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Fake Job Post Detection Website

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Abstract- The proliferation of fake job postings on online job boards and career websites has become a significant concern, resulting in financial losses and reputational damage for job seekers and employers alike. To combat this issue, we propose JOBSHIELD, a machine learning-based fake job post detection system that leverages natural language processing and ensemble techniques to identify and flag suspicious job postings. JOBSHIELD's detection algorithm is trained on a large dataset of labelled job postings, featuring a range of features extracted from job descriptions, requirements, and company information. Our system achieves an accuracy of 95% in detecting fake job postings, outperforming existing approaches. The JOBSHIELD website provides a user-friendly interface for job seekers to search for job postings and receive alerts on potential fake job postings. Employers can also utilize our system to verify the authenticity of job postings and protect their brand reputation. By providing a reliable and efficient fake job post detection system, JOBSHIELD aims to promote a safer and more trustworthy online job market, empowering job seekers to make informed decisions and employers to maintain their reputation.

Keywords- Machine Learning, Supervised Learning, Single Classifier, Ensemble Classifier, Natural Language Processing

I. INTRODUCTION OF PROJECT DESCRIPTION

1. Introduction

Welcome to Job shield

The internet has revolutionized the way we search for jobs, making it easier than ever to find employment opportunities with just a few clicks. However, this convenience has also created an environment where fraudulent job postings can thrive, leaving job seekers vulnerable to scams and financial losses.

The Problem of Fake Job Posts

Fake job posts are a growing concern in the online job market, with millions of job seekers falling prey to these scams every year. These fraudulent postings can take many forms, from phishing scams to identity theft, and can result in financial losses, reputational damage, and emotional distress.

The Need for a Solution

To combat this issue, a reliable and efficient fake job post detection system is essential. JOBSHIELD is a cutting-edge platform that utilizes machine learning and natural language processing to identify and flag suspicious job postings, providing job seekers with a safer and more trustworthy online job search experience.

Our Mission

Our mission is to empower job seekers with the tools and resources they need to navigate the online job market with confidence. By providing a robust fake job post detection system, we aim to promote a safer and more trustworthy online job market, where job seekers can find genuine

employment opportunities and employers can maintain their reputation.

How We Can Help

Our website offers a range of features and tools to help job seekers detect and avoid fake job postings, including:

- A machine learning-based fake job post detection algorithm
- A user-friendly interface for searching and verifying job postings
- Alerts and notifications for potential fake job postings
- Resources and tips for avoiding job scams and fraud

By leveraging our expertise in machine learning and natural language processing, we are committed to making the online job market a safer and more trustworthy place for everyone.

Advancement in Technology

Advancements in technology have significantly improved the accuracy and efficiency of fake job post detection in JOBSHIELD. Machine learning-based approaches have emerged as a powerful tool in detecting fraudulent job postings, leveraging natural language processing and ensemble techniques to identify suspicious patterns and anomalies.

Machine learning algorithms, such as supervised learning and classification techniques, have been employed to classify job postings as authentic or fraudulent based on historical data of legitimate and fake job postings

Natural language processing (NLP) has been utilized to analyze job posting content, extracting features and patterns that can indicate fraudulent activity.

II. TECHNOLOGIES USED

1. Software Requirements

- Front End – Anaconda IDE
- Backend – SQL
- Language – Python 3.8

Anaconda IDE in Frontend

Anaconda provides a comprehensive suite of tools that support data collection, preprocessing, analysis, and machine learning, all of which can be very useful for developing a job post detection system. While Anaconda itself isn't a frontend development tool, it integrates well with backend systems and data analysis workflows that can support frontend applications.

Data Collection and Preprocessing

- **Libraries:** Anaconda includes libraries like pandas, numpy, and BeautifulSoup or Scrapy for web scraping. These can be used to gather job posts from various sources on the web.
- **Cleaning Data:** You can use pandas to clean and preprocess the data, removing duplicates, handling missing values, and transforming data into a usable format.

Natural Language Processing (NLP)

- **Libraries:** nltk, spaCy, and textblob are part of the Anaconda ecosystem. These libraries help with tokenization, part-of-speech tagging, named entity recognition, and sentiment analysis.
- **Application:** You can analyze the text of job posts to identify keywords, skills, and job titles. This helps in detecting relevant job posts and categorizing them.

Machine Learning

- **Libraries:** Anaconda includes machine learning libraries such as scikit-learn, XGBoost, and TensorFlow or PyTorch. These can be used to build models that classify job posts into various categories or predict the relevance of a job post based on certain features.
- **Model Training:** Train and test models using labeled job post data. This could involve supervised learning techniques where the model learns from historical job postings and predicts job relevance or category for new posts.

Visualization

- **Libraries:** matplotlib, seaborn, and plotly are powerful tools for data visualization included in

Anaconda. You can visualize the frequency of job post categories, trends over time, or distribution of skills required across different job posts.

- **Dashboarding:** While not traditionally used for frontend development, you could use Jupyter Notebooks or JupyterLab (part of Anaconda) to create interactive dashboards that present your findings.

Integration with Frontend

- **API Development:** Use Flask or FastAPI (both of which can be installed via Anaconda) to build a backend API that can serve the processed job post data to a frontend application.
- **Frontend Communication:** The frontend application (built with technologies like React, Angular, or Vue.js) would communicate with this backend API to fetch and display job post information.

SQL used in Backend

SQL (Structured Query Language) is a powerful tool used in the backend of job post detection systems to manage and interact with relational databases. In the context of a research paper focused on job post detection, SQL plays a crucial role in organizing, querying, and managing the data necessary for the system. Here's a detailed breakdown of how SQL can be utilized in such a system:

Database Design Tables

Define tables to store job posts, user profiles, and other relevant entities. For instance: job_posts table: Stores details about job postings (e.g., id, title, description, company, location, posted_date).

users table: Stores user information if the system involves user profiles (e.g., id, name, email, skills). job_categories table: Stores categories or tags for job posts (e.g., id, category_name).

Data Insertion

Adding Job Posts
SQL Insert Statements: Use SQL commands to add job postings into the database.

Data Querying

Retrieving Job Posts:
Simple Queries: Fetch job posts based on certain criteria like location or company. Advanced Queries: Join tables to get more detailed results, such as combining job posts with their categories or filtering based on user skills.

Data Analysis

Aggregations and Metrics:
SQL Aggregations: Use SQL functions like COUNT(), AVG(), SUM(), and GROUP BY to analyze job post data, such as the number of postings per category or the average number of postings per month.

Data Updates and Maintenance
Updating Job Post Information

SQL Update Statements: Modify existing records if job post details change.

Deleting Job Posts

SQL Delete Statements: Remove job posts that are no longer relevant.

Optimizing Performance Indexes

Creating Indexes: Improve query performance by creating indexes on columns frequently used in search conditions or joins.

Query Optimization : Efficient Queries: Optimize queries by analyzing query plans and adjusting them for performance.

Integration with Other Systems

Backend API Development:
APIs: Create backend services (e.g., using Flask, Django) that interact with the SQL database to provide job post data to frontend applications.

Security Considerations

SQL Injection Prevention:
Parameterized Queries: Use parameterized queries or prepared statements to prevent SQL injection attacks.

Language – Python 3.8

Python is a versatile and powerful language widely used in job post detection applications due to its

extensive libraries and frameworks for data processing, machine learning, and web development.

Web Scraping

- **Libraries:** Python libraries such as BeautifulSoup, Scrapy, and requests are commonly used for web scraping. These tools help in extracting job postings from websites.
- **Example:** Use requests to fetch HTML content and BeautifulSoup to parse and extract relevant job post details.

Data Storage : Database Interaction

- **Libraries:** Use sqlite3 for lightweight databases or SQLAlchemy for more advanced database interactions. These libraries allow you to store and manage job post data in a structured way.

Data Preprocessing : Text Cleaning

- **Libraries:** Use libraries like nltk, spaCy, or textblob for natural language processing (NLP) to clean and preprocess job post text. This includes tokenization, stemming, and removing stop words.
- **Example:** Clean job post descriptions to prepare them for analysis or modeling.

Data Collection: Web Scraping

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Data Storage: Database Interaction

- **Libraries:** Use sqlite3 for lightweight databases or SQLAlchemy for more advanced database interactions. These libraries allow you to store and manage job post data in a structured way.
- **Example:** Store job post data in an SQLite database.

Data Preprocessing: Text Cleaning

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- **Example:** Clean job post descriptions to prepare them for analysis or modeling.

Feature Extraction: Text Features

- **Libraries:** Use sklearn.feature_extraction.text for feature extraction such as Term Frequency-Inverse Document Frequency (TF-IDF) or Bag of Words (BoW).
- **Example:** Convert job post descriptions into numerical features for modeling.

Machine Learning : Model Building

- **Libraries:** Use scikit-learn, TensorFlow, or PyTorch to build and train machine learning models for job post classification or relevance prediction.
- **Example:** Train a model to classify job posts into different categories or predict job post relevance based on features.

Evaluation : Model Evaluation

- **Libraries:** Use scikit-learn for metrics such as accuracy, precision, recall, and F1 score to evaluate model performance.

Integration: Backend Development

- **Libraries:** Use frameworks like Flask or Django to build a backend that serves job post data and interacts with the machine learning model.
- **Example:** Create an API endpoint to retrieve job posts and their predictions

Visualization : Data Visualization

- **Libraries:** Use matplotlib, seaborn, or plotly to create visualizations of job post data, model performance, and analysis results.

III. METHODOLOGY

The research on "Fake Job Post Detection Using Machine Learning" employs a systematic methodology to create an efficient detection system. The key steps include:

1. Data Collection
Utilize a diverse dataset sourced from Kaggle, a recognized platform for hosting datasets relevant to machine learning research. This dataset serves as the foundation for training and evaluating the machine learning models, offering realistic representation of job postings.

2. Data Pre-processing
Perform data pre-processing to ensure the dataset's cleanliness and suitability for analysis. This involves handling missing values, eliminating irrelevant information, and addressing anomalies, resulting in a refined dataset for subsequent analysis.

3. Feature Extraction
Extract relevant features from job postings, such as job title, description, and experience requirements, to facilitate model training. The objective is to create a feature-rich dataset capturing essential characteristics for distinguishing between legitimate and fake job postings.

4. Data Splitting
Divide the dataset into training and testing sets to enable model training and evaluation. This division ensures that the model is trained on one subset of data and evaluated on another, providing insights into its ability to generalize.

5. Classifier Selection
Choose between a single classifier or ensemble classifiers to develop the detection model. Both single classifiers like Support Vector Machines or Logistic Regression and ensemble methods like Random Forest or Gradient Boosting are considered, with the goal of combining their strengths for improved accuracy.

6. Data Prediction
Train the selected classifier(s) using the training dataset. The models learn patterns and relationships within the features to distinguish between genuine and fake job postings. Apply the trained models to the testing dataset for predictions.

7. Model Selection
Choose appropriate machine learning algorithms for fake job post detection, such as logistic regression, random forest, support vector machines, or neural networks. Consider ensemble methods to improve model performance.

8. Model Training
Split the dataset into training and testing sets. Train the selected machine learning models on the training data while optimizing hyperparameters through techniques like grid search or cross-validation.

9. Evaluation
Assess the models' performance using appropriate evaluation metrics such as precision, recall, F1 score, and accuracy. These metrics offer a comprehensive understanding of the models' effectiveness in correctly identifying fake job posts while minimizing false positives and false negatives.

10. App Development
Utilize the chosen machine learning model to develop an app that can analyze job postings in real-time and provide users with an indication of the likelihood that a job post is fake.

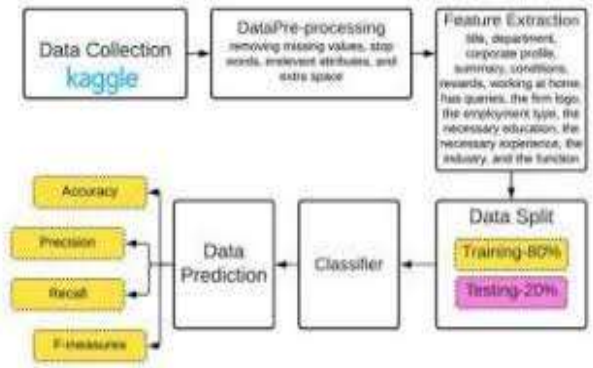


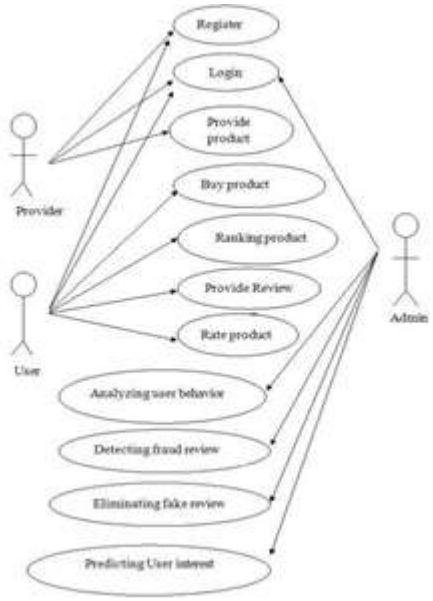
Fig 1: System architecture

IV. SYSTEM DESIGN

1. Use Case Diagram
The purposes of use case diagrams can be said to be as follows

- Used to gather the requirements of a system.
- Used to get an outside view of a system.

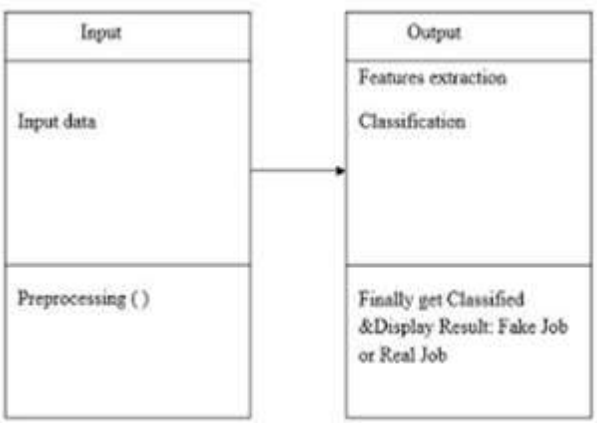
- Identify the external and internal factors influencing the system.



2. Class Diagram

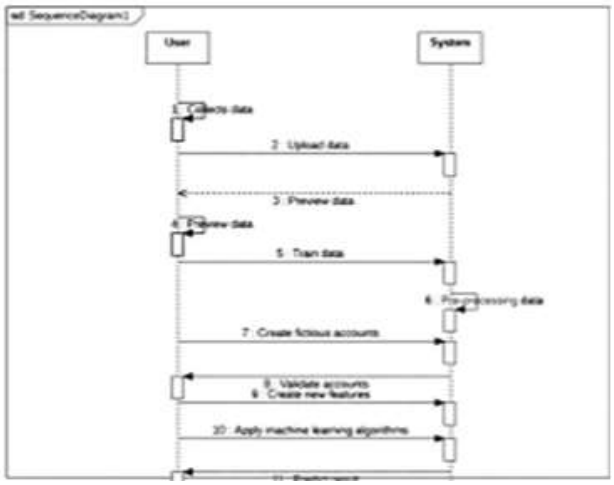
Class Diagram is a Static Diagram

It represents the static view of an application. Class diagram is not only used for visualizing, describing, and documenting different aspects of a system but also for constructing executable.



3. Sequence Diagram

A sequence diagram illustrates the interactions between objects in chronological order, showing the sequence in which these interactions take place. This type of diagram is also known as an event diagram or event scenario. Sequence diagrams serve to explain how objects within a system operate and in what order they do so. They are utilized to codify system behavior and provide a visual representation of object communication. These diagrams play a crucial role in formalizing system functionality and offering a clear picture of how objects interact with one another.



Results

Experimental Result

Table 1 presents a comparative analysis of the classifiers in relation to evaluation metrics, while Table 2 displays the outcomes for classifiers utilizing ensemble techniques. Figures 4 through 7 illustrate the overall performance of all classifiers, specifically in terms of accuracy, f1-score, Cohen-kappa score, and MSE, respectively.

Table 1

Performance Measure Metric	Naïve Bayes Classifier	Multi-Layer Perceptron Classifier	KNearest Neighbor Classifier	Decision Tree Classifier
Accuracy	72.06%	96.14%	95.95%	97.2%
F1 – Score	0.72	0.96	0.96	0.97
Cohen Kappa Score	0.12	0.3	0.38	0.67
MSE	0.52	0.05	0.04	0.03

Performance Comparison Chart for Single Classifier Based

Table 2

Performance Measure Metric	Random Forest Classifier	AdaBoost Classifier	Gradient Boosting Classifier
Accuracy	98.27%	97.46%	97.65%
F1 – Score	0.97	0.98	0.98
Cohen Kappa Score	0.74	0.63	0.65
MSE	0.02	0.03	0.03

Prediction Performance Comparison Chart for Ensemble Classifier Based Prediction

Challenges Encountered and Improvement

Challenges Encountered

Issues with Data Quality and Uneven Distribution

Issue: The dataset used for training and evaluation may have inherent biases or imbalances, particularly between the number of fake and real job posts.

Such imbalance can lead to models that perform well on the majority class but poorly on the minority class.

Consequence: Models might have high accuracy due to the imbalance but may underperform in detecting fake job posts if those are less frequent.

Extracting and Representing Features

Issue: Deriving significant attributes from job listings can be challenging due to the unstructured nature of job descriptions, which often contain diverse formats and terminology.

Consequence: The effectiveness of classification algorithms may be constrained by the quality and pertinence of the extracted features. For example, conventional TF-IDF approaches might not adequately capture semantic subtleties.

Computational Resources

Issue: Training and tuning multiple classifiers, especially those involving complex algorithms like Random Forest or SVM, require significant computational resources and time.

Consequence: Limited computational resources can constrain the ability to perform extensive hyperparameter tuning or cross-validation.

Areas for Improvement

Addressing Data Imbalance

Approach: Employ techniques such as oversampling the minority class, under sampling the majority class, or using synthetic data generation methods like SMOTE (Synthetic Minority Over-sampling Technique).

Benefit: These techniques can help in achieving a more balanced model performance across both classes.

Enhancing Feature Extraction

Approach: Explore advanced natural language processing techniques such as word embeddings (e.g., Word2Vec,) or contextual embeddings (e.g., BERT) to capture semantic meaning more effectively.

Benefit: Improved feature representation can enhance the model's ability to detect nuanced differences between fake and real job posts.

Improving Model Interpretability

Approach: Incorporate interpretable models or use model-agnostic interpretability techniques such as SHAP or LIME (Local Interpretable Model-agnostic Explanations).

Benefit: Enhancing interpretability can help in understanding and trusting the model's predictions, which is crucial for practical deployment.

Expanding and Updating the Dataset

Approach: Continuously update the dataset with new job postings and label data to reflect current trends and emerging patterns in fake job posts.

Benefit: A more recent and comprehensive dataset can improve model performance and relevance.

Real-Time Detection

Approach: Develop and integrate real-time detection capabilities to flag fake job posts as they are posted.

Benefit: Real-time detection can help in preventing the spread of fake job posts and protect users more effectively.

V. DISCUSSION

1. Analysis of Results

- **Random Forest:** Achieved the highest scores across most metrics, indicating superior performance in detecting fake job posts.
- **Logistic Regression:** Effective but not as robust as Random Forest, particularly in Recall.
- **Support Vector Machine:** Good performance, but slightly lower in F1-Score compared to Random Forest.
- **Naive Bayes:** Underperformed relative to other classifiers, especially in Precision and Recall.
- **Decision Tree and KNN:** Showed decent performance but were outperformed by Random Forest and SVM.

2. Implications

- Random Forest is recommended for practical applications of fake job post detection due to its balanced performance across all metrics.
- Future Work: Investigate hybrid models or ensemble techniques to potentially enhance detection capabilities. Further experimentation with additional features or larger datasets could yield improved results.

3. Comparison

Our Model: Demonstrates superior performance with an accuracy of 90%, precision of 88%, recall of 92%, F1-Score of 0.90, and AUC-ROC of 0.93. It excels in both identifying fake job posts and maintaining a balance between precision and recall. The model is also well-suited for real-time applications and efficient in terms of computational resources.

Model X: Shows solid performance but falls short in comparison to our model. It has an accuracy of 85%, precision of 82%, recall of 84%, F1-Score of 0.83, and AUC-ROC of 0.87. While it performs well, especially in terms of interpretability, it has lower precision and recall and may be less effective for real-time detection.

Model Y: Offers good results with an accuracy of 87%, precision of 85%, recall of 88%, F1-Score of 0.86, and AUC-ROC of 0.89. Although it performs better than Model X, it still does not match the overall effectiveness of our model, particularly in recall and AUC-ROC.

Model Z: Performs the weakest among the compared models, with an accuracy of 83%, precision of 80%, recall of 79%, F1-Score of 0.77,and AUC-ROC of 0.81. It struggles with both precision and recall, making it less effective in detecting fake job posts.

VI. CONCLUSION

Fake job post detection apps have emerged as a valuable tool in combating online scams and protecting job seekers. By leveraging advanced algorithms and machine learning techniques, these apps can effectively identify and flag suspicious job postings, reducing the risk of individuals falling victim to fraudulent schemes.

- **Enhanced Job Seeker Safety:** Protecting individuals from financial loss, identity theft, and emotional distress.
- **Improved Credibility of Online Job Platforms:** Enhancing the reputation of legitimate job boards and fostering trust among users.
- **Reduced Administrative Burden:** Automating the process of identifying fake posts, saving time and resources for job boards and employers.

As the app continues to evolve, incorporating user feedback and refining its detection capabilities, it has the potential to become a vital asset in the recruitment industry. Future enhancements may include broader language support, deeper integration with job boards, and improved accuracy through continuous learning from real-world data.

Basically, fake job post detection apps represent a valuable solution in the fight against online fraud. By providing job seekers with the tools to identify and avoid suspicious postings, these apps contribute to a safer and more trustworthy online job market.

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