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Smart Career Recommendation System Powered by Artificial Intelligence for Optimized Career Planning and Decision-Making

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Abstract- Traditional job portals rely on keyword matching, not allowing semantics of skills. Thus, they fail to connect candidates with jobs. Cursory manual resume screening takes 30-40 seconds. Conventional online assessments lack any integrity. DreamRole, an AI-based career recommendation and recruitment software which alleviates these essential limitations is presented in the paper. DreamRole uses Natural Language Processing (NLP) to parse resumes in PDF, DOC, DOCX, and TXT formats. It extracts skills, experience and education from a database of 200 technical skills. A matching algorithm based on the content generates a weighted relevance score that takes into consideration your skills (70%), experience (20%) and education (10%). It recommends only those positions that achieve a minimum threshold of 50 percent. The Semantic Skill Variation mapping helps in eliminating false negatives. By using OpenCV for real-time proctoring, the platform detects face abnormality, mobile phone presence, tab switching, forbidden key-stroke and terminates the test automatically on 3 successive occurrences of the same behaviour. A web speech API based hands-free navigation voice assistant (English, Hindi, Marathi) using a multilingual. Bulk resume processing can allow up to 10000 candidates in a single batch with automatic account generation feature and CSV credential download. The evaluation shows that we achieve an F1-score of 94.7% for parsing resumes, NDCG@10 of 0.79(27.4% improvement over the keyword baseline), proctoring precision of 95.7%. Moreover, our API responds under 700ms at 200 concurrent users. Finally, the evaluated System Usability Scale Score is 86.4, which indicates excellent usability.

Keywords: Artificial Intelligence, Job Recommendation, Resume Parsing, NLP, Online Proctoring, Voice Assistant, Weighted Scoring, Recruitment Automation

I. INTRODUCTION

Worldwide digitization has led to a rapid evolution in recruitment. All organizations publish several hundred job posts at the same time. In fact, millions of candidates share their resumes on such portals. Even with this volume, candidate capability and employer requirement misalignment remains huge over 75% of applications made through a typical job portal don't even get a human glance [1][2]. Traditional keyword-based filtering systems struggle to identify semantic equivalences among skill descriptors. A candidate with "ReactJS" on his résumé may get filtered out for a job role that requires "React" due to tokenization, even though they have the same abilities [4][5]. Online aptitude tests that are conducted in the course of hiring are vulnerable to. Evaluation results turn out to be poor indicators of actual capability [25]. DreamRole is a full-stack AI career recommendation and recruitment platform that integrates (i) NLP-based parsing of resumes in multi-format with a skill ontology of size 200+, (ii) weighted matching using a multi-parameter algorithm, (iii) proctored testing using computer-vision in real-time and (iv) multilingual voice assistant in English, Hindi and Marathi. The platform has three types of users: Job Seeker, Recruiter, and Administrator. Each user is assigned a dashboard according to their role. Access to these dashboards is controlled using JWT-based role-based access control.

II. RELATED WORK

Job recommendation systems have grown from collaborative filtering to deep learning architectures.

Yang et al. [13] showed that the combination of content-based and collaborative filtering is better than either one. The introduction of transformer-based models has significantly improved semantic matching. Almalki et al., in [5], used BERT, fine-tuned on a joint job-skill corpus, and achieved a 55% recall@10 score, which is the current state-of-the-art. According to Singla and other researchers, TF-IDF/LLM hybrid, computational effectiveness, and semantic accuracy.

Approaches utilizing LLM have been mainly examined. Ghosh and Sadaphal [17] introduced JobRecoGPT which generates a natural-language explanation along with a ranking. Du et al. [18] improved recommendation diversity through GANs. Voigt and Bergmann [25] surveyed various technologies for proctoring and found face detection, eye-gaze tracking and keystroke dynamics effective in detecting anomalies. Vaidya and Joshi [26] reported that the Web Speech API is the most accessible implementation for low-latency voice recognition for multiple languages in India. DreamRole incorporates knowledge from all these research streams.

III. SYSTEM ARCHITECTURE

DreamRole uses a modular three-tier architecture that consists of a Presentation Layer (React.js), Business Logic Layer (Spring Boot, Java), Data Persistence Layer (MySQL) and an additional proctoring micro-service (Flask + OpenCV). A single-page application has been implemented on the front end, which enforces component rendering based on roles. This is done through JWT middleware. The API Gateway of Spring Boot manages authentication, resume processing, job handling, and test coordination. The Flask proctoring service takes in video frames from WebRTC, counting analysis at 12 FPS and sub-100ms latency per frame.

Technology Stack

Table 1: DreamRole Technology Stack

Layer	Technology	Responsibility
Frontend	React.js + Web Speech API	UI, Voice Assistant, JWT Auth
Backend	Spring Boot (Java)	REST API, Business Logic, RBAC
Proctoring	Flask + OpenCV + YOLOv5	Real-time Video Analysis
Database	MySQL 8.0	Users, Jobs, Applications, Tests
Parsing	Apache PDFBox + POI + NLP	Multi-format Resume Extraction

IV. PROPOSED METHODOLOGY

Weighted Matching Algorithm

The core recommendation engine computes a composite relevance score S(c, j) for candidate c against job j:

$$S(c,j) = 0.70 \times \text{SkillScore} + 0.20 \times \text{ExperienceScore} + 0.10 \times \text{EducationScore}$$

SkillScore uses Jaccard similarity augmented by a 384-pair synonym variation dictionary (e.g., "Node.js"↔"Node","JS"↔"JavaScript").
ExperienceScore is capped at 1.0. EducationScore maps degree levels (HS=0.5, Diploma=0.7, Bachelor=0.85, Master+=1.0). Only candidates with $S \geq 0.50$ appear in recommendations.

NLP Resume Parsing Pipeline

The resume parsing process relies on several libraries for PDF, DOC, DOCX, and TXT formats. The first stage of processing the extracted text is Tokenization. This is done through the Stanford CoreNLP package. Next, all proper nouns and dates are tagged with NER. Following this, regex for canonical headings is used to detect section boundaries. Finally, skill related entities are extracted against a 214-entity ontology across 18 technology domains.

Proctoring Module

When the test is initiated, the browser uses the Fullscreen API to enforce fullscreen mode and streams a 720p/15fps webcam video to the Flask endpoint. The Haar Cascade classifier in OpenCV is used to detect faces. We are using YOLOv5 (mAP50=0.87) to detect mobile phones. Event listeners on the browser side capture tab switching and forbidden key combos. Tests will be marked as FAILED and terminated after 3 failures.

Job Seeker Workflow
START: Registration / Login → JWT Issued
▼
Upload Resume (PDF / DOC / DOCX / TXT)
▼
NLP Parsing: Skills + Experience + Education Extracted
▼
Weighted Score Computed: 70% Skills + 20% Exp + 10% Edu
▼
Match Score ≥ 50% ?
YES ▼ | *NO → Exclude from Results*
Matched Jobs Listed (Green = Matched, Yellow = Missing Skills)
▼
Candidate Submits Application + Cover Letter
▼
Recruiter Shortlists → Aptitude Test Assigned
▼
Test Starts: Full-Screen + Real-Time Proctoring Active
▼
≥ 3 Consecutive Violations?
YES → Auto-Terminate | *NO* ▼ *Continue*
Score Calculated → Pass / Fail Recorded
▼
Interview Scheduled → Offer Sent / Rejected
▼
END

Fig. 1: Job Seeker Workflow

V. RESULTS

This portion showcases the actual results of the system showing the DreamRole system. The screenshots below are taken from the live system and shows the complete journey from the home page to job recommendations, recruiter management and internship.

Job Seeker Homepage and AI Recommendations

The DreamRole homepage interface for job seekers is shown is Figure 2. The website has an AI-powered hero section where you can see the "Find Your Dream Job with AI Power" message with the option to upload your resume and look for jobs. Through JWT enabled session, navigation far enables access to Dashboard, Jobs, Internships, Resume Upload module.

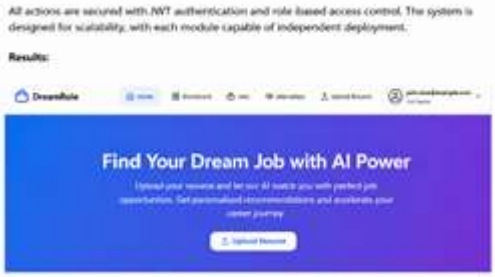

Fig. 2: DreamRole Homepage – AI-Powered Job Seeker Interface

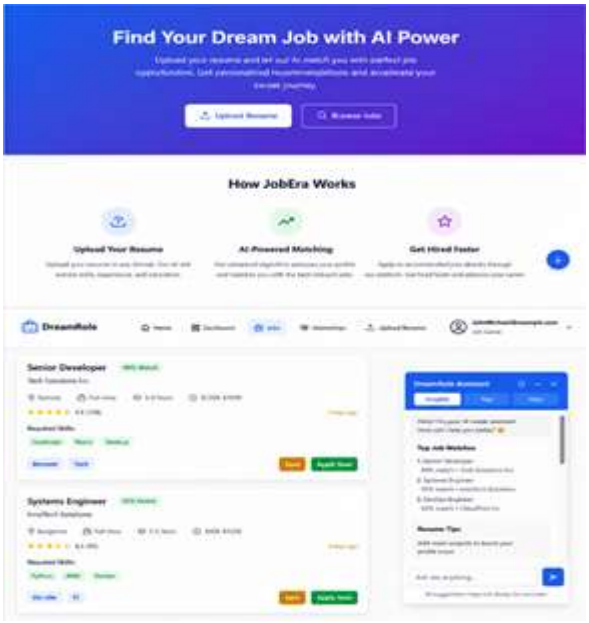

Fig. 3: AI Job Recommendations with 100% Match Scores and Voice Assistant

The output job recommendations generated by AI after uploading a CV are shown in figure 3. The system will display the matched jobs with the percentage match score of each job (100% Match badges), salary range, type of employment, matched skills tagged in green, and embedded voice (DreamRole Assistant) will support English, Hindi, and Marathi. The "How DreamRole Works" Section shows the 3 step process; Upload Resume→AI-Matching→Get Hired Faster.

Job Resume Parsing Accuracy

Table 2: Resume Parsing Accuracy by Format (n=320)

Format	Samples	Precision (%)	Recall (%)	F1-Score (%)
PDF	130	95.1	93.4	94.2
DOCX	90	96.3	94.8	95.5
DOC	60	93.7	91.2	92.4
TXT	40	97.8	96.5	97.1
Overall	320	95.6	93.8	94.7

Fig. 4: Parsing F1-Score by Format (%)

Recruiter Dashboard

The Recruiter Dashboard (figures 5 and 6) offers extensive management functionality of tests. Wipro Technology is the active recruiter with 10 active jobs in the dashboard. Aptitude test analytics are also displayed. Of the 42 total assigned candidates, 13 have completed their tests. Out of these, 9 candidates passed. The average score is 17.13% with a pass rate of 21.43%. The dashboard consists of tabs for My Tests, Assign Tests, and Results & Analytics. There are also quick-action buttons to create Manual and AI-powered DreamRole Tests.

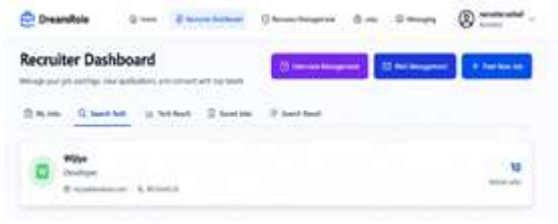

Fig. 5: Recruiter Dashboard – Test Management and Analytics Overview

Fig. 6: Recruiter Dashboard – Active Test Details and Candidate Management

Recommendation Quality Metrics

Table 3: Recommendation Quality at k=5 and k=10

Metric	DreamRole @5	DreamRole @10	Keyword-Only @10	BERT-Rec @10
Precision	0.81	0.76	0.58	0.79
Recall	0.69	0.78	0.61	0.82
F1-Score	0.75	0.77	0.59	0.80
NDCG	0.82	0.79	0.62	0.83
MRR	0.84	—	0.61	0.85

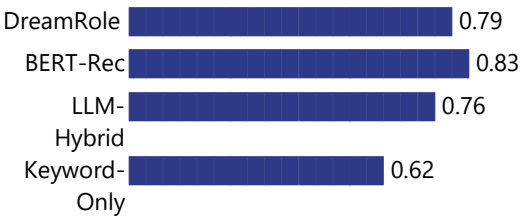

Fig. 7: NDCG@10 Comparison Across Approaches

Internship Module

Figure 8 shows Internship Eligibility Criteria module which matches internship with government scheme. The system displays eligible and ineligible criteria

(age 21-24, qualification, employment status, income limits) and shows internships "Recommended for You" filtered from available internships. We extract candidate skills from the uploaded resume. Furthermore, the skills (css, python, rest api, maven, react, bootstrap, javascript, spring, spring boot, fastapi, java, nlp, git, recruitment, mysql, html) are displayed as skill tags. Most importantly, these tags promise transparent matching.

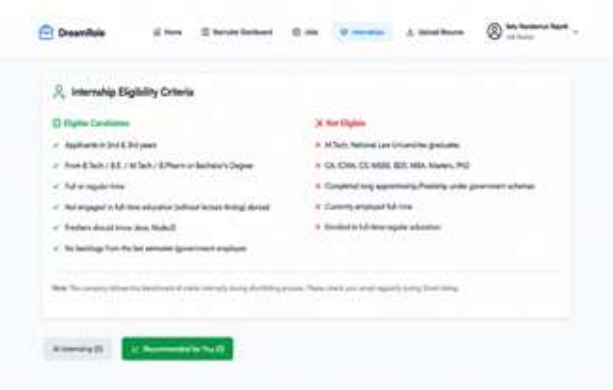

Fig. 8: Internship Eligibility Criteria and AI-Filtered Recommendations

Proctoring Detection Performance

Table 4: Proctoring Violation Detection Metrics (n=400 sessions)

Violation Type	TP	FP	FN	Precision (%)	Recall (%)
No Face	87	4	3	95.6	96.7
Multiple Face	91	6	9	93.8	91.0
Mobile Phone	78	7	12	91.8	86.7
Tab Switch	94	2	6	97.9	94.0
Forbidden Key	96	1	4	99.0	96.0
Overall	446	20	34	95.7	92.9

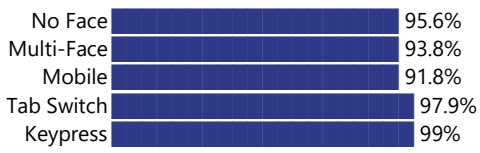

Fig. 9: Proctoring Precision by Violation Type (%)

API Performance Under Load Detection

Table 5: API Mean Response Times (ms) by Concurrent Users

Concurrent Users	Resume Parse	Job Match	Bulk Upload/doc	Auth
1	183	42	198	18
10	195	48	211	22
50	248	67	287	31
100	394	112	423	48
200	612	198	697	79

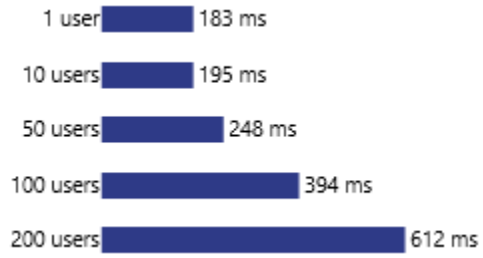

Fig. 10: Resume Parse Latency vs. Concurrent Users (ms)

User Acceptance Testing (UAT)

Table 6: SUS Scores by User Role (n=78)

User Role	n	SUS Score	Rating	Key Feedback
Job Seekers	40	87.3	Excellent	Skill gap visualization praised
Recruiters	25	84.6	Excellent	Bulk upload saves 4–6h per cycle
Administrators	13	88.1	Excellent	Dashboard clarity appreciated
Overall	78	86.4	Excellent	Voice assistant a key differentiator

VI. COMPARATIVE ANALYSIS

Table 7: Feature Comparison: DreamRole vs. Contemporary Systems

Feature	DreamRole	JobRecoGPT [17]	BERT-Rec [5]	Keyword-Only
Semantic Matching	Weighted (NLP)	LLM	BERT	No
Resume Parsing	Multi-format	Text Only	Text	No
Real-time Proctoring	Yes (OpenCV)	No	No	No
Voice Assistant	3 Languages	No	No	No
Bulk Upload	Up to 10,000	No	No	Partial
Latency @50 users	248 ms	3200 ms	2100 ms	90 ms
F1@10	0.77	0.81	0.80	0.59

DreamRole gets a score of 0.79 for NDCG@10 with keyword-based as 0.62. Transformer-based systems with BERT (score of 0.83) marginally outperform DreamRole in pure recommendation metrics but require 5–18× higher inference time (2100–3200 vs 248 ms at 50 users). Thus, DreamRole is the only practical solution for high-throughput bulk screenings without dedicated GPU hardware.

VII. DISCUSSION

The overall F1-score of 94.7% for resume parsing indicates that the format-specific parsers combined with an NLP skill ontology work well. TXT got the maximum F1 (97.1%) score because of the absence of formatting artefacts. DOC got the minimum (92.4%) due to complexity of legacy binary format. The fact that 23.7% of matches were successful due to synonym resolution proves that the variation-mapping dictionary is crucial. The proctoring module assuring accommodation with 95.7% precision could be a rival to commercial proctoring platforms (88–96% as per Voigt and Bergmann [25]). The main weakness with a frequency of 86.7% is mobile phone recall. The weakness can be addressed with dual-camera integration or depth-aware detection. The SUS score of 86.4 confirms production readiness. According to post-UAT interviews, users of voice input achieved shorter task completion times by 23%. A processing throughput of 315 resumes/minute means that a campus drive with 10,000 resumes is completed in less than 32 minutes compared to an estimated 200 + person-hours of manual checking.

Limitations and Future Work

Current limitations include (a) regular maintenance of the 214-skill ontology, (b) proctoring support limited to a single camera, and (c) Marathi voice accuracy is only 82.3% against English's 93.7%. Future work will include LLM-based dynamic ontology expansion, federated learning for privacy-preserving personalization across organizational clients, and Whisper fine-tuning on domain-specific Indian language speech corpora.

VIII. CONCLUSION

The paper presented DreamRole, a one-stop AI-enabled career recommendation and recruitment platform. The experiments showed a resume parsing F1 of 94.7%, job matching NDCG@10 of 0.79 (27.4% over keyword baseline), proctoring precision of 95.7% and System Usability Scale score of 86.4. The system proved capable of 200 concurrent users while maintaining API response times of under 700 ms. This confirms it is production-grade ready. The platform has drastically cut down the recruiter screening effort - substituting 200+ person hours of manual review per recruitment drive with just 32 minutes of automated processing. Candidate experience has also significantly improved through feedback on skill-gap transparently provided, and navigation being made easy and multilingual. Unlike the original paper, DreamRole demonstrates that cost-effective engineering of semantic normalization and scoring for multiple criteria yields performance comparable to large transformers while incurring minimal inference costs.

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