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AI Resume Screening System

Ashwini Patil[1], Tushar Patil[2]

Department of Computer Engineering

R. C. Patel Institute of Technology (RCPIT), Shirpur, Maharashtra, India

Abstract—Manual resume screening remains a significant bottleneck in technical recruitment, requiring recruiters to review large volumes of applications to identify candidates whose skills and experience align with job requirements, a process that is time-consuming and susceptible to reviewer inconsistency. This paper presents the design and development of an AI Resume Screening System that automatically extracts structured candidate information from uploaded resumes using natural language processing techniques and ranks candidates against a given job description using a semantic similarity scoring approach. The system parses resumes in PDF and DOCX formats to identify candidate skills, educational qualifications, and work experience, and computes a relevance score for each candidate against job-specific requirements using sentence-embedding-based semantic similarity combined with keyword-match weighting. The system was implemented using a Python-based natural language processing pipeline with a pretrained transformer model for entity extraction and sentence embeddings for similarity scoring, exposed through a web-based recruiter interface. The system was evaluated on a labeled dataset of resumes and job descriptions, comparing automated candidate rankings against rankings independently prepared by human recruiters, and measuring resume-parsing accuracy and end-to-end screening time. Results show that the system achieved resume field-extraction accuracy of 90.6%, its top-ranked candidates matched recruiter-prepared shortlists in 85.4% of evaluated cases, and average screening time per job posting was reduced by approximately 68% compared to fully manual review. These findings indicate that AI-assisted resume screening can substantially reduce recruiter workload while maintaining strong alignment with expert recruiter judgment.

Index Terms—*AI Resume Screening, Natural Language Processing, Resume Parsing, Semantic Similarity, Candidate Ranking, Named Entity Recognition, Recruitment Automation, Sentence Embeddings.*

I. INTRODUCTION

Technical recruitment commonly involves reviewing large volumes of resumes to identify candidates whose skills and experience align with a given job's requirements, a process that is time-consuming and subject to reviewer fatigue and inconsistency, particularly at scale during high-volume hiring cycles or campus placement drives. Manual screening also offers limited scalability as applicant volume grows relative to available recruiter time.

Recent advances in natural language processing, particularly pretrained transformer-based language models and sentence-embedding techniques, have enabled more accurate automated extraction of structured information from unstructured resume text and more semantically meaningful comparison between candidate qualifications and job requirements than earlier keyword-matching approaches.

This paper presents the design, development, and evaluation of an AI Resume Screening System that combines automated resume parsing with

B. Semantic Similarity for Candidate-Job Matching

Candidate-job matching approaches employing sentence-embedding-based semantic similarity have been shown in the literature to better capture conceptually related but differently worded skills (for example, matching "web development" to "front-end engineering") compared to purely keyword-based matching, improving alignment with human recruiter judgment.

III. SYSTEM DESIGN

A. System Architecture

The AI Resume Screening System comprises three core components: a resume-parsing module, a candidate-ranking module, and a recruiter-facing web interface, all supported by a backend database storing parsed candidate profiles, job descriptions, and ranking results, as summarized in Table I.

B. Resume Parsing Module

Uploaded resumes (PDF or DOCX) are processed through a text-extraction pipeline followed by a pretrained transformer-based named-entity recognition semantic-similarity-based candidate ranking, intended to reduce recruiter screening workload while maintaining strong alignment with expert recruiter judgment.

II. LITERATURE REVIEW

A. Automated Resume Parsing

Prior work on resume parsing has progressed from rule-based pattern matching to statistical and, more recently, transformer-based named-entity recognition approaches for extracting structured fields such as skills, education, and experience from unstructured resume text, with transformer-based approaches generally reporting improved extraction accuracy across varied resume formats and layouts.

model fine-tuned to identify candidate skills, educational qualifications, and work experience, populating a structured candidate profile.

C. Candidate Ranking Module

Job descriptions are similarly parsed to extract required skills and qualifications. Each candidate profile is scored against a given job description using a weighted combination of exact skill-keyword matches and semantic similarity, computed via sentence embeddings of extracted candidate skills and job requirements, producing a ranked candidate list for recruiter review.

TABLE I — Core Components of the AI Resume Screening System

Component	Function	Key Technique
Resume Parsing Module	Extract structured candidate data from resumes	Transformer-based named entity recognition
Candidate Ranking Module	Score and rank candidates against job description	Semantic similarity (sentence embeddings) + keyword matching
Recruiter Interface	Upload job descriptions and review ranked candidates	Web-based dashboard

IV. IMPLEMENTATION AND EVALUATION METHODOLOGY

The system was implemented using a Python-based natural language processing pipeline, with a pretrained transformer model fine-tuned on a labeled resume dataset for entity extraction, and a pretrained sentence-embedding model used to compute semantic similarity between extracted candidate skills and job-requirement text. The recruiter-facing interface was implemented as a web application allowing job-description upload and ranked candidate-list review.

Evaluation was conducted using a labeled dataset of resumes and corresponding job descriptions, with resume-parsing accuracy assessed against manually annotated ground-truth fields, and candidate-ranking relevance assessed by comparing the system's top-ranked candidates against independent shortlists prepared by human recruiters reviewing the same resume-job pairs. Screening-time reduction was estimated by comparing recruiter time on system-assisted versus fully manual review of a matched set of job postings.

V. RESULTS AND DISCUSSION

The resume-parsing module achieved an overall field-extraction accuracy of 90.6% across skills, education, and experience fields, as summarized in Table II. The system's top-ranked candidates matched recruiter-prepared shortlists in 85.4% of evaluated job-resume sets, indicating strong alignment with expert recruiter judgment, with most disagreements attributable to soft-skill and contextual factors not captured by the semantic-similarity scoring alone. Average recruiter screening time per job posting was reduced by approximately 68% when using the system compared to fully manual resume review, summarized in Table III, primarily due to the elimination of line-by-line manual resume reading during initial candidate shortlisting.

VI. CONCLUSION

This paper presented an AI Resume Screening System combining transformer-based resume parsing with semantic-similarity candidate ranking. Evaluation results showed strong resume-parsing accuracy (90.6%), close alignment with recruiter-prepared shortlists (85.4% agreement), and a substantial (~68%) reduction in recruiter screening time, supporting the practical value of AI-assisted resume screening in reducing recruiter workload while preserving alignment with expert judgment, though continued recruiter oversight remains important for factors beyond automated skill matching.

TABLE II — Resume Parsing Field-Extraction Accuracy

Field	Extraction Accuracy (%)
Skills	87.3
Education	93.8
Work Experience	90.7
Overall (average)	90.6

TABLE III — Summary of Evaluation Results

Metric	Result
Overall resume field-extraction accuracy	90.6%
Candidate-ranking agreement with recruiter shortlist	85.4%
Reduction in recruiter screening time	~68%

VII. REFERENCES

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