

Design and Implementation of a Smart NLP-Based Resume Screening Tool for Technology-Driven Recruitment

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ABSTRACT

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Modern recruitment increasingly depends on digital ecosystems in which speed, scalability, and objectivity are primary drivers of competitive advantage, and organisations routinely review large numbers of resumes for a single vacancy. Traditional resume screening is time-consuming, inconsistent, and highly dependent on manual judgment or simple keyword matching, which may cause qualified candidates to be overlooked when their resumes use different wording from the job description. This study presents the design and implementation of a smart Natural Language Processing (NLP)-based resume screening tool that supports automated resume analysis and candidate ranking. The system extracts resume text, preprocesses the content, identifies key information such as skills, education, and experience, and compares resumes with job descriptions using keyword matching and semantic similarity techniques. A weighted scoring mechanism combines both signals to generate a final relevance score, allowing candidates to be ranked according to their suitability for a given job role. The system was evaluated based on matching accuracy, ranking consistency, processing efficiency, and result interpretability. The findings indicate that the proposed system improves screening consistency and reduces manual effort while maintaining transparency through explainable scoring, directly addressing concerns about algorithmic bias and the lack of explainability reported in technology-driven recruitment. Therefore, the system provides a practical and scalable solution for supporting early-stage recruitment processes, particularly for small and medium-sized organisations seeking context-aware yet interpretable screening.

1. Introduction

The rapid advancement of Artificial Intelligence (AI) technologies has significantly transformed organisational operations across industries, particularly in human resource management and recruitment. The global labour market is transitioning from traditional hiring toward integrated

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digital ecosystems in which speed, scalability, and objectivity have become primary drivers of competitive advantage [1]. Modern organisations increasingly rely on Applicant Tracking Systems (ATS) to manage large volumes of job applications, streamline recruitment workflows, and improve hiring efficiency. These systems assist recruiters in handling hundreds of resumes received for a single vacancy, especially in graduate recruitment, internship programmes, and entry-level hiring. However, despite their widespread adoption, many existing ATS platforms continue to rely primarily on keyword-based filtering techniques that lack contextual understanding of resume content [2].

Resume screening is a critical stage of the recruitment process because it determines which candidates proceed to further evaluation. Traditional screening methods often require recruiters to review resumes manually and compare candidate qualifications against job requirements. This process is time-consuming, labour-intensive, and prone to inconsistency due to variations in human judgment and interpretation [3]. Furthermore, candidates possessing relevant skills and experience may be overlooked when their resumes use terminology different from that specified in the job description, resulting in unfair evaluation and reduced recruitment effectiveness.

Natural Language Processing (NLP), a subfield of Artificial Intelligence, offers promising solutions to these challenges by enabling computers to understand, process, and analyse human language. NLP techniques transform unstructured textual data into structured representations suitable for computational analysis. Through text preprocessing, information extraction, keyword matching, and semantic similarity analysis, NLP allows recruitment systems to evaluate resumes based on contextual meaning rather than exact keyword occurrence [4]. This capability improves candidate matching accuracy and supports more reliable recruitment decision-making.

The fairness and transparency of algorithmic hiring have also come under intensifying scrutiny. Prior work has shown that AI models trained on historical data can perpetuate demographic bias, and empirical studies of technology-driven recruitment report practitioner concern regarding the disproportionate screening-out of candidates from institutions or regions [5]. Many existing solutions focus primarily on automation rather than explainability and contextual understanding; several systems lack transparent scoring mechanisms, making it difficult for recruiters and applicants to understand how rankings are generated. In addition, some advanced approaches employ computationally intensive models that may not be practical for small and medium-sized organisations [6].

Existing literature therefore reveals a clear gap: traditional ATS platforms depend on keyword filtering and lack contextual awareness, while many AI-based alternatives prioritise automation over interpretable, resource-efficient screening. Addressing this gap is significant because a transparent, context-aware, and lightweight screening tool would improve both the accuracy and the fairness of early-stage recruitment while remaining deployable by resource-constrained organisations. Accordingly, the objective of this study is to design, implement, and evaluate a Smart NLP-Based Resume Screening Tool that integrates resume parsing, text preprocessing, information extraction, keyword matching, and semantic similarity analysis with explainable weighted scoring within a single web-based platform. The remainder of this manuscript is organised as follows: Section 2 describes the methodology and system design; Section 3 presents the results of system testing and evaluation; and Section 4 concludes the study and outlines future enhancements.

2. Methodology

The methodology adopted in this study follows an implementation-oriented research approach focused on the design, development, and evaluation of a Smart NLP-Based Resume Screening Tool. The objective of the methodology is to provide a systematic framework for transforming

unstructured resume data into measurable candidate rankings through the application of Natural Language Processing techniques. The methodology was designed to ensure that the proposed system produces accurate, consistent, and interpretable screening outcomes while remaining practical for real-world recruitment scenarios.

2.1 System Workflow and Architecture

The overall workflow of the proposed system consists of several sequential stages, namely data acquisition, text extraction, text preprocessing, information extraction, similarity computation, score generation, candidate ranking, and system evaluation. The process begins when users upload resumes and provide a job description through a web-based interface. Resumes are accepted in digital document formats and subsequently processed to extract textual content for analysis. The overall system architecture is illustrated in Figure 1.

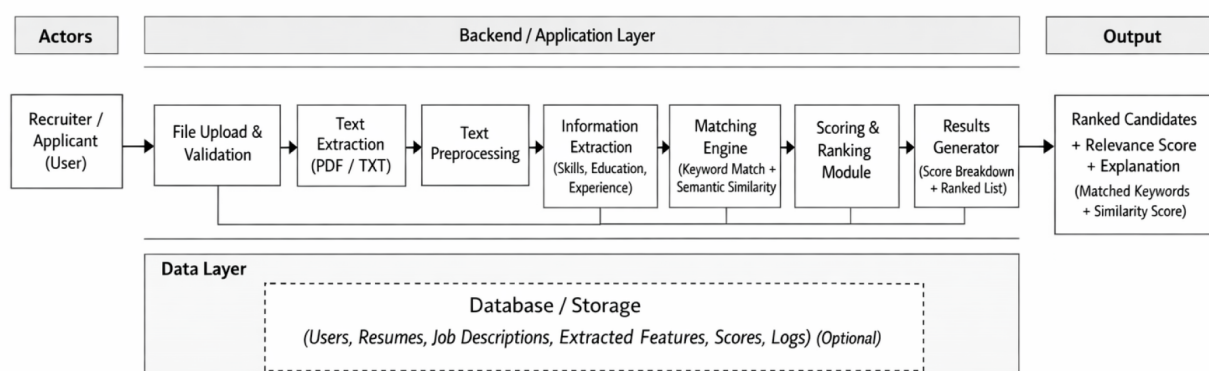


Fig. 1. Overall system architecture of the Smart NLP-Based Resume Screening Tool

The architecture is organised into interconnected modules, namely the Resume Upload Module, Text Extraction Module, Text Preprocessing Module, Information Extraction Module, Matching and Scoring Module, Ranking Module, and Result Visualisation Module. Each module performs a specific function within the screening pipeline while contributing to the overall objective of generating accurate and explainable candidate rankings. The modular design ensures maintainability, scalability, and efficient integration of NLP components, and it allows future enhancements to be incorporated without redesigning the entire system.

2.2 Text Extraction and Preprocessing

The first analytical stage involves text extraction, in which raw textual information is retrieved from uploaded resume documents through the Resume Upload and Text Extraction modules. Because resumes often contain inconsistent formatting, special characters, tables, and non-standard structures, the extracted content requires further processing before meaningful analysis can be performed. Accurate extraction is critical because errors introduced at this stage may negatively affect downstream processes such as information extraction and similarity computation [7].

The extracted text is then passed to the preprocessing module, which serves as a critical foundation for improving the quality and reliability of subsequent NLP operations. Text preprocessing consists of several standard techniques, including text cleaning, lowercase conversion, tokenization, stop-word removal, and lemmatization. Text cleaning removes unwanted symbols, punctuation, excessive whitespace, and formatting artifacts. Lowercase conversion standardises representation

so that words with different capitalisation are treated consistently. Tokenization divides content into individual tokens, stop-word removal eliminates frequently occurring words that contribute little semantic value, and lemmatization reduces words to their base forms to ensure consistent treatment of grammatical variations [4].

2.3 Information Extraction

Following preprocessing, the Information Extraction Module identifies and structures important candidate information, including technical skills, educational qualifications, work experience, certifications, and project involvement. Information extraction is essential because resumes are inherently unstructured and vary significantly in formatting and content organisation. By transforming extracted information into structured features, the system enables consistent comparison across different resumes and facilitates more reliable candidate evaluation [8].

2.4 Matching and Weighted Scoring

The matching process is divided into two complementary components: keyword matching and semantic similarity analysis. Keyword matching evaluates the overlap between resume content and job requirements by identifying shared terms, skills, and qualifications; this provides an efficient mechanism for detecting explicit matches. However, keyword matching alone may overlook candidates who describe relevant competencies using alternative terminology [2,3].

To address this limitation, semantic similarity analysis focuses on the contextual relationships between resumes and job descriptions rather than exact word matches. Both documents are transformed into vector representations that capture underlying semantic information, and a similarity measure is applied to determine the degree of alignment between candidate qualifications and job requirements. This enables the system to recognise equivalent skills and related concepts even when different wording is used, thereby improving matching accuracy and reducing false exclusions of qualified candidates [9-11].

The final relevance score is generated using a weighted scoring approach that combines the two signals, as expressed in Eq. (1). The weighting scheme places greater emphasis on semantic similarity because contextual understanding is considered more representative of actual candidate suitability than exact keyword occurrence; keyword matching nonetheless remains important for ensuring alignment with explicit job requirements.

$$Score_{final} = 0.4 \times Score_{keyword} + 0.6 \times Score_{semantic} \quad (1)$$

where $Score_{keyword}$ denotes the normalised keyword-matching score and $Score_{semantic}$ denotes the normalised semantic-similarity score, each bounded between 0 and 1. Once relevance scores are calculated, candidates are ranked in descending order; higher scores indicate stronger alignment between the resume and the job description. The ranked results are presented through the web interface, allowing recruiters to review candidate suitability and make informed shortlisting decisions.

2.5 Evaluation Criteria

To evaluate the effectiveness of the proposed system, four evaluation criteria were established, as summarised in Table 1. Matching accuracy measures the system's ability to identify relevant

candidates correctly. Ranking consistency evaluates whether identical inputs produce stable ranking outcomes across repeated executions. Processing efficiency measures the time required to complete the screening pipeline, and interpretability assesses the transparency and understandability of the generated scores and rankings [12]. Collectively, these criteria ensure that the system is not only technically functional but also practical, reliable, and suitable for supporting early-stage recruitment decision-making.

Table 1

Evaluation criteria used to assess the proposed screening system

Criterion	Description
Matching accuracy	Ability of the system to correctly identify and score relevant candidates against job requirements
Ranking consistency	Stability of ranking outputs when identical resumes and job descriptions are processed repeatedly
Processing efficiency	Time required to complete the full screening pipeline from upload to ranked output
Result interpretability	Transparency and understandability of the generated relevance scores and score explanations

3. Results

System testing was conducted to evaluate whether the Smart NLP-Based Resume Screening Tool fulfilled its functional requirements and achieved the project objectives. The testing process focused on validating the system's ability to upload resumes, extract textual content, preprocess data, compute matching scores, rank candidates, and present interpretable results. Evaluation was performed against the four criteria defined in Table 1: matching accuracy, ranking consistency, processing efficiency, and result interpretability.

3.1 Functional Verification

Functional testing was first conducted to ensure that each module operated correctly. The Resume Upload Module was tested using different resume files to verify that documents could be submitted through the web interface without errors, and the Text Extraction Module was tested to confirm that textual content could be extracted and passed to the preprocessing stage. Because resume formats vary significantly, successful extraction is important for maintaining the reliability of subsequent NLP processes [7]. The Text Preprocessing Module was then evaluated by observing whether raw resume text was properly cleaned, normalised, tokenized, and lemmatized; the results showed that the module removed unnecessary symbols, formatting noise, and common stop words before analysis, which improves the quality of the textual representations used for matching and similarity computation [4].

3.2 Matching Accuracy and Ranking Consistency

Matching-score testing was conducted by comparing sample resumes with selected job descriptions. The system produced higher relevance scores for resumes exhibiting stronger alignment with job requirements, including relevant skills, education, experience, certifications, and project information, while resumes with fewer matching qualifications received lower scores. This indicates that the weighted scoring mechanism was able to differentiate candidate suitability based

on both explicit keyword overlaps and contextual similarity. Ranking-consistency testing was performed by processing the same set of resumes and job descriptions multiple times; the system generated stable ranking outputs for identical inputs, indicating that the scoring and ranking mechanism was deterministic and reliable. Consistent ranking is important because unstable outputs reduce recruiter trust and weaken the credibility of automated decision-support tools [13,14].

3.3 Processing Efficiency and Interpretability

Processing efficiency was evaluated by observing the time taken to complete the screening pipeline, including resume upload, text extraction, preprocessing, similarity computation, and ranking. The system processed resumes within a reasonable time, making it suitable for early-stage recruitment scenarios where multiple applications must be reviewed quickly, and supporting prior findings that AI-assisted recruitment systems reduce manual workload and improve scalability [1, 12]. User Acceptance Testing was also conducted to assess usability and perceived usefulness, focusing on whether users found the interface easy to understand, the upload function simple, the ranking results clear, and the score explanation helpful. Feedback indicated that the system was understandable and useful, and that the presence of score explanations improved result interpretability by helping users understand how rankings were generated. This directly addresses the transparency and explainability concerns that constrain adoption of AI-assisted recruitment technologies [13,14].

3.4 Discussion

Overall, the testing results demonstrate that the proposed system improves resume screening efficiency, ranking consistency, and transparency. The integration of keyword matching and semantic similarity analysis allowed the system to evaluate both direct skill matches and contextual relationships between resumes and job descriptions, and these findings align with prior research showing that hybrid NLP-based approaches outperform basic keyword filtering in automated candidate matching [9-11]. Situating these outcomes within the broader picture of technology-driven recruitment, the explainable weighting scheme offers a pragmatic response to the efficiency–equity tension reported in empirical HR studies, where AI-only screening accelerates shortlisting but raises concerns about algorithmic bias and access [5]. By keeping the scoring transparent and computationally light, the system remains suitable for small and medium-sized organisations that lack the resources to deploy and audit complex deep-learning pipelines. The system is therefore considered a practical decision-support tool for early-stage recruitment screening.

4. Conclusions

This study presented the design and implementation of a Smart NLP-Based Resume Screening Tool developed to support early-stage recruitment screening. The project addressed several limitations of traditional resume screening, including excessive manual effort, inconsistent candidate evaluation, limited contextual understanding, and insufficient transparency in automated systems. By integrating text extraction, text preprocessing, information extraction, keyword matching, semantic similarity analysis, and explainable weighted scoring within a single web-based platform, the system evaluates resumes systematically and ranks them according to their relevance to a given job description. The evaluation confirmed that the system met its objectives: it generated meaningful relevance scores, produced consistent rankings, processed resumes efficiently, and provided

interpretable outputs that support recruitment decision-making, consistent with prior evidence that NLP-based systems improve screening efficiency, scalability, and matching accuracy while reducing reliance on purely manual evaluation [1,12].

Despite these positive outcomes, several opportunities for improvement remain. Future versions of the system may incorporate advanced machine-learning and deep-learning models to further enhance semantic understanding and matching accuracy and may be extended to support multilingual resume analysis for international recruitment contexts. Integrating recruiter-feedback mechanisms would allow the system to learn from historical hiring decisions and continuously improve its recommendations, while integration with online job portals, cloud-based deployment, real-time analytics, and advanced visualisation dashboards would increase practical applicability on a larger scale. Embedding periodic bias audits within the scoring pipeline would further strengthen fairness and align the tool with emerging data-protection and high-risk-AI expectations. As Artificial Intelligence continues to evolve, intelligent recruitment systems are expected to play an increasingly important role in supporting data-driven, transparent, and equitable hiring decisions [6,15].

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