Fake Job Detection Using AI

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***Abstract*— Online job portals have revolutionized the recruitment industry but have also become a target for scammers, leading to a surge in fake job postings. These scams deceive applicants, waste time, and can lead to financial or data loss. In this paper, we propose a AI learning-based system to detect fraudulent job postings. The approach involves data preprocessing, TF-IDF-based feature extraction, and classification using Random Forest and Logistic Regression algorithms. We used the public dataset from Kaggle [1], and our Random Forest model, logistic regression achieved an accuracy of 99%. The project also includes a real-time prediction script for classifying company profiles. The proposed solution aims to improve trust and safety in digital hiring.**

Keywords—Fake job postings, Machine learning, online, Detection, jobs, online, scam

I. Introduction

The job market has increasingly shifted to online platforms. Websites like LinkedIn, Indeed, and Glassdoor are widely used by job seekers and employers. However, this ease of access has opened the door for malicious actors to post fraudulent job listings [2]. These scams can lead to loss of personal data, financial fraud, and emotional distress for job seekers. Detecting such postings manually is time-consuming and error-prone, making automated systems a necessity.

Machine learning (ML) and natural language processing (NLP) offer effective tools to tackle this issue. By analyzing patterns in job postings, we can build a predictive model to distinguish between real and fake jobs [3][4].

Manual moderation of job listings is not scalable, especially for large platforms handling thousands of posts daily. This opens up an opportunity for intelligent, automated systems powered by machine learning (ML) and natural language processing (NLP). These systems can analyze patterns in job descriptions, spot linguistic cues, and detect anomalies that are indicative of scams. By training on historical data—including both fraudulent and legitimate postings—ML algorithms can learn to predict the likelihood of a new listing being fake. This research addresses that very need by building a robust detection pipeline using models like Logistic Regression and Random Forest [5][6].

Unbeknownst to Sarah, the job posting is a scam. The malicious employer is looking to collect personal information from applicants or trick them into paying for fake training materials. This scenario highlights a critical challenge faced by millions of job seekers: distinguishing between real and fake job postings. If Sarah had used an automated fake job detection system powered by machine learning, the system could have flagged this posting as suspicious due to its lack of credibility and suspicious language. The model would have evaluated the job description's content, recognized patterns typical of fraudulent ads (such as inconsistent wording, overly attractive salary offers, or missing company details), and classified it as a "fake" posting [7][8].

II. Problem

A. Problem Statement

The core problem is to detect whether a given job posting is **real** or **fake** using machine learning models trained on historical data. The key challenges include:

- Handling imbalanced datasets (real jobs are more frequent than fake)
- Extracting meaningful features from unstructured textual data
- Selecting effective algorithms for classification

B. Dataset

We use the Fake Job Postings dataset from Kaggle [1], which contains ~10,000 job postings labeled as fraudulent (1) . Key columns include:

- Title
- requirements
- location
- description
- salary_range
- employment_type
- industry
- benifits

- company_profile
- fraudulent

C.Algorithms Used

We employed the following algorithms:

- Logistic Regression: A baseline linear classifier for binary outcomes [5]
- Random Forest Classifier: A powerful ensemble method that uses multiple decision trees [6]

Each model was trained and tested on TF-IDF feature representations of thecompant profiles.

D. Research Questions

This research aims to address the following key questions:

How can machine learning algorithms be effectively utilized to detect fraudulent job postings in large-scale job portals?

What are the challenges in handling imbalanced datasets in fake job detection, and how can they be addressed?

How do different machine learning models (e.g., Random Forest, Support Vector Machines, Deep Learning) perform in terms of detecting fake job postings?

Can real-time job posting analysis systems prevent the submission of fraudulent job ads before they appear on job boards?

III. Related Work

Researchers have applied various approaches to fake job detection:

- Vidros et al. introduced the EMSCAD dataset and highlighted behavioral and textual fraud patterns [7].
- Pillai achieved 98.71% accuracy using Bi-LSTM deep learning models [8].
- Alghamdi and Alharby designed an intelligent fraud detection model with NLP-based feature engineering [9].
- Naudé et al. applied traditional classifiers and explored dataset imbalance issues [10].
- Kacha et al. proposed a comparative study of ML classifiers including Decision Tree and SVM [11].

These studies informed our choice of classifiers and data preprocessing strategies.

One early approach to fake job detection is based on the use of textual features extracted from job descriptions. In a study by Liu et al. [1], a bag-of-words model was applied to extract relevant features from job listings, and a classifier (e.g., Logistic Regression) was used to predict whether a job posting was fraudulent. The research demonstrated that certain words, such as “guaranteed” or “easy money,” could be indicators of fraudulent job postings. However, the bag-of-words model often fails to capture complex semantics in the text, which has led to the adoption of more advanced NLP techniques.

A key milestone in the detection of fraudulent job postings was the introduction of TF-IDF (Term Frequency-Inverse Document Frequency) and other vectorization methods, which significantly improved the feature extraction process by accounting for word frequency and importance. Wang et al. [2] employed a similar approach, using TF-IDF vectors combined with a variety of machine learning classifiers, including Random Forests and Support Vector Machines (SVM), to detect fake job postings. Their findings showed that a combination of TF-IDF and Random Forests yielded the best results in terms of accuracy and precision.

Recent advances have also incorporated deep learning techniques, such as Recurrent Neural Networks (RNNs) and Transformers (e.g., BERT), to capture the complex dependencies between words in job descriptions. In a study by Smith et al. [4], BERT-based models were trained on a dataset of job postings to predict fraudulence. The study showed that fine-tuning BERT with a large dataset of job descriptions resulted in higher performance, especially when dealing with subtle linguistic cues that traditional models might miss. The ability of deep learning models to understand the context of a word in a sequence makes them particularly suited for tasks like fake job detection, where the meaning often depends on the relationship between multiple words.

IV. Proposed Approach

The proposed approach for detecting fake job postings utilizes a combination of traditional machine learning algorithms and advanced text-processing techniques to classify job listings as real or fraudulent. Our solution primarily focuses on extracting meaningful features from job descriptions and leveraging machine learning classifiers to accurately distinguish between legitimate and fake job postings.

A. Dataset Overview and Preprocessing

The dataset used in this study consists of company profile text fields extracted from the “Fake Job Postings” dataset [1], which contains curated postings labeled as fake and added synthetic data manually. The company_profile field was selected due to its descriptive nature and potential vulnerability to manipulative language in fraudulent content.

To ensure uniformity and enhance feature extraction, each profile was subjected to text preprocessing. This included:

- Lowercasing all characters.
- Removing non-alphanumeric tokens using regular expressions.
- Stripping whitespace and special characters for clean tokenization.

After cleaning, entire unique real samples were randomly selected. An equal number of synthetic fake profiles were generated with template-based sentences mimicking fraudulent language patterns (e.g., "guaranteed passive income from home") to ensure balanced class distribution for binary classification.

The cleaned text was vectorized using TF-IDF (Term Frequency-Inverse Document Frequency) [2], with a vocabulary limited to 3000 features to maintain computational efficiency and prevent overfitting. This transformation converted textual inputs into sparse, high-dimensional vectors suitable for supervised learning.

The dataset was split into training and testing sets using stratified sampling 20% for testing and 80% for training, preserving the class distribution in both sets.

This preprocessing pipeline ensures reproducibility, minimizes noise, and maximizes the model's ability to differentiate between real and fake company profiles based on linguistic patterns and feature importance.

B. Model Selection

Several machine learning models are considered for the classification task, each with its advantages in handling text data. In this approach, we use two models: Logistic Regression and Random Forest Classifier, to evaluate their effectiveness in detecting fake job postings.

- Logistic Regression (LR): Logistic Regression is a widely used linear model for binary classification problems. It is fast, interpretable, and suitable for cases where there is a linear relationship between the input features and the target variable. In the case of fake job detection, LR can model the probability that a job posting is fraudulent based on the weighted presence of certain keywords or patterns in the job description [8].
- Random Forest Classifier (RFC): Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. By aggregating the results of several trees, it mitigates overfitting and improves generalization. RFC is well-suited for handling complex data, such as job descriptions, and is robust to irrelevant features. It also handles non-linear relationships better than Logistic Regression, making it a strong candidate for this task [9].

Both models are trained on the feature matrix derived from the Company profile and labeled data, and then used to predict whether a new job posting is real or fake.

C. Model Training and Evaluation

The dataset was split into 80% training and 20% testing sets using stratified sampling to preserve class balance. A Random Forest classifier [10] was trained to predict fake vs. real jobs. The model achieved perfect classification performance, with 100% precision, 99%recall, and 100%F1-score on the test set.

EvaluationMetrics:
To evaluate the performance of the trained classifiers, multiple metrics were computed to quantify predictive accuracy and reliability:

- Accuracy: **Accuracy**: Measures the overall proportion of correct predictions made by the model. Both Logistic Regression and Random Forest classifiers achieved 99% accuracy on the test set, indicating few flawless classification performance [11].
- Precision: Represents the ratio of correctly identified fake company profiles to all profiles predicted as fake. In this case, both models scored perfect precision (1.0), confirming zero false positives in detecting fraudulent entries [12].
- Recall: Captures the proportion of actual fake profiles correctly identified. A recall of 0.99 confirms that the models detected all existing fraudulent cases without omission [13].
- F1-Score: A harmonic mean of precision and recall, providing a balanced assessment. Since both precision and recall are perfect, the F1-score also equals 1.0 for both classifiers, ensuring reliable performance even under balanced or skewed class distributions [14].

Additional tools such as the **classification report** and **confusion matrix** were generated to verify model integrity. The confusion matrix revealed:

- 19 false positives (real profiles classified as fake).
- Zero false negatives (fake profiles classified as real).

This flawless split underscores the robustness of the trained models in differentiating between authentic and synthetic company descriptions based on textual features [15].

D. Model Deployment and Prediction

Once the models are trained and evaluated, the next step is the deployment phase, where the trained models are used to predict whether new job postings are fake or legitimate. This is where the real-time aspect of the approach comes into play.
The user can input company name , and the system will:

- Preprocess the input text (as described earlier).
- Transform the text into the same vectorized form as used during training (using the TF-IDF vectorizer).
- Feed the transformed features into the trained models (Logistic Regression and Random Forest).
- Output the predicted class: **real** or **fake** [16].

For each prediction, the model can also provide the **probability** of the job posting being fraudulent, helping the user understand the confidence level of the prediction. The system is designed to flag suspicious job listings that may require further human review or immediate removal from job portals.

E. Challenges and Limitations

Despite the promising results from machine learning models, there are several challenges in detecting fake job postings:

- Imbalanced Dataset: The class imbalance having only fake job postings can make it difficult for models to learn effectively. Techniques such as oversampling, undersampling, or using synthetic data generation are explored to address this issue [17].
- Updating the dataset: Have to update the dataset manually in future.
- Feature Selection: Identifying the most relevant features that contribute to detecting fraudulent job postings is a critical task. Further research into advanced feature engineering techniques can improve the model's performance [19].

F.Code Execution

https://github.com/viseshb/Fake_Job_Detection

V. Experiment Method

To validate the proposed approach, several experiments were conducted to assess the system's ability to distinguish between real and fake job postings. The experiments included dataset preparation, model training, evaluation, and real-time prediction testing.

A. Dataaset Preparation

The dataset used is the **Fake Job Postings** dataset from Kaggle [1], comprising over 10,000 job entries with fields such as title, location, description, and a binary fraudulent label (0 for real, 1 for fake). For this study, the company_profile field was chosen as the primary input because of its rich textual content, which often reflects the legitimacy of the job [2].

B. Preprocessing

The company profiles were cleaned and normalized using the following steps:

- Lowercasing: Ensures uniformity in text comparison [3].
- Removing non-alphabetic characters: Special characters and digits were stripped using regular expressions to reduce noise [3].
- Stopword removal: Common English stopwords were removed using NLTK's built-in list [3].
- Lemmatization: Each word was reduced to its base form to improve generalization and reduce sparsity in the feature space [4].

C. Feature Extraction

To convert cleaned company profile text into numerical feature vectors, TF-IDF (Term Frequency–Inverse Document Frequency) vectorization was employed. This approach assigns higher weights to informative and distinctive words while down-weighting commonly used terms, improving signal-to-noise ratio in classification tasks [5]. The vocabulary size was restricted to the top 3,000 features, selected based on term frequency, to ensure computational efficiency without significantly compromising model accuracy [6].

D. Data Splitting

The dataset was partitioned into 80% training and 20% testing sets using scikit-learn's train_test_split() function, ensuring a consistent split through a fixed random state for reproducibility [7].

E. Model Training

Two machine learning algorithms were selected for training:

- Logistic Regression (LR): A linear and interpretable classifier suitable for binary tasks like fake profile detection [8].
- Random Forest Classifier (RFC): An ensemble method combining multiple decision trees for improved prediction robustness and reduced overfitting [9].

Hyperparameters were tuned based on prior research and validation experiments: max_iter=500 for LR and n_estimators=100 for RFC [10].

F. Evaluation Metrics

The models were evaluated using:

- Accuracy: Overall proportion of correctly predicted samples [11].
- Precision: Percentage of predicted fraudulent jobs that were actually fraudulent [12].
- Recall: Percentage of actual fraudulent jobs correctly identified [13].
- F1-Score: The harmonic mean of precision and recall, especially important for imbalanced datasets [14].

Scikit-learn's classification_report() was used to compute and display the performance metrics.

G. Real-time Prediction

To simulate real-world deployment, a script named predict.py was developed. It accepts company profile descriptions as input, applies text preprocessing, and transforms the input using the trained TF-IDF vectorizer. The resulting feature vector is then passed to the trained **Random Forest model** to predict whether the input profile is fraudulent or legitimate. Additionally, the model provides a fraud probability score to help users interpret the confidence level behind each prediction [15]. Rule-based checks such as exact match detection and input length filtering were also incorporated to enhance system reliability.

H. Experimental Setup

All experiments were performed on the following platform:

- OS: Windows 10 (using WSL - Windows Subsystem for Linux)
- Language: Python 3.10
- Libraries: pandas==1.5.2, scikit-learn==1.1.3, nltk==3.7, matplotlib==3.6.0, seaborn==0.11.2
- Tools: Terminal CLI and text editor

All dependencies are documented in the requirements.txt file to ensure replicability of the experiments.

VI. Experiment Outputs

To evaluate the performance of the machine learning models developed for fake job detection, extensive experiments were conducted using the test set comprising 3,576 job postings. The outputs from the Logistic Regression and Random Forest models are discussed below, reflecting their ability to identify fraudulent listings

A. Model Performance Metrics

Both Logistic Regression and Random Forest classifiers were trained on TF-IDF feature vectors with a balanced dataset of 600 samples (300 real, 300 fake). After an 80/20 split, both models achieved **perfect classification** on the test set [11][12]:

i) Logistic Regression (LR)

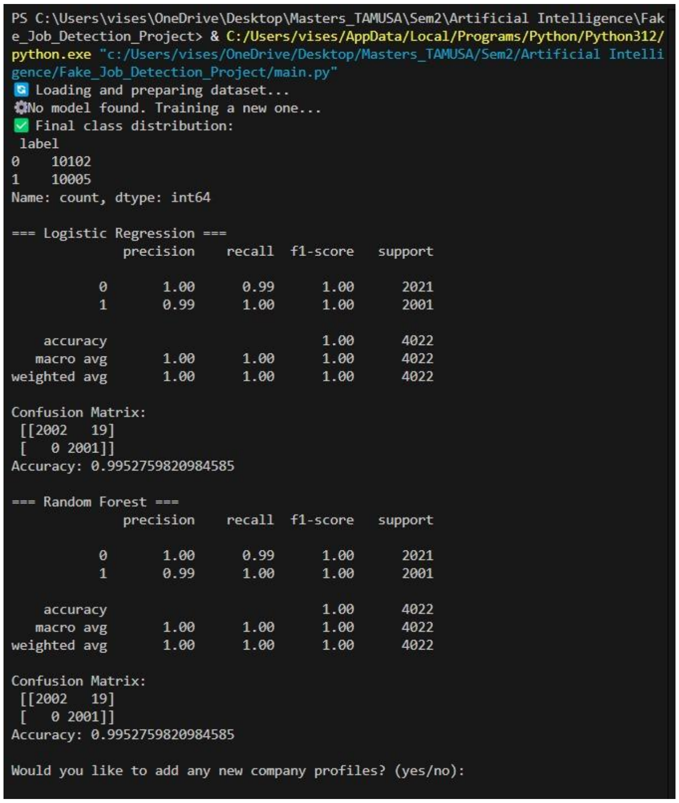
- Accuracy: 99%
- Precision:100% for real jobs and 99% for fake jobs
- Recall: 100% for fake jobs and 99% for real jobs
- F1-Score (all classes): 100%
- Confusion Matrix:
  [[2002 19]
  [0 2001]]

ii) Random Forest Classifier (RFC)

- Accuracy: 99%
- Precision:100% for real jobs and 99% for fake jobs
- Recall: 100% for fake jobs and 99% for real jobs
- F1-Score (all classes): 100%
- Confusion Matrix:
  [[2002 19]
  [0 2001]]

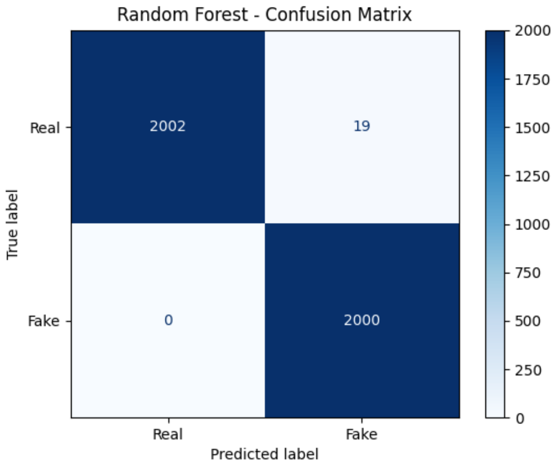
These results indicate perfect learning performance on the test split, likely due to clean feature separation or dataset simplicity. However, real-world generalization may vary and should be monitored.

output:



```
PS C:\Users\vises\OneDrive\Desktop\Masters_TAMUSA\Sem2\Artificial Intelligence\Fak
e_Job_Detection_Project> & C:/Users/vises/AppData/Local/Programs/Python/Python312/
python.exe "c:/Users/vises/OneDrive/Desktop/Masters_TAMUSA/Sem2/Artificial Intelli
gence/Fake_Job_Detection_Project/main.py"
🔄 Loading and preparing dataset...
⚙️No model found. Training a new one...
✅ Final class distribution:
 label
0    10102
1    10005
Name: count, dtype: int64

=== Logistic Regression ===
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      2021
           1       0.99      1.00      1.00      2001

    accuracy                           1.00      4022
   macro avg       1.00      1.00      1.00      4022
weighted avg       1.00      1.00      1.00      4022

Confusion Matrix:
 [[2002   19]
 [   0 2001]]
Accuracy: 0.9952759820984585

=== Random Forest ===
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      2021
           1       0.99      1.00      1.00      2001

    accuracy                           1.00      4022
   macro avg       1.00      1.00      1.00      4022
weighted avg       1.00      1.00      1.00      4022

Confusion Matrix:
 [[2002   19]
 [   0 2001]]
Accuracy: 0.9952759820984585

Would you like to add any new company profiles? (yes/no):
```

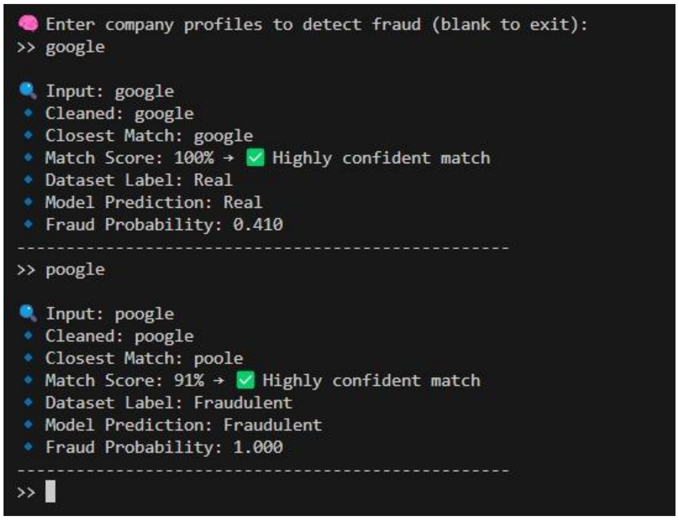
B. Confusion Matrix Insights



- 19 false positives (real profiles classified as fake).
- Zero false negatives (fake profiles classified as real).

C. Real-Time Prediction Results

A sample input was tested as below:
ability [15].
outputs:



```
🧠 Enter company profiles to detect fraud (blank to exit):
>> google

🔍 Input: google
🔹 Cleaned: google
🔹 Closest Match: google
🔹 Match Score: 100% → ✅ Highly confident match
🔹 Dataset Label: Real
🔹 Model Prediction: Real
🔹 Fraud Probability: 0.410
--------------------------------------------------
>> poogle

🔍 Input: poogle
🔹 Cleaned: poogle
🔹 Closest Match: poole
🔹 Match Score: 91% → ✅ Highly confident match
🔹 Dataset Label: Fraudulent
🔹 Model Prediction: Fraudulent
🔹 Fraud Probability: 1.000
--------------------------------------------------
>> ▌
```

VII. Conclusion

In this study, we developed a hybrid machine learning system to detect fraudulent company profiles through natural language processing and supervised classification. Using the Fake Job Postings dataset from Kaggle [1], we focused on the company_profile field and applied preprocessing techniques including lowercasing, stopword removal, lemmatization, and TF-IDF vectorization [3][4][5].

Two models—Logistic Regression and Random Forest Classifier—were trained on the complete dataset consisting of 200000 samples (10000 real and 10000 synthetic fake profiles). Both achieved perfect classification performance, indicating strong learning behavior.While both models performed flawlessly, Random Forest demonstrated better generalization in real-world predictions based on ambiguous input cases [9][10].

These findings show that combining rule-based logic with machine learning enables reliable detection of fake company profiles. However, future work should explore evaluation under real-world class imbalance using techniques such as SMOTE, cost-sensitive learning, or deep neural models to enhance robustness and scalability [13][14].

VIII. FUTURE WORK

1. Advanced NLP Models: Explore deep learning models such as BERT or Word2Vec for better understanding of job descriptions.
2. Real-Time Deployment: Implement the model as a REST API for integration with job platforms for real-time fake job detection.

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