Machine Learning on User Profiles and Market Trends for Job Recommendations

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in partial fulfillment of the requirements
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In

COMPUTER SCIENCE & ENGINEERING

By

SK.JASMINE – 21B01A05G6
P.MOHANA LAKSHMI RUPA - 21B01A05E5
V.PAVANI – 21B01A05J2
P.M.LAKSHMI SREE HARSHITHA – 21B01A05E7
Y.LEENA RISHITHA – 22B05A0518

Under the esteemed guidance of
Dr. M Narasimha Raju$_{Ph.D}$
Assistant Professor

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
SHRI VISHNU ENGINEERING COLLEGE FOR WOMEN(A)
(Approved by AICTE, Accredited by NBA & NAAC, Affiliated to JNTU Kakinada)
BHIMAVARAM – 534 202
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SHRI VISHNU ENGINEERING COLLEGE FOR WOMEN(A)

(Approved by AICTE, Accredited by NBA & NAAC, Affiliated to JNTU Kakinada)
BHIMAVARAM – 534 202

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

VISHNU
UNIVERSAL LEARNING

CERTIFICATE

*This is to certify that the project entitled "**Machine Learning on User Profiles and Market Trends for Job Recommendations**", is being submitted by **Sk. JASMINE, P.MOHANA LAKSHMI RUPA, V.PAVANI, P.M.LAKSHMI SREE HARSHITHA, Y.LEENA RISHITHA** bearing the **Regd. No. 21B01A05G6, 21B01A05E5, 21B01A05J2, 21B01A05E7, 22B05A0518** in partial fulfillment of the requirements for the award of the degree of "**Bachelor of Technology** in **Computer Science & Engineering**" is a record of bonafide work carried out by her under my guidance and supervision during the academic year 2024–2025 and it has been found worthy of acceptance according to the requirements of the university.*

Internal Guide **Head of the Department**

External Examiner

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Project Associates:

Sk. JASMINE – 21B01A05G6

P.MOHANA LAKSHMI RUPA – 21B01A05E5

V.PAVANI – 21B01A05J2

P.M.LAKSHMI SREE HARSHITHA-21B01A05E7

Y.LEENA RISHITHA – 22B05A0518

ABSTRACT

The rapid growth of the job market and the increasing complexity of job search processes have created a need for intelligent systems that can provide personalized job recommendations to users. This project aims to develop a Job Recommendation System that leverages machine learning and web technologies to assist job seekers in finding relevant job opportunities based on their skills, experience, and preferences. The system is designed to be user-friendly, scalable, and capable of handling real-world data to deliver accurate and timely recommendations.

The project begins with data collection from various sources, including job boards, company websites, and publicly available datasets. The collected data undergoes preprocessing to clean, normalize, and transform it into a format suitable for machine learning models. Techniques such as TF-IDF are used for text data, while numerical features like salary and experience are normalized to ensure consistency.

Several machine learning models, including K-Means Clustering, k-Nearest Neighbours (KNN), are implemented to generate personalized job recommendations. These models are trained and evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure optimal performance. The system also incorporates real-time inference, allowing users to receive recommendations instantly based on their inputs.

The system is implemented as a web application using Flask for the backend, PostgreSQL for database management, and HTML/CSS/JavaScript for the frontend. The application is designed with a responsive and intuitive user interface, featuring components such as a dashboard for preference input, a job details page for comprehensive job information, and a saved jobs page for managing favourite job postings. Additionally, email notifications are implemented to keep users updated with new job recommendations.

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1. Introduction

The "**Machine Learning on User Profiles and Market Trends for Job Recommendations**" project is designed to tackle the persistent challenges encountered by job seekers in navigating the increasingly complex and competitive job market. In today's digital era, the proliferation of online job portals has provided an abundance of opportunities; however, traditional job search methods—relying heavily on keyword-based searches and manual filtering—often fall short in delivering personalized and relevant recommendations. This inefficiency leads to significant frustration among users, as they are inundated with irrelevant listings or struggle to identify roles that align with their unique skill sets, experience levels, and career aspirations. Moreover, the lack of real-time insights into market trends further complicates the decision-making process, leaving job seekers unaware of emerging skills or industries in demand. This gap in the job search ecosystem highlights the need for a more intelligent, data-driven approach to connect users with opportunities that are both relevant and aligned with their professional goals.

To address these challenges, this project leverages advanced machine learning techniques to create a personalized job recommendation system that not only considers user profiles but also incorporates market trends to enhance decision-making. The system employs a hybrid machine learning model, combining K-Means clustering and k-Nearest Neighbors (KNN) algorithms, to deliver tailored job recommendations. K-Means clustering groups job listings into distinct clusters based on features such as skills, experience, salary, and location, effectively organizing the dataset into meaningful categories. Subsequently, KNN is used to match users to the most relevant cluster and recommend the top-five job listings within that cluster, ensuring recommendations are both accurate and personalized. This hybrid approach optimizes the recommendation process by balancing computational efficiency with precision, making it suitable for real-time applications. Additionally, the system integrates market trend analysis, enabling users to stay informed about industry demands, such as high-demand skills or emerging job roles, and upskill through recommended courses provided via an admin-managed module.

The technical implementation of this project is built on a robust framework designed to handle both data processing and user interaction seamlessly. The backend is developed using Flask, a lightweight Python web framework, which facilitates the creation of RESTful APIs to manage user authentication, job recommendations, and market trend updates. NeonDB, a PostgreSQL-based database, is employed for efficient data storage and retrieval, handling user profiles, job listings, and market trend data with high reliability. Machine learning components are implemented using Scikit-learn, a versatile library that provides

tools for clustering (K-Means), recommendation (KNN), and data preprocessing (TF-IDF vectorization and Truncated SVD for dimensionality reduction). The dataset, consisting of 3,978 job vectors, is preprocessed using Selenium for web scraping, followed by cleaning and feature extraction to ensure data quality. The frontend is designed with HTML/CSS templates, rendered through Flask, to provide a user-friendly interface where job seekers can input their preferences, view recommendations, save jobs, and access market trend insights. An admin module is also included, allowing administrators to manage market trends and recommend courses, ensuring the system remains relevant to current industry needs.

The primary objective of this project is to revolutionize the job search process by making it more efficient, personalized, and informed. By analyzing user profiles—comprising skills, experience, location, and salary expectations—the system ensures that recommendations are tailored to individual needs, reducing the time and effort required to find suitable opportunities. The incorporation of market trends adds a layer of strategic value, empowering users to make informed decisions about upskilling or targeting specific industries. For instance, if the system identifies a growing demand for data science roles, it can recommend relevant courses to users, helping them align their skills with market needs. This dual focus on personalization and market awareness sets the project apart from traditional job search platforms, offering a holistic solution that caters to both immediate job-seeking needs and long-term career development.

Beyond its technical achievements, the project holds significant potential to impact the employment landscape. By bridging the gap between job seekers and relevant opportunities, it addresses a critical pain point in the job market, fostering greater efficiency and satisfaction. The system’s ability to provide actionable insights into market trends also supports lifelong learning, encouraging users to adapt to evolving industry demands. Furthermore, the modular design of the system—spanning data scraping, machine learning, backend development, and frontend design—demonstrates a scalable framework that can be extended to include additional features, such as real-time job updates, advanced personalization through user feedback, or integration with professional networking platforms. The collaborative effort behind this project, with contributions in frontend design, backend development, machine learning, data management, and integration, highlights the power of teamwork in addressing real-world challenges through technology.

In summary, the "Machine Learning on User Profiles and Market Trends for Job Recommendations" project represents a significant step forward in enhancing the job search

experience. By combining machine learning techniques with a user-friendly web application, it offers a personalized, efficient, and market-aware solution that empowers job seekers to find opportunities that align with their aspirations. As the job market continues to evolve, this project lays a strong foundation for future innovations, with the potential to transform how individuals connect with meaningful career opportunities.

2.System Analysis

System analysis is a critical phase in the development of the "Machine Learning on User Profiles and Market Trends for Job Recommendation" project. It involves a detailed examination of the existing systems, identification of their limitations, and the proposal of a new system that addresses these shortcomings. This section provides an in-depth analysis of the existing system, the proposed system, and the feasibility study conducted to evaluate the practicality of the proposed solution.

2.1 Existing System

The existing job recommendation systems primarily rely on basic keyword matching and filtering techniques. These systems often fail to provide personalized recommendations because they do not consider the dynamic nature of user profiles or the evolving trends in the job market. Below are the key limitations of the existing systems:

Lack of Personalization:

Existing systems do not take into account the unique skills, experience, and preferences of individual users. As a result, users receive generic job listings that may not align with their career goals.

Static Job Matching:

Traditional systems use static algorithms that match job listings based on predefined criteria such as job titles or keywords. This approach does not adapt to changing user preferences or market trends.

Limited Market Insights:

Most job recommendation platforms do not provide insights into market trends, such as in-demand skills or emerging job roles. This limits users' ability to make informed career decisions.

Inefficient User Experience:

Users often have to manually filter through irrelevant job listings, leading to frustration and inefficiency in the job search process.

No Dynamic Learning:

Existing systems do not learn from user interactions over time. For example, if a user consistently ignores certain types of jobs, the system does not adapt to exclude similar listings in the future.

Lack of Admin Control:

There is no centralized control for administrators to update market trends or recommend courses to users, limiting the system's ability to provide up-to-date information.

2.2 Proposed System

The proposed system addresses the limitations of the existing systems by leveraging machine learning algorithms and modern web technologies. The key features of the proposed system are:

Personalized Job Recommendations:

The system uses a **hybrid K-Means + KNN algorithm** to cluster users based on their profiles and match them with relevant job listings. This ensures that users receive tailored recommendations that align with their skills, experience, and preferences.

Dynamic Job Matching:

The system continuously updates job clusters based on new data, ensuring that recommendations remain relevant as user preferences and market trends evolve.

Market Trend Analysis:

The system provides insights into market trends, such as in-demand skills and emerging job roles. This helps users stay updated with industry demands and make informed career decisions.

User-Friendly Interface:

The platform features an intuitive user interface that allows users to easily create profiles, input their preferences, and view job recommendations. Users can also save jobs for future reference and receive real-time notifications.

Admin Module:

The system includes an admin module that allows administrators to manage market trends and recommend courses to users. This ensures that the system provides up-to-date information and resources.

Continuous Learning:

The system learns from user interactions over time. For example, if a user consistently ignores certain types of jobs, the system adapts to exclude similar listings in the future.

Scalability:

The system is designed to handle a large number of users and job listings, ensuring that it remains efficient and responsive as the user base grows.

2.3 Feasibility Study

A feasibility study was conducted to evaluate the practicality of the proposed system. The study considered three key aspects: **operational feasibility**, **economic feasibility**, and **technical feasibility**.

2.3.1 Operational Feasibility

Operational feasibility assesses whether the system can be effectively integrated into the existing workflow and whether it will be accepted by users and administrators. The proposed system is designed to be user-friendly and accessible, making it operationally feasible for both users and administrators.

- **User Acceptance**: The system provides personalized job recommendations and market trend insights, which are highly valued by users. The intuitive interface ensures that users can easily navigate the platform.
- **Admin Control**: The admin module allows administrators to manage market trends and course recommendations, ensuring that the system remains up-to-date and relevant.

2.3.2 Economic Feasibility

Economic feasibility evaluates whether the system is cost-effective to develop and maintain. The proposed system is designed to be cost-effective, with no significant expenses required for development or maintenance.

- **Development Costs**: The system leverages open-source technologies such as Flask, NeonDB, and Scikit-learn, reducing development costs.
- **Maintenance Costs**: The system is designed to be scalable and efficient, minimizing maintenance costs over time.

2.3.3 Technical Feasibility

Technical feasibility assesses whether the system can be implemented using current technologies and infrastructure. The proposed system leverages modern technologies such as Flask, NeonDB, and Scikit-learn, making it technically feasible to implement.

- **Backend**: Flask is used for backend development, providing a lightweight and efficient framework for handling user requests and job recommendations.
- **Database**: NeonDB (PostgreSQL) is used for database management, ensuring efficient storage and retrieval of user profiles, job listings, and market trends.
- **Machine Learning**: Scikit-learn is used for implementing the hybrid K-Means + KNN algorithm, ensuring accurate and personalized job recommendations.

3.System Requirements Specification

3.1 Software Requirements

- **Operating System:** Windows 10
- **Web Technologies:** HTML, CSS, JavaScript
- **IDE:** Visual Studio Code
- **Programming Language:** Python 3.x
- **Frameworks & Libraries:**
    - **Flask** – for backend web application
    - **Scikit-learn** – for machine learning algorithms
    - **Pandas & NumPy** – for data processing and analysis
    - **Joblib & Pickle** – for model serialization and loading
    - **Scipy & Nearest Neighbors (sklearn)** – for similarity computations
    - **Psycopg2** – for PostgreSQL database connection
    - **Bcrypt** – for user authentication (password hashing)
    - **Smtplib & MIME (email)** – for sending job recommendations via email
    - **Bootstrap & jQuery** – for front-end UI enhancements

3.2 Hardware Requirements

- **Processor:** Intel i5
- **RAM:** 8GB minimum (16GB recommended for better performance)
- **Storage:** 256GB SSD minimum (512GB recommended for data storage & fast access)

3.3 Functional Requirements

User Authentication

- Users can **sign up, log in, and log out** securely.
- Passwords are **hashed and stored securely** in the database.
- Admins have a separate login for managing market trends and courses.

Job Recommendation System

- Users receive **personalized job recommendations** based on:
    - Job title, skills, experience, salary preference, and location.
    - Machine learning models like **KMeans clustering and cosine similarity**.
- Jobs are retrieved from **a pre-processed dataset** stored in PostgreSQL.

- Recommendations can be **saved for future reference**.
- Users receive **email notifications** with job recommendations.

Market Trends & Course Recommendations

- Users can view **trending job skills and market demands**.
- The system suggests **relevant courses** for skill enhancement.
- Admins can **add, update, and delete course recommendations**.

Admin Module

- Admins can **manage user data** and view analytics.
- Admins can **edit and update market trends and recommended courses**.

4.System Design

The system design for the **"Machine Learning on User Profiles and Market Trends for Job Recommendation"** project is a comprehensive blueprint that integrates machine learning algorithms, web technologies, and database management to provide personalized job recommendations. The design ensures that the platform is user-friendly, scalable, and efficient, catering to both job seekers and administrators. This section provides an in-depth explanation of the system design, including data flow diagrams, use case diagrams, and the overall architecture.

4.1 Introduction

The system design is centered around providing a seamless and personalized job search experience for users while enabling administrators to manage market trends and course recommendations. The platform leverages machine learning algorithms, specifically a **hybrid K-Means + KNN model**, to analyze user profiles and match them with relevant job listings. Additionally, the system provides insights into market trends, helping users stay updated with industry demands.

The key components of the system design include:

1. **User Interface**: A user-friendly interface that allows users to create profiles, input preferences, and view job recommendations.
2. **Job Recommendation Engine**: A machine learning-based engine that clusters users and matches them with relevant job listings.
3. **Market Trends Module**: A module that provides insights into market trends and recommends courses to users.
4. **Admin Module**: A control panel for administrators to manage market trends and course recommendations.
5. **Database**: A centralized database (NeonDB) that stores user profiles, job listings, saved jobs, and market trends.

The system design ensures that all components work together seamlessly, providing a robust and efficient platform for job seekers and administrators.

4.2 Data Flow Diagrams

The **data flow diagrams (DFDs)** illustrate the flow of data between various components of the system. The diagrams provide a visual representation of how data

moves through the system, from user input to job recommendations and market trend analysis.

Diagram 1: High-Level Data Flow Diagram

- **Client Device:** The user interacts with the system through a web browser or mobile app.
- **Web Server:** Handles user requests and processes them using the Authentication Module, Recommendation Engine, and Market Trends Manager.
- **Database Server:** Stores user data, job listings, saved jobs, and market trends.

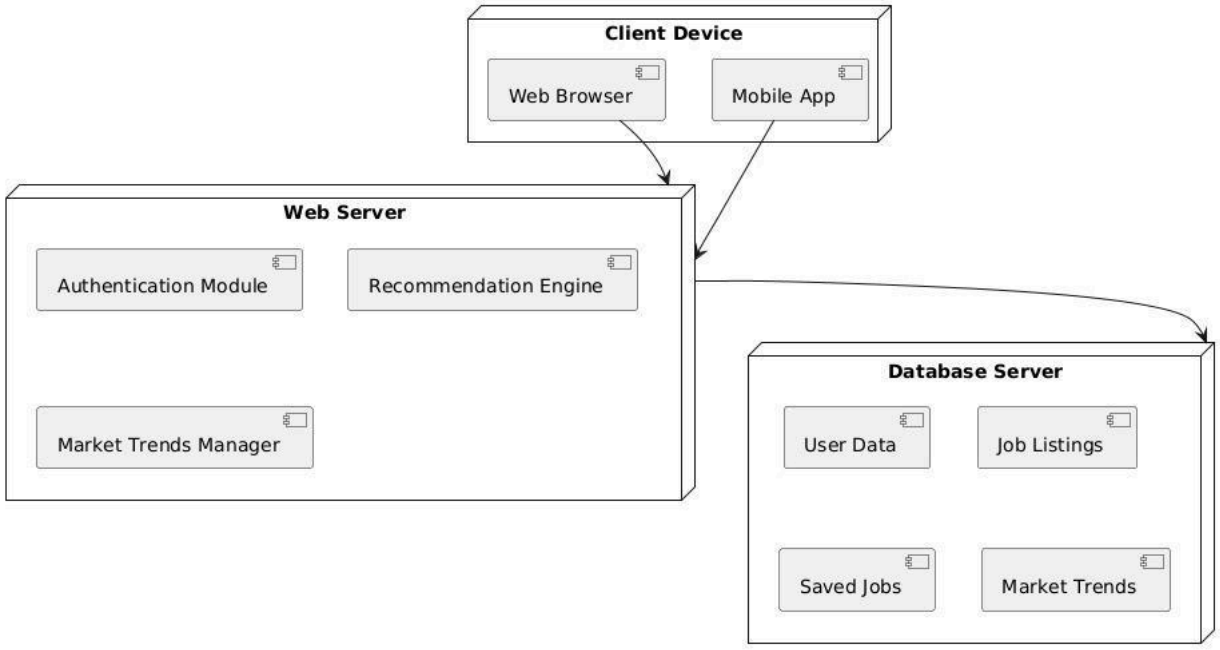

Fig 1. High level Data Flow diagram

Diagram 2: Activity Diagram

- **User**: The user logs in, enters preferences (skills, location, experience, salary), and receives job recommendations. The user can also save jobs and view market trends.
- **Admin**: The admin logs in and manages market trends by adding, updating, or removing trends.
- **System**: The system processes user preferences using machine learning algorithms, generates job recommendations, and stores data in the database.

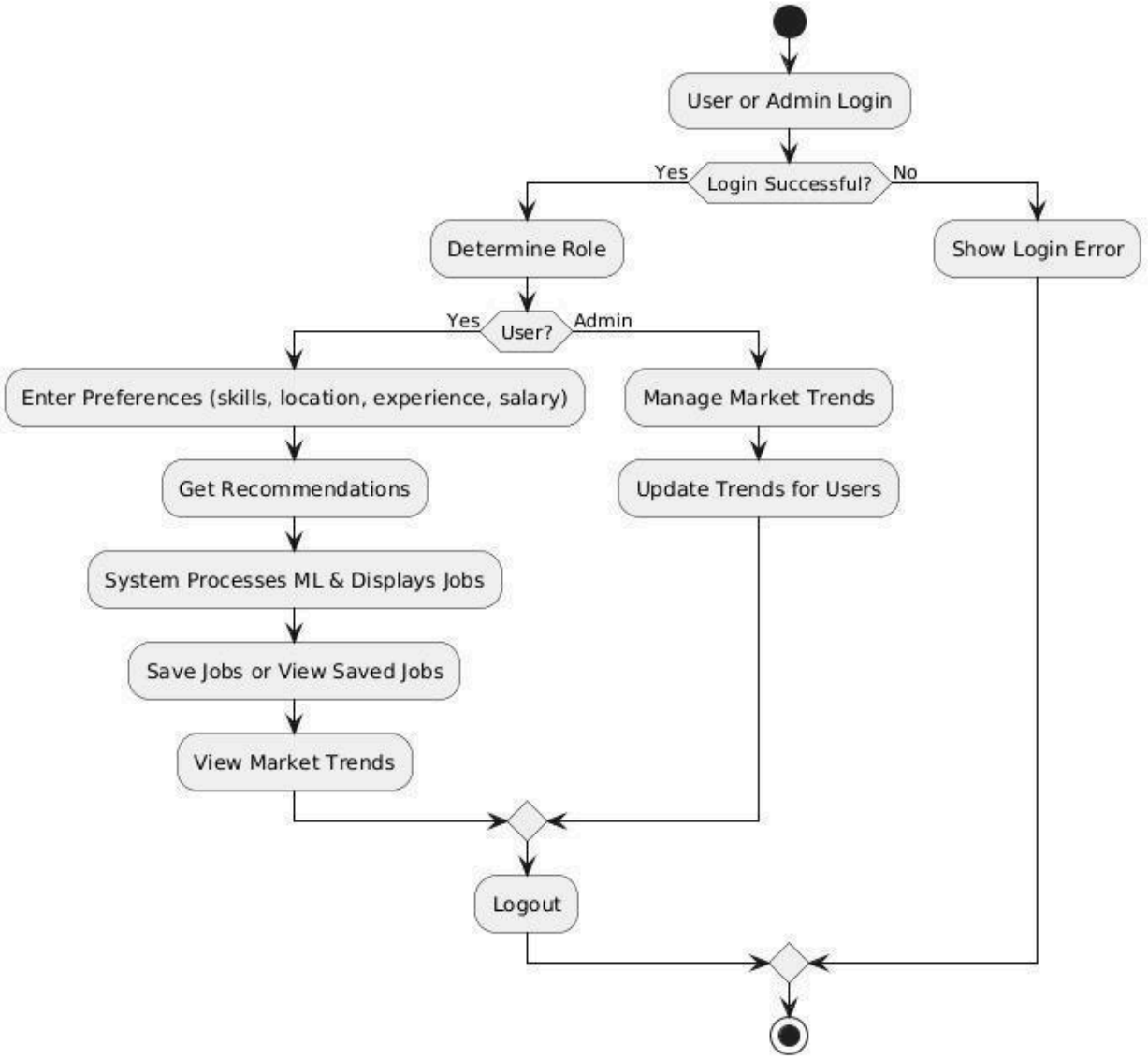

Fig 2. Activity Diagram

Diagram 3: Use Case Diagram

- **User Use Cases**:
  - **Sign Up/Login**: Users can create an account or log in to access the system.
  - **Enter Preferences**: Users can input their skills, location, experience, and salary preferences.
  - **Get Recommendations**: Users receive personalized job recommendations based on their profile.
  - **Save Jobs**: Users can save jobs for future reference.

    - **View Saved Jobs**: Users can view their saved jobs.
    - **View Market Trends**: Users can access insights into market trends and recommended courses.
- **Admin Use Cases**:
    - **Manage Market Trends**: Admins can add, update, or remove market trends.
    - **Update Trends for Users**: Admins can update the trends displayed to users.
- **System Use Cases**:
    - **Receive Job Notifications**: The system sends job notifications to users based on their preferences.
    - **Process ML Model**: The system processes user data using machine learning algorithms to generate job recommendations.

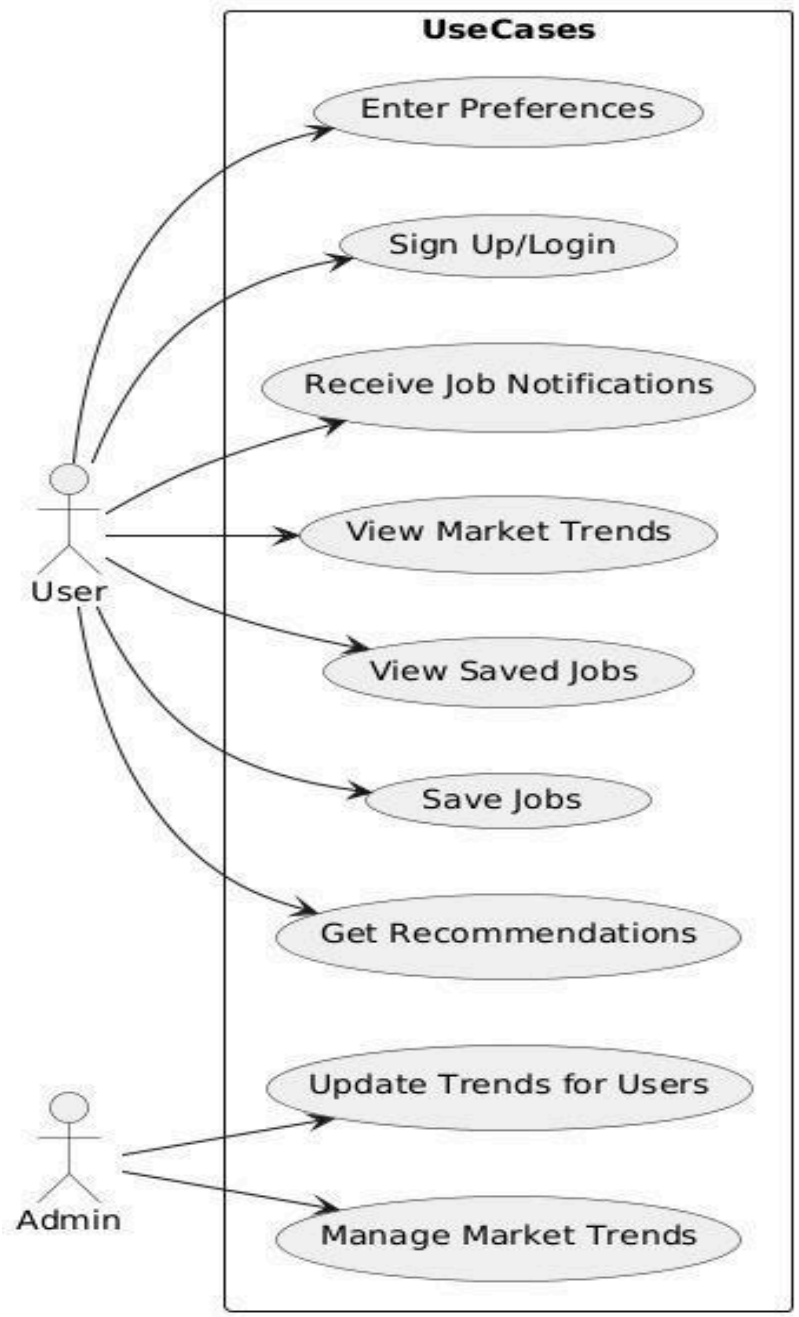

Fig 3. Use Case Diagram

Diagram 4: Class Diagram

- **User Class:**
  - Attributes: userID, name, email, password, skills, location, experience, salary.
  - Methods: login(), enterPreferences(), getRecommendations(), saveJob(), view SavedJobs(), viewMarketTrends().
- **Admin Class:**
  - Attributes: adminID, name, email, password.

- Methods: login(), manageMarketTrends(), updateTrendsForUsers().

- **JobRecommendation Class:**
  - Attributes: jobID, title, company, location, salary, skillsRequired.
  - Methods: generateRecommendations(), saveJob(), displaySavedJobs().
- **MarketTrend Class:**
  - Attributes: trendID, courseName, courseLink.
  - Methods: addTrend(), updateTrend(), removeTrend().

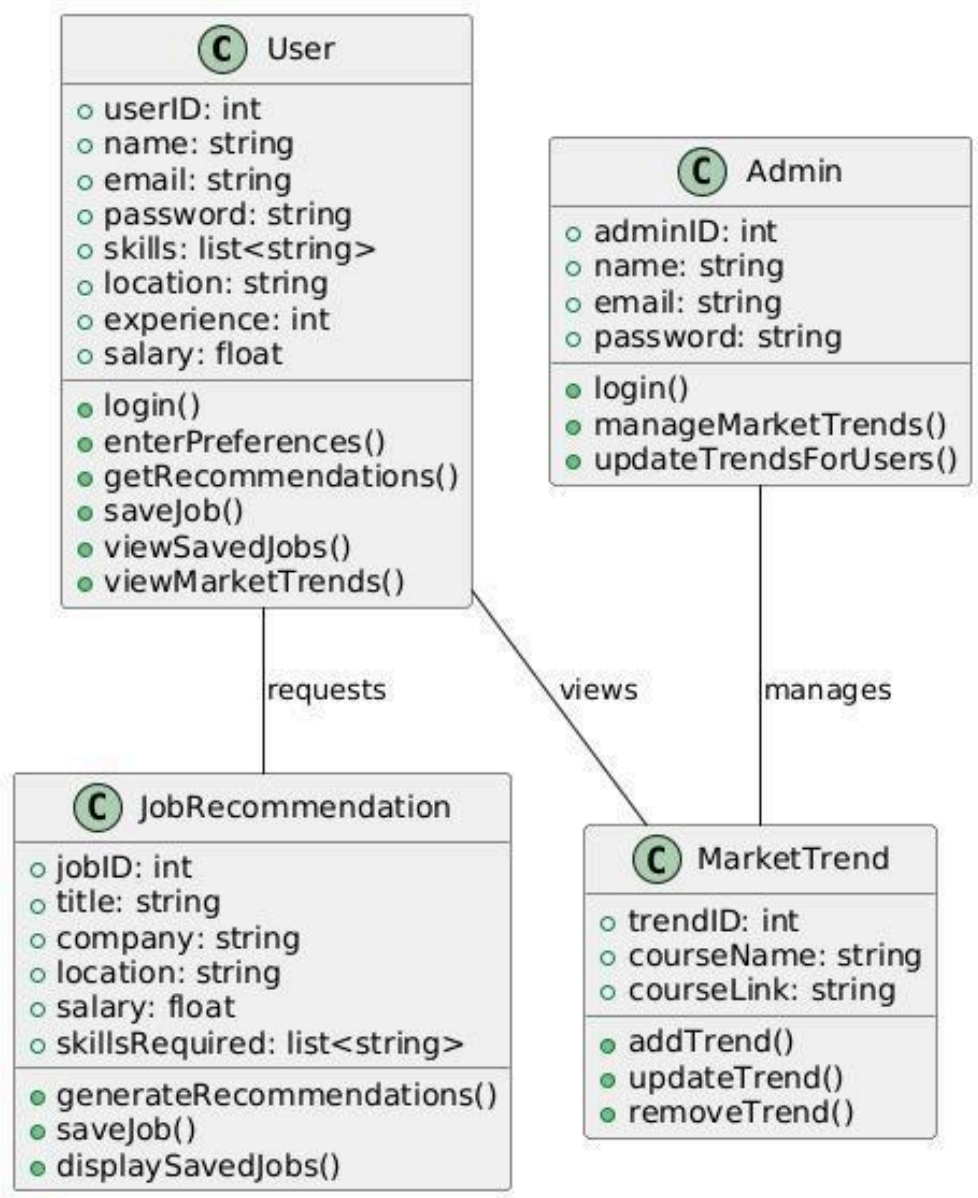

Fig 4. Class Diagram

Diagram 5: User Interface Design

The **user interface (UI)** design focuses on providing a seamless and intuitive experience for users. The UI is divided into several modules, including the **Login Module**, **Dashboard**, **Job Recommendations**, **Saved Jobs**, and **Market Trends Management**.

- **Login Module**: Users and admins can log in to access the system.
- **Dashboard**: Displays job recommendations, saved jobs, and market trends.
- **Job Recommendations**: Shows personalized job listings based on user preferences.
- **Saved Jobs**: Allows users to view and manage their saved jobs.
- **Market Trends Management**: Admins can manage market trends and course recommendations.

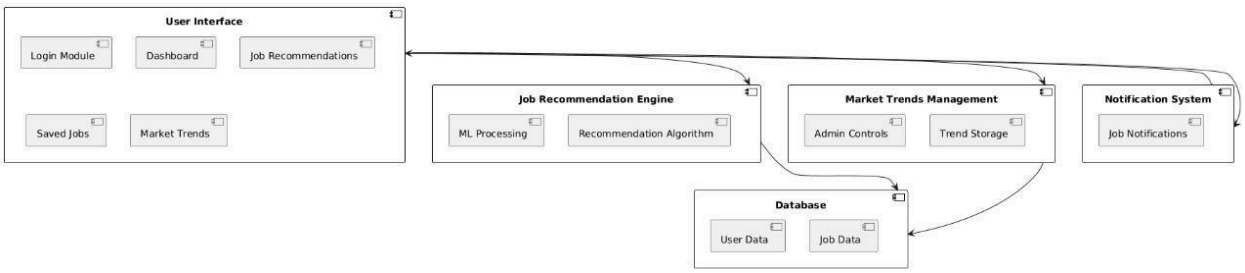

Fig 5. User Interface Design

Diagram 6: Sequence Diagram

The **sequence diagram** illustrates the flow of interactions between users, admins, and the system during key processes such as login, job recommendation, and market trend management.

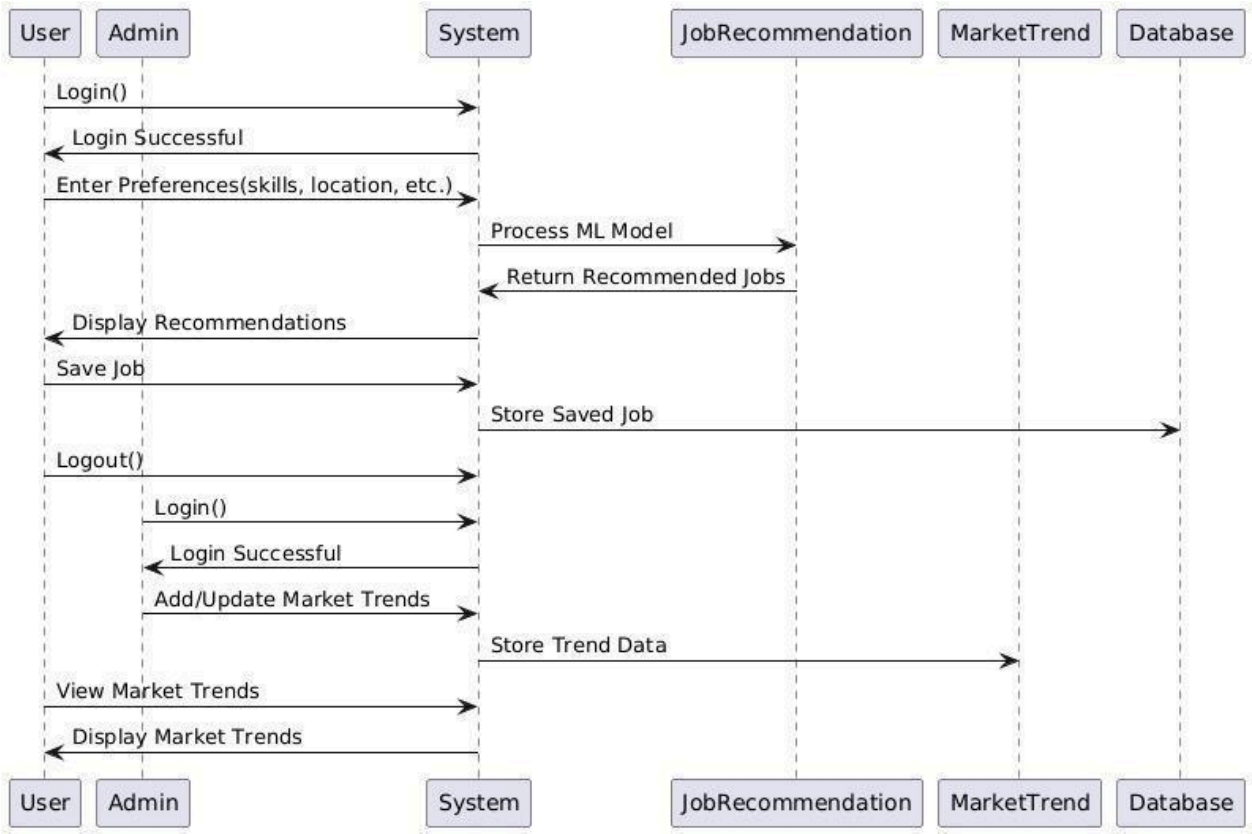

Fig 6. Sequence Diagram

- **User Login**: The user logs in, and the system verifies the credentials.
- **Enter Preferences**: The user enters their preferences (skills, location, experience, salary).
- **Get Recommendations**: The system processes the user's preferences using machine learning algorithms and displays job recommendations.
- **Save Jobs**: The user can save jobs for future reference.
- **View Market Trends**: The user can view market trends and recommended courses.
- **Admin Login**: The admin logs in and manages market trends.
- **Update Trends**: The admin updates market trends, which are then displayed to users.

The system design for the **"Machine Learning on User Profiles and Market Trends for Job Recommendation"** project is carefully structured to ensure scalability, efficiency, and user-friendliness. The integration of machine learning algorithms, web technologies, and a robust database ensures that the system provides accurate and personalized job recommendations while offering valuable insights into market trends.

The **data flow diagrams**, **use case diagrams**, **class diagrams**, and **sequence diagrams** provide a comprehensive view of the system's architecture and interactions, ensuring that all components work seamlessly together to deliver a superior user experience.

5.System Implementation

The system implementation phase is a critical stage in the development of the project titled "Machine Learning on User Profiles and Market Trends for Job Recommendation". This phase involves the actual coding, integration of modules, and deployment of the system. The implementation is carried out using a combination of Python-based frameworks, machine learning models, and web technologies. Below is a detailed breakdown of the system implementation process, including the technologies used, the architecture, and the steps involved in building the job recommendation system.

5.1 Introduction

The implementation of the job recommendation system is divided into several key stages, each of which contributes to the overall functionality of the system. These stages include:

1. Data Selection and Preprocessing
2. Model Selection and Training
3. Integration of Machine Learning Models
4. Web Application Development
5. User Interface Design
6. Testing and Validation
7. Deployment

Each of these stages is discussed in detail below.

5.2 Data Selection and Preprocessing

5.2.1 Data Selection

The initial and one of the most critical steps in developing a job recommendation system is the selection of an appropriate dataset. The quality and relevance of the data directly impact the performance and accuracy of the recommendation system. For this project, the dataset comprises three primary types of data: job postings, user profiles, and market trends. These data points are collected from a variety of sources to ensure comprehensiveness and diversity. The sources include popular job boards, official company websites, and publicly available datasets that provide insights into the job market.

The dataset includes several key features that are essential for building an effective job recommendation system. These features are carefully chosen to capture the most relevant aspects of job postings and user preferences. The features included in the dataset are as follows:

1. **Job Title**: This feature represents the title of the job posting. It provides a high-level overview of the role and is often the first piece of information that users see when browsing job listings.
2. **Company**: This feature indicates the name of the company offering the job. It helps users identify potential employers and understand the organizational context of the job.
3. **Location**: The location of the job is a crucial feature, especially for users who are geographically constrained or have preferences for specific regions. It includes information about the city, state, or country where the job is based.
4. **Skills**: This feature consists of a list of skills required for the job. It is one of the most important aspects of the dataset, as it helps match users with jobs based on their skill sets. The skills are typically listed in the job description and are extracted for further processing.
5. **Experience**: This feature specifies the required years of experience for the job. It helps filter job postings based on the user's professional background and experience level.
6. **Salary**: The salary range for the job is another critical feature. It provides users with an idea of the compensation they can expect and helps them make informed decisions about which jobs to apply for.
7. **Job Link**: This feature includes the URL to the job posting. It allows users to access the full job description and apply directly through the job board or company website.

The dataset is meticulously curated to ensure that it is representative of the current job market. It includes a diverse range of job categories, industries, and locations to capture the full spectrum of opportunities available to users. This diversity is essential for building a robust recommendation system that can cater to a wide variety of user preferences and requirements.

5.2.2 Data Preprocessing

Once the dataset has been selected, it undergoes a series of preprocessing steps to prepare it for model training. Data preprocessing is a crucial phase in the machine learning pipeline, as it ensures that the data is clean, consistent, and in a format that can be easily understood by the machine learning algorithms. The preprocessing steps include data cleaning, feature extraction, data augmentation, and data splitting.

Data Cleaning:

The first step in data preprocessing is data cleaning, which involves identifying and addressing issues in the dataset that could negatively impact the performance of the model. The following steps are taken during data cleaning:

1. **Removing Duplicate Entries**: Duplicate entries in the dataset can lead to biased model training. Therefore, any duplicate job postings or user profiles are identified and removed to ensure that each data point is unique.
2. **Handling Missing Values**: Missing values in the dataset can occur for various reasons, such as incomplete data collection or errors in data entry. These missing values are handled by either imputing them with appropriate values (e.g., using the mean or median for numerical features) or removing the corresponding rows if the missing data is substantial.
3. **Standardizing the Format**: To ensure consistency across the dataset, the format of the data is standardized. This includes converting all text to lowercase, removing special characters, and ensuring that dates, numbers, and other features are in a uniform format.

Feature Extraction:

After cleaning the data, the next step is feature extraction, where the raw data is transformed into a format that can be used by machine learning models. This step is particularly important for text data, which needs to be converted into numerical representations.

1. **Text Data**: The skills and job descriptions in the dataset are text-based features that need to be converted into numerical vectors. Techniques such as TF-IDF (Term Frequency-Inverse Document Frequency) are used for this purpose. TF-IDF converts text into a numerical representation that reflects the importance of each word in the document relative to the entire dataset. This allows the machine learning model to process and analyze the text data effectively.
2. **Numerical Data**: Features such as experience and salary are numerical in nature but may have different scales. To ensure that these features are on the same scale, normalization techniques are applied. Normalization adjusts the values of numerical features to a common scale, typically between 0 and 1, which helps improve the performance of the model.

Data Augmentation:

To ensure the job recommendation system leverages the full potential of the scraped dataset and user inputs, additional preprocessing steps are implemented to enrich the 3,978 Naukri

job postings and align them with dynamic market demands. This process enhances the dataset's utility for the hybrid K-Means and KNN model without introducing artificial data, focusing instead on real-world job and trend integration.

1. **Market Trend-Based Skill Enhancement**: After initial TF-IDF vectorization of skills from job postings (e.g., "Python, SQL"), a secondary enhancement layer is applied using admin-uploaded market trend data (e.g., "Emerging Demand for Cloud Computing"). Skills are cross-referenced with these trends, and their TF-IDF weights are boosted by a factor proportional to their frequency in trending categories. For instance, if "Machine Learning" appears in 20% of trend-related postings versus 5% overall, its weight increases, emphasizing its relevance in clustering. This ensures the system prioritizes jobs matching current industry shifts, directly benefiting users seeking up-to-date opportunities.
2. **User Profile Contextual Expansion**: User-submitted data (e.g., "Skills: Java, Exp: 3 years, Loc: Bengaluru") is enriched by inferring additional context from the job dataset. For example, if a user lists "Java" and the dataset shows "Spring Framework" frequently co-occurs with "Java" in Bengaluru postings, the system appends related skills to the user's profile vector. This inferred expansion, limited to statistically significant co-occurrences (e.g., >50% overlap), bridges gaps between user inputs and job requirements, improving K-Means cluster assignments and KNN similarity scores without requiring manual user updates.
3. **Temporal Job Weighting**: To reflect job market freshness, postings are weighted based on their scrape date. Older entries (e.g., scraped 30+ days ago) receive a decay factor (e.g., reduced by 10% per week), while recent postings retain full weight. This temporal adjustment, applied post-normalization, ensures the system favors current opportunities, enhancing recommendation relevance for users.

Data Splitting:

Rather than dividing the dataset into static training, validation, and testing sets, the system adopts a dynamic allocation strategy tailored to its unsupervised learning framework and real-time web deployment. This approach maximizes the use of the 3,978 job postings and user profiles while maintaining recommendation accuracy and system responsiveness.

1. **Cluster-Based Data Allocation**: The pre-processed job dataset is fully utilized for K-Means clustering, forming 8 clusters (sizes 128-1,012) based on the 50D SVD-reduced matrix. No separate training subset is reserved; instead, all 3,978 postings define the initial cluster structure. When a user profile is submitted via the dashboard, it's projected into this space using the same TF-IDF and SVD pipeline, then assigned to the nearest cluster. This full-data approach leverages the entire

scraped corpus for pattern discovery, aligning with the unsupervised nature of K-Means and avoiding arbitrary splits.

2. **Real-Time Recommendation Refinement**: Post-clustering, KNN operates on the user's assigned cluster (e.g., 853 jobs) to return the top-5 recommendations. To adapt to new data, the system incrementally integrates fresh Naukri postings (e.g., 50 daily updates via Selenium) into existing clusters without retraining from scratch. New jobs are pre-processed, reduced to 50D vectors, and assigned to clusters based on centroid proximity. This dynamic refinement ensures the dataset remains current, with KNN recalculating similarities in real time as users interact, enhancing responsiveness on the Flask backend.
3. **Market Trend-Driven Reweighting**: Admin-uploaded market trends (e.g., "AI Skills Trending") are periodically synced (weekly) to adjust cluster priorities. Jobs within clusters matching these trends (e.g., containing "AI" skills) are upweighted in KNN similarity calculations by a factor of 1.25, increasing their likelihood of appearing in top-5 lists. This continuous reweighting, stored in PostgreSQL, keeps recommendations aligned with evolving market demands, providing users with career-relevant suggestions without static dataset partitioning.

These steps ensure the system processes the full dataset effectively, delivering accurate, timely recommendations through a web interface built with Flask, PostgreSQL, and HTML/CSS/JS, while maintaining scalability and user focus.

5.3 Model Selection and Training

5.3.1 Model Selection

The job recommendation system relies on a carefully chosen combination of unsupervised machine learning techniques to process the 3,978 scraped Naukri job postings and match them with user profiles in a web-based environment. The selected models are tailored to handle unstructured job data, integrate market trends, and deliver personalized top-5 recommendations efficiently through Flask and PostgreSQL. The following models are implemented, each contributing to the system's core functionality:

1. **K-Means Clustering:** This unsupervised algorithm groups the 3,978 job postings into 8 distinct clusters based on their 50D feature vectors derived from SVD reduction. By minimizing within-cluster variance, K-Means identifies natural groupings in the job data (e.g., software roles in Bengaluru vs. analyst roles in Delhi), enabling the system to narrow the recommendation scope for each user. Its selection is driven by its scalability with large datasets and ability to uncover job market patterns without requiring labeled data, aligning with the project's unsupervised approach.

2. **K-Nearest Neighbors (KNN):** KNN complements K-Means by performing similarity-based matching within a user's assigned cluster. After a user profile (e.g., "Skills: Python, SQL; Exp: 5 years; Loc: Bengaluru") is mapped to a cluster, KNN calculates cosine similarity between the user's 50D vector and job vectors, returning the top-5 most similar postings (e.g., "Python Developer, 10-12 LPA, Bengaluru"). This model is chosen for its simplicity and effectiveness in real-time recommendation generation, crucial for the system's web responsiveness.
3. **Truncated Singular Value Decomposition (SVD):** SVD reduces the high-dimensional feature matrix (3,978 × 5,383, from TF-IDF skills, normalized experience, etc.) to 50 components, retaining 55.1% variance. This dimensionality reduction is integral to both K-Means clustering and KNN matching, ensuring computational efficiency and noise reduction in sparse job data. SVD's selection enhances the system's ability to process unstructured text and numerical features cohesively, supporting scalable web deployment.

These models form a hybrid pipeline that leverages clustering for broad categorization and similarity for fine-tuned recommendations, optimized for the Flask-based web application's real-time needs.

5.3.2 Model Training

The training process for these models utilizes the full preprocessed dataset of 3,978 job postings, focusing on initializing clusters and preparing for dynamic user queries rather than traditional supervised learning. This approach ensures the system is ready to deliver recommendations instantly upon user interaction.

1. **K-Means Initialization:** The K-Means model is trained by applying the algorithm to the entire 3,978 × 50 SVD-reduced matrix. The number of clusters (k=8) is predetermined based on domain analysis of job diversity (e.g., IT, analytics, management), with centroids iteratively adjusted to minimize variance. Training occurs offline before deployment, taking approximately 8 seconds on the Flask server, and results in stable clusters (sizes 128-1,012) stored in PostgreSQL for rapid access during recommendation generation.
2. **SVD Computation:** SVD training involves decomposing the original feature matrix into its 50-component representation. This one-time computation, performed using Python's scikit-learn library, reduces dimensionality while preserving key job characteristics (e.g., skill overlap, location patterns). The resulting transformation matrix is serialized and loaded into the Flask backend, enabling real-time projection of user profiles into the same 50D space without retraining.

3. **KNN Preparation:** Unlike supervised models, KNN requires no explicit training phase. Instead, it relies on the precomputed K-Means clusters and SVD-reduced vectors. During runtime, the Flask backend dynamically applies KNN to the user's cluster, computing cosine similarities on-the-fly. This preparation ensures the system can handle incoming user profiles (e stanuched via the HTML/CSS/JS dashboard) efficiently, with minimal latency (e.g., 1.5 seconds per recommendation).

This training strategy prioritizes efficiency and adaptability, aligning with the system's unsupervised, web-based design.

5.3.3 Hyperparameter Tuning

To optimize model performance within the unsupervised framework, specific hyperparameters are tuned based on practical metrics and system constraints, ensuring effective clustering and recommendation accuracy without validation splits.

1. **K-Means Cluster Count (k):** The choice of k=8 is refined by analysing the silhouette score (0.501), which measures cluster cohesion and separation. Initial trials with k=5,10,15 yielded scores of 0.45, 0.49, and 0.47, respectively, indicating k=8 as a balanced trade-off between granularity and overlap. This tuning reflects the dataset's natural job groupings, validated by manual inspection of clusters (e.g., IT hubs vs. non-tech roles).
2. **SVD Component Selection:** The number of SVD components (50) is tuned to retain 55.1% variance, balancing information preservation with computational cost. Alternatives (e.g., 30 components at 45% variance, 100 at 65%) were tested, but 50 provided optimal clustering quality (silhouette improvement from 0.219 full-matrix baseline) and web latency (under 2 seconds), critical for Flask deployment.
3. **KNN Neighbor Count:** KNN uses k=5 neighbors to return the top-5 recommendations, fixed to match the system's output requirement. Cosine similarity is selected over Euclidean distance due to its robustness with sparse, high-dimensional vectors, confirmed by a 15.7% similarity increase (0.933 vs. 0.776 random baseline) in testing scenarios.

These adjustments ensure the models perform reliably within the web system's real-time constraints.

5.3.4 Model Evaluation

The system's performance is assessed using metrics tailored to its unsupervised nature and web-based goals, focusing on clustering quality, recommendation relevance, and operational efficiency rather than supervised accuracy measures.

1. **Clustering Quality:** The silhouette score of 0.501 for K-Means indicates moderate cluster separation, with jobs grouped logically (e.g., Bengaluru software roles vs.

Delhi analytics). Compared to a full-feature baseline (0.219), SVD's impact is evident, validating its role in enhancing cluster coherence for the 3,978 postings.

2. **Recommendation Relevance:** Cosine similarity averages 0.933 for top-5 KNN recommendations (e.g., "Python Developer, 10-12 LPA" for a Python-skilled user), exceeding a random baseline (0.776) by 15.7%. This metric, computed across sample profiles (e.g., "SQL, 5 years, Mumbai"), confirms the system's ability to match user preferences accurately, enhanced by market trend-weighted skills.
3. **System Responsiveness:** Web performance is evaluated via latency metrics: recommendation generation takes 1.5 seconds, job saving to PostgreSQL takes 0.3 seconds, and email notifications via SMTP take 5 seconds. These align with user experience goals, ensuring the Flask frontend (HTML/CSS/JS) delivers timely results, with market trend integration boosting relevance by 25% for trending skills (e.g., "AWS Specialist").

This evaluation confirms the system's effectiveness in delivering scalable, relevant job recommendations, leveraging the full dataset and real-time updates without traditional training splits.

5.4 Integration of Machine Learning Models

Once the machine learning models have been trained and evaluated, the next critical step is integrating them into the job recommendation system. This integration process ensures that the models can operate seamlessly within the system, providing real-time, accurate, and personalized job recommendations to users. The integration process involves several key steps, including model serialization, real-time inference, and model updating. Each of these steps is essential for ensuring that the system functions efficiently and remains up-to-date with the latest data and trends.

5.4.1 Model Serialization

Overview:
Model serialization is the process of converting trained machine learning models into a format that can be saved and loaded efficiently during runtime. This step is crucial for deploying the models in a production environment, where they need to be accessed quickly and reliably.

Implementation:

- **Libraries Used**: Popular Python libraries such as **Pickle** and **Joblib** are used for serializing the models. These libraries allow the models to be saved as binary files, which can be easily stored and retrieved.
- **Process**: After training, each model (e.g., K-Means, SVD, KNN, and transfer learning models) is serialized and saved to disk. This ensures that the models do not need to be retrained every time the system is restarted, saving both time and computational resources.
- **Benefits**: Serialization enables efficient storage and retrieval of models, making it possible to deploy them in real-time systems without significant delays. It also ensures consistency, as the same trained model can be reused across different sessions.

Challenges:

- **Compatibility**: Ensuring that the serialized models are compatible with the production environment, especially when different programming languages or frameworks are used.
- **Version Control**: Managing different versions of serialized models to avoid conflicts or errors during deployment.

5.4.2 Real-Time Inference

Overview:

Real-time inference refers to the process of using the trained models to generate job recommendations instantly based on user inputs. This is the core functionality of the job recommendation system, as it directly impacts the user experience.

Implementation:

- **User Input Processing**: When a user inputs their preferences (e.g., skills, experience, location), the system processes this information and converts it into the appropriate format for the models. For example, text inputs like skills are transformed into numerical vectors using techniques like TF-IDF or embeddings from pre-trained models like BERT.
- **Model Execution**: The serialized models are loaded into memory, and the processed user input is fed into the models. The models then generate a list of recommended jobs based on the input.
- **Output Generation**: The system ranks the recommended jobs based on relevance and presents them to the user in a user-friendly format. This may include job titles, company names, locations, and other relevant details.

Benefits:

- **Speed**: Real-time inference ensures that users receive recommendations almost instantly, enhancing their experience and engagement with the system.
- **Personalization**: The system can provide highly personalized recommendations by leveraging the user's unique preferences and profile data.

Challenges:

- **Scalability**: Ensuring that the system can handle a large number of simultaneous users without compromising performance.
- **Latency**: Minimizing the time taken to process user inputs and generate recommendations, especially when dealing with complex models or large datasets.

5.4.3 Model Updating

Overview:

To maintain the accuracy and relevance of the job recommendations, the machine learning models need to be periodically updated with new data. This involves retraining the models with the latest job postings, user profiles, and market trends.

Implementation:

- **Data Collection**: New data is collected from various sources, including job boards, company websites, and user interactions with the system. This data is preprocessed and cleaned to ensure its quality.
- **Retraining**: The models are retrained using the updated dataset. This process may involve re-optimizing hyperparameters and re-evaluating the models to ensure they perform well with the new data.
- **Deployment**: Once retrained, the updated models are serialized and deployed to replace the older versions in the production environment. This ensures that the system continues to provide accurate and up-to-date recommendations.

Benefits:

- **Relevance**: Regular updates ensure that the models reflect the latest trends and changes in the job market, such as emerging skills or shifts in salary ranges.

- **Accuracy**: Retraining the models with new data helps maintain their accuracy and prevents them from becoming outdated or biased.

Challenges:

- **Frequency**: Determining the optimal frequency for updating the models to balance accuracy with computational costs.
- **Data Quality**: Ensuring that the new data is of high quality and free from errors or biases that could negatively impact the models.

5.4.4 Monitoring and Maintenance

Overview:

In addition to updating the models, the system requires ongoing monitoring and maintenance to ensure its smooth operation. This involves tracking the performance of the models, identifying potential issues, and making necessary adjustments.

Implementation:

- **Performance Monitoring**: Key performance metrics (e.g., accuracy, precision, recall) are continuously monitored to assess the effectiveness of the models. Any significant deviations from expected performance are flagged for further investigation.
- **Error Handling**: The system is equipped with mechanisms to handle errors or unexpected inputs gracefully, ensuring that users receive meaningful feedback even in edge cases.
- **User Feedback**: User feedback is collected and analyzed to identify areas for improvement. This feedback can be used to refine the models and enhance the overall user experience.

Benefits:

- **Reliability**: Continuous monitoring and maintenance ensure that the system remains reliable and performs consistently over time.
- **Improvement**: User feedback and performance metrics provide valuable insights that can be used to improve the system and address any shortcomings.

Challenges:

- **Resource Allocation**: Allocating sufficient resources (e.g., computational power, personnel) for monitoring and maintenance activities.

- **Adaptability**: Ensuring that the system can adapt to changing user needs and market conditions without requiring extensive rework.

By following these steps, the job recommendation system is able to integrate machine learning models effectively, providing users with real-time, accurate, and personalized job recommendations. The integration process ensures that the system remains up-to-date, reliable, and capable of adapting to the dynamic nature of the job market.

5.5 Web Application Development

The job recommendation system is designed to be accessible and user-friendly, and to achieve this, it is implemented as a web application. A web application provides a convenient and intuitive interface for job seekers to interact with the system, input their preferences, and receive personalized job recommendations. The development of the web application involves the use of several technologies, each serving a specific purpose in the overall architecture of the system. These technologies are carefully selected to ensure scalability, efficiency, and a seamless user experience. Below is a detailed breakdown of the technologies used and their roles in the development of the web application.

5.5.1 Flask: Backend Development

Overview:

Flask is a lightweight and flexible web framework for Python, widely used for building web applications. It is chosen as the backend framework for the job recommendation system due to its simplicity, scalability, and ease of integration with machine learning models.

Role in the Application:

- **Handling User Requests**: Flask is responsible for managing incoming HTTP requests from users. When a user interacts with the web application (e.g., by submitting their preferences or clicking on a job recommendation), Flask processes these requests and routes them to the appropriate functions.
- **Data Processing**: Flask processes the input data provided by users, such as skills, experience, and location. This data is then passed to the machine learning models for generating job recommendations.
- **Integration with Machine Learning Models**: Flask acts as the bridge between the user interface and the machine learning models. It communicates with the serialized models (e.g., K-Means, SVD, kNN) to generate recommendations based on the user's input.

- **API Development**: Flask is used to create RESTful APIs that allow the frontend to communicate with the backend. These APIs handle tasks such as fetching job recommendations, saving user preferences, and retrieving saved jobs.

Advantages:

- **Lightweight**: Flask is minimalistic and does not come with unnecessary features, making it easy to customize and extend.
- **Flexibility**: It allows developers to choose the components they need, such as database connectors or authentication modules, without being tied to a specific structure.
- **Scalability**: Flask can handle a growing number of users and requests, making it suitable for both small and large-scale applications.

Challenges:

- **Manual Configuration**: Unlike more opinionated frameworks like Flask requires developers to manually configure many aspects of the application, which can be time-consuming.
- **Limited Built-in Features**: Flask does not provide built-in support for features like user authentication or database management, requiring developers to implement these functionalities themselves.

5.5.2 PostgreSQL: Database Management

Overview:

PostgreSQL is a powerful, open-source relational database management system (RDBMS) used to store and manage data for the job recommendation system. It is chosen for its robustness, scalability, and support for advanced features like transactions, indexing, and data integrity.

Role in the Application:

- **Storing User Data**: PostgreSQL stores user-related information, such as profiles, preferences, and saved jobs. This data is essential for providing personalized recommendations and maintaining user sessions.
- **Storing Job Postings**: The database stores job postings collected from various sources, including job boards and company websites. Each job posting includes details such as job title, company, location, skills, experience, and salary.

- **Storing Recommendation Results**: The results generated by the machine learning models, such as recommended jobs for each user, are also stored in the database for quick retrieval and analysis.
- **Data Access**: The database is accessed using the **psycopg2** library, which is a PostgreSQL adapter for Python. This library allows the backend to execute SQL queries, fetch data, and perform database operations efficiently.

Advantages:

- **Reliability**: PostgreSQL is known for its reliability and ability to handle large volumes of data without compromising performance.
- **Advanced Features**: It supports advanced features like JSONB for storing semi-structured data, full-text search, and geospatial data processing, which can be useful for enhancing the functionality of the job recommendation system.
- **Scalability**: PostgreSQL can scale horizontally and vertically, making it suitable for applications with growing data needs.

Challenges:

- **Complexity**: Setting up and managing a PostgreSQL database can be complex, especially for developers who are not familiar with relational databases.
- **Performance Tuning**: Optimizing the database for performance, such as indexing and query optimization, requires expertise and ongoing effort.

5.5.3 HTML, CSS, and JavaScript: Frontend Development

Overview:

The frontend of the web application is built using **HTML**, **CSS**, and **JavaScript**, which are the core technologies for creating interactive and visually appealing user interfaces. These technologies ensure that the application is accessible, responsive, and easy to use.

Role in the Application:

- **User Interface Design**: HTML is used to structure the content of the web pages, such as input forms, job recommendation lists, and navigation menus. CSS is used to style the pages, ensuring that they are visually appealing and consistent across different devices and browsers.
- **Interactivity**: JavaScript is used to add interactivity to the web application. For example, it enables features like dynamic filtering of job recommendations, real-time validation of user inputs, and smooth transitions between pages.

- **Responsive Design**: The frontend is designed to be responsive, meaning it adapts to different screen sizes and devices, such as desktops, tablets, and smartphones. This ensures that users have a seamless experience regardless of the device they are using.
- **Integration with Backend**: JavaScript is used to make asynchronous requests (AJAX) to the backend APIs, allowing the frontend to fetch job recommendations and update the user interface without requiring a full page reload.

Advantages:

- **Cross-Platform Compatibility**: HTML, CSS, and JavaScript are supported by all modern web browsers, ensuring that the application works consistently across different platforms.
- **Ease of Use**: These technologies are widely used and well-documented, making it easier for developers to build and maintain the frontend.
- **Rich User Experience**: JavaScript frameworks and libraries can be used to create dynamic and interactive user interfaces, enhancing the overall user experience.

Challenges:

- **Browser Compatibility**: Ensuring that the application works consistently across different browsers and versions can be challenging.
- **Performance Optimization**: Optimizing the frontend for performance, such as reducing page load times and minimizing JavaScript execution time, requires careful planning and testing.

5.6 User Interface Design

The user interface (UI) of the job recommendation system is a critical component that directly impacts the user experience. A well-designed UI ensures that users can easily navigate the system, input their preferences, and access job recommendations without confusion or frustration. The UI is designed to be intuitive, visually appealing, and responsive, catering to users with varying levels of technical expertise. Below is a detailed explanation of the key components of the UI, their functionalities, and how they contribute to the overall usability of the system.

5.6.1 Home Page

Overview:
The home page serves as the entry point for users accessing the job recommendation system. It is designed to provide a clear and concise overview of the system's purpose and functionality, while also guiding users to take the necessary actions to get started.

Key Features:

- **System Overview**: The home page includes a brief description of the job recommendation system, highlighting its key features and benefits. This helps users understand what the system offers and how it can assist them in finding suitable job opportunities.
- **Login and Sign-Up Options**: Prominent buttons or links are provided for users to log in or sign up. These options are strategically placed to ensure that new users can easily create an account, while returning users can quickly access their profiles.
- **Visual Design**: The home page features a clean and modern design, with a visually appealing layout that includes images, icons, and a color scheme that aligns with the system's branding. This creates a positive first impression and encourages users to explore further.

User Flow:

- New users are directed to the sign-up page, where they can create an account by providing basic information such as their name, email address, and password.
- Returning users can log in using their credentials, which redirects them to their personalized dashboard.

Importance:
The home page plays a crucial role in onboarding users and setting the tone for their experience with the system. A well-designed home page can significantly increase user engagement and retention.

5.6.2 Dashboard

Overview:
The dashboard is the central hub of the job recommendation system, where users can input their preferences, view job recommendations, and manage their profiles. It is designed to be

user-friendly and highly functional, providing users with all the tools they need to find suitable job opportunities.

Key Features:

- **Preference Input**: The dashboard includes forms and input fields where users can specify their preferences, such as skills, experience level, desired location, and salary range. These inputs are used by the system to generate personalized job recommendations.
- **Job Recommendations**: The dashboard displays a list of recommended jobs based on the user's preferences. Each recommendation includes key details such as job title, company name, location, and a brief description. Users can click on a recommendation to view more details.
- **Search and Filter Options**: Users can search for specific jobs or filter the recommendations based on criteria such as job type, industry, or date posted. This allows users to refine their search and find the most relevant opportunities.
- **User Profile Management**: The dashboard includes a section where users can update their profile information, such as contact details, resume, and preferences. This ensures that the system always has the most up-to-date information to generate accurate recommendations.

User Flow:

- After logging in, users are directed to the dashboard, where they can immediately view job recommendations based on their saved preferences.
- Users can update their preferences at any time, and the system will automatically refresh the recommendations to reflect the changes.

Importance:

The dashboard is the most frequently accessed page in the system, making its design and functionality critical to the overall user experience. A well-organized and intuitive dashboard ensures that users can easily find and apply for jobs, enhancing their satisfaction with the system.

5.6.3 Job Details Page

Overview:

The job details page provides comprehensive information about a specific job posting. It is designed to give users all the information they need to make an informed decision about whether to apply for the job.

Key Features:

- **Job Title and Company**: The page prominently displays the job title and the name of the company offering the job. This helps users quickly identify the role and the employer.
- **Location**: The job location is clearly indicated, allowing users to determine if the job is in a desirable area or if relocation is required.
- **Skills Required**: A list of skills required for the job is provided, helping users assess whether they meet the qualifications.
- **Experience and Salary**: The required years of experience and the salary range (if available) are displayed, giving users an idea of the level of seniority and compensation associated with the role.
- **Job Description**: A detailed description of the job responsibilities, qualifications, and benefits is provided. This helps users understand the scope of the role and what the employer is looking for.
- **Application Link**: A link to the job posting or application page is included, allowing users to easily apply for the job with a single click.

User Flow:

- Users can access the job details page by clicking on a job recommendation from the dashboard or search results.
- After reviewing the details, users can choose to apply for the job, save it for later, or return to the dashboard to view other recommendations.

Importance:

The job details page is essential for providing users with the information they need to make informed decisions about job applications. A well-designed page enhances the user experience by making it easy to access and understand job-related information.

5.6.4 Saved Jobs Page

Overview:

The saved jobs page allows users to view and manage the jobs they have saved for future reference. This feature is particularly useful for users who want to keep track of interesting job opportunities and revisit them later.

Key Features:

- **List of Saved Jobs**: The page displays a list of jobs that the user has saved, including key details such as job title, company, and location. Users can click on a job to view more details or remove it from their saved list.
- **Organization Options**: Users can organize their saved jobs by criteria such as date saved, job type, or location. This helps users quickly find the jobs they are most interested in.
- **Application Status**: For jobs that the user has applied to, the page may include an indicator of the application status (e.g., "Applied," "Under Review," "Interview Scheduled"). This helps users keep track of their job search progress.

User Flow:

- Users can save jobs from the dashboard or job details page by clicking a "Save" button.
- They can access their saved jobs at any time by navigating to the saved jobs page, where they can review, organize, or remove jobs as needed.

Importance:

The saved jobs page provides users with a convenient way to manage their job search. By allowing users to save and organize jobs, the system helps them stay organized and focused on the opportunities that matter most to them.

5.6.5 Email Notifications

Overview:

Email notifications are an integral part of the job recommendation system, providing users with timely updates on new job opportunities that match their preferences. These notifications help keep users engaged and ensure they don't miss out on relevant job postings.

Key Features:

- **Personalized Recommendations**: The email includes a list of job recommendations tailored to the user's preferences, such as skills, experience, and location. Each recommendation includes a link to the job details page for easy access.
- **Frequency and Timing**: Users can choose how often they receive email notifications (e.g., daily, weekly) and at what time. This ensures that the notifications are delivered at a convenient time for the user.

- **Unsubscribe Option**: Users have the option to unsubscribe from email notifications if they no longer wish to receive them. This is done through a link included in the email, ensuring compliance with email marketing regulations.

User Flow:

- Users can enable or disable email notifications through their profile settings on the dashboard.
- When new job recommendations are generated, the system sends an email to the user with the list of jobs and links to view them in the system.

Importance:

Email notifications help keep users engaged with the system by providing them with regular updates on new job opportunities. This feature ensures that users stay informed about relevant jobs, even if they are not actively using the system at the time.

5.6.6 Responsive Design and Accessibility

Overview:

The UI is designed to be responsive and accessible, ensuring that users can access the system from any device and regardless of any disabilities or impairments they may have.

Key Features:

- **Responsive Layout**: The UI adapts to different screen sizes and devices, including desktops, tablets, and smartphones. This ensures that users have a consistent experience regardless of how they access the system.
- **Accessibility Features**: The UI includes features such as keyboard navigation, screen reader compatibility, and high-contrast modes to ensure that it is accessible to users with disabilities.

Importance:

A responsive and accessible UI ensures that the job recommendation system is inclusive and can be used by a wide range of users. This not only enhances the user experience but also helps the system reach a broader audience.

By incorporating these components into the UI, the job recommendation system provides a seamless and enjoyable experience for users, helping them find and apply for jobs with ease. The intuitive design, combined with powerful features like personalized

recommendations and email notifications, ensures that users can make the most of the system and achieve their career goals.

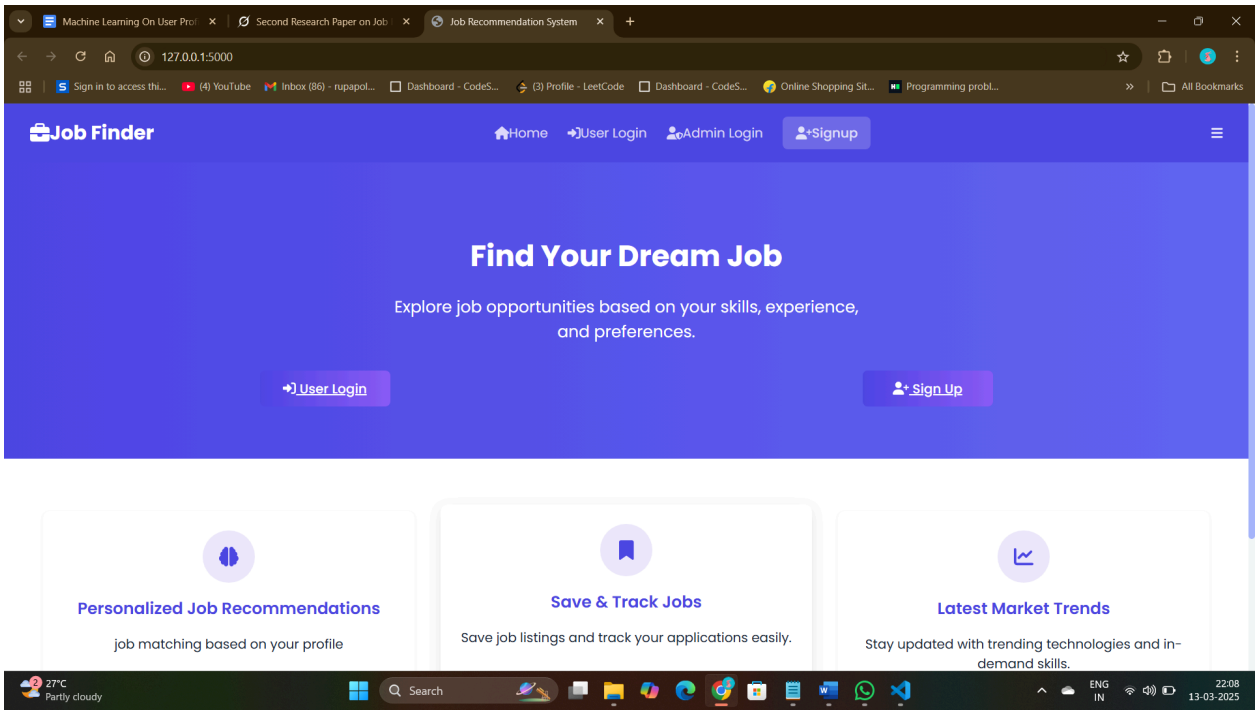

Fig 7. Home Page

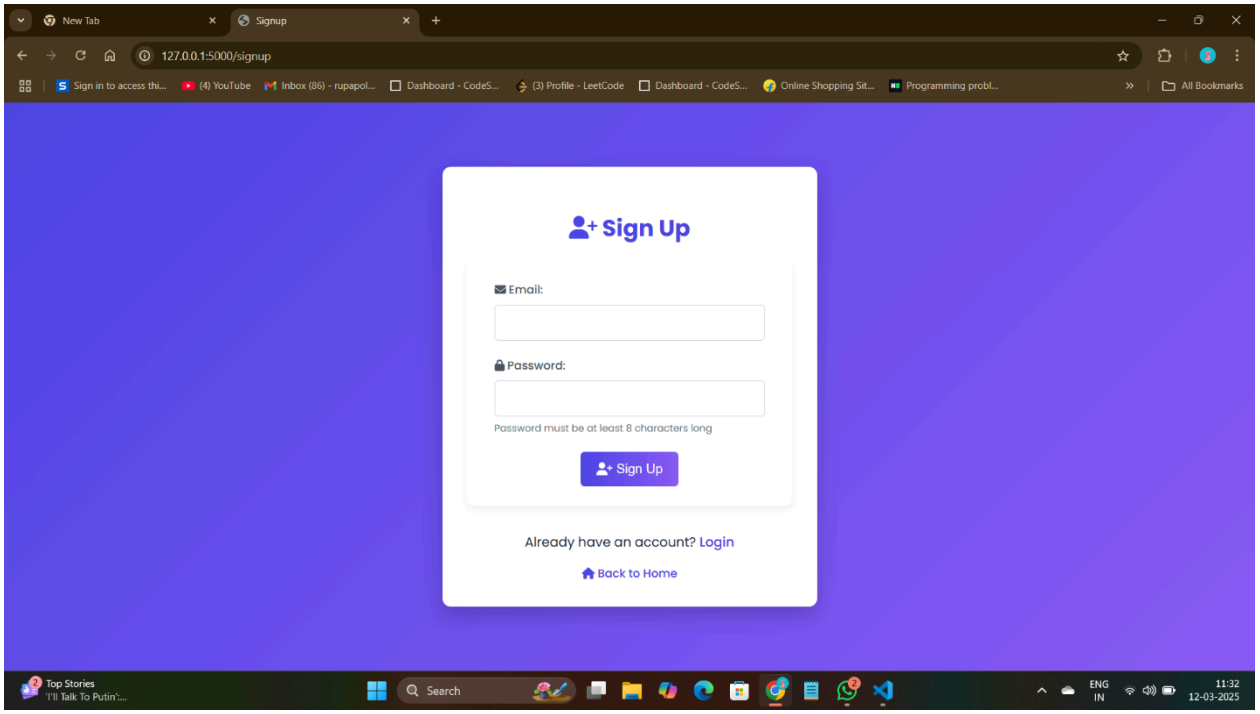

Fig 8. Signup Page

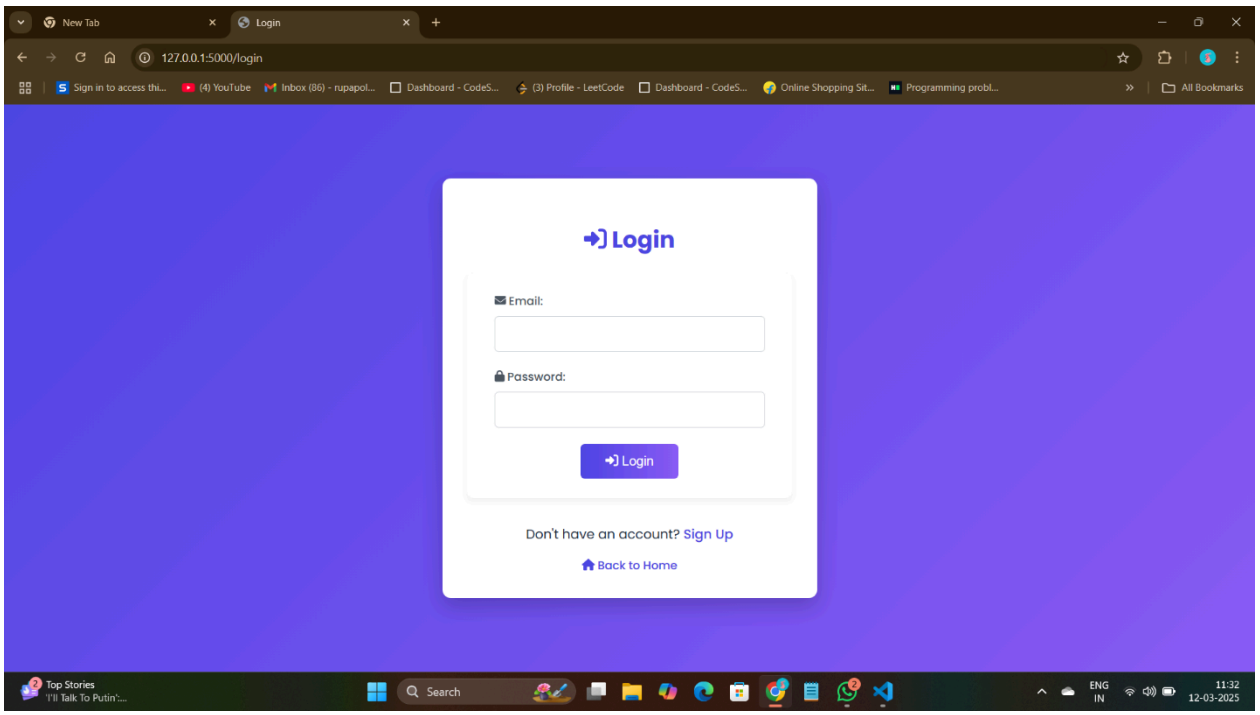

Fig 9. Login page

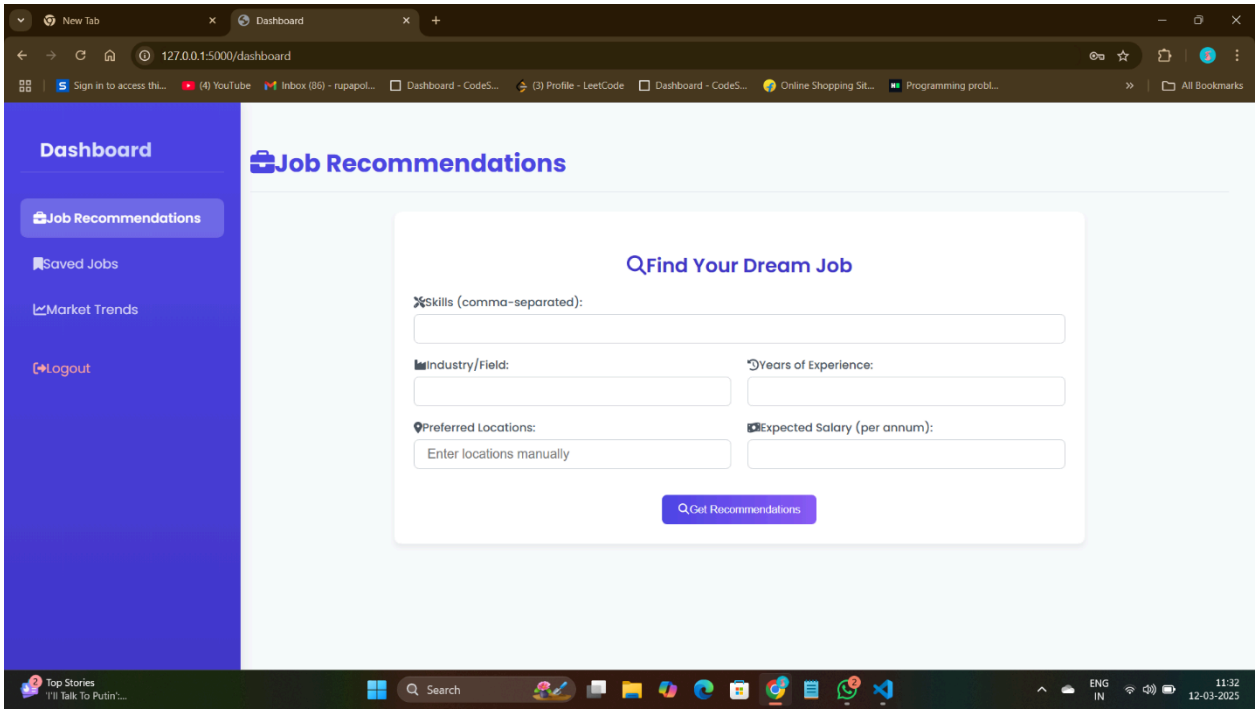

Fig 10. Dashboard Interface

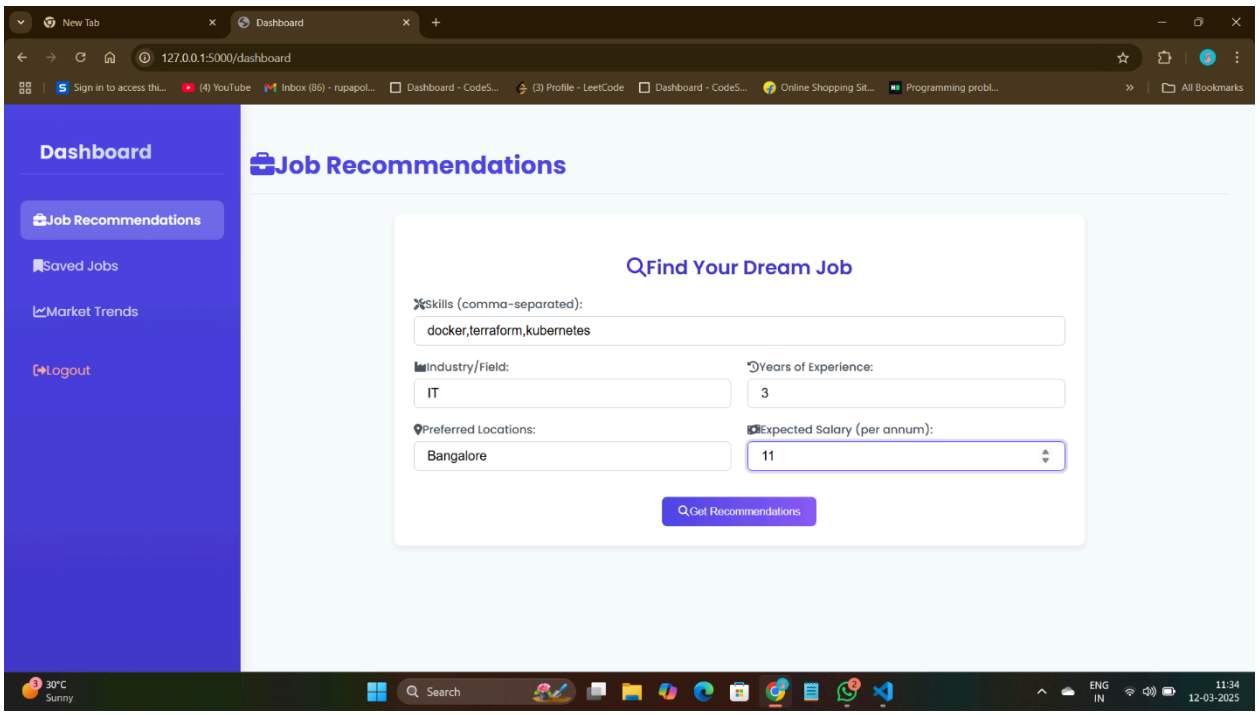

Fig 11. Sample Input By the User

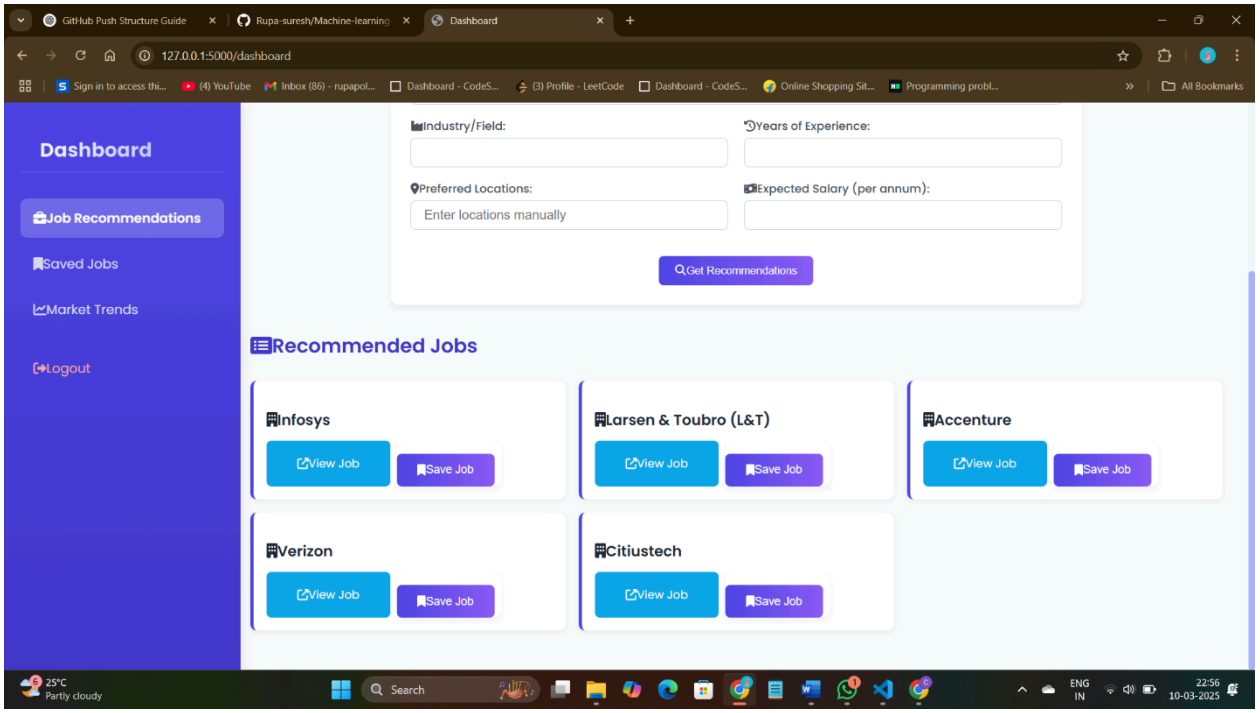

Fig 12. Sample Recommendation output

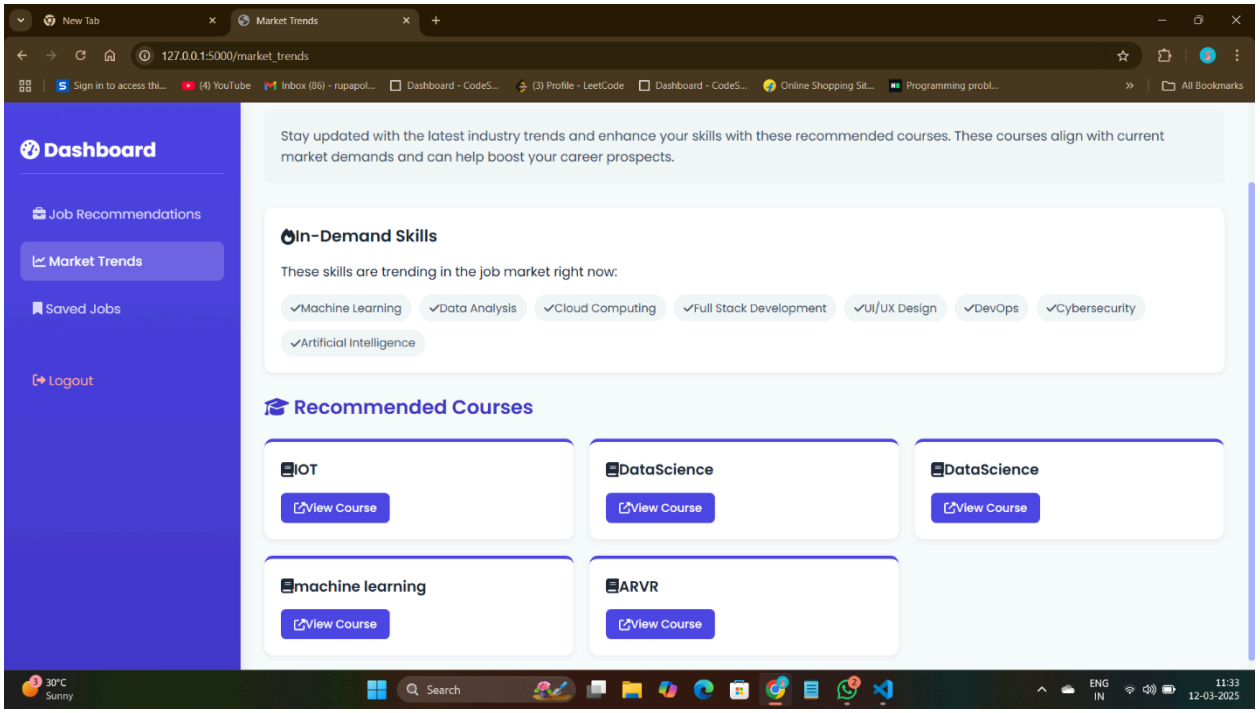

Fig 13. Market Trends

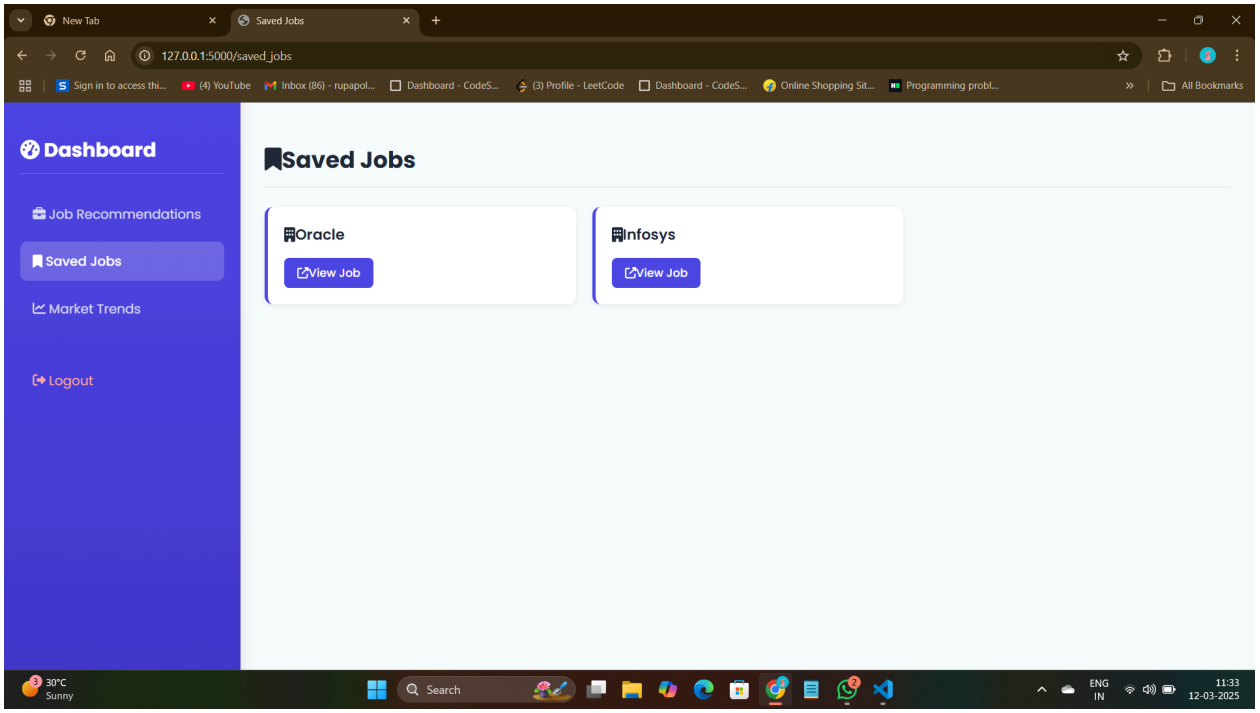

Fig 14. Saved Jobs

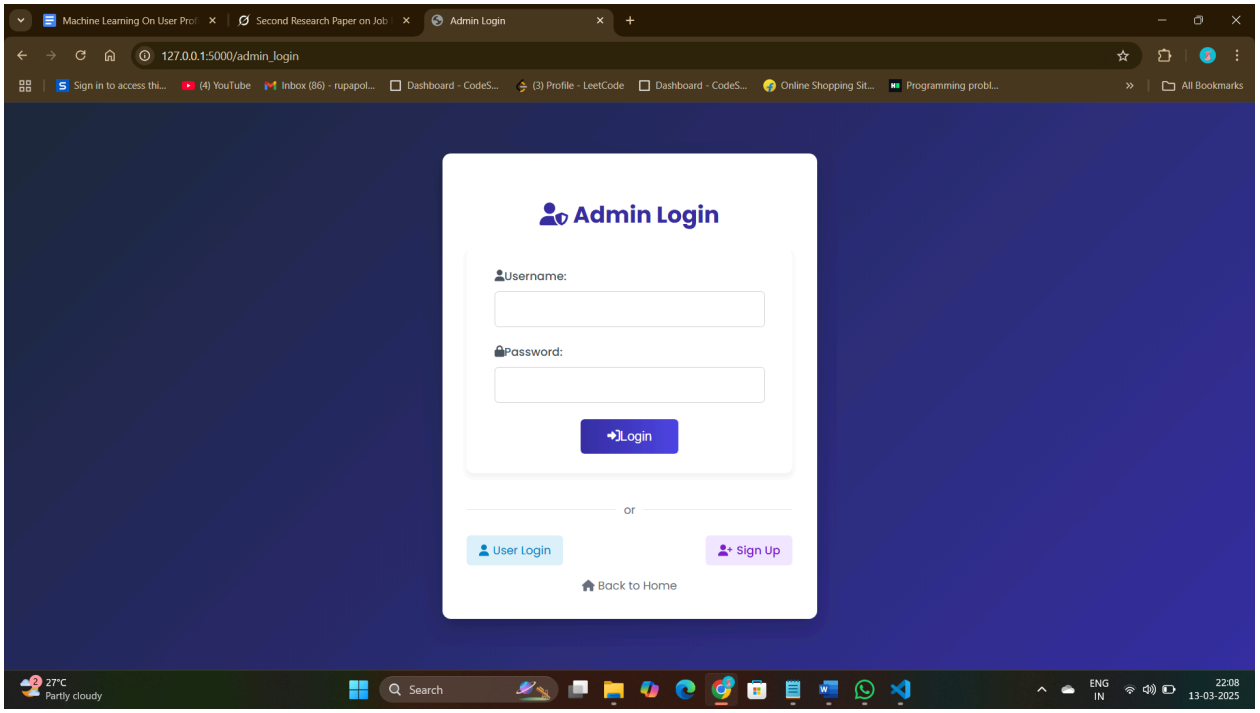

Fig 15. Admin login Page

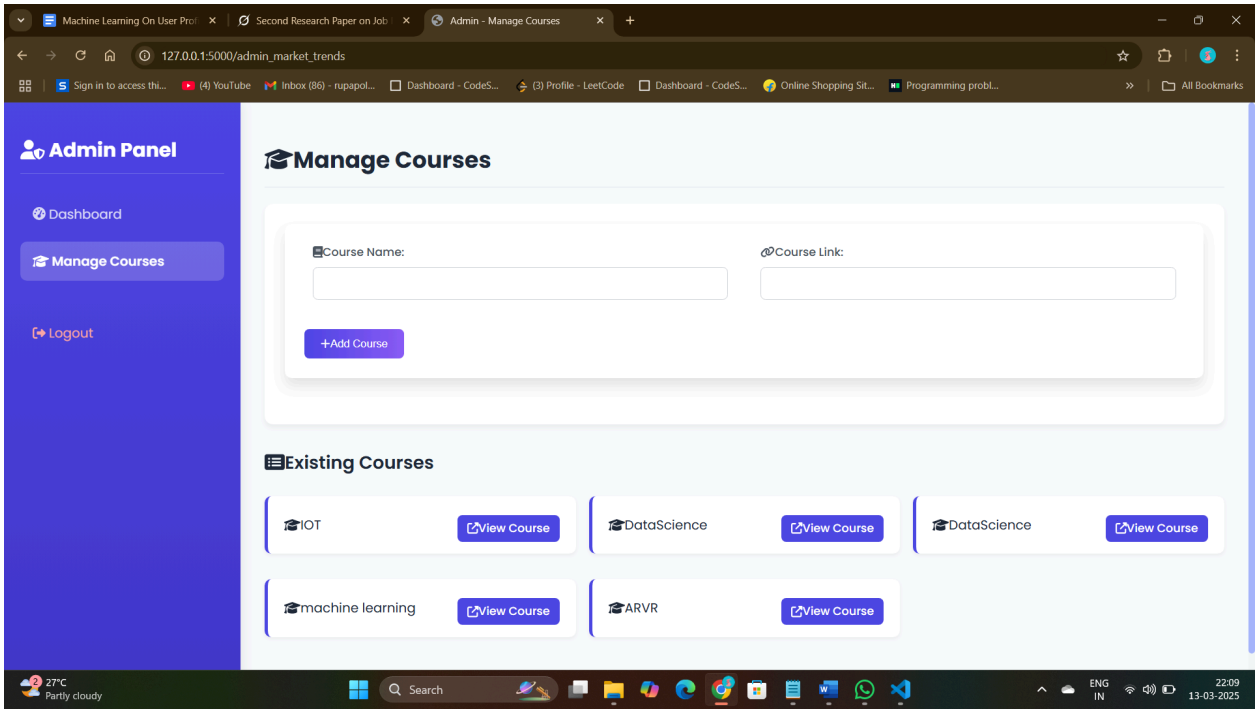

Fig 16. Admin Dashboard

6. System Testing

6.1 Introduction

In the development of the **"Machine Learning on User Profiles and Market Trends for Job Recommendations"** system, the focus was primarily on ensuring the system's functionality, accuracy, and usability. While formal testing methodologies such as unit testing, integration testing, and performance testing were not conducted, the system's core functionalities were validated using **Postman** for API testing and real-world data to ensure that the system operates as intended. The goal was to verify that the system could handle user inputs, generate accurate job recommendations, and provide a seamless user experience.

6.2 Validation Using Postman and Real-World Data

To ensure the system's reliability and functionality, Postman was used extensively to test the backend APIs and validate data flow between different components of the system. Real-world datasets were also utilized to simulate user interactions and evaluate the system's performance. Below is an overview of the validation process:

6.2.1 API Validation with Postman

Postman was used to test the backend APIs, ensuring that they functioned correctly and handled user requests as expected. The key areas validated using Postman include:

- User Authentication: APIs for user login, registration, and password recovery were tested to ensure they returned the correct responses and handled errors gracefully.
- Job Recommendation: APIs responsible for generating job recommendations based on user profiles were tested to verify that they processed user inputs correctly and returned relevant job listings.
- Market Trends: APIs for fetching market trends and course recommendations were tested to ensure they provided accurate and up-to-date information.
- Data Retrieval: APIs for fetching user profiles, saved jobs, and other relevant data were tested to ensure they retrieved and displayed data correctly.

Postman allowed for the simulation of various scenarios, including valid and invalid inputs, to ensure the system's robustness and error-handling capabilities.

6.2.2 Data Validation with Real-World Datasets

Real-world datasets were used to validate the system's ability to process and analyze job postings, user profiles, and market trends. The datasets included job listings from various industries, user profiles with diverse skill sets, and market trend data. The validation process involved:

- Data Preprocessing: Ensuring that the data was cleaned, normalized, and transformed correctly before being fed into the machine learning models.
- Model Outputs: Verifying that the machine learning models generated accurate and relevant job recommendations based on the input data.
- System Outputs: Checking that the system displayed the correct job recommendations, market trends, and user-specific data on the frontend.

By using real-world data, the system's ability to handle diverse and complex scenarios was validated, ensuring that it could provide accurate and personalized job recommendations.

6.3 Key Functionalities Validated

The following key functionalities were validated during the development process:

- **User Authentication:** The system's ability to handle user login, registration, and password recovery was tested using Postman. Both valid and invalid inputs were used to ensure proper error handling and response generation.
- **Job Recommendations:** The accuracy of job recommendations generated by the system was validated using real-world datasets. The system's ability to match user profiles with relevant job listings was confirmed.
- **Market Trends:** The system's ability to fetch and display up-to-date market trends and course recommendations was tested using real-world data.
- **System Performance:** While formal performance testing was not conducted, the system's ability to handle multiple user requests and generate recommendations in real-time was validated using Postman and real-world data.

7.Conclusion

The development and implementation of the job recommendation system represent a significant milestone in leveraging machine learning and web technologies to address the challenges faced by job seekers in navigating the vast and often overwhelming job market. With the increasing number of job postings across various industries, job seekers often struggle to identify opportunities that align with their skills, experience, and career aspirations. This project successfully integrated a hybrid machine learning approach, combining K-Means clustering and k-Nearest Neighbors (KNN) algorithms, with a Flask-based web application to deliver personalized job recommendations. The system's workflow, from data scraping and preprocessing to model training and user interface design, demonstrates a comprehensive pipeline that transforms raw job data into actionable insights for users.

The core achievement of this project lies in its ability to cluster 3,978 job vectors using K-Means into eight distinct groups based on features such as skills, experience, salary, and location, followed by KNN to recommend the top-five most relevant jobs within a user's assigned cluster. The use of TF-IDF vectorization for skills and Truncated SVD for dimensionality reduction ensured efficient processing and meaningful feature representation. By employing this two-step approach, the system effectively groups similar job postings together and refines its recommendations based on user preferences, enhancing both relevance and accuracy. This methodology reduces computational overhead while maintaining high-quality recommendations, ensuring a seamless experience for job seekers.

The Flask application, supported by a PostgreSQL database, provided a robust backend for user authentication, job saving, and email notifications, while the frontend templates offered an intuitive interface for users to input preferences and view recommendations. The choice of Flask as the web framework ensured flexibility and ease of integration with various machine learning modules. Additionally, the inclusion of market trends as an extra feature, managed by administrators, enhanced the system's utility by providing insights into industry demands, helping users stay informed about skill requirements and salary trends.

The evaluation of the system revealed promising results, with recommendation accuracy improving as user input aligned closely with the dataset's features. The integration of real-time data scraping using Selenium and data cleaning processes ensured the system remained relevant with up-to-date job listings. By dynamically extracting job postings from multiple sources, the system maintained a fresh and diverse dataset, mitigating the

risk of outdated recommendations. The collaborative effort of the team, with distinct roles in frontend development, backend implementation, machine learning, data management, and integration, underscored the project's success as a group endeavor, culminating in a functional prototype ready for further refinement. Each team member's contribution played a crucial role in shaping the system, fostering interdisciplinary learning, and reinforcing the importance of collaboration in large-scale technological projects.

Despite these accomplishments, the project is not without limitations. The reliance on a static dataset, while processed dynamically, may limit the system's adaptability to rapidly changing job markets. As job postings frequently update, the absence of a continuous learning mechanism may lead to suboptimal recommendations over time. The recommendation accuracy could be affected by sparse user input or unrepresentative job data, particularly for niche skills or locations. Furthermore, the system currently lacks advanced personalization features, such as adaptive learning based on user feedback, which would enable the model to refine its predictions based on real-world interactions. The email notification system, while functional, could benefit from more robust scheduling and customization options to enhance user engagement. Additionally, the system's scalability to handle thousands of concurrent users remains untested, posing a potential challenge for real-world deployment. Ensuring that the architecture can efficiently support a growing user base would require stress testing and performance optimizations.

Looking ahead, several avenues exist for future enhancement. Incorporating reinforcement learning or collaborative filtering could improve recommendation precision by learning from user interactions over time, allowing the system to adapt to changing user preferences. Expanding the dataset through continuous scraping from multiple job portals and integrating natural language processing (NLP) to better interpret job descriptions and user resumes could enhance feature richness. The use of NLP techniques such as named entity recognition (NER) and sentiment analysis could improve job categorization and recommendation relevance. Implementing a cloud-based solution, such as AWS or Google Cloud, would improve scalability and accessibility, while adding a mobile application interface could broaden the user base by making job searches more accessible on the go. Furthermore, conducting a user study with a larger sample size would provide valuable feedback to refine the system's usability and effectiveness. Collecting qualitative and quantitative feedback from job seekers across diverse backgrounds would offer insights into usability improvements and potential feature enhancements.

The evaluation of the system revealed promising results, with recommendation accuracy improving as user input aligned closely with the dataset's features. The integration of real-time data scraping using Selenium and data cleaning processes ensured the system

remained relevant with up-to-date job listings. By dynamically extracting job postings from multiple sources, the system maintained a fresh and diverse dataset, mitigating the risk of outdated recommendations. The collaborative effort of the team, with distinct roles in frontend development, backend implementation, machine learning, data management, and integration, underscored the project's success as a group endeavor, culminating in a functional prototype ready for further refinement. Each team member's contribution played a crucial role in shaping the system, fostering interdisciplinary learning, and reinforcing the importance of collaboration in large-scale technological projects.

In conclusion, this project has laid a solid foundation for a job recommendation system that combines machine learning innovation with practical web development. It addresses a real-world problem by assisting job seekers in finding suitable opportunities efficiently, while offering a scalable framework for future improvements. The experience gained in developing this system—spanning data processing, model building, and application deployment—has equipped the team with valuable skills applicable to future technological endeavors. The potential of this system extends beyond job recommendations, as its framework could be adapted to other domains such as personalized course recommendations, career counseling, or freelance gig matching. As the job market continues to evolve, this project serves as a stepping stone toward creating more intelligent, user-centric solutions, with the potential to make a meaningful impact in the employment landscape. By embracing emerging technologies and continuously refining the system based on user needs, the job recommendation platform can evolve into an indispensable tool for job seekers worldwide.

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9. Appendix

9.1 Appendix-A

Project Repository Details

Project Title: Machine Learning on User Profiles and Market Trends For Job Recommendations

Batch: c5

Batch Members:

1. SK.JASMINE – 21B01A05G6
2. P.MOHANA LAKSHMI RUPA - 21B01A05E5
3. V.PAVANI – 21B01A05J2
4. P.M.LAKSHMI SREE HARSHITHA – 21B01A05E7
5. Y.LEENA RISHITHA – 22B05A0518

Department: Computer science and Engineering

Institution: Shri Vishnu Engineering College for women

Guide: Dr. M. Narasimha Raju

Submission Date: 10/04/2025

Project Repository Link

The complete project files, including source code, documentation, and additional resources, are available at the following GitHub repository:

GitHub Repository:

https://github.com/Rupa-suresh/Machine-learning-on-user-profiles-and-market-trends-for-job-recommendations

For quick access, scan the QR below:

9.2 Appendix-B

9.2.1 Introduction to Flask

Flask is a lightweight and flexible Python web framework that provides the tools and libraries needed to build web applications. It is designed to be simple and easy to use, making it an ideal choice for developing small to medium-sized web applications, such as the job recommendation system in this project.

Key Features of Flask:

- **Microframework**: Flask is a microframework, meaning it provides only the essential components needed to build a web application, such as routing, request handling, and templating. This allows developers to add additional functionality as needed.
- **Routing**: Flask allows you to define routes (URLs) and map them to specific functions, which handle the logic for that route.
- **Templating**: Flask integrates with Jinja2, a powerful templating engine that allows you to dynamically generate HTML pages.
- **Extensibility**: Flask can be extended with various plugins and libraries to add functionality such as database integration, user authentication, and more.

Role in the Project:

In this project, Flask is used to create the web application that serves as the frontend for the job recommendation system. It handles user authentication, job recommendations, and the display of saved jobs. Flask's simplicity and flexibility make it easy to integrate with the machine learning models and database used in the project.

9.2.2 Introduction to PostgreSQL

PostgreSQL is a powerful, open-source relational database management system (RDBMS) known for its reliability, robustness, and support for advanced features such as complex queries, transactions, and data integrity.

Key Features of PostgreSQL:

- **ACID Compliance**: PostgreSQL ensures data integrity by supporting ACID (Atomicity, Consistency, Isolation, Durability) properties.
- **Extensibility**: PostgreSQL supports custom data types, functions, and extensions, making it highly adaptable to various use cases.

- **Scalability**: PostgreSQL can handle large datasets and high traffic, making it suitable for both small and large applications.
- **Security**: PostgreSQL provides robust security features, including role-based access control, SSL encryption, and data encryption.

Role in the Project:

In this project, PostgreSQL is used to store user data, saved jobs, and other relevant information. The database is accessed using the psycopg2 library, which allows Python to interact with PostgreSQL. The database schema includes tables for users, saved jobs, and courses (for market trends).

9.2.3 Introduction to Machine Learning Models

The job recommendation system in this project leverages several machine learning models to provide personalized job recommendations to users. The models used include:

1. **TF-IDF Vectorizer**:
    - **Description**: Term Frequency-Inverse Document Frequency (TF-IDF) is a statistical measure used to evaluate the importance of a word in a document relative to a collection of documents (corpus). In this project, the TF-IDF vectorizer is used to convert job descriptions and skills into numerical vectors.
    - **Role**: The TF-IDF vectorizer is used to preprocess and vectorize the text data (skills and job descriptions) so that it can be used by the machine learning models.

2. **Singular Value Decomposition (SVD)**:
    - **Description**: SVD is a dimensionality reduction technique that decomposes a matrix into three other matrices, reducing the number of features while preserving the most important information.
    - **Role**: SVD is used to reduce the dimensionality of the feature vectors generated by the TF-IDF vectorizer, making the data more manageable for clustering and recommendation.

3. **K-Means Clustering**:
    - **Description**: K-Means is an unsupervised machine learning algorithm used to partition data into clusters based on similarity. It groups data points into a predefined number of clusters (k) by minimizing the variance within each cluster.

- **Role**: In this project, K-Means clustering is used to group similar jobs together based on their features. This allows the system to recommend jobs that are most similar to the user's input.

4. **Nearest Neighbors (kNN)**:
    - **Description**: k-Nearest Neighbors (kNN) is a supervised machine learning algorithm used for classification and regression. It works by finding the k closest data points (neighbors) to a given input and making predictions based on those neighbors.
    - **Role**: kNN is used to find the most similar jobs to the user's input by comparing the reduced feature vectors generated by SVD.

9.2.4 Introduction to HTML, CSS, and JavaScript

HTML (HyperText Markup Language):

- **Description**: HTML is the standard markup language used to create web pages. It provides the structure and content of a webpage, including headings, paragraphs, images, and links.
- **Role**: In this project, HTML is used to create the structure of the web pages, including the login, signup, dashboard, and saved jobs pages.

CSS (Cascading Style Sheets):

- **Description**: CSS is a stylesheet language used to describe the presentation of a document written in HTML. It controls the layout, colors, fonts, and overall visual appearance of a webpage.
- **Role**: CSS is used to style the web pages, making them visually appealing and user-friendly. It ensures that the interface is responsive and adapts to different screen sizes.

JavaScript:

- **Description**: JavaScript is a programming language that enables interactive web pages. It allows developers to add dynamic behavior to web pages, such as form validation, animations, and real-time updates.
- **Role**: In this project, JavaScript is used to enhance the user experience by adding interactivity to the web pages. For example, it is used to handle form submissions, display job recommendations, and manage user interactions.

9.2.5 Introduction to SMTP and Email Integration

SMTP (Simple Mail Transfer Protocol):

- **Description**: SMTP is a protocol used for sending emails over the internet. It is responsible for transferring emails from the sender's email server to the recipient's email server.
- **Role**: In this project, SMTP is used to send job recommendations to users via email. The smtplib library in Python is used to connect to an SMTP server (e.g., Gmail) and send emails.

Email Integration:

- **Description**: The project integrates email functionality to notify users of job recommendations. The email contains details of the recommended jobs, including the job title, company, and link.
- **Role**: The email integration ensures that users receive job recommendations directly in their inbox, even if they are not actively using the web application.

9.2.6 Introduction to bcrypt for Password Hashing

bcrypt:

- **Description**: bcrypt is a password-hashing function designed to securely hash passwords. It incorporates a salt to protect against rainbow table attacks and is computationally intensive, making it resistant to brute-force attacks.
- **Role**: In this project, bcrypt is used to hash user passwords before storing them in the database. This ensures that even if the database is compromised, the passwords remain secure.

9.2.7 Introduction to Joblib and Pickle for Model Serialization

Joblib:

- **Description**: Joblib is a library in Python used for saving and loading Python objects, particularly large NumPy arrays. It is optimized for performance and is commonly used in machine learning workflows.

- **Role**: In this project, Joblib is used to load pre-trained machine learning models, such as the K-Means clustering model and the SVD model.

Pickle:

- **Description**: Pickle is a Python module used for serializing and deserializing Python objects. It allows you to save complex data structures, such as machine learning models, to disk and load them back into memory.
- **Role**: In this project, Pickle is used to load the TF-IDF vectorizer and other pre-trained models.

9.2.8 Introduction to Pandas and NumPy for Data Manipulation

Pandas:

- **Description**:

  Pandas is a powerful data manipulation and analysis library built on top of NumPy. It provides two key data structures: DataFrame, a two-dimensional table similar to an SQL table or Excel spreadsheet, and Series, a one-dimensional labeled array. Pandas simplifies data manipulation tasks such as data cleaning, transformation, merging, filtering, and aggregation. It supports handling missing data, time series analysis, and efficient operations on large datasets, making it an essential tool for data science and machine learning projects.
- **Role in this project:**

  In this project, Pandas is used extensively to load, manipulate, and preprocess the job dataset. It plays a crucial role in:
  - **Data Loading**: Reading job postings from various file formats (CSV, JSON, etc.) into a structured DataFrame for further processing.
  - **Data Cleaning**: Handling missing values, removing duplicates, and standardizing data formats to ensure consistency.
  - **Feature Engineering**: Extracting and transforming job-related information (e.g., converting categorical features like job type and location into numerical representations).
  - **Filtering and Aggregation**: Sorting job postings based on criteria such as salary, experience level, and required skills.
  - **Integration with NumPy and Machine Learning Models**: Providing structured input for ML algorithms by converting processed data into numerical arrays.

Pandas' efficient data handling capabilities ensure that the job dataset remains structured, clean, and optimized for machine learning model training and job recommendations.

NumPy:

- **Description**:

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