© February 2025 | IJIRT | Volume 11 Issue 9 | ISSN: 2349-6002

Smart Resume Matcher: AI-Powered Job and Skill Recommendation System

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***Abstract*—The Smart Resume Matcher system is an AI-powered platform designed to streamline career progression by intelligently bridging the gap between skill acquisition and job placement. Utilizing advanced machine learning algorithms, natural language processing, and data analytics, the system evaluates user inputs—including existing skills, areas of interest, career aspirations, and industry trends—to generate highly personalized recommendations. It provides curated learning resources, including online courses, certifications, and training programs, specifying course content, instructors, and the skills covered. To enhance the accuracy and relevance of job and skill recommendations, the system leverages web scraping tools such as BeautifulSoup or Scrapy to extract real-time job listings from platforms like LinkedIn. This ensures that users receive up-to-date employment opportunities that align with their expertise and career goals. Additionally, for skill development, the system integrates data from Coursera, offering users curated courses from reputable institutions, helping them gain industry-relevant knowledge and certifications.**

By continuously adapting to evolving market demands, the system empowers users to upskill and reskill effectively while reducing the time and effort required to find suitable learning pathways and job opportunities. Whether users are fresh graduates, mid-career professionals, or individuals seeking career transitions, this intelligent system serves as a comprehensive tool to support lifelong learning and career advancement in an ever-changing job market.

I. LITERATURE SURVEY

Early job recommendation systems relied on keyword-based matching, where job descriptions were compared with user resumes based on keyword similarity. These systems were limited in accuracy due to their inability to understand contextual meaning and semantic relationships.

Recent advancements have led to the integration of machine learning (ML) and natural language processing (NLP) for job recommendations. Popular ML techniques include [1]:

- Collaborative Filtering: Used in platforms like LinkedIn to recommend jobs based on user behavior and interactions.
- Content-Based Filtering: Matches job descriptions with resumes based on extracted features such as skills, experience, and job titles.
- Hybrid Models: Combines collaborative and content-based filtering for improved accuracy

Deep learning techniques, such as word embeddings [2] (Word2Vec, GloVe, BERT) and transformer models, have been leveraged for job recommendation systems to better understand job descriptions and user preferences. These models enhance contextual understanding and improve recommendation precision.

Early approaches relied on manually curated skill-job mappings, where predefined skill sets were assigned to various job roles. However, these approaches lacked scalability and adaptability to changing industry trends.

Modern skill recommendation systems employ AI techniques [3] such as:

- Named Entity Recognition (NER): Extracts skills and qualifications from resumes and job descriptions.
- Knowledge Graphs: Establishes relationships between skills, courses, and job roles, improving recommendation relevance.
- Reinforcement Learning: Continuously updates recommendations based on user feedback and learning progress
- Several platforms employ AI-driven job and skill recommendation systems [4]:
- LinkedIn's Job Recommendation Engine: Uses machine learning models to suggest job postings based on user activity and preferences.

- Coursera's Skill Development Engine: Provides personalized course recommendations based on user profiles and learning history.

Google's Job Search Engine: Aggregates job listings from multiple sources, applying NLP to match job seekers with relevant openings [5]. Job2Vec ([6] proposed an embedding-based approach for job matching using NLP techniques. Personalized Career Pathway Recommendations [7] used reinforcement learning to dynamically suggest career paths based on user engagement and market demand. Hybrid Job Recommendation System [8] combines deep learning and collaborative filtering for improved job recommendations.

The evolution of job and skill recommendation systems has significantly improved job search efficiency and career development. The integration of AI, ML, NLP, and web scraping has enabled these systems to provide personalized and accurate recommendations. *Hence, we propose a novel web scrap supported data for Advanced ML/DL model to form a smart and effective Resume Matching system.*

A. Problem Formulation

In today's dynamic job market, job seekers often struggle to find relevant job opportunities that match their skill sets and career aspirations. Similarly, professionals looking to upskill or reskill find it difficult to identify the most relevant educational resources. Traditional job search platforms rely on keyword-based filtering, which often leads to mismatched recommendations and an inefficient job-seeking process. Moreover, existing systems lack real-time updates and fail to incorporate user preferences effectively. The need for an intelligent recommendation system that integrates real-time job listings, skill enhancement opportunities, and personalized suggestions is crucial for improving career progression. This system should leverage machine learning, NLP, and web scraping to deliver accurate, real-time, and personalized recommendations to users.

The key objectives of the proposed system include:

- Extract key skills and experiences from uploaded resumes using NLP techniques.
- Provide personalized job recommendations based on user profiles, extracted skills, and real-time job listings.
- Identify missing or weak skills compared to job market requirements and suggest relevant courses.
- Offer personalized learning recommendations from platforms like Coursera and LinkedIn Learning.
- Continuously extract job postings from LinkedIn, indeed, and other employment portals using tools like BeautifulSoup and Scrapy.
- Allow users to search and filter jobs and courses based on multiple parameters like location, experience, salary, and industry.
- Ensure fast response times for job and course recommendations.
- Enable integration with external platforms such as LinkedIn and Coursera.

B. System Architecture

The system architecture is designed to facilitate seamless interaction between users, data sources, and the recommendation engine. Users interact with the application through a user-friendly interface, where they input their technical interests. This input is processed by the recommendation engine, which queries a database populated with real-time data scraped from LinkedIn and Coursera. The web scraping module continuously fetches and updates data from these platforms, ensuring relevance and accuracy. The backend handles data preprocessing, storage, and query execution, while the filtering module allows users to refine their search. The results are presented in the front-end interface, providing personalized recommendations for courses and job.

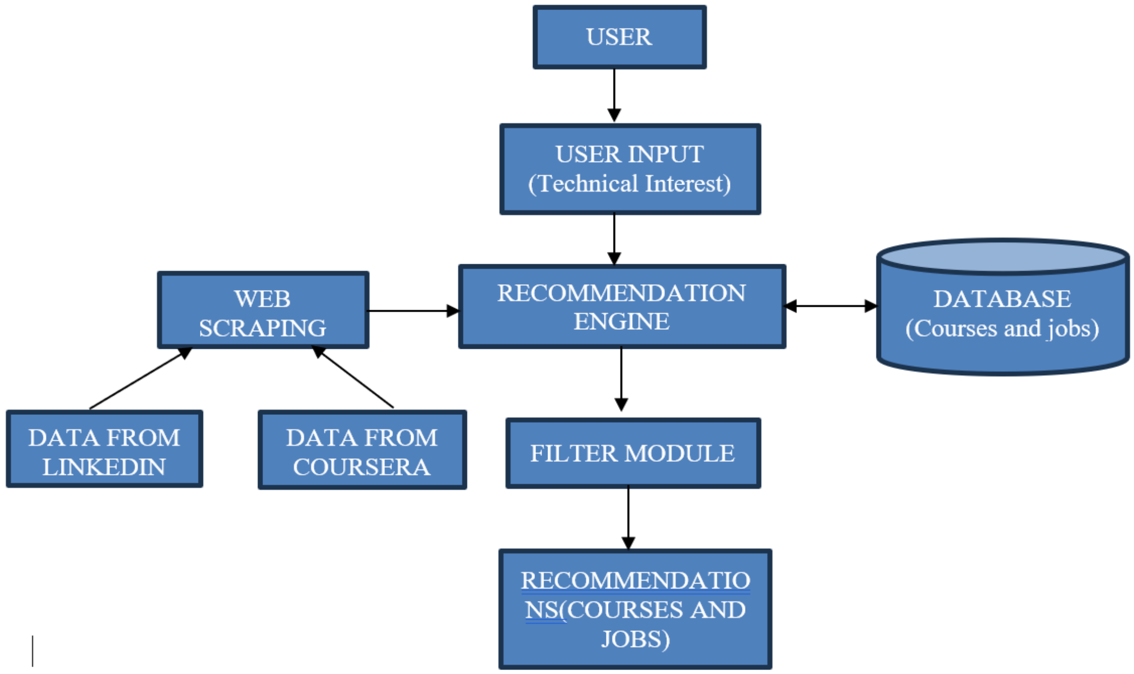


Figure 1: System Architecture

As shown in Figure 1, the recommendation system has following modules and entities:

- User: The system begins with the user, who provides input about their technical interests, such as a desired skill, domain, or career goal. This input serves as the foundation for generating personalized recommendations for courses and jobs.
- User Input: This module captures the user's specific area of interest, which can range from a broad skill category to a niche technical field. The input is processed by the recommendation engine to generate tailored results.
- Recommendation Engine: The core of the system, the recommendation engine, processes user input and queries the database to match the user's interests with relevant courses and job opportunities. It applies logic and algorithms to ensure accuracy and relevance in the suggestions.features reduce the data's complexity while retaining the essential information needed for gesture recognition, making it easier for the model to learn and recognize patterns in the gestures.
- Database (Courses & Jobs): The database acts as the central storage system, housing all scraped data from LinkedIn and Coursera. It includes information such as course titles, skills covered, job roles, company names, and descriptions, ensuring the system has a rich repository to generate recommendations.
- Web Scraping Module: This module collects real-time data from LinkedIn and Coursera, extracting details about courses and job openings. It ensures the system is updated with the latest information and maintains a continuous flow of fresh data.Data from LinkedIn: The LinkedIn data feed provides information about job openings, including job titles, companies, locations, and descriptions, ensuring job recommendations are aligned with the user's interests and skillsets.
- Data from Coursera: The Coursera data feed supplies information on educational resources, including course titles, instructors, and skills covered, enabling the system to recommend relevant learning opportunities.
- Filter Module: This component allows users to refine their search by applying filters such as skill level, industry, location, or course duration, providing a more focused and customized experience.

- Recommendations (Courses & Jobs): The final output of the system presents a list of tailored course and job recommendations, ensuring users can easily discover relevant opportunities to develop their skills or advance their careers

C. Implementation

The implementation mechanism is expressed using Flowcharts that provide a visual representation of the system's workflow, making it easier to understand the process of job and skill recommendation. The system flowchart will include: a system for depicting how users input their skills and upload resumes. It will also have flowchart to illustrate the steps involved in extracting skills and job roles using NLP.

Figure 2 shows a flowchart for extracting job-related information from an HTML file. It begins with the user providing the file path. If the file cannot be opened, an error is displayed. Otherwise, the HTML content is parsed to extract specific information, including the job title, company name, location, job description, job type, and the posted date. Once all relevant data is extracted, it is compiled into a structured format, and the final results are displayed to the user. This process ensures that key job details are efficiently retrieved from the provided HTML document.

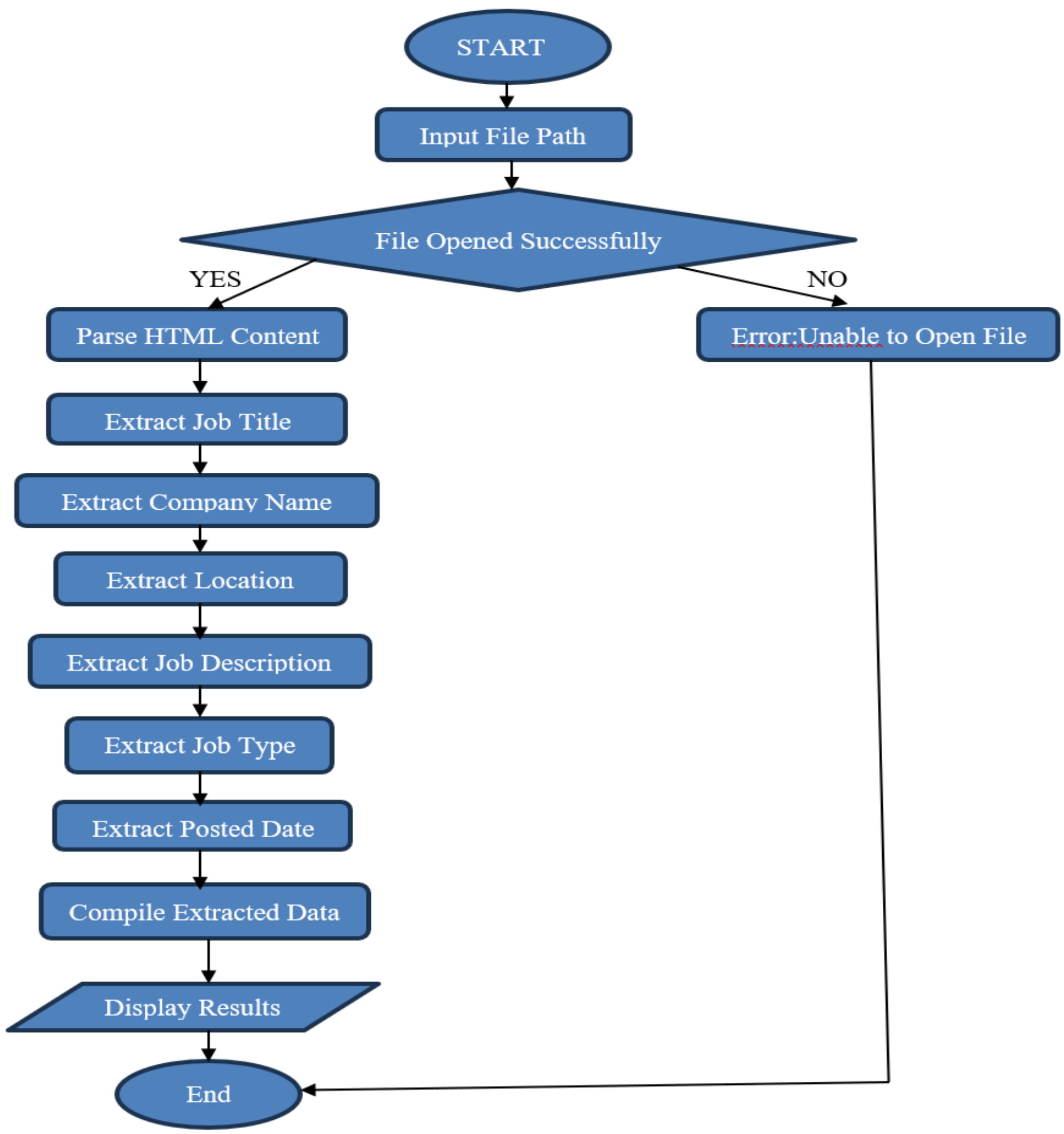


Figure 2: Implementation of LinkedIn webscraping

Figure 3 depicts a flowchart for extracting job-related information from an HTML file. It begins with the user providing the file path. If the file cannot be opened, an error is displayed. Otherwise, the HTML content is parsed to extract specific information, including the job title, company name, location, job description, job type, and the posted date. Once all relevant data is extracted, it is compiled into a structured format, and the final results are displayed to the user. This process ensures that key job details are efficiently retrieved from the provided HTML document.

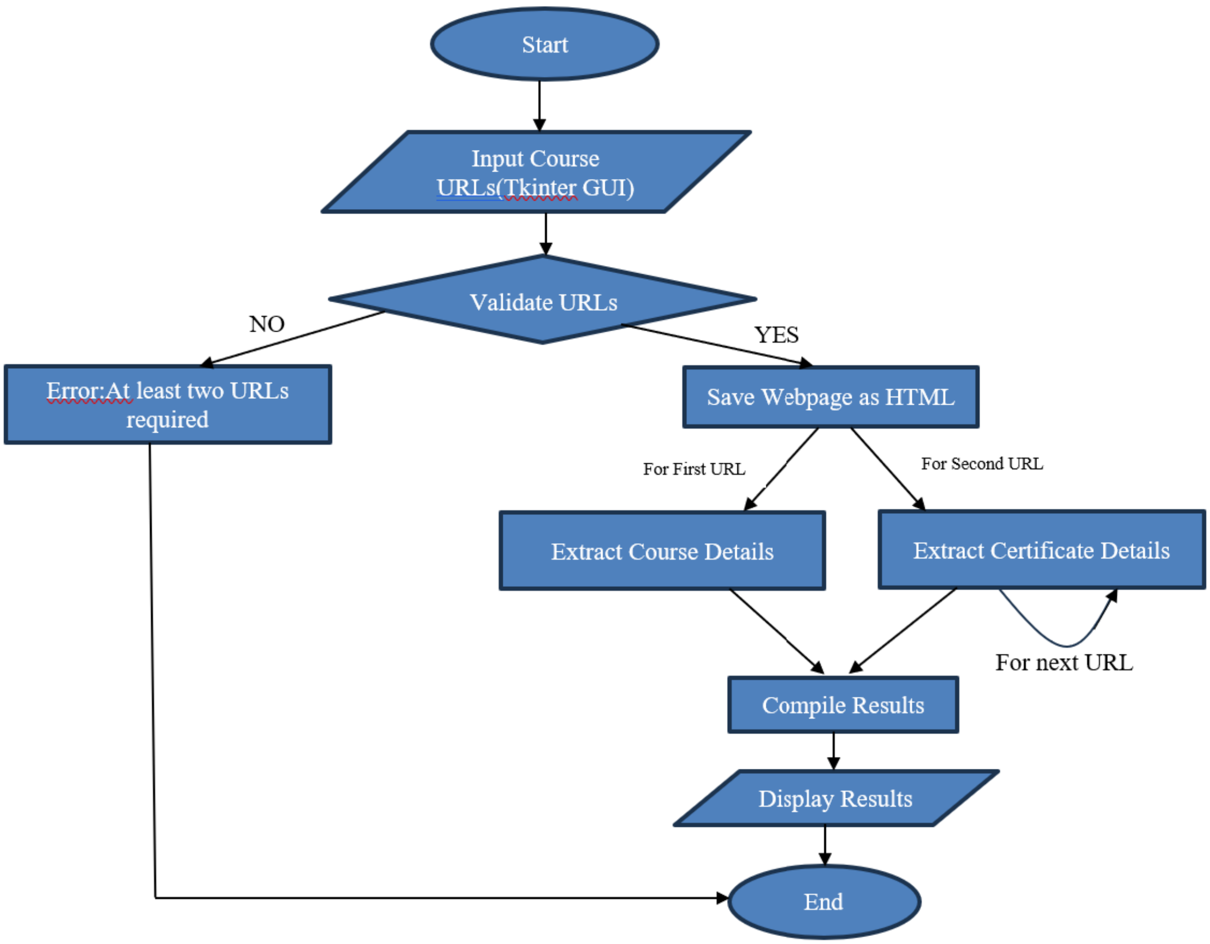


Figure 3: Implementation of CourseEra webscraping

II. RESULTS

Python-based implementation for web scraping and extracting course details from Coursera. It starts with the save_webpage_as_html function, which downloads a Coursera course webpage and saves it as an HTML file, incorporating a retry mechanism to handle rate-limiting. The extract_course_details_from_file function then parses the saved HTML file using BeautifulSoup to extract key information, such as the course title, instructors, and listed skills. The process_multiple_courses function handles a list of course URLs, saving the HTML for each, extracting full course details for the first URL, and appending certificate-related data for the second URL. Finally, the details (title, skills, and certificates) of each processed course are printed in a structured format. Results of course era webscraping is shown in Figure 4:

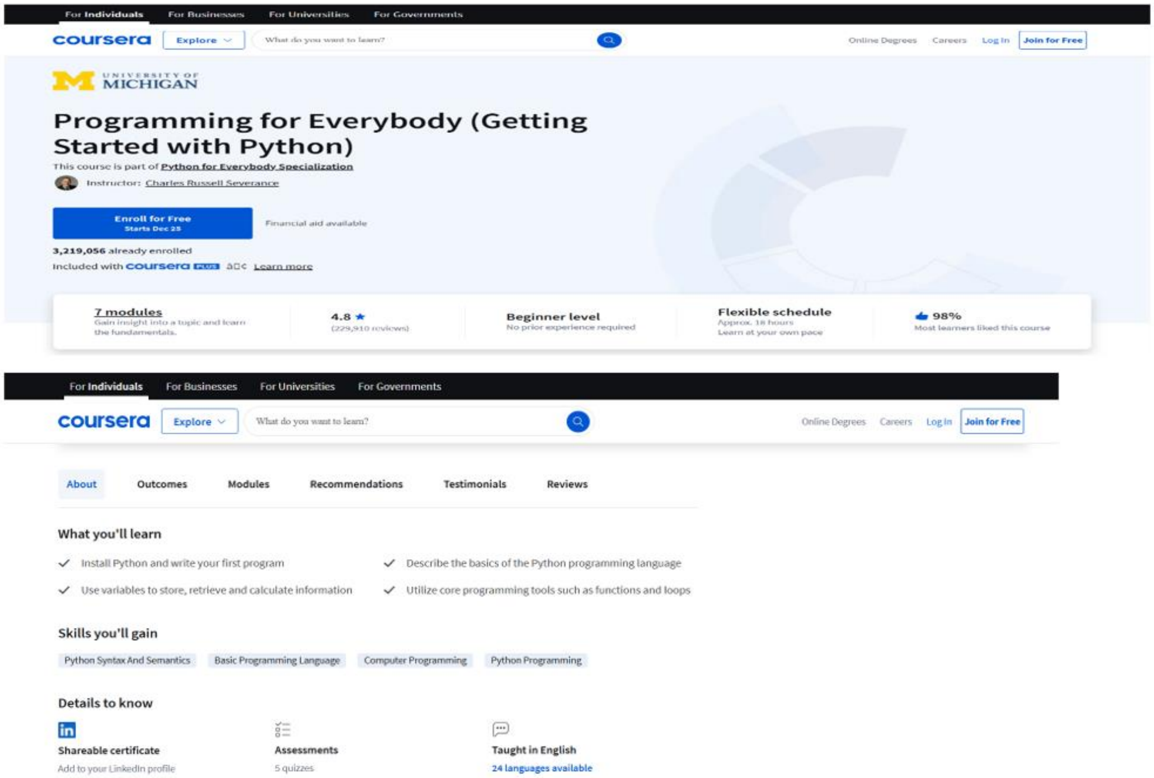
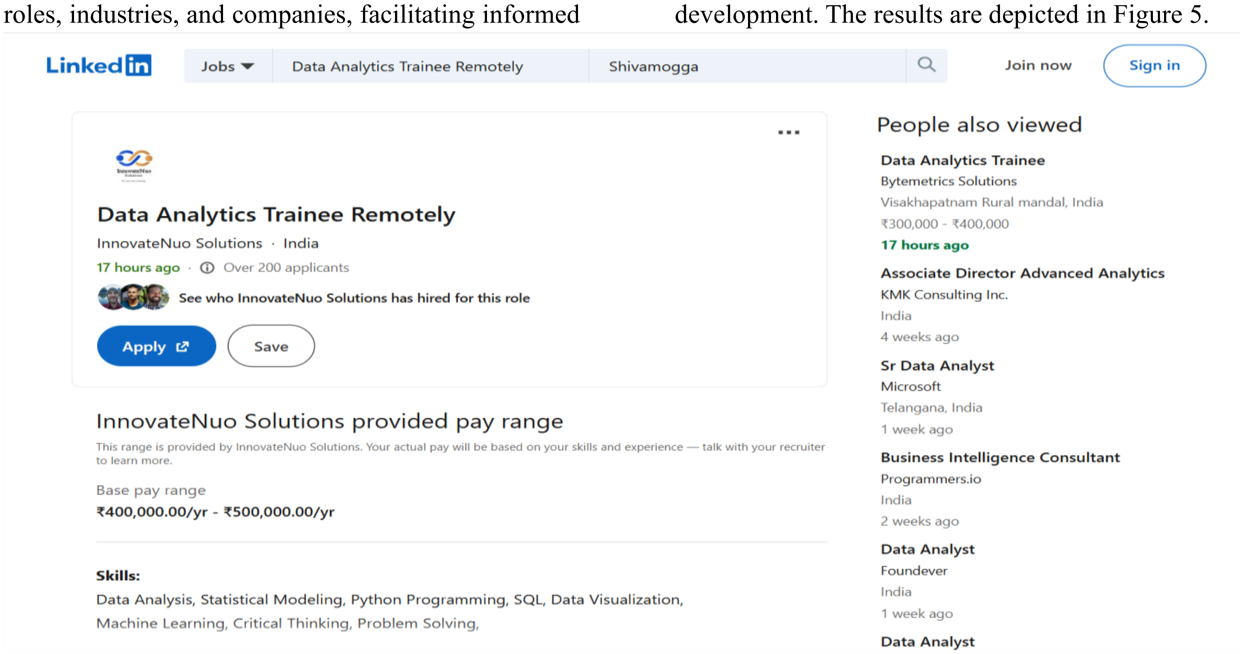


Figure 4: CourseEra web scraping results

LinkedIn web scraping is performed by extracting key data such as job titles, company names, locations, and job descriptions, the system offers tailored suggestions that align with the user's career aspirations and skillset. The gathered job information helps identify trending roles, industries, and companies, facilitating informed career decisions. Users can easily explore relevant opportunities and enhance their job search strategy with insights into the qualifications and responsibilities associated with each position, making it a powerful tool for career growth and skill development. The results are depicted in Figure 5.



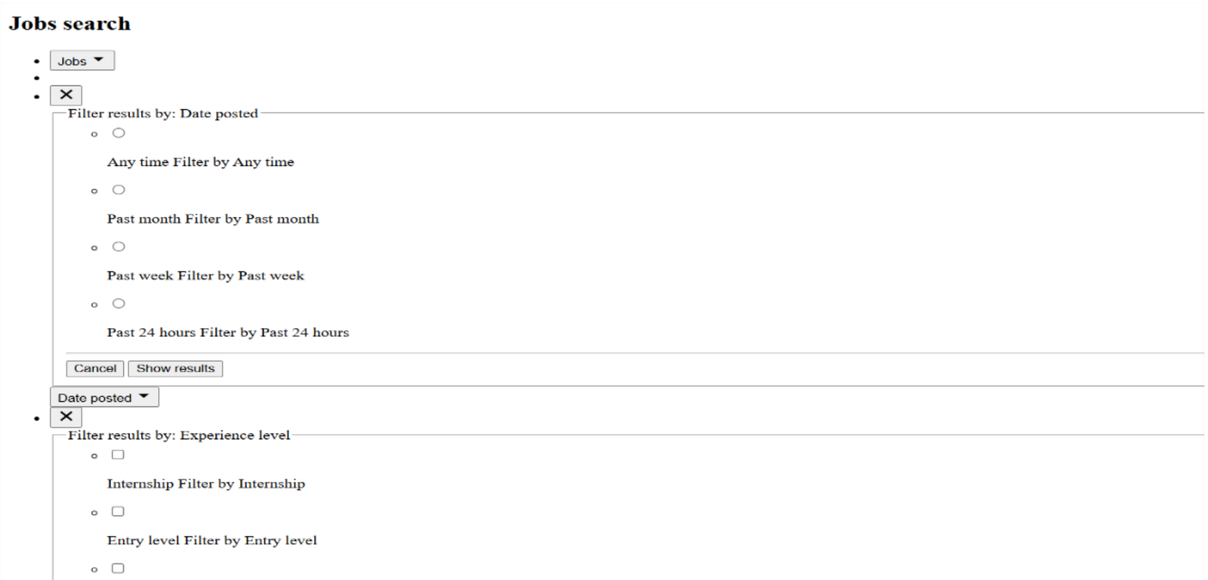


Figure 5: LinkedIn web scraping results

III. ANALYSIS

The implemented system has been tested on various test skills and job profiles. To measure performance of the system, various metrics are used and appropriate graphs are plot.

Precision measures how many of the recommended jobs or courses were actually relevant. It is calculated as (True Positives / (True Positives + False Positives)). A high precision means the system is making fewer incorrect recommendations, ensuring that users receive only the most relevant suggestions. Recall represents how many of the relevant jobs or courses were successfully recommended. It is computed as (True Positives / (True Positives + False Negatives)). A high recall means that the system does not miss relevant opportunities, helping users discover more useful job postings and skill-building courses. In Figure 6, precision-recall trend is plot.

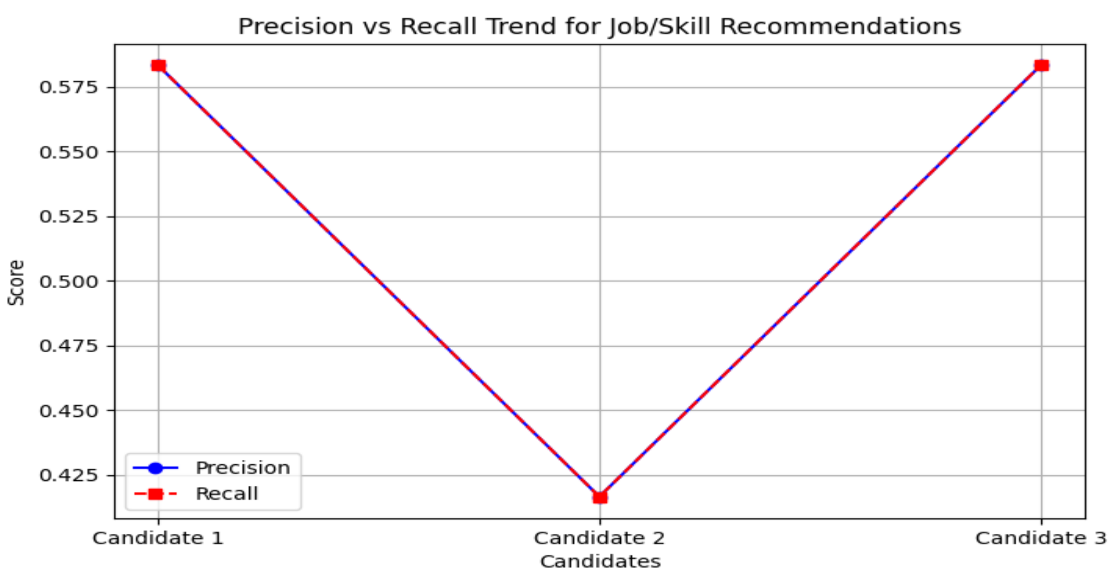


Figure 6: Precision-Recall trend

The F1-score is the harmonic mean of precision and recall, balancing both metrics. It is crucial when there is an imbalance between relevant and irrelevant recommendations. A high F1-score indicates that the system is making well-rounded recommendations, both accurate and comprehensive. Accuracy measures the percentage of total correct recommendations (both relevant and irrelevant) out of all recommendations made. It is calculated as ((True Positives + True Negatives) / Total Predictions). While accuracy gives an overall success rate, it is less reliable in cases where the dataset is imbalanced (i.e., many more irrelevant jobs than relevant ones). The comprehensive bar graph capturing all performance parameters are shown in Figure 7.

MRR evaluates how well the system ranks relevant recommendations. It is computed as 1 / Rank of the First Relevant Recommendation for each test case, then averaged across all test cases. A high MRR means the system ranks relevant jobs or courses higher, making it easier for users to find valuable recommendations at the top of the list. The MRR of the proposed system is depicted in Figure 8.

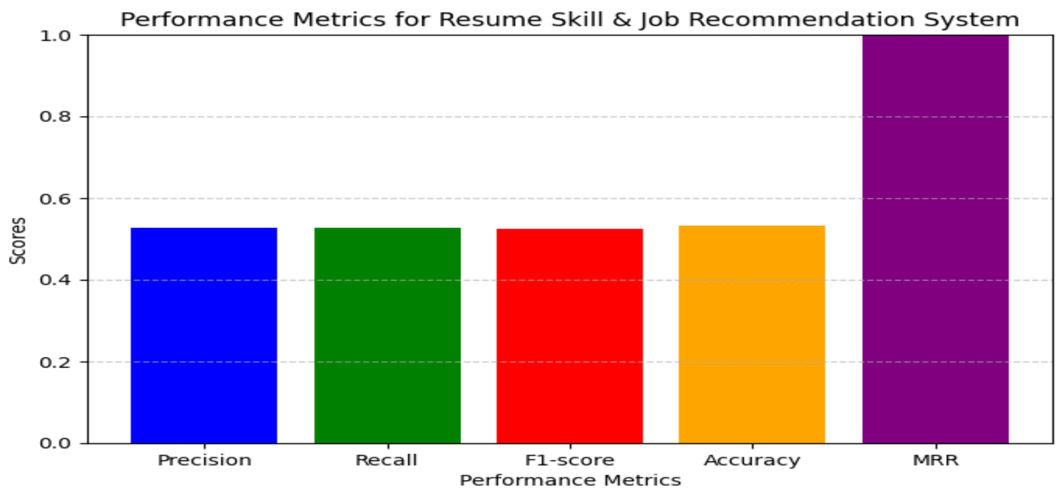


Figure 7: Plot of various performance metrics

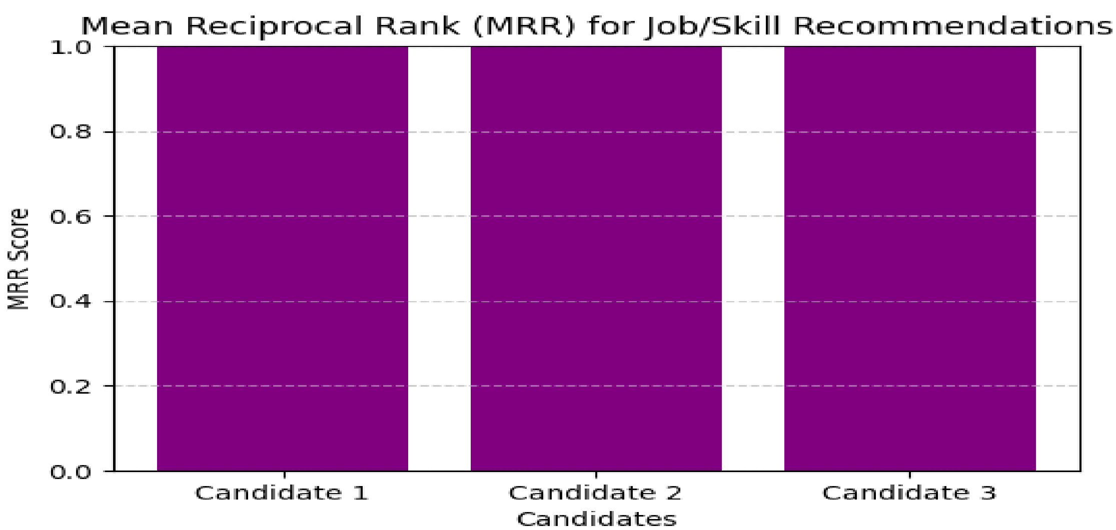


Figure 8: MRR trend analysis

A Confusion Matrix is a performance evaluation tool used to measure how well the system classifies job or skill recommendations as relevant or not. The plot of confusion matrix of the proposed system is shown in Figure 9.

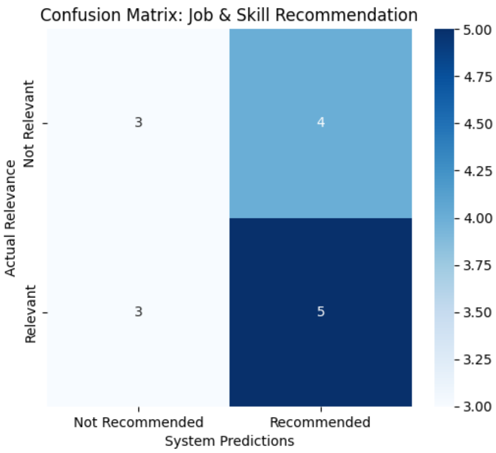


Figure 9: Confusion Matrix

IV. CONCLUSION

The Resume Skill and Job Recommendation System presents a promising solution to the challenges faced by individuals in bridging the gap between their skills and suitable career opportunities. By leveraging advanced technologies such as web scraping, APIs, and machine learning, the system simplifies the process of identifying relevant job roles and skill-enhancing courses tailored to user interests. The proposed system not only provides a personalized and efficient platform for job seekers but also serves as a guide for continuous skill development, which is crucial in today's fast-evolving job market. Its ability to recommend curated opportunities and courses based on user input demonstrates the practical applicability of technology in solving real-world problems. Features like geolocation for local jobs, mobile app integration, and multilingual support can boost accessibility and can be taken up in the future. The system can be further enhanced by adding analytics dashboards and gamified elements to improve user engagement and progress tracking.

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