this model can evolve into a scalable, adaptive solution for both individual job seekers and platform administrators.

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