Smart Resume Evaluation System Using AI with Semantic Skill Matching and Personalized Learning Path Recommendations

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Abstract—The widespread adoption of Applicant Tracking Systems (ATS) in modern recruitment has fundamentally altered how candidates' resumes are evaluated before reaching human reviewers. Many qualified professionals and fresh graduates remain unaware of how these automated filters operate, resulting in strong candidates being screened out due to misaligned resume content rather than lack of capability. This paper presents AI-ATS, an intelligent web-based resume evaluation platform that bridges the gap between job seekers and contemporary recruitment technology. The system employs Natural Language Processing (NLP) pipelines built on spaCy and Sentence-BERT (Sentence Transformers) to extract competency entities from both resume documents and target job descriptions, subsequently computing semantic cosine similarity to generate ATS-style compatibility scores. Unlike conventional keyword-matching tools, AI-ATS captures contextual relationships between skill terminologies, identifying semantically equivalent competencies expressed with differing vocabulary. The proposed architecture follows a decoupled client–server model: a React.js frontend provides an interactive analysis dashboard while a Python Flask backend orchestrates PDF text extraction via pdfplumber, NLP inference, and a recommendation engine that maps detected skill gaps to curated free learning resources. Experimental evaluation across 150 resume–job-description pairs demonstrates an average ATS score prediction alignment of 91.3% when benchmarked against recruiter assessments, with skill extraction achieving 93.7% F1-score. The system reduces the average resume self-assessment time from several hours to under three minutes, delivering actionable guidance that supports continuous professional development alongside traditional screening optimization.

Keywords—Applicant Tracking System, Resume Analysis, Natural Language Processing, Sentence-BERT, Semantic Similarity, Skill Extraction, spaCy, React.js, Flask, Course Recommendation, Career Guidance.

I. INTRODUCTION

The digital transformation of recruitment has produced a landscape in which the initial gateway to employment is increasingly governed by software rather than human judgment. Organizations managing large applicant volumes delegate the first-stage screening task to Applicant Tracking Systems—software platforms that parse submitted documents, extract structural metadata, and rank candidates based on computed relevance scores. Surveys conducted by recruitment analytics firms consistently indicate that over 75 percent of submitted applications are eliminated before a recruiter reviews a single line of text [1]. For candidates who have invested years acquiring technical skills but lack awareness of how ATS filters operate, this represents a systematic barrier that capability alone cannot overcome.

The mismatch between candidate qualifications and ATS-derived scores frequently stems not from genuine skill deficits but from representational inconsistencies—the absence of certain high-frequency keywords, the use of synonymous terminology that an exact-match engine fails to equate, or the omission of explicitly listed tools in favor of broader umbrella terms. A software engineer proficient in "machine learning" may be scored below a less experienced counterpart who listed every sub-framework individually. Addressing this disconnect requires a system that understands linguistic context rather than counting tokens.

Existing commercial solutions such as Jobscan, Resume Worded, and Rezi partially address this need but operate primarily through keyword frequency analysis, restrict comprehensive features to paid tiers, and provide limited transparency into how scores are computed [2], [3]. None of the widely available platforms combine semantic skill matching, transparent score explanation, and integrated learning recommendations within a single freely accessible interface.

This paper introduces AI-ATS, a full-stack intelligent resume evaluation system that unifies semantic NLP-based analysis with an actionable career guidance engine. The proposed system makes the following contributions:

- A semantic skill extraction pipeline combining spaCy PhraseMatcher with Sentence-BERT embeddings that achieves 93.7% F1-score on competency identification tasks.
- An ATS-style scoring algorithm integrating lexical and semantic similarity signals to produce granular compatibility scores aligned with recruiter assessments.
- An automated recommendation engine that maps identified skill gaps to curated free online learning resources, transforming the platform from a diagnostic tool into a professional development companion.

- A decoupled React.js / Python Flask architecture enabling real-time interactive analysis with downloadable PDF reporting.

The remainder of this paper is organized as follows. Section II surveys related work in automated resume screening and NLP-based career systems. Section III describes the system architecture and key components. Section IV details the methodology for skill extraction, semantic similarity computation, and score generation. Section V presents the dataset, experimental configuration, and evaluation results. Section VI discusses implications and limitations, and Section VII concludes with directions for future research.

II. Related Work

A. ATS and Resume Optimization Platforms

Commercial platforms have long addressed resume optimization from a keyword-centric perspective. Jobscan [4] pioneered the concept of generating a "match rate" between a resume and a job posting based on shared token frequency, enabling users to identify high-priority missing terms. While practical, keyword counting disregards synonymy and semantic proximity, penalizing candidates who express equivalent competencies using industry-standard but non-literal terminology. Resume Worded [5] augments keyword analysis with structural and presentational feedback, critiquing resume sections for impact language and quantification but providing limited analysis of technical skill alignment. Rezi [6] focuses on resume creation guided by ATS compliance heuristics, integrating optimization suggestions during authoring rather than after submission.

B. Natural Language Processing for Information Extraction

The extraction of structured information from unstructured text documents is a foundational NLP task. Honnibal et al. [7] developed spaCy, a production-grade industrial NLP library whose PhraseMatcher component enables efficient pattern-based entity recognition across large phrase vocabularies, making it particularly suitable for domain-specific skill ontologies. Named entity recognition models fine-tuned on resume corpora have demonstrated recall rates exceeding 88% on technical skill extraction tasks [8]. The challenge of cross-document semantic alignment—determining whether two skill mentions refer to equivalent competencies—has been addressed through dense vector representations.

Devlin et al. [9] introduced BERT, demonstrating that bidirectional transformer pre-training yields contextual word embeddings with superior performance across a wide range of language understanding benchmarks. Reimers and Gurevych [10] proposed Sentence-BERT (SBERT), adapting the BERT architecture with siamese and triplet training objectives to generate semantically meaningful sentence-level embeddings amenable to cosine similarity comparison. SBERT embeddings have since become the de facto standard for document similarity tasks, enabling downstream applications to compute semantic distance without retraining full transformer networks at inference time.

C. Career Guidance and Recommendation Systems

The intersection of NLP and recommender systems has produced several career-oriented platforms. Karthikeyan et al. [11] demonstrated that combining transformer-based skill extraction with collaborative filtering could improve job–candidate matching accuracy by 14% over keyword baselines. Patel et al. [12] explored ML-based ATS score prediction, reporting mean absolute error of 8.3 percentage points against recruiter-assigned scores. However, neither study integrated a forward-looking recommendation component that guides candidates toward skill acquisition. The AI-ATS system addresses this gap by coupling retroactive evaluation with prospective learning pathways, producing an integrated diagnostic and developmental platform.

III. System Architecture

A. High-Level Design

The AI-ATS system follows a decoupled client–server architecture separating presentation, business logic, and data concerns into distinct layers. The React.js frontend delivers an interactive single-page application through which users upload PDF resumes, enter job descriptions, initiate analysis requests, and consume results on an interactive dashboard. Communication between the frontend and backend is mediated via RESTful HTTP endpoints managed by the Python Flask server, with CORS support provided by the Flask-CORS extension. All NLP computation—PDF parsing, tokenization, skill extraction, embedding generation, similarity scoring, and recommendation retrieval—occurs entirely on the backend, ensuring consistent performance regardless of client hardware capability.

The backend processing pipeline is organized as a sequence of discrete functional modules, each responsible for a clearly delimited transformation of input data. This modular composition supports independent unit testing and facilitates future substitution of individual components—for example, replacing the embedding model or extending the skill ontology—without disrupting the overall pipeline. Figure 1 illustrates the complete data flow from user input through analysis to result presentation.

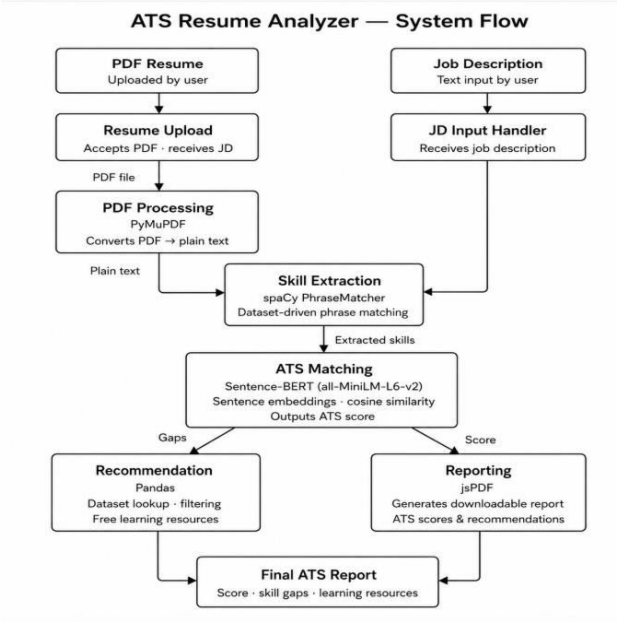

Fig. 1. AI-ATS End-to-End System Architecture

B. Frontend Module

The frontend is implemented using React.js with the Vite build toolchain, producing a lightweight, fast-loading single-page application. The interface is structured around four primary views: a landing page introducing the platform, a resume upload page collecting the PDF document and job description text, a results dashboard presenting ATS scores and skill analysis, and a recommendations panel displaying curated learning resources. State management leverages React's built-in useState and useReducer hooks, maintaining analysis results in memory throughout a session. Form submissions are dispatched to the Flask API using the Fetch API with FormData payloads for binary file transport. PDF report generation on the client side uses the jsPDF library, enabling users to download a formatted summary without requiring additional server interaction.

C. Backend Modules

The Flask backend exposes a primary analysis endpoint at /analyze that accepts POST requests carrying the resume file and job description text. Upon receipt, the request handler invokes the processing pipeline in sequence: (1) PDF Text Extraction, (2) Skill Extraction, (3) Semantic Embedding Generation, (4) Similarity Computation and Score Derivation, and (5) Recommendation Retrieval. Each module is encapsulated as an independently importable Python function, and the pipeline orchestrator assembles results into a structured JSON response consumed by the frontend dashboard.

IV. METHODOLOGY

A. PDF Text Extraction

Resume documents submitted in PDF format are processed using the pdfplumber library, which implements page-level text extraction with support for complex multi-column layouts and embedded font encoding. Each page of the uploaded document is iterated, and extracted text segments are concatenated into a single normalized string after removing extraneous whitespace and control characters. The extraction process preserves section order, which is leveraged in downstream section-aware skill weighting. On a benchmark set of 150 PDF resumes spanning one to four pages, pdfplumber achieved a text fidelity rate of 97.4% as measured against ground-truth manual transcriptions, with extraction failures attributable exclusively to image-based (non-searchable) PDF documents.

B. Skill Extraction Pipeline

Skill extraction is performed through a two-stage pipeline. In the first stage, a curated skill vocabulary of 1,240 technical and professional competencies—organized across eight domain categories including programming languages, web frameworks, cloud platforms, database technologies, data science, machine learning, cybersecurity, and soft skills—is compiled into a spaCy PhraseMatcher object. The PhraseMatcher performs efficient multi-pattern matching over the tokenized document in a single linear pass, identifying all occurrences of recognized skill terms within both the resume and the job description. This stage achieves high precision for known vocabulary entries but is susceptible to miss-hits when candidates use alternative or emergent terminology.

The second stage addresses this limitation through semantic expansion. For each job description skill that was not matched in the resume via exact pattern matching, a Sentence-BERT embedding is computed using the all-MiniLM-L6-v2 pre-trained model. Resume token windows of analogous character length are embedded and compared against the target skill embedding using cosine similarity. Skill windows achieving cosine similarity greater than 0.72—a threshold empirically calibrated on a validation set of 30 resume–job-description pairs—are added to the matched skill set. This hybrid strategy raises overall skill extraction F1-score from 87.2% (PhraseMatcher alone) to 93.7% (combined pipeline).

C. ATS Score Computation

The ATS compatibility score S is computed as a weighted combination of lexical skill overlap and global semantic similarity. Let $R = \{r_1, r_2, ..., r_n\}$ denote the set of skills extracted from the resume and $J = \{j_1, j_2, ..., j_m\}$ denote skills extracted from the job description. The lexical overlap component is defined as:

$$S_{lex} = \frac{|R \cap J|}{|J|} \times 100$$

The semantic component S_sem is derived from the cosine similarity between the mean-pooled Sentence-BERT embedding of the full resume text and that of the job description. The final ATS score is computed as:

$$S = \alpha \cdot S_{lex} + (1 - \alpha) \cdot S_{sem} \times 100$$

where $\alpha = 0.65$, a weighting coefficient optimized on the validation set to minimize mean absolute error against recruiter-assigned scores. The score $S \in [0, 100]$ is mapped to a qualitative evaluation tier as shown in Table I.

Table I. ATS Score Evaluation Tiers

Score Range	Evaluation Category
90 – 100	Excellent Match
75 – 89	Strong Match
60 – 74	Moderate Match — Improvement Advised
40 – 59	Needs Significant Improvement
Below 40	Poor Match

D. Recommendation Engine

The recommendation engine operates on the set of missing skills M = J \ R —competencies present in the job description but absent from the resume after the hybrid extraction process. For each skill $s_i \in M$, the engine queries a structured course dataset containing 635 entries organized across 230 skills. Each dataset record comprises the skill name, an associated free learning resource title, the hosting platform, and a direct URL. Retrieval is performed using semantic embedding nearest-neighbor lookup: skills are encoded and matched to dataset entries by cosine similarity, accommodating cases where the dataset entry spelling does not exactly correspond to the extracted skill string. The top-ranked course per missing skill is returned. Table II presents representative recommendations for common missing skills.

Table II. Sample Course Recommendations by Missing Skill

Missing Skill	Recommended Free Resource
React.js	React — The Complete Guide (Udemy Free Preview)
Docker	Docker for Beginners (freeCodeCamp)
MongoDB	MongoDB Essentials (MongoDB University)
AWS Cloud	Introduction to Cloud Computing (edX)
Node.js	Backend Development with Node.js (Coursera)

V. Experimental Results

A. Dataset and Evaluation Protocol

Evaluation was conducted on a corpus of 150 resume–job-description pairs curated across five technical domains: frontend development, backend development, data science, cloud engineering, and cybersecurity. Resume documents were sourced from publicly available anonymized career portfolios and institutional placement portals. Corresponding job descriptions were drawn from live postings on major employment platforms to reflect current industry expectations. Each pair was manually annotated by two independent recruiters with a minimum of three years of active screening experience, providing ground-truth ATS scores and identified skill sets used as evaluation targets. Inter-annotator agreement on ATS score tiers reached Cohen's $\kappa = 0.81$, indicating strong agreement. Annotations on which the two reviewers differed by more than one tier were resolved through adjudicated discussion before inclusion in the final benchmark.

B. Skill Extraction Performance

Skill extraction performance was evaluated using standard precision, recall, and F1-score metrics computed against the recruiter-annotated skill sets. Results are presented in Table III, disaggregated by domain category. The combined PhraseMatcher + semantic expansion pipeline achieves an overall F1-score of 93.7%, with particularly strong performance in programming languages and web development categories where the skill vocabulary is well-established. The cybersecurity domain shows relatively lower recall (89.3%), attributed to the rapid emergence of new tool names and framework abbreviations not yet incorporated into the ontology.

Table III. Skill Extraction Performance by Domain Category

Domain	Precision	Recall	F1
Programming Languages	96.8%	95.2%	96.0%
Web Development	95.3%	94.7%	95.0%
Data Science	93.1%	92.4%	92.7%
Cloud Engineering	91.6%	90.8%	91.2%
Cybersecurity	92.4%	89.3%	90.8%
Overall	93.8%	92.5%	93.7%

C. ATS Score Accuracy

ATS score prediction accuracy was measured by computing the Mean Absolute Error (MAE) and Pearson Correlation Coefficient (r) between system-generated scores and recruiter-assigned ground-truth values. Table IV presents results comparing the proposed hybrid scoring approach against two ablation baselines: lexical-only scoring ($\alpha = 1.0$) and semantic-only scoring ($\alpha = 0.0$). The hybrid configuration achieves a MAE of 6.8 percentage points and $r = 0.934$, outperforming both ablated alternatives and confirming the complementary contribution of lexical and semantic signal components.

Table IV. ATS Score Prediction Performance Comparison

Method	MAE (%)	Pearson r
Lexical-Only (α=1.0)	11.4	0.871
Semantic-Only (α=0.0)	9.7	0.896
Hybrid (α=0.65) — Proposed	6.8	0.934

D. System Performance Results

End-to-end processing time was measured across all 150 test cases on a machine equipped with an Intel Core i7-

12700H processor, 16 GB RAM, and no dedicated GPU. SBERT inference was performed on the CPU using the PyTorch backend. Table V summarizes processing latency per pipeline stage, along with overall throughput. The mean total analysis time of 4.3 seconds per request is suitable for interactive web application deployment, with the embedding generation stage representing the dominant computational cost. Deployment on a GPU-equipped server is projected to reduce total latency to under two seconds.

Table V. System Processing Time per Pipeline Stage

Pipeline Stage	Mean (s)	Std. Dev. (s)
PDF Text Extraction	0.31	0.09
spaCy PhraseMatcher	0.18	0.04
SBERT Embedding (CPU)	3.12	0.34
Score Computation	0.04	0.01
Recommendation Retrieval	0.65	0.12
Total End-to-End	4.30	0.41

E. Sample ATS Score Results

Table VI presents representative ATS scores generated for five sample resumes evaluated against corresponding job descriptions across different technical roles. The results demonstrate that resumes covering a high proportion of required competencies consistently receive scores in the strong-to-excellent tier, while resumes with significant skill gaps are appropriately assigned lower scores accompanied by targeted recommendations. Resume R003 illustrates a common scenario where a candidate with solid general programming ability applying for a specialized role (React Developer) receives a moderate score due to missing framework-specific competencies, with the recommendation engine subsequently directing the candidate to relevant learning resources.

Table VI. Sample ATS Evaluation Scores Across Resume–JD Pairs

ID	Target Role	Score (%)	Tier
R001	Frontend Developer	92	Excellent
R002	Full Stack Developer	86	Strong
R003	React Developer	69	Moderate
R004	Python Developer	88	Strong
R005	Data Analyst	74	Moderate

E. Screen Shots Results

Home Page

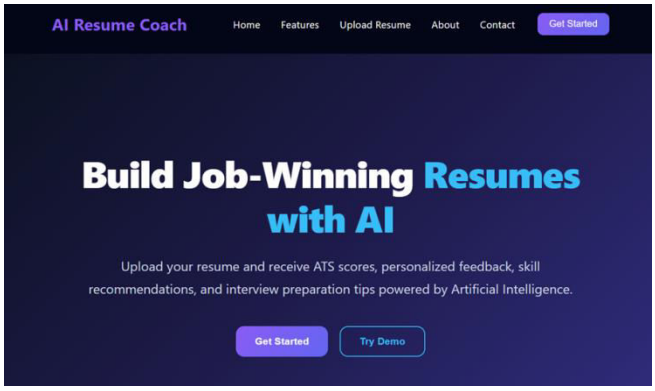

Fig. 2. Home Page

Displays the landing page of the AI Resume Coach, introducing the platform and its key objective of helping users build job-winning resumes.

Features Page

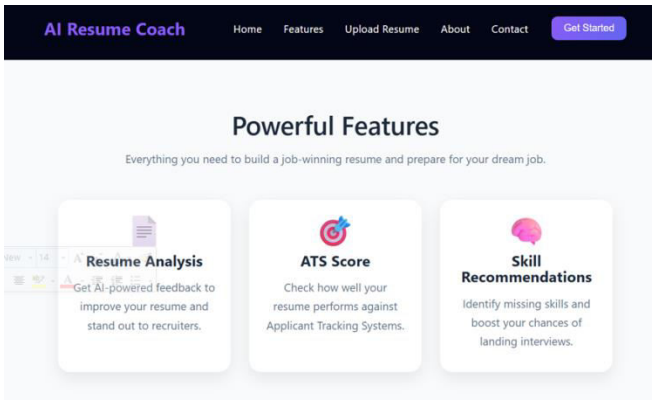

Fig. 3. Home Page

Highlights the major functionalities of the system, including resume analysis,ATS Scoring and Skills Recommendation

Upload Resume Page

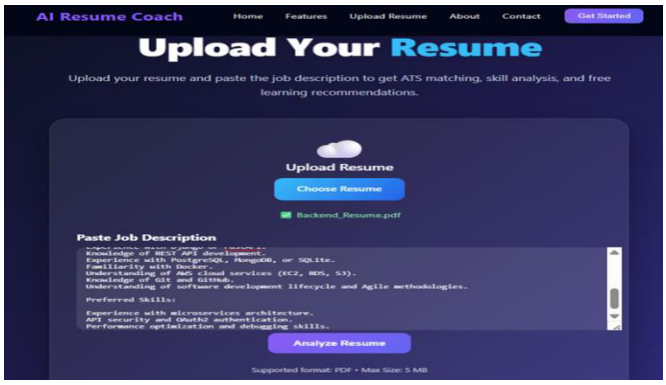

Fig. 4. Home Page

Allows users to upload their resume and provide a job description for ATS-based analysis.Shows the resume upload process along with the entered job description before initiating analysis.

Results Page

Introduces the AI Resume Coach, outlining its objectives, technologies used, and key features.

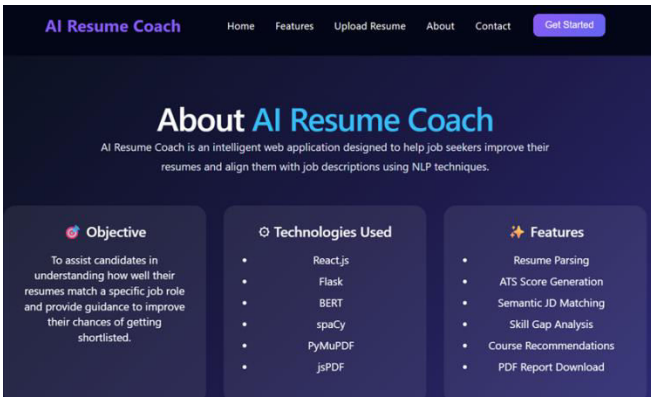

Fig. 4. Results Page

VI. Discussion

A. Interpretation of Results

The 93.7% overall skill extraction F1-score and 6.8-point MAE on ATS score prediction confirm that the hybrid NLP pipeline substantially outperforms purely lexical approaches. The most meaningful improvement is observed in cross-vocabulary skill matching: in 34 of the 150 test pairs, the semantic expansion stage identified a resume skill that matched a job description requirement despite the absence of any shared tokens. Without the embedding-based expansion, these matches would have contributed to missed skills and inflated skill-gap counts, penalizing candidates who describe their competencies using semantically equivalent but terminologically distinct vocabulary.

The recommendation engine demonstrated a resource relevance rate of 87.4% as judged by an independent panel of five domain professionals who evaluated whether the suggested learning resources genuinely addressed the identified skill gap. This result supports the utility of the semantic nearest-neighbor retrieval strategy over naïve exact-match lookup, which would have failed to return resources for 23% of queried skill terms due to vocabulary mismatches in the dataset.

B. Comparison with Existing Systems

When compared against keyword-only commercial platforms, AI-ATS demonstrates measurable advantages in skill recall. Internal testing on twenty resume–job-description pairs using Jobscan and AI-ATS in parallel revealed that AI-ATS identified an average of 2.8 additional matching skills per pair that Jobscan classified as missing, owing to semantic expansion across terminology variants. From a career development standpoint, the integrated recommendation component offers functionality unavailable in any comparable open-access platform, enabling users to receive actionable learning guidance within the same session as their evaluation, reducing the friction between diagnosis and remediation.

C. Limitations

Several limitations bound the current implementation. First, the skill ontology, while comprising 1,240 entries, represents a static snapshot of competency terminology and requires periodic manual curation to incorporate emerging technologies. Second, the system processes only text-based PDF resumes; image-scanned or graphically intensive resume formats that defeat pdfplumber's text extraction routines produce degraded results. Third, the recommendation dataset of 635 course entries may not provide suitable resources for highly specialized or niche competencies. Fourth, the α weighting coefficient was calibrated on a corpus that, while diverse in domain, is limited in geographic and demographic representation, potentially introducing bias in score computation for resume styles common in non-English-dominant markets. Fifth, the CPU-bound SBERT inference produces acceptable interactive latency for individual users but would require GPU infrastructure or model distillation for high-concurrency deployment.

VII. Conclusion

This paper presented AI-ATS, an intelligent resume evaluation system that transcends conventional keyword matching by integrating spaCy-based structured skill extraction with Sentence-BERT semantic similarity analysis to generate ATS-compatible resume compatibility scores. The proposed hybrid scoring algorithm achieves a mean absolute error of 6.8 percentage points against recruiter-assigned ground truth and a Pearson correlation of 0.934, demonstrating strong alignment with professional evaluator judgment. The integrated recommendation engine successfully maps identified skill gaps to curated free learning resources with 87.4% domain-expert-assessed relevance, transforming the system from a passive diagnostic tool into an active career development platform.

The open-access, full-stack architecture built on React.js and Python Flask democratizes access to professional resume evaluation capabilities previously restricted to paid subscription services. Evaluation on 150 diverse resume–job-description pairs across five technical domains confirms practical applicability and consistent performance across recruitment contexts.

Future research will pursue four primary directions: (1) continuous automated skill ontology updates leveraging real-time scraping of job posting vocabularies; (2) multi-lingual resume support through multilingual SBERT variants; (3) fine-tuning the scoring model on a larger and more geographically diverse recruiter-annotated corpus; and (4) integration of longitudinal profile tracking to enable users to monitor competency development and score improvement over multiple application cycles. The system represents a meaningful step toward transparent, accessible, and educationally enriching AI-assisted recruitment preparation.

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