

AI POWERED RESUME SCREENING AND CANDIDATE RANKING SYSTEM FOR EFFICIENT RECRUITMENT

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ABSTRACT

The exponential growth of online job applications has made manual resume screening inefficient and prone to bias. This paper presents an AI-Powered Resume Screening and Candidate Ranking System that automates recruitment using Natural Language Processing and Machine Learning techniques. The system evaluates resumes against job descriptions and computes Applicant Tracking System (ATS) scores based on skill relevance, experience, and textual similarity. It supports PDF and DOCX resumes and provides transparent rejection feedback to candidates. Recruiters can efficiently rank applicants using an intuitive dashboard. Experimental results demonstrate reduced screening time, improved consistency, and enhanced decision-making, making the system

suitable for large-scale and data-driven recruitment.

KEY WORDS: *Resume Screening, Applicant Tracking System, Natural Language Processing, Machine Learning, Candidate Ranking*

INTRODUCTION

Recruitment plays a vital role in organizational success, yet traditional hiring processes are often manual, time-consuming, and inconsistent. Recruiters must evaluate large volumes of resumes, increasing the likelihood of human bias and overlooked talent. Basic keyword-based filtering tools lack contextual understanding and fail to identify suitable candidates accurately. Recent advances in Artificial Intelligence and Natural Language Processing enable

automated analysis of unstructured resume data.

By leveraging machine learning algorithms, recruitment systems against job requirements. The objective of this research is to design an intelligent resume screening and candidate ranking system that generates ATS scores, provides transparent feedback, and supports data-driven hiring decisions.

LITERATURE REVIEW

Desai et al. (2025) proposed an AI-powered resume screening system using TF-IDF and cosine similarity to match resumes with job descriptions, significantly reducing manual effort. Kumar et al. (2025) introduced an AI-based Applicant Tracking System integrating NLP for resume parsing and ranking, showing improved accuracy over keyword filtering.

Khatri et al. (2025) developed an automated screening framework categorizing candidates based on job fit. Although these studies demonstrate efficiency improvements, limitations remain in semantic understanding, transparency, and explainability, motivating the proposed approach.

RELATED WORK

Existing recruitment automation systems focus on resume parsing, skill extraction, and relevance scoring using NLP and machine learning. Techniques such as TF-IDF, cosine similarity, and rule-based matching are commonly employed. While these systems improve screening speed and consistency, many lack explainable decision-making and meaningful feedback for candidates. The proposed system addresses these gaps by integrating weighted scoring and rejection reason generation to enhance transparency.

EXISTING METHOD

Current recruitment methods rely on manual screening or basic automated tools. Keyword-based systems often miss contextual relevance and may introduce bias. Existing AI-based screening approaches depend heavily on term frequency and struggle with varied resume formats. Most systems do not provide detailed feedback to applicants, reducing trust and clarity in hiring decisions.

PROPOSED METHOD

The proposed AI-powered system integrates NLP preprocessing, TF-IDF vectorization,

cosine similarity, and weighted ATS scoring to evaluate resumes accurately. It supports multiple resume formats and generates transparent rejection reasons. Recruiter and candidate dashboards enable efficient interaction, ranking, and application tracking, resulting in fair and scalable recruitment automation.

ARCHITECTURE

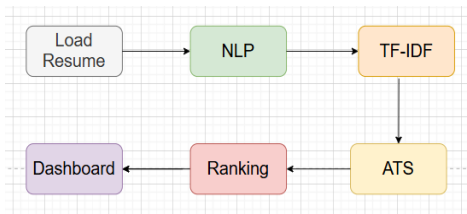


Fig-1: System Architecture

METHODOLOGY DESCRIPTION

Users authenticate through secure login mechanisms. Recruiters post job requirements, while candidates upload resumes. The system extracts and preprocesses resume text, converts it into feature vectors, and computes similarity scores. ATS scores are generated using weighted criteria, candidates are ranked, and transparent feedback is displayed through dashboards.

RESULTS AND DISCUSSION

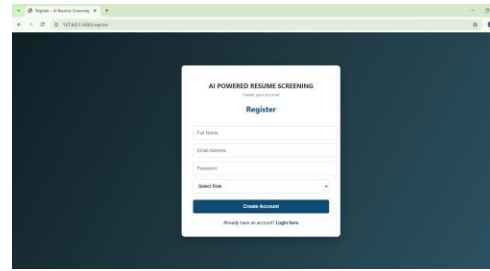


Fig-2: Sign In page

In the above figure we have a sign page in which we have to fill name, email, password and role selection.

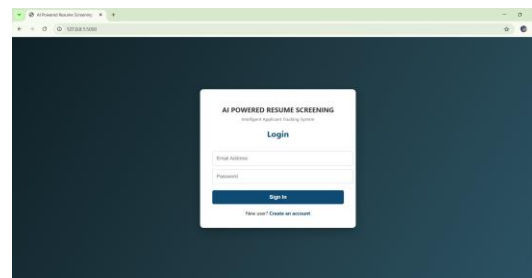


Fig-3: Login page

In the above figure we have a login page in which we have to fill valid email and password.

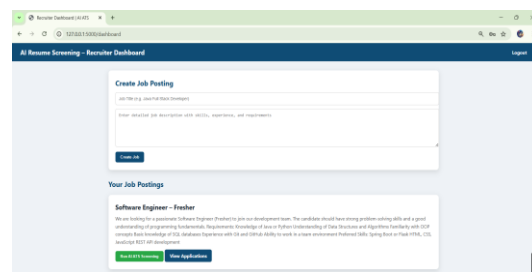


Fig-4: Recruiter Dashboard

In the above we can create a job by providing job title and job description and after creating it shown under the Job Postings.

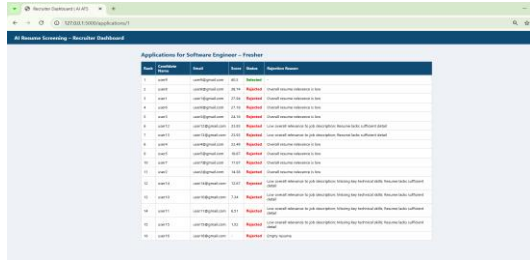


Fig-5: Applicant Details

In the above figure we have the details of applicants in that we have status, rejection reason, ATS score and applicant personal details.

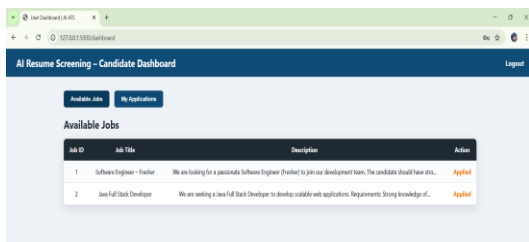


Fig-6: Candidate Dashboard

In the above figure we have seen the candidate dashboard in that we have the available jobs and Application details.

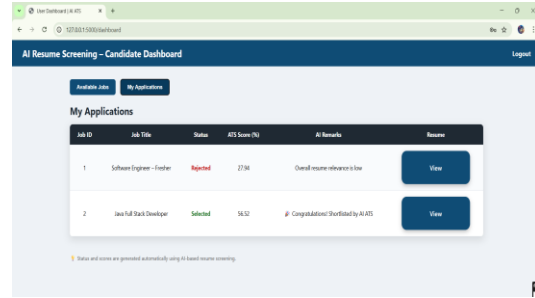


Fig-7: Application Details

In the above figure we have seen the Candidate status and ATS score and Rejection reason.

CONCLUSION AND FUTURE ENHANCEMENT

Conclusion

The AI-based real-time waste sorting system using YOLO and deep learning successfully automates the detection, classification, and counting of waste materials in recycling plants. By integrating computer vision with object tracking, the system accurately identifies different waste categories such as plastic, glass, metal, organic, and e-waste. The use of OpenCV for preprocessing and Flask for real-time monitoring enhances system performance and usability. Compared to manual sorting, the proposed solution reduces human effort, improves efficiency, ensures worker safety, and delivers faster,

more reliable results. Overall, the system provides a scalable and intelligent approach for modern waste management in smart recycling facilities.

Future Enhancements

Future improvements can include integrating robotic arms for automatic physical segregation of detected waste. Enhancing the model with larger and more diverse datasets can improve accuracy under varying conditions. The system can be extended with IoT sensors for smart plant automation and real-time data sharing. Implementing edge computing can reduce latency and enable faster processing. Additionally, incorporating predictive analytics can help forecast waste patterns, while improving performance in low-light or complex environments will make the system more robust and practical for real-world deployment.

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