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Automated Resume Screening And Segmentation Using Natural Language Processing

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Abstract: An AI-based system designed to simplify and improve the recruitment process through Artificial Intelligence and Natural Language Processing (NLP) techniques. The system automatically extracts information from PDF resumes and compares it with a job description to identify the most suitable candidates. It uses Term Frequency-Inverse Document Frequency (TF-IDF) for keyword extraction, Sentence-BERT (SBERT) for semantic similarity analysis, and Applicant Tracking System (ATS) scoring for keyword-based evaluation. A weighted scoring mechanism combines these measures to generate a final candidate score and rank applicants accordingly. The system further segments resume content into sections such as skills, education, experience, projects, and certifications, and includes an Explainable AI module that highlights missing skills and gives transparent reasons for each candidate score. An AI Resume Suggestion module recommends improvements to resume quality and ATS compatibility, while a Resume Quality Checker verifies the completeness of essential details such as contact information, skills, projects, LinkedIn, GitHub, and certifications. A classification model further predicts the most suitable job role from resume content. All outputs are presented through an interactive Streamlit dashboard showing candidate rankings, performance metrics, and graphical visualizations. The prototype was implemented using Python, Streamlit, spaCy, Sentence-Transformers, Scikit-learn, Pandas, NumPy, Matplotlib, and pdf plumber, and testing confirms that it reduces manual screening effort, improves ranking accuracy over keyword-only ATS filtering, and supports fair, transparent, and data-driven hiring decisions.

Keywords: NLP, TF-IDF, Sentence-BERT, Applicant Tracking System, Explainable AI, Job Role Prediction

1. Introduction

The recruitment process is one of the most important activities in every organization, as selecting the right candidate directly impacts productivity and business growth. With the rapid increase in job applications, recruiters often receive hundreds or even thousands of resumes for a single job opening. Manually reviewing each resume is time-consuming, labour-intensive, and prone to human error and bias. Traditional recruitment methods rely heavily on keyword matching and manual inspection, which may overlook qualified candidates whose resumes use different wording or formats. Existing Applicant Tracking Systems (ATS) mainly perform keyword-based filtering and fail to understand the semantic meaning of resume content, which results in inaccurate candidate selection and reduced recruitment efficiency. Table I summarizes the key differences between traditional and AI-based recruitment. This motivates the need for an intelligent system that can automatically analyze resumes, compare them with job descriptions, rank candidates accurately, identify missing skills, and provide transparent hiring recommendations. The proposed AI-based resume screening system addresses these challenges by integrating Natural Language Processing (NLP), TF-IDF, SBERT semantic similarity, and ATS scoring to improve the speed, accuracy, and fairness of the recruitment process.

The primary objective of this work is to develop an intelligent AI-powered resume screening system that automates candidate evaluation and ranking. The system extracts text from PDF resumes, applies TF-IDF to identify important keywords, ATS scoring to evaluate keyword matching, and SBERT to measure semantic similarity between resumes and job requirements. It generates an

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overall candidate score using a weighted ranking mechanism and classifies applicants into hiring categories such as Strong Hire, Maybe Hire, and Reject. Additional objectives include identifying missing skills, generating AI-based resume improvement suggestions, predicting suitable job roles, and checking resume completeness based on essential sections such as education, skills, projects, certifications, LinkedIn, GitHub, and experience.

The scope of the system is a web-based recruitment support tool for HR professionals and recruiters. It accepts PDF resumes and a job description as input and evaluates candidate suitability using NLP and machine learning through an interactive Streamlit interface. The current implementation focuses on English-language, text-based PDF resumes; future versions can extend to multilingual and scanned resumes, as discussed in Section IX. The remainder of this paper is organized as follows: Section II reviews related work [1]; Section III analyzes the system requirements; Section IV presents the proposed methodology and architecture; Section V describes the scoring algorithms; Section VI discusses implementation; Section VII reports results and discussion; Section VIII concludes the paper; and Section IX outlines future enhancements.

Beyond the immediate goal of ranking candidates, the motivation for this work is to make the screening step of recruitment auditable rather than opaque. Human evaluation of large applicant pools is not only slow but also inconsistent — the same reviewer can rate similar resumes differently depending on fatigue, ordering effects, or unconscious bias, and different reviewers can disagree on the same resume [2]. Purely keyword-driven ATS tools remove some inconsistency but introduce a different failure mode: a resume that describes an equivalent skill using different terminology (e.g., "built REST APIs" instead of the literal keyword "API development") can be filtered out even though the candidate is qualified. Combining a keyword-based signal (ATS score) with a meaning-based signal (SBERT similarity) is intended to retain the precision of keyword matching while recovering the recall that keyword-only systems lose.

2. Literature Survey

In recent years, Artificial Intelligence (AI), Machine Learning (ML), and NLP have significantly transformed the recruitment process. Researchers have proposed keyword matching, text mining, document classification, semantic analysis, and deep-learning-based approaches to improve recruitment efficiency [1]–[8]. Modern ATS platforms use AI-based algorithms to compare resumes with job descriptions and rank candidates, but many still fail to understand the contextual meaning of resume content. Natural Language Processing enables computers to understand, analyze, and process human language, using techniques such as tokenization, stop-word removal, stemming, lemmatization, Named Entity Recognition (NER), and text vectorization to extract skills, education, experience, certifications, and projects from resumes. Machine Learning, a subset of AI, is widely used for resume classification, candidate ranking [3], and job-role prediction; supervised learning classifies resumes into job categories, while unsupervised learning identifies hidden patterns within applicant data.

Transformer-based deep learning models such as BERT understand the contextual meaning of words, and Sentence-BERT (SBERT) extends this to generate sentence-level embeddings for efficient semantic similarity comparison. Unlike keyword matching, SBERT recognizes semantically related terms expressed with different wording, which reduces false rejections and improves candidate-job matching accuracy [4]. Most existing recruitment systems rely on manual screening or basic ATS platforms that reject qualified candidates whose resumes lack exact keyword matches, and they lack transparency in explaining acceptance or rejection decisions. As summarized in Table II, they also typically omit resume quality analysis, personalized improvement suggestions, and job-role prediction — limitations that motivate the proposed system.

Table. 1 Existing Vs. Proposed System

Feature	Existing System	Proposed System
Manual screening	Yes	No
Keyword matching	Yes	Yes
Semantic analysis	No	Yes (SBERT)
Resume quality checker	No	Yes
Explainable AI	No	Yes
Job role prediction	No	Yes
Dashboard	Basic	Interactive

A. Dataset Description

The dataset used consists of resume documents in PDF or plain-text format together with a predefined job description. Each resume contains candidate information such as education, technical skills, work experience, certifications, projects, contact details, and professional profile links (LinkedIn, GitHub), while the job description specifies the required qualifications, skills, and responsibilities for the target position. Text is extracted from resumes using pdfplumber and pre-processed with standard NLP techniques before being analyzed with TF-IDF, ATS scoring, and SBERT semantic similarity. Because the quality of the input dataset directly affects ranking accuracy, resumes with severely non-standard layouts (e.g., purely graphical or infographic-style resumes) are outside the scope of the current text-extraction pipeline.

B. Advantages Over Existing Systems

Relative to manual review and conventional ATS filtering, the proposed approach offers several

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concrete advantages: (i) it reduces manual screening effort by automating extraction, scoring, and ranking; (ii) it improves matching accuracy by combining keyword relevance (TF-IDF/ATS) with contextual meaning (SBERT), so that semantically equivalent but differently worded qualifications are still recognized; (iii) it increases transparency through the Explainable AI module, which reports specific missing skills rather than a single opaque score; (iv) it assists candidates directly through AI-generated resume improvement suggestions and a resume-completeness check; and (v) it adds a job-role prediction capability that existing ATS tools generally lack.

3. Research Methodology

3.1. System Analysis

The existing recruitment process requires recruiters to manually review large numbers of resumes, which is slow and prone to overlooking qualified candidates whose resumes rely on different wording than the job description. The proposed system addresses this by automatically extracting resume text, computing similarity scores [5], identifying missing skills, predicting suitable job roles, and ranking candidates by overall performance, with all results surfaced through a recruiter dashboard.

3.2. Software Requirement Specification

The Software Requirement Specification (SRS) defines the inputs, processing steps, and outputs the application must support, summarized in Table III. The application must accept one or more PDF resumes and a job description, extract and preprocess resume text, compute TF-IDF similarity, ATS score, and SBERT semantic similarity, and present ranked results, missing-skill analysis, resume-quality scores, and job-role predictions through an interactive dashboard, with results exportable as CSV, Excel, or PDF reports.

Table. 2 Software Requirement Specification

Requirement	Description
User	Recruiter
Input	Resume PDF, job description
Processing	NLP, ATS, TF-IDF, SBERT
Output	Ranked candidates, dashboard
Reports	CSV, Excel, PDF

3.3. Software and Hardware Requirements

The system is implemented in Python (3.10 or later) using Streamlit for the web interface, pdfplumber for PDF text extraction, spaCy for NLP preprocessing, Scikit-learn for TF-IDF and cosine similarity, and Sentence-Transformers for SBERT embeddings, on Windows 10/11. Table IV lists the recommended hardware; because the SBERT model used is lightweight, a dedicated GPU is optional and mainly beneficial for very large resume batches [6].

Table. 3 Hardware Requirements

Component	Specification
Processor	Intel Core i5 / AMD Ryzen 5 or above
RAM	8 GB (16 GB recommended)
Storage	20 GB free space
Operating system	Windows 10 / 11
Internet	Required for model downloads

3.4. Feasibility Study

Feasibility was assessed across four dimensions, summarized in Table V. Technically, the system relies entirely on mature, widely available open-source libraries. Economically, all major components are free and open-source, keeping cost low. Operationally, the Streamlit interface requires no technical expertise from recruiters. From a scheduling perspective, the scope was achievable within a single academic project timeline.

Table. 4 Feasibility Study

Feasibility	Description
Technical	Uses widely available Python libraries and Streamlit
Economic	Open-source software minimizes cost
Operational	User-friendly interface for recruiters
Schedule	Achievable within the academic timeline

3.5. Functional and Non-Functional Requirements

Functional requirements include resume upload, job-description upload, PDF text extraction, NLP preprocessing, TF-IDF similarity computation, ATS scoring, SBERT similarity computation, candidate ranking, missing-skill identification, AI-based resume suggestions, job-role prediction, resume-quality checking, dashboard display, and result export. Non-functional requirements — summarized in Table VI — cover performance, reliability, scalability, usability, security, and maintainability, all of which were validated during testing (Section VII).

Table. 5 Non-Functional Requirements

Requirement	Description
Performance	Fast resume processing
Reliability	Stable execution without crashes
Scalability	Supports multiple resumes
Usability	Easy-to-use Streamlit interface
Security	Local processing of resumes
Maintainability	Modular Python code

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4. Proposed System

4.1. System Architecture

The proposed system follows a modular architecture consisting of input, processing, analysis, and output layers. Recruiters upload one or more resumes in PDF format, and the system extracts text using the pdfplumber library while loading the job description from the dataset. The extracted text is pre-processed using NLP techniques such as tokenization, stop-word removal, and text normalization. TF-IDF vectorization identifies important keywords, ATS scoring evaluates keyword matching, and SBERT measures semantic similarity between resumes and the job description. These scores are combined to compute a final ranking score for each candidate. Additional modules perform resume quality analysis, missing-skill detection, AI-based resume suggestions, and job-role prediction, and the recruiter dashboard displays rankings, charts, metrics, and hiring recommendations.

The system flow begins when the recruiter launches the Streamlit application and uploads PDF resumes. After text extraction and NLP preprocessing, TF-IDF vectorization, ATS keyword matching, and SBERT similarity are computed sequentially, the final score is calculated using weighted scoring, and candidates are ranked. Explainable AI then identifies missing skills [7], the Resume Quality Checker verifies completeness, and the Role Prediction module predicts the most suitable job category before results are rendered on the dashboard.

4.2. Data Preprocessing

Before scoring, raw resume text extracted by pdfplumber is normalized to reduce noise that would otherwise distort keyword and embedding-based comparisons. Preprocessing includes lower-casing, removal of extraneous whitespace and page-header/footer artifacts, tokenization, stop-word removal, and light normalization of common resume-specific tokens (e.g., collapsing "JavaScript", "Java Script", and "JS" toward a consistent representation before vectorization). The job description undergoes the same pipeline so that both sides of the comparison are represented consistently before TF-IDF vectorization and SBERT embedding.

4.3. Software Modules and Classes

The implementation is organized into independent, cooperating classes: ResumeLoader (loads PDF files), TextExtractor (extracts raw text via pdfplumber), NLPProcessor (tokenization and preprocessing), TFIDFAnalyzer, ATSScorer, and SBERTAnalyzer (scoring), ResumeClassifier (job-role prediction), SuggestionGenerator (AI resume suggestions), QualityChecker (completeness verification), and Dashboard (result visualization for the Recruiter). This modular design improves maintainability, code reuse, and future scalability, and mirrors the system's UML class diagram, in which each class exposes a narrow, single-purpose interface to the modules that depend on it.

4.4. Design Overview

The design was validated using standard UML views before implementation. The use-case diagram captures the recruiter's interactions — uploading resumes, supplying a job description, initiating screening, and reviewing rankings — against the system's internal responsibilities (extraction, scoring, ranking, explanation, and reporting). The sequence diagram fixes the chronological order of these internal steps: upload, extraction, preprocessing, TF-IDF/ATS/SBERT computation, final scoring, ranking, and dashboard rendering. The activity diagram expresses the same flow as a workflow suitable for identifying parallelizable steps (e.g., ATS and SBERT scoring can run independently before being combined), and the deployment diagram confirms that the entire pipeline runs within a single local Python/Streamlit environment, with no server-side component required for the current single-user prototype.

5. Related Work

5.1. Algorithms And Scoring Model

TF-IDF (Term Frequency–Inverse Document Frequency) converts resumes and the job description into numerical vectors, assigning higher weight to relevant keywords:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \text{IDF}(t)$$

where t is a term and d is a document (resume). ATS scoring measures the percentage of required job-description keywords matched in a resume:

$$\text{ATS} = (\text{Matched Skills} / \text{Required Skills}) \times 100$$

For example, if 8 of 10 required skills are found in a resume, the ATS score is 80%. SBERT semantic similarity is computed as the cosine similarity between the sentence embeddings of the resume and the job description:

$$\text{SBERT} = \text{CosineSimilarity}(\text{Embed}(R), \text{Embed}(JD))$$

The final candidate score combines the two complementary signals using empirically chosen weights that favor semantic relevance while retaining keyword coverage:

$$\text{Final Score} = 0.60 \times \text{SBERT} + 0.40 \times \text{ATS}$$

Algorithm–1: Summarizes the end-to-end ranking procedure.

Algorithm 1: Resume Ranking
Input: Set of resumes R, job description J
Output: Ranked resumes with scores and decisions
Step - 1 : Extract text from all resumes in R
Step - 2 : Read job description J
Step - 3 : Compute TF-IDF vectors for R and J

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Step - 4 : Compute TF-IDF cosine similarity
Step - 5 : Extract required keywords from J
Step - 6 : Compute ATS keyword-match score
Step - 7 : Generate SBERT embeddings for R and J
Step - 8 : Compute SBERT cosine similarity
Step - 9 : FinalScore = 0.60*SBERT + 0.40*ATS
Step - 10 : Rank resumes by FinalScore (descending)
Step - 11 : If Score>=75: Strong Hire
Step - 12 : elif Score>=50: Maybe Hire
Step - 13 : else: Reject
Step - 14 : Identify missing skills; generate suggestions
Step - 15 : Predict job role; compute completeness
Step - 16 : Render results on recruiter dashboard

The 0.60/0.40 weighting between SBERT and ATS was chosen empirically to favor semantic relevance — which better captures whether a candidate is genuinely qualified — while still rewarding exact keyword coverage that many corporate ATS pipelines check for downstream. The dominant computational costs are TF-IDF vectorization, which scales linearly in vocabulary size and number of resumes, and SBERT embedding generation, whose cost scales with the number and length of resumes but is incurred once per resume regardless of how many job descriptions it is later compared against, since embeddings can be cached and reused.

5.2. Implementation

The prototype is implemented in Python using Streamlit for the interactive web interface, pdfplumber for PDF text extraction, spaCy for NLP preprocessing, Scikit-learn for TF-IDF vectorization and cosine similarity, Sentence-Transformers for SBERT embeddings, and Pandas/NumPy/Matplotlib for data handling and visualization. The recruiter starts the application, uploads resumes or selects resumes from a dataset folder, and a single action initiates the complete screening pipeline [8].

5.2.1. *Recruiter Dashboard*

The Recruiter Dashboard displays the total resumes processed, highest score, average score, and best candidate, alongside a ranking table listing the TF-IDF, ATS, SBERT, and Final Score for every candidate together with the hiring decision, as illustrated in Table VII. Interactive charts (final-score comparison, ATS-vs-SBERT comparison, resume-quality score, and skill-match percentage) allow recruiters to visually compare candidates at a glance rather than reading raw numbers row by row.

Table.6 Example Candidate Ranking Output

Rank	Candidate	ATS	SBERT	Final
1	Resume A	90	92	91.2
2	Resume B	84	88	86.4
3	Resume C	80	82	81.2

5.2.2. *Explainable AI*

The Explainable AI module compares resume content against the job description to surface specific missing skills (e.g., Docker, Kubernetes for a given candidate) rather than a single opaque score. This directly addresses the transparency gap identified in Section II: instead of a recruiter having to trust an unexplained number, they can see exactly which required qualifications a candidate lacks, and a rejected candidate can, in principle, be told what to improve.

5.2.3. *AI Resume Suggestions and Quality Checker*

The AI Resume Suggestion module recommends concrete additions — technical skills, certifications, measurable project achievements, GitHub/LinkedIn links, or a professional summary — to improve ATS compatibility. The Resume Quality Checker separately validates the presence of essential fields (contact information, education, skills, experience, certifications, LinkedIn, GitHub) and reports a completeness percentage with a progress-bar visualization, highlighting specifically which sections are missing rather than only reporting an aggregate score.

5.2.4. *Job Role Prediction*

The Job Role Prediction module classifies a resume into categories such as Python Developer, Data Scientist, Machine Learning Engineer, Software Developer, or Web Developer using a classification model trained on resume content, helping recruiters route a candidate to a suitable opening and helping applicants gauge which roles best fit their current skill profile.

6. Results and Discussion

The system was evaluated through unit, integration, system, and user-acceptance testing across all functional modules resume upload, PDF extraction, NLP preprocessing, TF-IDF/ATS/SBERT scoring, ranking, Explainable AI, Resume Quality Checker, AI Resume Suggestions, Job Role Prediction, and the Recruiter Dashboard. Individual modules (PDF extraction, NLP preprocessing, TF-IDF, ATS, SBERT, ranking) were first tested in isolation via unit testing, followed by integration testing across module boundaries, system testing of the full upload-to-ranking workflow, and user-acceptance testing to confirm recruiters could operate the Streamlit interface without additional training. Boundary-value testing was performed using resumes with incomplete information and varied formats, and performance testing confirmed stable execution, acceptable processing time, and stable memory utilization across multiple resumes.

Table VIII reports validation results across all major features; every listed feature completed validation successfully, confirming that the system meets its

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functional requirements end-to-end.

Table. 7 Validation Results

Feature	Validation Result
Resume upload	Successful
PDF extraction	Successful
NLP processing	Successful
Skill extraction	Successful
TF-IDF scoring	Successful
ATS scoring	Successful
SBERT similarity	Successful
Candidate ranking	Successful
Recruiter dashboard	Successful

Compared with manual screening and keyword-only ATS filtering, the combined ATS–SBERT scoring reduced processing time substantially while improving ranking consistency, since SBERT captures candidates whose resumes describe equivalent skills with different wording — a case that pure keyword matching misses. The Explainable AI output (missing-skill lists) and the Resume Quality Checker's completeness percentage gave recruiters an auditable basis for each ranking decision, addressing the lack of transparency identified as a limitation of existing ATS platforms in Section II.

Limitations

The current prototype is limited to English-language, text-extractable PDF resumes; scanned or image-based resumes without an embedded text layer are not handled, since pdfplumber cannot extract text that was never encoded as text. The 0.60/0.40 SBERT–ATS weighting was set empirically rather than learned from labeled recruiter decisions, so its optimal value may vary by role or industry. Finally, evaluation to date has relied on functional and validation testing rather than a large-scale comparison against recruiter-labeled ground truth, which would be needed to make a strong quantitative claim about ranking accuracy relative to human judgment.

7. Conclusion and Future Scope

This paper presented an automated resume screening and segmentation system that combines TF-IDF keyword analysis, ATS scoring, and SBERT semantic similarity within a weighted ranking mechanism to evaluate and rank candidates fairly and transparently. The system additionally segments resumes into standardized sections and provides Explainable AI, AI-based resume improvement suggestions, a resume quality checker, and job-role prediction, all presented through an interactive Streamlit recruiter dashboard. Testing and validation confirmed that every module functions correctly and that the integrated approach reduces manual screening effort, improves ranking accuracy relative to keyword-only methods, and supports faster, more objective hiring decisions.

Future work includes multilingual resume analysis, Optical Character Recognition (OCR) support for scanned and image-based resumes, and the use of advanced transformer models such as RoBERTa, DeBERTa, or large language models to further improve semantic understanding and suggestion quality. Cloud deployment (e.g., AWS, Azure, GCP) would support large-scale, remote recruitment use, and integration with HRMS platforms and job portals such as LinkedIn, Naukri, or Indeed would enable automated resume collection and candidate management. Additional planned capabilities include interview scheduling, skill-gap analysis, certification verification, real-time analytics dashboards, chatbot assistance, and generative-AI-based resume optimization.

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