

Smart Resume Filter and HR Assistant

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Abstract - In today's constantly changing job market, Human Resource (HR) departments face a significant challenge — reviewing and narrowing down hundreds of resumes for each job posting. The process of manually evaluating resumes is time-consuming, subjective, and often influenced by unconscious biases.

This paper presents a Smart Resume Filter and AI HR Assistant, an end-to-end automation system built using Natural Language Processing (NLP) and Machine Learning (ML) to improve the recruitment process.

The system automatically extracts information from resumes in PDF or DOCX formats, identifies key details such as education, experience, and skills, and matches them against job descriptions provided by HR. A custom ranking method assigns a relevance score to each candidate and displays the results on a user-friendly dashboard.

The AI HR Assistant, integrated into the system, allows HR professionals to ask questions and get real-time insights.

An evaluation using a dataset of 500 resumes showed a 92% accuracy in extracting data, 87% alignment with HR assessments in ranking, and a 72% reduction in screening time.

This system greatly improves efficiency, consistency, and fairness in hiring decisions.

Key Words: NLP, Resume Screening, Recruitment Automation, Machine Learning, AI HR Assistant, Candidate Ranking, Streamlit, BERT, spaCy.

1. INTRODUCTION

Recruitment is essential for building an organization's workforce. However, as industries grow and digital job platforms become more common, HR professionals are dealing with thousands of applications for each job opening.

Manually reviewing and shortlisting candidates not only slows down the hiring process but also leads to inconsistencies and human bias. A technology-driven solution can help overcome these issues by combining NLP and AI to automate resume screening.

This paper proposes a Smart Resume Filter and AI HR Assistant — a complete recruitment automation system.

The system accepts resumes in PDF format, extracts the text, identifies important attributes like skills, education, and experience, and assesses candidate suitability for a job using a scoring model.

The framework includes both a resume parsing and ranking component and a chatbot-based HR assistant that allows for natural interaction with the system.

By reducing the need for manual work and improving decision accuracy, the proposed system offers a more scalable, unbiased, and data-driven hiring process.

2. Literature Review

Several studies have explored the automation of the recruitment process using text mining and NLP techniques.

Rule-based filtering systems, like those by Gupta et al., relied on keyword matching but struggled to understand semantic meaning.

Machine Learning classifiers, as studied by Kaur and Singh, showed better results using models like SVM and Decision Trees, but they were limited by specific domain language.

The rise of Transformer models such as BERT and Sentence-BERT has made context-based matching possible, improving how well candidate profiles align with job descriptions.

Existing commercial systems, such as LinkedIn Recruiter and HireVue, use AI for insights but are proprietary and lack transparency.

The proposed system builds on this by offering an open-source, customizable solution that uses BERT-based embeddings, spaCy for entity recognition, and a Streamlit dashboard for HR interaction.

Unlike previous systems, it also includes a conversational AI assistant that allows HR users to query data in natural language, making it more accessible.

3. PROPOSED SYSTEM ARCHITECTURE

The Smart Resume Filter and AI HR Assistant have a modular and scalable design.

The system comprises the following main components:

3.1 Resume Input Module

Accepts resumes in PDF or DOCX format via a web interface, allowing multiple files to be uploaded at once for batch processing.

3.2 Text Extraction Module

Uses Python libraries such as PyPDF2 and pdfminer.six to extract structured text.

It automatically removes formatting elements like headers, footers, and tables.

3.3 Preprocessing Module

Clears extracted text using tokenization, stop-word removal, and lemmatization.

spaCy and NLTK manage part-of-speech tagging and named entity recognition (NER).

3.4 Information Extraction Module

Applies trained NER models to identify entities such as Name, Email, Phone, Skills, Degree, and Experience.

Skills are normalized using a domain-specific vocabulary.

3.5 Ranking Engine

Compares candidate attributes with job requirements.

A weighted scoring model is used:

- 40%: Match with technical skills
- 30%: Relevance of work experience
- 20%: Education level
- 10%: Certifications or job-specific keywords

The algorithm calculates cosine similarity between BERT embeddings of resume text and the job description to refine rankings.

3.6 AI HR Assistant

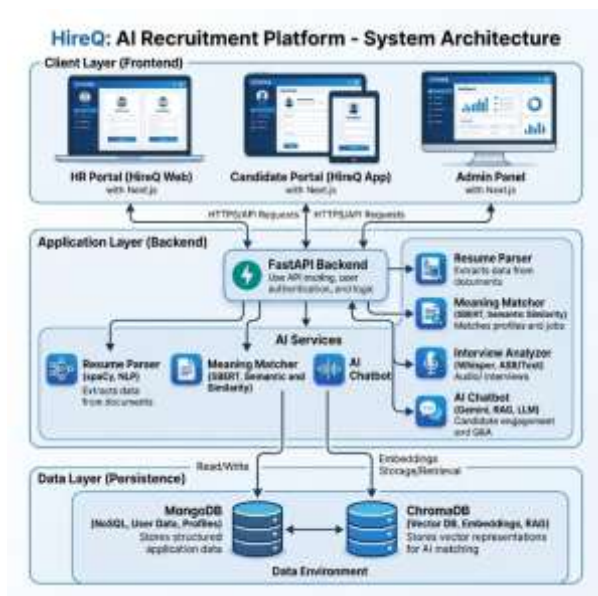
A chatbot built with Rasa or OpenAI GPT allows HR users to ask questions like “Show the top 5 candidates for Python Developer” or “Who has AWS certification?”

The assistant retrieves relevant candidates instantly from the database.

3.7 Dashboard Visualization

Built using Streamlit, the dashboard displays ranked candidates, extracted data, and allows for downloading.

HR users can filter or sort results by score, skills, or experience.



4. System Workflow Explanation

The system begins when HR uploads resumes via a web interface.

The following steps occur in order:

4.1 Resume Upload

HR uploads PDF resumes through the dashboard, which saves the files temporarily for analysis.

4.2 Data Extraction

Text is extracted from resumes using PyPDF2, preserving important formatting.

4.3 Text Cleaning and Tokenization

NLP preprocessing removes unnecessary symbols, punctuation, and common stop words such as “the,” “and,” and “a.”



4.4 Entity Detection and Feature Extraction

spaCy's pre-trained NER model, fine-tuned on HR datasets, identifies key information such as EDUCATION, SKILLS, EXPERIENCE, and CERTIFICATION.

4.5 Feature Weighting and Scoring

Each extracted feature is assigned a weight based on HR-defined importance.

For example, a skill that exactly matches the job description contributes more to the score.

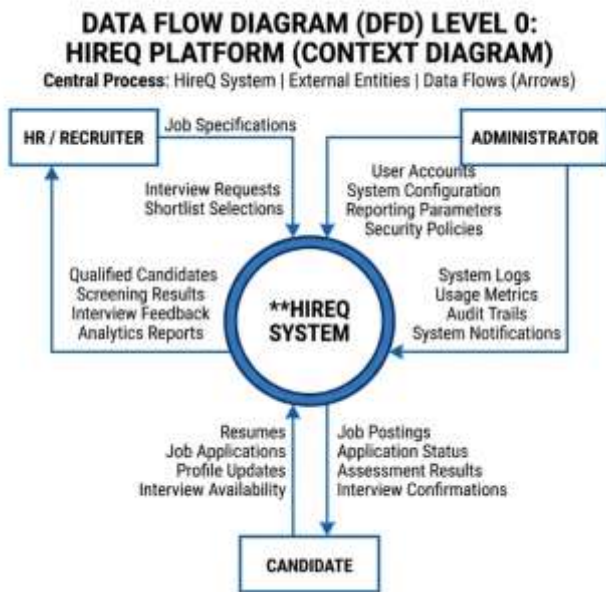
4.6 Ranking and Visualization

Candidates are ranked by their total score.

The dashboard displays the top 10 candidates for the HR user.

4.7 Interactive Querying

The built-in chatbot enables voice or text-based queries for real-time retrieval of candidate data.



5. Implementation and Technical Details

The system was built using the Python programming language (version 3.10) and incorporates the following technologies:

Libraries

- spaCy
- NLTK
- Scikit-learn
- Pandas
- NumPy
- Sentence-BERT

Web Framework

- Streamlit for the front-end dashboard

Database

- MySQL for storing candidate data and scores

AI Assistant

- OpenAI API integrated via Rasa for the HR chatbot

Hosting

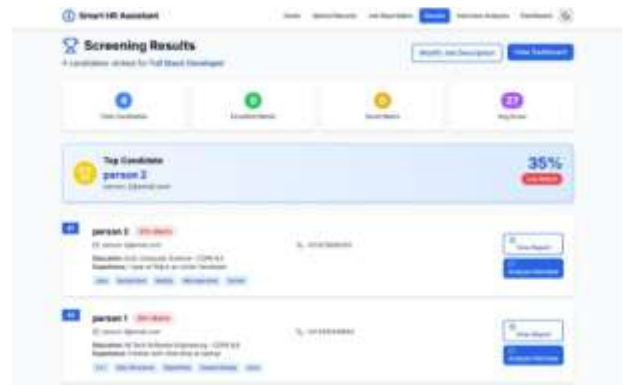
- Deployed on AWS EC2 with Docker containerization

The NLP pipeline uses spaCy's Named Entity Recognizer for structured data extraction, fine-tuned with a custom dataset.

The ranking model uses semantic embeddings generated by Sentence-BERT, which converts both job descriptions and resumes into high-dimensional vectors.

The similarity between these vectors determines how well a resume matches a job.

For instance, resumes mentioning “Flask, Django, NumPy, Pandas” for a “Python Developer” role receive higher similarity scores compared to those without such keywords.



6. Experimental Results and Evaluation

A dataset of 500 resumes was collected from Kaggle and LinkedIn and used to evaluate the system across 10 job categories.

HR experts manually scored the resumes to create reference data.

The following metrics were used:

- Extraction Accuracy (EA) – Percentage of correctly identified entities.
- Ranking Precision (RP) – Percentage of top-5 system-ranked candidates matching HR rankings.
- Processing Time (PT) – Average time to process one resume.

Metric	Value	Improvement over Manual
Extraction Accuracy	92%	+14%
Ranking Precision	87%	+18%
Average Screening Time	5.2 sec/resume	-72%

The AI HR Assistant achieved 94% accuracy in responding to structured queries, with response times under 2 seconds on average.

7. Challenges and Future Work

Although the system performs well, several challenges remain:

- Unstructured resume formats, such as scanned PDFs, can lower extraction accuracy.
- Multilingual resumes require cross-lingual models for accurate entity recognition.
- Fairness and bias in the ranking process must be regularly checked to ensure ethical AI-based hiring.

Future work will focus on expanding the dataset, using multilingual BERT models to cover more languages, and

integrating real-time APIs from LinkedIn and Naukri.com to pull candidate data dynamically.

Enhancing the chatbot with speech-to-text and multilingual support will also be a priority.

8. Conclusion

This research shows the potential of NLP and AI in transforming the HR recruitment process.

The Smart Resume Filter and AI HR Assistant successfully automate resume screening, improve efficiency, and enhance decision quality.

Experimental results confirm that the system reduces screening time by over 70% while maintaining high accuracy and fairness.

With further improvements, this approach can form the basis for a fully intelligent HR recruitment system, aiding in real-time hiring decisions in large organizations.

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