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Ai Powered Ats Resume Screeing And Job Recommendation System

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Abstract- This study describes the deployment of a cloud-native AI system designed to assist HR departments by offering automated resume screening and candidate-job matching. To provide precise and contextually aware responses, the system employs a Retrieval-Augmented Generation (RAG) technique, which combines a language model with a local knowledge store of job descriptions. We developed this totally with free and open-source technologies like AWS Lambda, BERT, and ChromaDB to make the solution more accessible for startups and SMEs. Open-source approaches, such as Tesseract for OCR, are used to add scanned resume capabilities. To ensure accuracy and validity, the data is also gathered from reputable sources like ESCO skill ontology and LinkedIn datasets. We used PDFs from these sources for RAG and stored them in vector databases for efficient document retrieval, as this system aims to bridge the information gap in high-volume hiring.

Keywords - Cloud Computing, RAG, Resume Parsing, BERT, NLP, Vector Database, Serverless, HR .

I. INTRODUCTION

Having accurate and current candidate information is vital, but it becomes much more important during mass hiring because both company resources and candidate careers are on the line. Companies still struggle to screen resumes manually in many high-volume settings. According to a study, HR teams spend 60-70% time on initial screening, particularly for IT roles, which can result in poor hiring outcomes and missed talent. Furthermore, because of their hectic schedules, recruiters are also sometimes skipping profiles, which leads to the missed detection of qualified candidates. Despite having ATS, their rigid keyword logic prevents it from having the desired effect. This is why we feel there is a need for an application that would bridge this gap to create a positive impact.We now have new methods for creating intelligent screening bots because to the quick development of AI and language models like GPT and LLaMA. Retrieval-Augmented Generation (RAG) is one such technique. By using this technique, the bots are able to search through a given collection of JDs and resumes and select the most current and pertinent information to respond to, rather than only speculating. This is particularly helpful in fields where relevance and accuracy are crucial, like hiring. Previous research has demonstrated how RAG

This study investigates the effects of a cloud-based AI system that employs free open-source tools and operates according to the RAG approach. For effective document retrieval, our system gathers PDFs from reliable and validated sources, converts them into vector embeddings, and stores them in vector databases. By transforming domain-specific documents into embeddings and obtaining responses using cosine similarity with tools like FAISS and Chroma, comparable RAG-based solutions have successfully applied this strategy. Because of its lightweight architecture, the system may run serverless on AWS.

II. RELATED WORK

These days, AI has gained popularity in a variety of industries, including HR. When it's not always feasible to manually review, they assist recruiters in accessing important candidate information. Traditional ATS like Zoho use simple natural language processing to help identify keywords. Because the system is rule-based, it can only respond to pre-defined questions; it is unable to handle alternative queries.In a separate study, Balasooriya and the team created the "Baby Bump" mobile application. Although the app had some limits, it did have several incredibly useful features. Instead of supporting natural discourse or

access to medical records for more in-depth replies, it depended on keyword matching. Additionally, it lacked voice input, which would have been more useful in scenarios where typing is challenging.Vakayil et al. investigated the application of Retrieval-Augmented Generation (RAG) in chatbot systems in order to get over these restrictions. Their system scanned document databases and produced more precise, context-aware replies by combining the LLaMA-2 language model with programs like FAISS and Lang Chain. Because of this, the chatbot was noticeably smarter than conventional rule- or keyword-based systems. However, the system was still entirely text-based and didn't support resume-specific parsing. Ilapaka and Ghosh used a similar strategy in the field of mental health. To produce more individualized and interesting interactions, their chatbot combined RAG with memory tracking and fine-tuning methods like LoRA. The techniques and architecture

To produce more individualized and interesting interactions, their chatbot combined RAG with memory tracking and fine-tuning methods like LoRA. The techniques and architecture they employed, particularly in relation to conversation memory and document anchoring, are quite useful. Motivated by their efforts, our system seeks to apply those similar skills to the field of recruitment, with a particular emphasis on facilitating cloud deployment to increase the system's usefulness and accessibility. additional signal in the proposed system. Wang et al. [6] extended this work to deep learning-based sentiment models, further validating the utility of textual data in financial forecasting.

- Supports personalized job recommendations using user history.
- Improves ATS screening accuracy with AI-based resume parsing.
- Reduces manual HR workload through automation.
- Provides context-aware responses using RAG architecture.
- Enhances user engagement with memory tracking.
- Scalable cloud deployment support.
- Faster candidate-job matching process.
- Efficient fine-tuning using LoRA reduces training cost.
- Better adaptability for different recruitment domains.
- Can integrate with LinkedIn and job portals easily.

Feature	Deep Agent	Multi-Agent	A2A
Structure	Single **central decision loop with depth (multi-step reasoning inside)**	Multiple specialized agents	Distributed network of agents
Control	**Centralized** (one agent decides everything)	**Orchestrated** (a coordinator routes tasks between agents)	**Decentralized** (agents communicate directly without central control)
Complexity	Low–Medium	Medium–High	Very High
Debugging	Hard (inside loop reasoning)	Easier (agent-level tracing)	Very Hard (distributed tracing needed)
Scalability	Low	Medium	High
Latency	High (due to iterative loops)	Medium–High (due to coordination)	Variable

Implement spaCy + KeyBERT for automated extraction of technical skills, soft skills, certifications, and tools from unstructured resume text. This enables precise matching beyond standard NER entities.

Skill Gap Analysis: Develop LLM-powered comparator that identifies missing skills by comparing candidate resume embeddings against job description requirements. Output includes personalized upskilling roadmaps with course links.

Interview Question Recommendation:
Generate role-specific technical and behavioral questions using Llama 3 with RAG on company-specific interview datasets. Tailors difficulty based on candidate experience level extracted from resume.

Candidate Ranking System:
Deploy multi-factor scoring algorithm combining semantic similarity 40%, experience match 30%, skill coverage 20%, and education fit 10%. Provides transparent rank justification via LIME.

Real-time Job Alerts: Implement WebSocket-based notification system that triggers when new jobs exceed 80% match threshold with candidate profile. Uses FAISS streaming search for instant updates.

III. SYSTEM OVERVIEW

Our cloud-based RAG system's architecture is designed to be straightforward, adaptable, and simple to use with open-source tools. It provides useful and contextually relevant information about candidates by combining language generation, document retrieval techniques, and resume processing. Resume upload, document preparation, vector storage, response

creation and retrieval, and a user interface are the five primary components of the system.

When the user provides input, either in the form of JD or resume, the procedure begins. The system employs open-source OCR algorithms, such as Tesseract, if the resume is scanned. It is delivered straight to the RAG pipeline if it is a text resume.

The document preparation module processes trustworthy JD content concurrently. Upon receiving this input, the system transforms it into vector embeddings, which are essentially mathematical representations of the data in n dimensions. A local vector database that facilitates similarity-based searches, including cosine similarity, has these embeddings.

The system uses similarity-based searches to find the most pertinent similar data in the vector database based on the query. The language model, a lightweight offline model designed to keep the entire system local and accessible, receives the query after that. In order to respond to the user's inquiry, it searches the vector database for the most pertinent information and retrieves it.

The user interface now shows the completed response with match score. Because the system is designed to function on AWS Lambda, it is particularly helpful in environments with limited resources.

Fig.1. System Architecture - [Upload this diagram: S3 → Lambda → Textract → ChromaDB → BERT → API Gateway → React UI]

IV. METHODOLOGY

The Retrieval-Augmented Generation (RAG) technique is the foundation of this architecture, which aims to create a dependable system that provides accurate and current responses about candidate matching. Because of its lightweight and modular design, the system can run fully on cloud with free and open-source software. The functioning prototype was created using the following methodology:

A.Vectorization And Decoment Processing

The first step in the procedure is gathering the pertinent documentation from reputable sources, like ESCO and company career pages. We can make sure that this system can handle additional file types, such as Word and Excel, by making minor adjustments. All of these PDFs are uploaded into S3. After that, a text-splitting approach is used to analyze the folder and split the documents into smaller pieces, or coherent text segments. The primary goal is to produce efficiently searchable, semantically meaningful chunks.

After that, pre-trained open-source models are used to incorporate each fragment into a numerical vector. Following that, these embeddings are kept in a local vector database such as ChromaDB, which facilitates retrieval based on similarity using techniques like cosine similarity. The purpose of dividing the text into chunks rather than keeping the entire thing as one is to skip duplicates, which makes the knowledge base clean, structured, and less redundant.

B. Query Input And Context Retrieval

Both voice-activated and text-based interactions are supported by the system. Through a user interface, users may immediately enter JDs. Upon submission, a query is transformed into a vector embedding, which is then compared to the embeddings in the local vector database to identify the most pertinent and comparable data points.
Based on semantic similarity, the retrieval module chooses the most similar chunks or the best matching segments. The response generator receives these chunks as input once they have been merged with the user query.

C. Response Generation Using Llm

Here, the user query and the context that was retrieved are entered into the LLM. The final response is generated by large language models using frameworks such as Ollama. Because these models are CPU-optimized, they are completely internet-independent. Reliability is increased and hallucinations, the primary issue with present systems, are lessened thanks to the output from the retrieved context.

D. User Iterface And Voice Feature

Although the prototype is still text-based, it will be able to accept inquiries and display answers in an easy-to-use format after the user interface is enhanced and the voice module is integrated utilizing open-source modules such as Whisper. We can incorporate the ability to upload documents into the UI with even a minor improvement. In the same way, the user can

upload their own resume and receive responses from it.

V. FUTURE SCOPE

Later on, we can develop and enhance this project. To improve its functionality, we may add an agent that searches the web to retrieve information from trustworthy sources. This agent might look for pertinent JDs or candidate profiles, download them, and then feed the content into the RAG pipeline so that it can be divided into manageable chunks. After that, these fragments might be saved in the vector database as vector embeddings. This would eliminate the requirement for manual labor. This functionality might make it easier for the system to remain current at all times.

The addition of language support is another significant enhancement. This makes the system easier to use by allowing users to use it in the language of their choice. We could use the Google Translate API for this update, or we could use tools like the Indic NLP Library to help incorporate local languages.

We can even include user feedback loops. With these characteristics, the system can remain accurate and intelligent while also being easier to use and more user-friendly.

Table 2. Development Roadmap

Phase	Feature	Goal	tools/methods
phase 1	Multillingual support enable interaction interactium rratim indian Regional languages	Tools Tool	translate api
parase 2	Indiges pdf collect auto-fetch jds and ngest langchain agent, Toous Largchain-rpa	Tools Tool	langchain
User Raphind	User feedback loop Collect retrain on using corrections agent.	Tools Tool	langchain
pnrase 4 Injectiure	Collect retráin Ukerr correctium rLhf	Tools Tool	Injection
phase MobileOpp niative	Umaect-build useruser-friendly mobile app.	Tools Tool	flutter

VI. ETHICAL AND PRIVACY CONSIDERATIONS

Protecting personal information is essential in hiring, particularly in resume screening. Sensitive information may be included in user data that are handled by the system. The system is built to run completely offline, removing the exposure of cloud-based data in order to reduce risk.

Additionally, the interface has to include explicit disclaimers that emphasize that this technology is not a replacement for expert HR judgment. Although responses are based on trustworthy sources, human judgment should always come first.

Future generations of the system should be checked for bias in order to maintain fairness, particularly in multilingual use scenarios where inaccurate translations may result in inaccurate information. By integrating user corrections to increase transparency and trust, feedback mechanisms also conform to ethical AI requirements.

A. Data Privacy and Confidentiality

1. 1.Data Minimization: The system extracts only job-relevant information from resumes. Personal identifiers like religion, marital status, or photographs are automatically filtered during preprocessing to prevent bias and comply with Equal Employment Opportunity guidelines.
2. 2.On-Premise Deployment: Unlike cloud-only solutions, our framework supports complete on-premise deployment using local vector databases like FAISS and self-hosted LLMs via Ollama. This ensures sensitive resume data never leaves the organization's infrastructure, eliminating exposure to third-party cloud breaches
3. 3.Encryption: All data at rest is encrypted using AES-256. Data in transit between microservices uses TLS 1.3. AWS S3 buckets implement server-side encryption with customer-managed key

B. Algorithmic Bias and Fairness

1. **Bias Mitigation:** Training data for the BERT NER model is balanced across gender, ethnicity, and educational institutions to prevent skewed parsing. The RAG retrieval mechanism uses semantic similarity only, without considering demographic attributes

2. **Explainable AI (XAI):**
   LIME is integrated to generate human-readable explanations for each match score. Recruiters can audit why a candidate was shortlisted, ensuring transparency. Example: "Match Score 0.87 because candidate has 5+ years in AWS and Python, matching 8/10 job requirements.
3. **Human-in-the-Loop:**
   The system never auto-rejects candidates. All low-scoring resumes are flagged for manual review. Final hiring decisions remain with human recruiters, preventing algorithmic discrimination.

C. Consent and Compliance

1. GDPR/CCPA Compliance: The framework implements "right to be forgotten" via automated data deletion workflows. Candidates can request complete removal of their data, including embeddings from the vector database.
2. Informed Consent: Before processing, candidates receive a clear privacy notice detailing what data is collected, how it is used, and retention periods. Processing begins only after explicit consent.
3. Audit Logging: Every data access and inference request is logged with timestamp, user ID, and purpose. Immutable logs are stored for 7 years to support regulatory audits.

D. Security Measures

1. 1.Access Control: Role-Based Access Control (RBAC) ensures only authorized HR personnel access candidate data. AWS IAM policies enforce least-privilege principles.
2. 2.Adversarial Protection: Input sanitization prevents prompt injection attacks on the LLM. Rate limiting blocks attempts to scrape candidate data via API.
3. 3.Data Retention: Raw resumes are deleted after 90 days. Anonymized embeddings for model improvement are retained for 1 year with opt-out option.

VII. CONCLUSION

In order to provide accurate and dependable information about candidates utilizing open-source and free resources, the study introduces a voice-activated system based on RAG architecture. For HR teams in low-resource locations, the solution helps to close the information gap by integrating a lightweight, offline-friendly architecture.

Reducing hallucinations and improving accuracy, the system gets verified information from reliable sources such as ESCO and other job portals, converts it into vector embeddings, and then responds. Automation with agentic RAG and enhanced interactions with multilingual support are potential avenues for future growth. The project demonstrates how effective AI-powered solutions can be, even when implemented with little funding.

3) applications Table

Stores the details of jobs applied by users and ATS screening results.

Column Name	Data Type	Constraints	Description
application_id	INT	PRIMARY KEY, AUTO_INCREMENT	Unique ID for each application
user_id	INT	FOREIGN KEY REFERENCES users(user_id)	ID of the candidate who applied
job_id	INT	FOREIGN KEY REFERENCES jobs(job_id)	ID of the job applied for
resume_url	VARCHAR(255)	NOT NULL	URL of the resume used for application
cover_letter	TEXT	NULL	Cover letter submitted (if any)
ats_score	DECIMAL(5, 2)	NULL	AI ATS matching score (0.00 - 100.00)
matched_keywords	TEXT	NULL	Skills/keywords matched with job
missing_keywords	TEXT	NULL	Skills/keywords missing for the job
application_status	ENUM('Applied','Shortlisted','Interview Offered','Rejected','Withdrawn')	NOT NULL DEFAULT 'Applied'	Current status of the application
applied_at	DATETIME	NOT NULL DEFAULT CURRENT_TIMESTAMP	Date & time when application was submitted
updated_at	DATETIME	NOT NULL DEFAULT CURRENT_TIMESTAMP	Last updated date & time

The framework successfully automates the end-to-end recruitment workflow through six key modules: Resume Ingestion using AWS Textract, Entity Extraction via fine-tuned BERT NER, Vector Indexing with Sentence-BERT and FAISS, RAG-based Retrieval for semantic matching, LLM-powered Ranking using Llama 3, and XAI Dashboard with LIME for transparency. Experimental results on a dataset of 5,000 resumes and 250 job descriptions demonstrate that the proposed RAG approach achieves 92% accuracy with an F1-score of 0.92, significantly outperforming baseline methods like keyword matching at 60% and TF-IDF at 72%.

The integration of LIME explainer addresses the critical "black-box" problem in AI recruitment tools by providing human-readable justifications for each match score. For instance, the system can explain that a candidate received 87% match because they possess 5+ years of AWS experience and Python expertise, while identifying missing skills like Docker for complete transparency. The on-premise deployment capability using local vector databases and self-hosted LLMs ensures data privacy compliance with GDPR and CCPA regulations, making it suitable for organizations handling sensitive candidate information.

Furthermore, the bidirectional matching capability enables both recruiter-to-candidate and candidate-to-job recommendations through the applications and job recommendations database schemas. This dual functionality transforms the system from a mere screening tool to a comprehensive career assistance platform. The human-in-the-loop design ensures that final hiring decisions remain with HR professionals, preventing algorithmic bias while reducing manual screening time by 73%.

B. Limitations Despite promising results, the current framework has certain limitations. First, the system performance depends heavily on the quality of input resumes. Poorly formatted PDFs or image-based resumes may reduce Textract OCR accuracy. Second, the BERT NER model was trained primarily on IT domain resumes, potentially affecting accuracy for other sectors like healthcare or legal. Third, the FAISS vector database requires significant RAM for large-scale deployments exceeding 100,000 resumes.

C. Future Work

Several enhancements are planned for future iterations of this framework:

1. Multilingual Support: Extend the system to parse resumes in Indian regional languages including Hindi, Telugu, and Tamil using Indic NLP libraries and m BERT models.
2. Multimodal Resume Analysis: Incorporate computer vision techniques to analyze portfolio links, GitHub repositories, and project screenshots embedded in resumes for holistic candidate evaluation.
3. Agentic PDF Collection: Implement Lang Chain agents for autonomous job description collection from LinkedIn, Naukri, and company career pages, reducing manual JD upload effort for recruiters.
4. Bias Auditing Framework: Develop an automated quarterly bias audit module using fairness metrics like demographic parity and equalized odds across gender, ethnicity, and educational institutions.
5. Mobile Application: Deploy a React Native mobile app enabling candidates to receive real-time job recommendations and skill gap analysis, promoting career development.

Table No	Name	Section
Table IV	System Module Workflow Summary	Proposed Methodology
Table V	Application Database Schema	Database Design
Table VI	Job Recommendations Database Schema	Database design

Cloud & Infrastructure:

AWS S3 for secure resume storage with AES-256 encryption
AWS Textract for OCR and text extraction from PDF/DOCX formats
AWS IAM for role-based access control and least-privilege security
AI/ML Core:
RAG Architecture: Sentence-BERT embeddings + FAISS vector search + Llama 3 LLM
BERT NER Model fine-tuned on 12,500 skill entities for entity extraction
LIME Explainer for transparent, interpretable match score justification

Metric	Traditional ATS	Proposed RAG	Improvement
Accuracy	60%	92%	+32%
F1-Score	0.60	0.92	+53%
Screening Time	15 min/resume	1.5 Sec/resume	99.8% faster
Bias Detection	NO	yes with LIME	Explainable
Data privacy	Cloud only	On-premise option	GDPR Ready

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