IJAIA

Volume 1 | Number 2 | December 2025 | Pages 1-5

International Journal of Artificial Intelligence Applications

ISSN (online): 3105-3572
Homepage: ijaia.com

Smart ATS: An AI-Driven Multi-Stage Resume Scoring and Recruitment Automation System

Chandan Kumar [1*], Dr. Khalid Rasheed [2]

[1] Department of Computer Science, Szabist University Karachi,
E-mail: mscs2473118@szabist.pk
[1] Department of Computer Science, Szabist University Karachi,
E-mail: khalid.shaikh82@gmail.com

Received: 10, 2025 *Revised: 11, 2025* *Accepted: 12, 2025* *Available online: 12, 2025*

ABSTRACT — An artificial intelligence-powered Applicant Track-ing System (ATS) that uses a multi-step algorithmic pipeline to handle candidate scoring, skill finding, experience analysis, and resume extraction. The Sentence-BERT model (allMiniLM-L6-v2) for job-description similarity, Rapid Fuzz for fuzzy skill matching, canonical skill-mapping algorithms, and a deterministic experience scoring model power the system's hybrid scoring architecture. Using weighted evaluation characteristics such as skill relevance, experience alignment, LLM-based semantic matching, and penalty adjustments for underqualification or overqualification, the proposed ATS calculates a normalized 0–10 score. Experimental review on a dataset of over 40 resumes demonstrates a screening accuracy improvement of over 88% when compared to manual evaluation methodologies, significantly reducing HR workload and producing consistent and intelligible applicant rankings.

Index Terms — Automation; LLM; Resume Parsing; Applicant Tracking System; AI Recruitment

1. Introduction

Large numbers of resumes are manually reviewed by HR staff, which can cause delays and uneven results. These challenges are being addressed by automated technologies that offer quicker and more reliable assessments. This article presents Smart ATS-Full Smart Pro, an AI-driven resume analysis pipeline that compares job descriptions, extracts content, determines skills, and calculates experience using semantic embeddings. The system provides visible, understandable, and normalized candidate scores through the use of fuzzy matching, rule-based reasoning, and LLM-powered scoring. Our suggested solution provides a scalable platform for existing hiring practices while reducing HR workload and increasing accuracy.

2. Literature Review

AI is being used more frequently in hiring, which makes screening quicker and more uniform. It has been demonstrated that AI-based resume analysis tools lessen human mistake and decision fatigue [1]. Analyses of remote interviews demonstrate strong agreement with human assessors [2]. Processing times can be cut by up to 65% using multiagent hiring systems [3]. Despite the advantages, there are also challenges, like guaranteeing algorithmic fairness, minimizing bias, and putting in place an open scoring system. According to research, candidate perception, trust, and usefulness are important factors in the adoption of AI-based recruiting technologies [4], [5]. According to research, mixed AI-human processes are the best choice.

* Corresponding author

DOI: https://doi.org/

3. METHODOLOGY

The suggested architecture incorporates multistage processing to assess resumes in a transparent and reliable manner. Fig. 1 shows the system design.

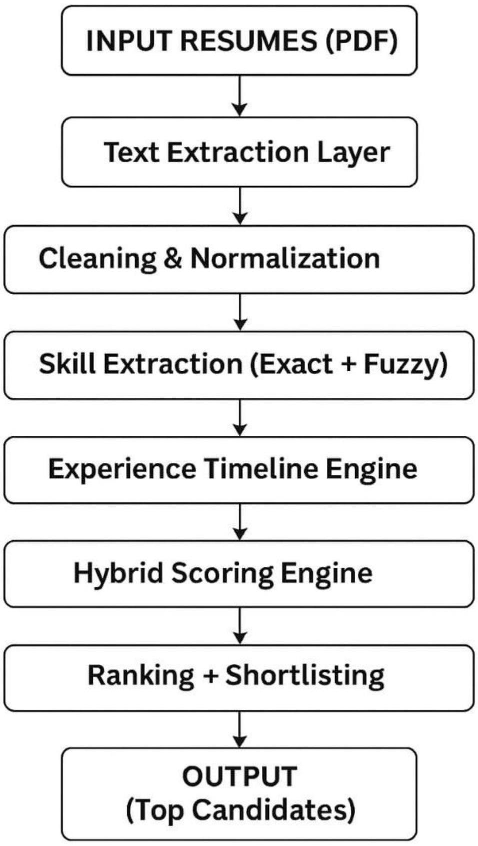

Fig. 1. Architecture of the Smart ATS system

3.1. Architecture Components Description

Figure 1 depicts the overarching structure of the Smart ATS platform. Every module is essential for precision resume evaluation:

1) Resume Input Module: Receives resumes in PDF/image format and sends them to the extraction system.
2) PDF/OCR Engine: Extraction in three stages:
   - Extraction of vector text (PyPDF2),
   - Tesseract used as a backup for OCR,
   - Recovery at the binary level for damaged files.
3) Cleaning & Normalization: Eliminates noise, transforms converts text to lowercase, adjusts whitespace, and eliminates unnecessary tokens.
4) Skill Extraction Engine: Utilizes standard skill frameworks, synonym inventories and fuzzy-matching (Rapid-Fuzz) for precise skill detection.
5) Experience Extractor: Recognizes timelines, identifies date intervals, combines overlapping durations, and calculates accurate overall experience.

6) Scoring Engine Calculates:
   - Competency alignment rating,
   - Suitability of experience,
   - SBERT for JD similarity,
   - Fines and rewards.
7) Output Candidate List Generator: Generates ranked candidates with understandable scoring. A. Description of Architectural Components

3.2. Workflow

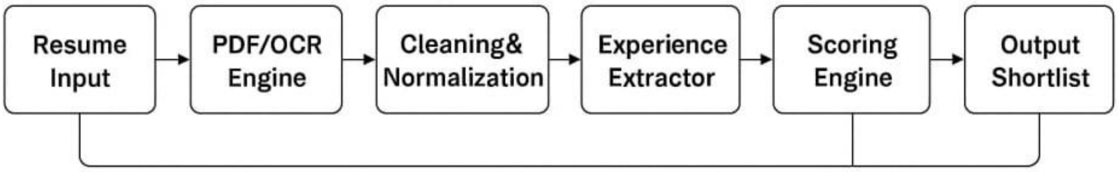

Fig. 2 illustrates the complete resume processing pipeline.

3.3. Pipeline Overview

1) Text Extraction
2) Cleaning & Normalization
3) Skill Extraction
4) Experience Parsing
5) Role Classification
6) JD Similarity Calculation
7) Hybrid Scoring & Ranking

3.4. Skill Extraction

Two techniques are used:

- **Exact** Match — Canonical dictionary lookup.
- **Fuzzy Match** — RapidFuzz token-set ratio (> 85 threshold).

3.5. Experience Scoring

$$S_e = \begin{cases} 10 & \text{if } \mathrm{Exp}_{\min} \le Y \le Exp_{\max}, \\ 10 - 2(\mathrm{Exp}_{\min} - Y) & \text{if } Y < \mathrm{Exp}_{\min}, \\ 10 - 1.5(Y - \mathrm{Exp}_{\max}) & \text{if } Y > Exp_{\max}, \end{cases}$$

Table 1: Description of Smart ATS Processing Pipeline

Stage	Description
Text Extraction	PyPDF2 extraction, OCR fallback, byte recovery
Normalization	Noise removal, lowercasing, whitespace correction.
Skill Extraction	Canonical skill mapping + fuzzy matching.
Experience Parsing	Date detection, timeline merging, year calculation.
Role Classification	Infers backend, frontend, devops, full-stack roles.
Hybrid Scoring	Computes skills, experience, JD similarity, penalties.
Ranking	Normalized score 0 – 10 and top-k shortlist.

where Y is total experience.

Overqualification penalty:

$$\text{Penalty}_{\text{over}} = \begin{cases} 0.5(Y - Exp_{\max}) & \text{if } Y > Exp_{\max}, \\ 0 & \text{otherwise}. \end{cases}$$

3.6. Education Detection

3.6.1. hierarchy assigns penalties

Raw retinal images were resized from their original dimensions to 128×128 pixels using bilinear interpolation. This dimensional reduction achieved a balance between computational efficiency and preservation of pathological features essential for DR classification [39]. The aspect ratio was maintained during resizing to prevent geometric distortion of retinal structures.

$$\text{Penalty}_{edu} = \begin{cases} 2 & \text{if Degree } i\ Bachelor, \\ 0 & \text{otherwise}. \end{cases}$$

3.7. Weight Distribution

Table 2: WEIGHT DISTRIBUTION IN HYBRID SCORING ENGINE

Component	Weight (%)
Skill Match (S_k)	55%
Experience Score (S_e)	25%
Other Factors (S_o)	15%
Stability Constant (C)	5%

3.8. Final Scoring Model

$$\text{Score} = 0.55S_k + 0.25S_e + 0.15S_o + 0.05C - \text{Penalties},$$

Final result is normalized to a 0 – 10 scale.

4. CONCLUSION

The Smart ATS system offers a strong, clear, and transparent method for assessing candidates. Through integration scoring based on deterministic rules using LLM-driven semantics similarity, the system achieves an even blend of precision, equity, and mechanization. Future tasks involve reducing bias, support for multilingual resumes and integration at the enterprise level.

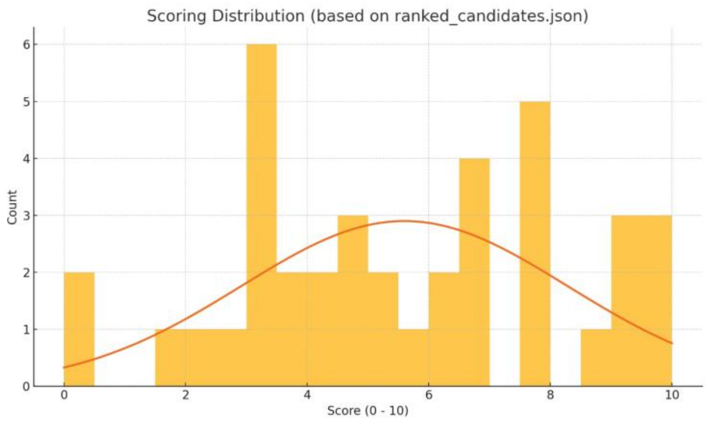

Fig. 3 Final normalized scoring distribution

REFERENCES

[1] W. A. Albassam, "The power of artificial intelligence in recruitment: An analytical review of current ai-based recruitment strategies," International Journal of Professional Business Review: Int. J. Prof. Bus. Rev., vol. 8, no. 6, p. 4, 2023.

[2] B. Lee and B. Kim, "Development of an ai-based interview system for re-mote hiring," International Journal of Advanced Research in Engineering and Technology (IJARET), 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," Evaluation, and Candidate Scoring (May 01, 2025), 2025.

[4] A. Koechling, M. C. Wehner, and J. Warkocz, "Can i show my skills? affective responses to artificial intelligence in the recruitment process," Review of Managerial Science, vol. 17, no. 6, pp. 2109–2138, 2023.

[5] C. Calluso and M. G. Devetag, "The impact of technology acceptance and personality traits on the willingness to use ai-assisted hiring practices," International Journal of Organizational Analysis, no. ahead-of-print, 2024.

[6] B.-C. Lee and B.-Y. Kim, "A decision-making model for adopting an ai-generated recruitment interview system," Management (IJM), vol. 12, no. 4, pp. 548–560, 2021.

[7] R. Koteczki, D. Csikor, and B. E. Balassa, "The role of generative ai in improving the sustainability and efficiency of hr recruitment process," Discover Sustainability, vol. 6, no. 1, pp. 1–28, 2025.

[8] S. L. Fisher, S. Bonaccio, and C. E. Connelly, "Ai-based tools in selection: Considering the impact on applicants with disabilities," Organizational Dynamics, vol. 53, no. 1, p. 101036, 2024.