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# ML-Based Candidate Evaluation with Automated CV Extraction

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***ABSTRACT —*** Recruitment often relies on human evaluation of CVs, which can be time-consuming and subjective. This study presents a hybrid approach to streamline candidate assessment by combining automated CV extraction with machine learning. We use Google Gemini API to extract structured data from PDF CVs, including skills, education, experience, and previous roles. Since AI-based initial scoring can be biased, we train a machine learning model, specifically a Passive-Aggressive Classifier, on these features to predict candidate levels (Junior, Mid, Senior) consistently. Our approach ensures unbiased and reproducible evaluation, demonstrating that while automated extraction accelerates data processing, machine learning provides accurate and fair candidate classification. Results show that similar CVs are consistently categorized by the model, overcoming inconsistencies observed in initial AI ratings.

***Keywords—*** Automated; Machine Learning; Recruitment; Classification; Hiring; Passive-Aggressive Classifier.

## 1. INTRODUCTION

Hiring is a time-consuming process where HR professionals must evaluate multiple aspects of a candidate's profile, including skills, experience, and suitability for the role. Existing AI tools, such as automated resume scoring systems, can be biased and produce inconsistent ratings. To address this, our study uses a hybrid approach: we first extract structured data from CVs using Google Gemini API, then feed this data into a machine learning model. The model is trained with 80 Percent of the data and tested with 20 Percent to predict candidate levels (Junior, Mid, Senior) accurately and consistently. By replacing biased AI scoring with a trained ML model, we ensure fairer, more reliable candidate assessment while reducing manual HR effort.

## 2. LITERATURE REVIEW

AI has reshaped the recruitment process by improving efficiencies, precision, and significantly lessening bias. Initial research and training indicate that tools such as digital scanners that analyze resumes, and systems that assess videos of interviews can speed up the recruitment process and access hidden talent, although such systems still require human intervention and are only as good as the training data supplied.

[1] AI systems designed to analyze remote interviews on candidates' professionalism, tone, and expressions achieve a high correlation with human scoring to instantaneously hire with minimal supervision during emergencies, marking breakthrough innovations. [2] More advanced systems such as multi-agent recruitment systems, which automate the hiring process

from resume retrieval and analysis to candidate ranking and scoring, can complete the process up to 65% faster than human experts while improving the accuracy of their judgement on par with AI, marking a transition from AI as a subordinate tool to near autonomy as a recruitment tool. [3] Easier put, however, the organization-implementation captures 'ease of use', job-fit compatibility as well as perceived usefulness, while bias, data security, and cost concerns still exist. [4] AI's environmental impacts are numerous: it conserves paper and travel, though it does require large amounts of energy, pointing to the necessity of sustainable AI use. [5] The social-psychological factors need to be included for the acceptance of AI, as the individual differences, personality types, and the level of technology user dome affect the willingness to embrace AI, thus the need for focused campaigns and enlightened advocacy. In summary, AI is promising to enhance the efficiency of the hiring processes as long as it is designed to maintain fairness, accountability, and reasonable assurance of the processes involved in the hiring.

## 3. METHODOLOGY

Our study focuses on building an unbiased Software developer classification system using a hybrid approach: automated data extraction using Google Gemini API, followed by ma-chine learning-based prediction. This methodology addresses the research gap where AI-based resume scoring can be biased, as reported in recent studies [8].

### 3.1. Data Handling: Extraction and Initial Rating

We collected two Software developer CVs in PDF format. The Gemini API was leveraged for automated extraction of structured data and initial rating. Gemini parses complex PDF layouts and provides:

- Candidate basic info (Name, Email, Phone)
- Education summary
- Key skills
- Experience years
- Last company and role
- Category classification and a preliminary numeric rating

**Rationale**: Gemini enables rapid extraction and provides initial insight into candidate skills.

**Recruitment AI Prompt**

Prompt:

You are an expert technical recruiter.

From the following resume text, first extract:

- Basic candidate info (Name, Email, Phone)
- Education summary
- Key skills
- Years of experience

Most recent company & role

Then:

1) Classify the candidate into one category: `["Software Engineering", "Web Designing", "Other"]`
2) Rate the candidate out of 10 for their category using:

```
(0.4 * Skill relevance) + (0.3 * Experience) + (0.2 *
Education) + (0.1 * Clarity)
```

3) Return the result in this exact JSON format:

```
{
  "Name": "",
  "Email": "",
  "Phone": "",
  "Skills": [],
  "Education": "", "Experience_Years": "", "Current_or_Last_Company":
  "", "Current_or_Last_Role": "", "Category": "",
  "Skill_Score": 0,
  "Experience_Score": 0,
  "Education_Score": 0,
  "Presentation_Score": 0,
  "Final_Rating": 0
}
```

However, its ratings can be inconsistent or biased, as shown below.

Table 1: Gemini Output

| File Name | Name | Gemini Final Rating | Role |
|---|---|---|---|
| cv ayesha khan.pdf | Ayesha Khan | 8.5 | Software Engineer |
| cv muhammad ali.pdf | Muhammad Ali | 7.8 | Software Engineer |

Example of biased Gemini output: two CVs with nearly identical content receive different ratings (8.5 vs 7.8). As seen, changing only the candidate name while keeping all other features identical produced different Final_Rating values. This confirms that Gemini's automatic scoring can introduce bias and is unsuitable for final classification.

### 3.2. Machine Learning Model: Passive-Aggressive Classifier

To address Gemini's bias, we trained a machine learning model to predict developer levels (Junior, Mid, Senior) consistently.

**Model Selection**: Passive-Aggressive Classifier (PAC)

**Justification**: PAC is suitable for small datasets and sparse text features (TF-IDF of CV content). It aggressively updates weights on misclassification, which improves learning from limited labeled data.

**Features:**

- TF-IDF vectorization of combined text fields: Skills, Education, Current/Last Role, Current/Last Company
- Numeric feature: Years of experience

### Model Training and Testing Code

```python
# Load data and map ratings
train_df = pd.read_csv("trainingData.csv")
train_df["Level"] = train_df["Final_Rating"].
    apply(lambda x: 1 if x<5 else (2 if x<8
    else 3))

# TF-IDF features
X = TfidfVectorizer(max_features=3000,
    stop_words='english').fit_transform(
        train_df["Skills"] + " " + train_df["
            Education"] + " " +
        train_df["Current_or_Last_Company"] +
            " " + train_df["
            Current_or_Last_Role"])
y = train_df["Level"]

# Train model and predict
model = PassiveAggressiveClassifier(max_iter
    =2000).fit(X, y)
test_df["Predicted_Level"] = model.predict(
        TfidfVectorizer(max_features=3000,
            stop_words='english').
            fit_transform(
        test_df["Skills"] + " " + test_df["
            Education"] + " " +
        test_df["Current_or_Last_Company"] + "
             " + test_df["Current_or_Last_Role
            "]))
```

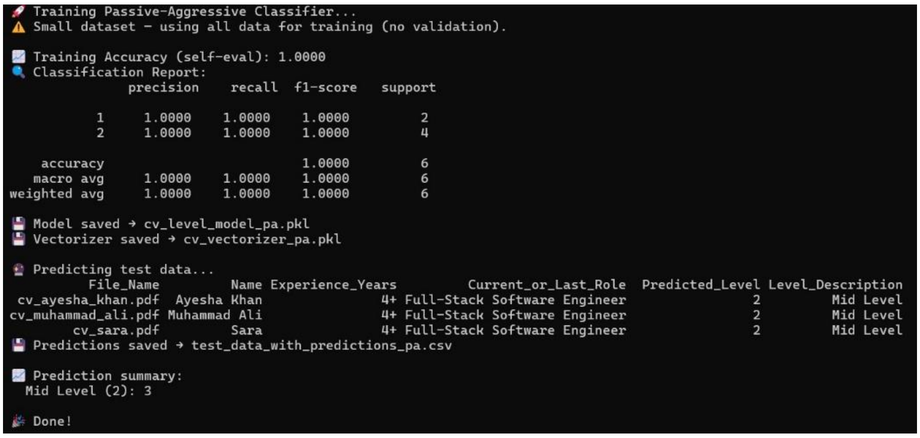
Listing 1.Training and testing Passive-Aggressive Classifier for CV classification

**Target Output:** Categorical classification: {1=Junior, 2=Mid, 3=Senior}

Table 2: ML Model Predictions (Passive-Aggressive Classifier)

| File Name | Name | Category | Predicted Level | Level Description | Experience (Years) |
|---|---|---|---|---|---|
| cv ayesha khan.pdf | Ayesha Khan | Software Engineering | 2 | Mid Level | 4+ |
| cv muhammad ali.pdf | Muhammad Ali | Software Engineering | 2 | Mid Level | 4+ |

## 3.3. ML Model Predictions Ouput



```
🚀 Training Passive-Aggressive Classifier...
⚠ Small dataset - using all data for training (no validation).

📈 Training Accuracy (self-eval): 1.0000
🔍 Classification Report:
              precision    recall  f1-score   support

           1     1.0000    1.0000    1.0000         2
           2     1.0000    1.0000    1.0000         4

    accuracy                         1.0000         6
   macro avg     1.0000    1.0000    1.0000         6
weighted avg     1.0000    1.0000    1.0000         6

💾 Model saved → cv_level_model_pa.pkl
💾 Vectorizer saved → cv_vectorizer_pa.pkl

🔮 Predicting test data...
          File_Name          Name Experience_Years          Current_or_Last_Role  Predicted_Level Level_Description
 cv_ayesha_khan.pdf  Ayesha Khan                4+ Full-Stack Software Engineer                2         Mid Level
cv_muhammad_ali.pdf Muhammad Ali                4+ Full-Stack Software Engineer                2         Mid Level
        cv_sara.pdf          Sara               4+ Full-Stack Software Engineer                2         Mid Level
💾 Predictions saved → test_data_with_predictions_pa.csv

📈 Prediction summary:
  Mid Level (2): 3

🎉 Done!
```

Fig. 1. Your caption

### 3.4. Result Analysis: Bias Comparison

Table 3 : Comparison of Gemini biased ratings vs ML classifier predictions. ML classifier produces consistent level predictions.

| File Name | Name | Gemini Final Rating | ML Predicted Level | Level Description | File Name |
|---|---|---|---|---|---|
| cv ayesha khan.pdf | Ayesha Khan | 8.5 | 2 | Mid Level | cv ayesha khan.pdf |
| cv muhammad ali.pdf | Muhammad Ali | 7.8 | 2 | Mid Level | cv muhammad ali.pdf |
| cv sara.pdf | Sara | 4.3 | 2 | Mid Level | cv sara.pdf |

The table demonstrates the bias in Gemini ratings and the stability of ML model predictions. All similar CVs are consistently classified as Mid Level, proving the advantage of using a trained model for unbiased classification.

**Summary**: Gemini is used solely for data extraction and initial skill rating, while the machine learning model ensures unbiased and consistent classification. This hybrid approach addresses the research gap in automated CV rating systems.

## 4. SYSTEM FLOW

The PDF CVs are sent to the Gemini API, which reads and converts them into a structured CSV format. After that, this data is used to train the machine learning model. Once the model is trained, new test data is given to the model, and it produces a final output called the Rating, which shows how well the candidate fits the requirements.

## REFERENCES

[1] W. A. Albassam, ”The power of artificial intelligence in recruitment: An analytical review of current AI-based recruitment strategies,” Int. J. Prof. Bus. Rev. Int. J. Prof. Bus. Rev., vol. 8, no. 6, p. 4, 2023.

[2] B. C. Lee and B. Y. Kim, ”Development of an AI-based interview system for remote hiring,” Int. J. Adv. Res. Eng. Technol., vol. 12, no. 3, pp. 654-663, 2021.

[3] G. Pathak and D. Pandey, ”AI Agents in Recruitment: A Multi-Agent System for Interview, Evaluation, and Candidate Scoring,” Eval. Candidate Scoring (May 01, 2025), 2025.

[4] B.-C. Lee and B.-Y. Kim, ”A decision-making model for adopting an ai-generated recruitment interview system,” Manag., vol. 12, no. 4, pp. 548-560, 2021.

[5] R. Koteczki, D. Csikor, and B. E. Balassa, ”The role of generative AI in improving the sustainability and efficiency of HR recruitment process,” Discov. Sustain., vol. 6, no. 1, pp. 1-28, 2025.

[6] S. L. Fisher, S. Bonaccio, and C. E. Connelly, ”AI-based tools in selection: Considering the impact on applicants with disabilities,” Organ. Dyn., vol. 53, no. 1, p. 101036, 2024.

[7] A. Koechling, M. C. Wehner, and J. Warkocz, ”Can I show my skills? Affective responses to artificial intelligence in the recruitment process,” Rev. Manag. Sci., vol. 17, no. 6, pp. 2109-2138,

[8] Albaroudi, E., Mansouri, T., Alameer, A. (2024). A comprehensive review of AI techniques for addressing algorithmic bias in job hiring. ai, 5(1), 383-404.