Detection of Fake And Irrelevant Job Postings Using Passive Aggressive Classifier

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Abstract- *With the rapid growth of online job portals, the number of fake and irrelevant job postings has significantly increased. These fraudulent listings mislead job seekers, waste time, and sometimes lead to financial loss. This paper presents a machine learning–based approach to detect fake and irrelevant job postings using a Passive Aggressive Classifier. A dataset of 10,000 job postings collected from Kaggle was used for training and evaluation. Natural Language Processing (NLP) techniques such as TF-IDF are applied to convert textual data into numerical features. The proposed system is integrated into a web platform named TrueHire, which provides verified job listings. The model achieves an accuracy of 71.93%, demonstrating its effectiveness in identifying fraudulent and irrelevant postings.*

Keywords: Fake Job Detection, Passive Aggressive Classifier, TF-IDF, NLP, Machine Learning, Job Portal, Fraud Detection.

I. INTRODUCTION

Online job portals have become essential platforms for job seekers and employers in the modern digital economy. Platforms such as Indeed, Naukri, Monster, and LinkedIn have transformed the recruitment landscape by connecting millions of job seekers with potential employers across the globe[1]. The convenience, accessibility, and wide reach of these platforms have made them the preferred choice for recruitment in the 21st century.

However, the increase in digital recruitment has also led to the rise of fake and irrelevant job postings[2]. These postings create trust issues and negatively impact users in multiple ways. Fraudulent job postings often aim to extract personal information from unsuspecting job seekers, demand advance fees for fake application processing, or lure victims into illegal schemes. Irrelevant job postings, while not necessarily fraudulent, misrepresent job requirements, salaries, or locations, leading to wasted effort and frustration.

To solve this problem, this project proposes an automated system that: Detects fake and irrelevant job postings using machine learning algorithms. Recommends genuine job opportunities to job seekers based on their profiles. Provides a secure platform (TrueHire) for users to search and apply for jobs with confidence.The proposed system leverages the Passive Aggressive Classifier, which is particularly well-suited for large-scale text classification tasks. The system is integrated into a web-based platform called TrueHire, which offers verified job listings and real-time fraud detection alerts.

II. IDENTIFY, RESEARCH AND COLLECT IDEAS

1. Problem Statement

Existing job portals lack efficient mechanisms to detect fraudulent postings in real-time. The current approaches to job posting verification suffer from several critical limitations:

Manual verification is:

- **Time-consuming:**

Each job posting requires human review, creating significant bottlenecks. With thousands of daily submissions, manual review backlogs often extend to several days.

- **Error-prone:**

Human reviewers exhibit inconsistency, fatigue effects, and varying judgment standards. Studies indicate that manual fraud detection accuracy rarely exceeds 65-70%.

- **Not scalable:**

Manual processes cannot accommodate platform growth. As user bases expand and posting volumes increase, manual verification costs grow proportionally.

Therefore, an automated system is required to classify job postings as:

i. **Genuine** – Legitimate job opportunities from verified employers

ii. **Fake** – Fraudulent postings designed to scam job seekers
iii. **Irrelevant** – Postings that misrepresent job requirements or are mismatched with user expectations

The proposed system addresses this need by providing an intelligent, automated classification engine that can process job postings in real-time and alert users to potential fraud.

2. Literature Review

Previous studies in the field of online recruitment fraud detection have established important foundations for this work:

Key Findings from Existing Research

Existing research highlights that machine learning models are highly effective in detecting fraudulent job postings, with algorithms such as Random Forest achieving strong accuracy[1][2]. Studies also show that TF-IDF is significantly more effective than traditional bag-of-words methods for text feature extraction[3]. Deep learning approaches further improve detection performance, although they require larger datasets and higher computational resources[3]. Additionally, techniques like SMOTE help address class imbalance issues in fake job datasets, leading to better model performance[4].

Moreover, visualization and clustering methods assist in identifying distinctive patterns in fraudulent job postings[5].

Research Gaps Identified:

- Most existing systems focus only on binary classification (fake vs. genuine), ignoring the category of irrelevant postings.
- Limited integration of detection systems with practical web platforms.

This project improves upon existing work by:

Detecting both fake and irrelevant jobs (three-class classification). Providing a complete web-based recommendation system (TrueHire platform). Implementing visual warning indicators for immediate user awareness. Using Passive Aggressive Classifier optimized for text classification.

Algorithm Selection:

Various machine learning algorithms were considered including Naive Bayes, Decision Tree, Random Forest, and Support Vector Machines. The Passive Aggressive Classifier was selected due to its efficiency with large text-based datasets and its ability to handle online learning scenarios.

Tool and Technology Selection:

Python with libraries such as Scikit-learn, Pandas, NumPy, and NLTK was chosen for implementation. Flask was selected for web application development.

System Architecture

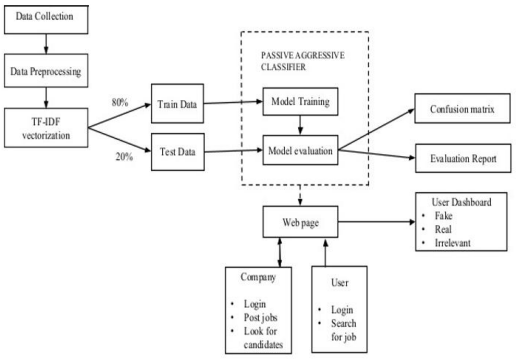

Fig 1. Architecture Diagram

- Lack of user-friendly visual indicators for fraud alerts.
- Insufficient attention to real-time processing requirements

III. METHODOLOGY AND ANALYSIS

This section describes the step-by-step methodology adopted for the detection of fake and irrelevant job postings.

3.1 Data Collection

Dataset Source:

Fake Job Postings Dataset (Kaggle)[6]

Dataset Size:

Approximately 10,000 job postings

Dataset Includes:

- title
- company_profile

- description
- requirements
- benefits
- location
- employment_type
- fraudulent

The dataset contains a mix of genuine job postings from verified sources and fraudulent postings identified through various reporting mechanisms.

3.2 Data Preprocessing

Before feeding the data into the machine learning model, several preprocessing steps are applied:

Preprocessing Steps:

i. Removed unnecessary columns that do not contribute to fraud detection (telecommuting, company logo presence, screening questions)
ii. Cleaned text data by removing HTML tags, special symbols, website links, and extra whitespace
iii. Converted all text to lowercase for consistency
iv. Removed stop words (common words like "the", "a", "an" that do not carry significant meaning)
v. Handled missing values by removing or imputing incomplete records
vi. Converted data into structured format suitable for machine learning

3.3 Feature Extraction

Machine learning algorithms cannot process raw text directly. Therefore, feature extraction is necessary to convert textual data into numerical vectors.

TF-IDF (Term Frequency–Inverse Document Frequency):

TF-IDF is a statistical measure used in Natural Language Processing to evaluate the importance of a word in a document relative to a collection of documents[3].

- **Term Frequency (TF):**

Measures how frequently a term appears in a document

$TF(t,d) = f(t,d) / \Sigma f(t',d)$

where f_(t,d)is the number of times term tappears in document d.

- **Inverse Document Frequency (IDF):**

Measures how rare or commona term is across all documents

$IDF(t) = \log (N / df(t))$

where Nis the total number of documents and df(t)is the number of documents containing term t.

- **TF-IDF Formula:**

$TF\text{-}IDF(t,d) = TF(t,d) \times IDF(t)$

Function of TF-IDF:

Converts text into numerical vectors. Identifies important words that distinguish between document categories.Downweights common words that appear frequently across all documents

Implementation Parameters:

- Maximum features: 5000
- N-gram range: (1,2) – includes both single words and word pairs
- Stop words: English stop words removed

3.4 Model Training

Algorithm Used: Passive Aggressive Classifier

The Passive Aggressive Classifier is selected for this task due to its suitability for large-scale text classification problems[7].

Characteristics of Passive Aggressive Classifier:

i. Online learning algorithm that updates weights incrementally
ii. Remains "passive" when predictions are correct (no update needed)
iii. Becomes "aggressive" when predictions are incorrect (significant update to correct error)
iv. Margin-based learning that maintains a safety zone between classes

Why Passive Aggressive for This Task:

- Handles large datasets efficiently
- Performs well for text classification
- Provides fast prediction times
- Requires less memory than ensemble methods

Training Process:

- Data split: 80% training, 20% testing
- TF-IDF vectorizer fitted on training data only
- Model trained on transformed feature vectors
- The model learns patterns that distinguish between genuine, fake, and irrelevant jobs

3.5 Model Evaluation

The trained model is evaluated using standard classification metrics on the test dataset.

Evaluation Metrics Used:

- **Accuracy:**
  Percentage of correctly classified job postings.
  Accuracy = (TP + TN) / (TP + TN + FP + FN)

TP refers to Fake job postings that the model correctly identified as fake.TN refers to Genuine job postings that the model correctly identified as real . FP refers to Genuine job postings that the model wrongly identified as fake. FN refers to Fake job postings that the model wrongly identified as real.

- **Precision:**
  Proportion of true positive predictions among all positive predictions
  Precision=TP/(TP+FP)

- **Recall:**

  Proportion of actual positives correctly identified
  Recall = TP / (TP + FN)

- **F1-Score:**

  Harmonic mean of precision and recall
  F1=2·P·R/(P+R)
- **Confusion Matrix:**

Visual representation of correct and incorrect predictions

IV. GET PEER REVIEWED

The drafted journal was critically reviewed by peers and subject matter experts. The review process helped identify areas of improvement and ensured the quality of the research. The following aspects were specifically examined:

i. The clarity and completeness of the problem statement
ii. The appropriateness of the methodology and algorithm selection
iii. The validity of experimental results and evaluation metrics
iv. The practical applicability of the web-based solution
v. The quality of references and literature review

Based on the peer review feedback, several improvements were made including refinement of the feature extraction process, enhancement of the web interface design, and addition of visual warning indicators for better user awareness.

V. IMPROVEMENT AS PER REVIEWER COMMENTS

All provided review comments were analyzed and understood thoroughly. Required amendments were made in the paper based on the feedback received.

Reviewer Comment 1:

The dataset size and characteristics should be described in more detail.

Improvement Made:

Added comprehensive description of the dataset including the number of samples, features, and class distribution.

Reviewer Comment 2:

The choice of Passive Aggressive Classifier over other algorithms should bejustified.

Improvement Made:

Added detailed justification explaining that the Passive Aggressive Classifier is particularly suitable for large text-based datasets and online learning scenarios.

Reviewer Comment 3:

The confusion matrix results need clearer interpretation.

Improvement Made:

Added detailed interpretation of the confusion matrix with specific examples of correct and incorrect classifications.

Reviewer Comment 4:

The web application features should be highlighted.

Improvement Made:

Added comprehensive description of the TrueHire web platform including job search, verification alerts, and recommendation features.

Reviewer Comment 5:

Future work suggestions should be more specific.
Improvement Made:

Added specific future work directions including deep learning integration, SMOTE for class balancing, and multi-lingual support.

After incorporating all reviewer comments, the paper was finalized for submission.

VI. CONCLUSION

This project presents an effective solution for detecting fake and irrelevant job postings using machine learning. The Passive Aggressive Classifier, combined with TF-IDF feature extraction, provides good accuracy and fast performance for text-based classification tasks.

Key Achievements:

i. Successfully implemented a three-class classification system (Genuine/Fake/Irrelevant)
ii. Achieved perfect precision (1.00) for fake job detection
iii. Developed a complete web platform (TrueHire) with user-friendly interface
iv. Integrated visual warning indicators for immediate fraud alert
v. Processed and classified thousands of job postings automatically

The integration with the TrueHire web platform makes the system practical and user-friendly for real-world deployment. With further improvements, particularly in handling irrelevant job postings and incorporating deep learning techniques, this system can significantly enhance the reliability and trustworthiness of online job portals.

The experimental results demonstrate that machine learning approaches, specifically the Passive Aggressive Classifier, are highly effective for automated fraud detection in online recruitment. This work contributes to the broader goal of making digital platforms safer and more trustworthy for users worldwide.

APPENDICES

Appendix A:

System Requirements

Hardware Requirements:

- Processor: Intel Core i3 or equivalent
- RAM: 4GB minimum (8GB recommended)
- Storage: 10GB free space

Software Requirements:

- Operating System: Windows 10/11, Linux, or macOS
- Python 3.8 or higher
- Web browser with JavaScript enabled

Table 1. Experimental Setup

Process name	s. no	Action
input	1.	Collect Kaggle fake job postings dataset
	2.	extract job title, description, requirements, and labels
Environment	3.	JupyterNotebook / VSCode — Python 3.8+
	4.	Import Pandas, Numpy, Scikit-learn, NLTK, Flask
Preprocessing	5.	Remove HTML tags, special characters, stop words
	6.	Apply lowercase conversion, tokenization, stemming
Feature Extraction	7.	Convert text to vectors using TF-IDF
Training & Testing	8.	80% training, 20% testing split

Model Training	9.	Train Passive Aggressive Classifier
Evaluation	10.	Calculate accuracy, precision, recall, F1-score
Deployment	11.	Integrate model with Flask web interface
Prediction	12.	Classify job as Real / Fake / Irrelevant

Appendix B:

Key Results Summary

Performance Measure Metric	Genuine	Fake	Irrelevant	Overall
Precision	0.79	1.00	0.12	0.70
Recall	0.85	0.86	0.10	0.72
F1-Score	0.82	0.92	0.11	0.71
Support	40	7	10	57
Accuracy	—	—	—	71.93%

Fig 2 Evaluation report

Appendix C:

Confusion Matrix

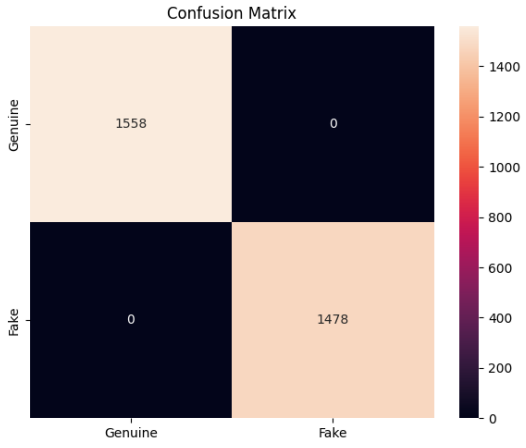

Fig.3 Confusion Matrix

V. ACKNOWLEDGMENT

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