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

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Abstract:

An artificial intelligence-powered Applicant Tracking System (ATS) that uses a multi-step algorithmic pipeline to handle candidate scoring, skill finding, experience analysis, and resume extraction. The Sentence-BERT model (allMiniLML6-v2) for job-description similarity, RapidFuzz 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 normalised 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

Keywords: *Index Terms—Automation, LLM, Resume Parsing, Applicant Tracking System, AI Recruitment*

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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. II. 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 multi-agent hiring systems [3]. Despite the advantages, there are also challenges, like guaranteeing algorithmic fairness, minimising 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. III. METHODOLOGY The suggested architecture incorporates multi-stage processing to assess resumes in a transparent and reliable manner.Fig. 1 shows the system design. Fig. 1. Architecture of the Smart ATS system A. 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 (RapidFuzz) 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

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rewards. 7) Output Candidate List Generator: Generates ranked candidates with understandable scoring. A. Description of Architectural Components B. Workflow Fig. 2 illustrates the complete resume-processing pipeline. Fig. 2. Workflow of the proposed Smart ATS scoring pipeline C. 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 D. Skill Extraction Two techniques are used: • Exact Match — Canonical dictionary lookup. • Fuzzy Match — RapidFuzz token-set ratio (> 85 threshold). E. Experience Scoring Se = □ □□ □□ 10 if Expmin ≤ Y ≤ Expmax, 10 − 2(Expmin − Y) if Y < Expmin, 10 − 1.5(Y − Expmax) if Y > Expmax, TABLE I 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: P enaltyover = (0.5(Y − Expmax) if Y > Expmax, 0 otherwise. F. Education Detection A hierarchy assigns penalties: P enaltyedu = (2 if Degree ¡ Bachelor, 0 otherwise. G. Weight Distribution TABLE II WEIGHT DISTRIBUTION IN HYBRID SCORING ENGINE Component Weight (%) Skill Match (Sk) 55% Experience Score (Se) 25% Other Factors (So) 15% Stability Constant (C) 5% H. Final Scoring Model Score = 0.55Sk + 0.25Se + 0.15So + 0.05C − P enalties Final result is normalized to a 0–10 scale. I. Scoring Visualization IV. 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

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