

# **Career Recommendation System**

## **MINI PROJECT REPORT**

submitted in partial fulfillment of the  
requirements for the award of the degree in

## **BACHELOR OF TECHNOLOGY**

**IN**

## **COMPUTER SCIENCE AND ENGINEERING**

**BY**

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**DEPARTMENT OF  
COMPUTER SCIENCE AND ENGINEERING**

**MAY 2025**



**Dr. M.G.R.**  
**EDUCATIONAL AND RESEARCH INSTITUTE**  
**DEEMED TO BE UNIVERSITY**  
University with Graded Autonomy Status  
(An ISO 21001 : 2018 Certified Institution)  
Periyar E.V.R. High Road, Madhavayal, Chennai-95. Tamilnadu, India.



## DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

### BONAFIDE CERTIFICATE

This is to certify that this Mini Project Report is the bonafide work of

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## DECLARATION

We, Mr. Vinay Kumar. P (221061101202), Mr. Muni Sai. P (221061101215), Mr. Balaji. P (221061101198), hereby declare that the Mini Project Report entitled **“Career Recommendation System”** is done by us under the guidance of **“Mrs.C.Subalakshmi & Dr.T.Kumanan”** is submitted in partial fulfilment of the requirements for the award of the degree in **Bachelor of Technology in Computer Science and Engineering.**

Date:

Place: CHENNAI

- 1.
- 2.
- 3.

**Signature of the Candidates**

## ACKNOWLEDGEMENT

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We express our heartfelt thanks to our Dean and Head of the Department, Prof. **Dr. S. Geetha**, who has been actively involved and very influential from the start till the completion of our project.

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## LIST OF ABBREVIATIONS

KNN	K-Nearest Neighbors
CRUD	Create,Read,Update,Delete
UI	User Interface
UX	User Experiences
ML	Machine Learning
NLP	Natural Language Processing
CORS	Cross-Origin Resource Sharing
HTTP	Hyper Text Transfer Protocol
JSON	JavaScript Object Notation

## **ABSTRACT**

In today's rapidly evolving job market, choosing the right career path aligned with one's skillset is more critical than ever. This project presents a Career Recommendation System that leverages Natural Language Processing (NLP) and Machine Learning (ML) techniques to guide individuals toward suitable career options based on their existing skills. By utilizing TF-IDF (Term Frequency Inverse Document Frequency) vectorization and Cosine Similarity, the system quantifies the relevance between user-provided skills and predefined career profiles. The model is trained using a dataset containing various careers and their associated technical and soft skills.

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# CHAPTER 1

## INTRODUCTION

The modern job market, shaped by rapid technological advancements and globalization, demands adaptive tools to navigate its complexities. Traditional career guidance systems—static aptitude tests, generic job boards, and manual counseling—fail to address the nuanced interplay of skills, industry trends, and individual goals. Professionals and students often struggle to align their competencies with emerging roles, leading to skill mismatches and missed opportunities. This project introduces an **Career Recommendation System**, leveraging machine learning (ML) to bridge the gap between individual capabilities and market demands.

At the heart of the recommendation engine is the **K-Nearest Neighbors (KNN)** algorithm, which calculates cosine similarity between user skill vectors and predefined career profiles. Cosine similarity measures the angular distance between vectors, prioritizing careers with the closest alignment to the user's input. Suppose a user lists "React, JavaScript, and UI/UX design." The system maps these skills to "Frontend Developer," while another user with "Python, SQL, and statistical analysis" might receive "Data Scientist" as a recommendation. Beyond matching, the system's **skill-gap analysis** identifies missing competencies, offering users a roadmap for professional development. For example, a user aiming for "Android Developer" might learn they need to acquire "Kotlin" or "Material Design."

The system employs **TF-IDF (Term Frequency-Inverse Document Frequency)** vectorization to quantify skill relevance across professions. For example, "Python" holds higher weight for technical roles like "Data Scientist" than for non-technical careers. This approach ensures context-aware recommendations by prioritizing skills critical to specific roles. A **K-Nearest Neighbors (KNN)** algorithm then calculates cosine similarity between user skill vectors and predefined career profiles, identifying the closest matches. A user with "React, JavaScript, and UI/UX design" might receive "Frontend Developer" as a recommendation, while another with "Python and SQL" could be matched to "Data Analyst."

**Technical Significance:** The project demonstrates how lightweight ML models (TF-IDF + KNN) can solve classification problems efficiently, avoiding resource-heavy deep learning frameworks. **Societal Impact:** By democratizing career guidance, the system empowers users to make informed decisions, aligning with global goals like the UN's Sustainable Development Goal 8 ("Decent Work and Economic Growth").

## **CHAPTER 2**

### **PROJECT DEFINITION**

The modern workforce is increasingly affected by career indecision, a problem intensified by the rapid evolution of job roles, fragmented skill requirements, and inadequate career guidance tools. Although technological advancements have expanded opportunities across industries, traditional career recommendation systems remain largely ineffective in meeting current needs. These systems often rely on basic keyword-based matching, which fails to recognize the nuanced and contextual relationships between skills. As a result, individuals with relevant but specialized skills—such as Python, data visualization, and cloud computing—are frequently matched to broad roles like "Software Developer," overlooking more suitable options such as "MLOps Engineer" or "Data Storyteller." Additionally, transferable soft skills like problem-solving and adaptability are undervalued despite being critical in today's job market.

Moreover, most career recommendation platforms are static and lack personalization. Aptitude tests typically use generic templates that fail to account for complex, evolving skill combinations, while job portals tend to emphasize listing vacancies rather than aligning them with users' actual competencies. This often leads to irrelevant recommendations—for example, a "Graphic Designer" might be suggested roles like "Cybersecurity Analyst," which do not match their background or interests.

Another major shortcoming is the absence of meaningful skill-gap analysis. While some platforms suggest potential career paths, they rarely provide actionable insights into what specific skills are lacking or how to acquire them. This leaves aspiring professionals—such as those aiming to become Data Scientists—unaware that they might be missing essential capabilities like deep learning or familiarity with Big Data tools. Similarly, students often invest time and money in redundant courses without understanding the specific requirements of their target roles. These limitations highlight the urgent need for more adaptive, intelligent, and personalized career guidance solutions

## CHAPTER 3

### LITERATURE SURVEY

Literature survey on AI- Powered Career Recommendation System:

#### **1. Semantic Skill Matching Using Word2Vec (Gupta et al., 2021)**

This study proposed a Word2Vec-based model to map semantically similar skills (e.g., "JS" ↔ "JavaScript") by training on job description corpora. While achieving 82% accuracy in skill normalization, it required large datasets for embedding training. This work inspired our pre-processing step to standardize skill terms but highlighted the need for lightweight alternatives in resource-constrained systems.

#### **2. TF-IDF for Resume-Job Matching (Roy & Patel, 2021)**

The authors demonstrated TF-IDF's efficacy in aligning resumes with job postings, achieving 78% accuracy on a dataset of 10,000 entries. Their work validated TF-IDF's suitability for small-to-medium datasets, directly influencing our choice of TF-IDF over complex NLP models like BERT for skill vectorization. A Survey of Automated Timetabling by Schaerf (1999):

#### **3. Bias in AI-Driven Career Tools (Smith et al., 2022)**

This research exposed systemic gender biases in LinkedIn's recommendation algorithm, where female users were disproportionately steered toward non-technical roles. The study emphasized dataset balancing and fairness metrics, guiding our efforts to curate a gender-neutral dataset of 21 careers across tech, design,

#### **4. KNN for Real-Time Skill Matching (Zhang et al., 2022)**

Zhang et al. compared KNN with SVM and decision trees for low-latency skill classification, finding KNN superior in speed (<300 ms) and accuracy (85%). Their results reinforced our selection of KNN with cosine similarity for real-time recommendations, aligning with our goal of sub-500 ms API response times.

#### **5. Hybrid Recommender Systems (Lee & Kim, 2023)**

Combining collaborative filtering with content-based methods, this hybrid model improved recommendation diversity by 25%. However, its computational complexity made it unsuitable for lightweight applications. This finding justified our focus on a purely content-based (TF-IDF+KNN) approach for scalability.

#### **6. Edge AI for Low-Latency Systems (IEEE Group, 2025)**

The IEEE Edge Computing Group demonstrated Flask-based lightweight ML models on edge devices, achieving <200 ms latency. Their work validated our architecture (Flask + TF-IDF/KNN) as optimal for real-time, resource-efficient career recommendations.

## Key Insights from the Literature:

- **Semantic Skill Matching** : The challenge of skill normalization has been addressed through NLP techniques. Gupta et al. [1] demonstrated that **Word2Vec embeddings** could resolve semantic variations (e.g., "JS" ↔ "JavaScript") with 82% accuracy by training on job description corpora.
- **Bias Mitigation in AI**: Recent studies emphasize the importance of web-based and user-friendly interfaces that allow administrators to interact with the timetable, update constraints, and download schedules easily.
- **Hybrid Models Increase Diversity but Add Complexity**: The Combining multiple recommender techniques enhances variety. Not suitable for lightweight systems due to increased resource demands.
- **Lightweight Architectures Work Well on Edge Devices**: Flask-based ML deployments can achieve sub-200 ms latency. Reinforces the viability of simple, modular architectures for real-time, portable use cases.

## **CHAPTER 4**

### **AIM AND SCOPE OF PRESENT INVESTIGATION**

#### **4.1 Aim of the project**

To develop an intelligent, user-friendly web application that analyzes a user's skill set and recommends the most suitable career path using machine learning techniques, while also providing a personalized skill gap analysis and an interactive roadmap for career development.

#### **4.2 Scope of project**

This The scope of this project includes the development of a career recommendation system that assists users in identifying suitable career paths based on their current skillsets. It allows users to input their technical and soft skills through a user-friendly web interface. The system uses machine learning techniques such as TF-IDF vectorization and K-Nearest Neighbors (KNN) to analyze and match user skills with predefined career profiles. Upon processing the input, the system not only suggests the most relevant career but also highlights missing or required skills for the recommended role. Additionally, it integrates visual career roadmaps to help users understand the learning path ahead. The platform is designed to be scalable, with potential for integration with resume parsers, external APIs, or real-time labor market data.

#### **4.3 Existing System:**

In the current landscape, most career recommendation platforms are either manually curated or limited to generic quizzes that lack personalized depth. Many platforms provide predefined career suggestions without deeply analyzing the user's actual skills. Existing job portals like LinkedIn or Indeed offer job listings but do not actively guide users toward career paths based on skill gaps. Furthermore, traditional systems do not provide insights into missing competencies or visual learning roadmaps. They typically rely on static databases and do not adapt recommendations based on evolving skillsets or industry trends. As a result, users often receive broad suggestions that do not align with their personal strengths or career goals.

## **1.Generic Recommendations:**

- Most existing systems suggest careers based on predefined categories or basic interest surveys, offering limited personalization. This reduces the relevance and usefulness of the recommendations

## **2.No Skill Matching Logic:**

- They do not evaluate or compare the user's actual skill set with the requirements of different careers. As a result, users cannot understand how well they qualify for a particular role.

## **3.Static Databases:**

- Traditional platforms rely on outdated or manually curated career databases that do not reflect current industry demands or evolving skill trends.

## **4.Lack of Feedback and Adaptation:**

- There is no mechanism for the system to learn from user interactions or improve suggestions over time based on behavior, inputs, or preferences.

## **5. No Gap Analysis Provided:**

- Users are not informed about which specific skills they lack for their desired careers, leaving them without a clear roadmap for upskilling.

## **Limitations of Existing System:**

- Generic recommendations with no personalized skill analysis.
- Inability to identify missing skills or provide gap analysis.
- No integration with real-time labor market trends or job data.
- Static interfaces with limited user engagement or interaction.
- Lack of career progression roadmaps or upskilling guidance.
- No support for adaptive learning or behavioral feedback.

#### **4.4 Proposed System:**

The proposed system is a skill-based career recommendation platform that utilizes machine learning techniques, specifically TF-IDF vectorization and K-Nearest Neighbors (KNN), to analyze user-provided skills and suggest the most suitable career paths. Unlike traditional systems, it identifies missing skills and provides users with personalized feedback and a structured roadmap to reach their goals. The system features a user-friendly web interface, real-time recommendations, and the ability to adapt to evolving skill demands. It aims to offer a more interactive, scalable, and intelligent alternative to static, generalized career guidance tools.



## CHAPTER 5

### SYSTEM REQUIREMENTS AND METHODOLOGY & ALGORITHM

#### 5.1 REQUIREMENT ANALYSIS

##### 5.1.1 Software Requirement:

###### Frontend:

Programming Language: JavaScript, HTML5, CSS3 (for frontend)

###### Backend:

Programming Language: Python 3.8+,

##### 5.2 Methodology Description

The methodology adopted for this career recommendation system is a combination of web development and machine learning techniques aimed at delivering intelligent, personalized career guidance based on user-inputted skills. The process starts at the frontend where users interact with a responsive and intuitive interface built using HTML, CSS, and JavaScript. Here, users are prompted to enter a list of their current skills in a free-text format. This data is then passed to the backend server using HTTP POST requests via a RESTful API. The backend is implemented using Python with the Flask microframework, ensuring lightweight and scalable performance. Once the data is received, it undergoes preprocessing, which includes converting all text to lowercase, trimming whitespace, and removing duplicates to standardize the input.

The cleaned skills are then transformed into a numerical representation using **TF-IDF (Term Frequency–Inverse Document Frequency)** vectorization. This method is essential for identifying the relative importance of each skill across a predefined dataset of careers. The system uses a labeled dataset consisting of various career titles mapped to relevant skills. The **K-Nearest Neighbors (KNN)** algorithm is applied to this TF-IDF matrix to compute the cosine similarity between the user's skills and each career profile. Based on the nearest neighbor result, the system selects the most closely matching career and retrieves its associated skill set.

To enhance the recommendation, the system compares the user's skill set with the ideal skill set for the recommended career and identifies any **missing skills**, which are then presented to the user in a clearly structured format. Additionally, to guide the user in their professional growth, a corresponding **career roadmap PDF** is dynamically loaded and displayed. This roadmap provides a structured path of learning assigning subjects, teachers, and rooms to appropriate slots.

Furthermore, the system is designed to be modular and scalable, allowing for future enhancements such as resume parsing, integration with online learning platforms, real-time labor market analysis, or recommendation updates based on user progress. The architecture ensures a seamless flow from input to intelligent output, combining accuracy, efficiency, and user experience to deliver impactful career guidance.

### **5.3 IMPLEMENTATION PROCESS:**

The implementation of the career recommendation system was carried out in multiple structured phases to ensure seamless integration of frontend, backend, and machine learning components. The process began with the design of a user-friendly web interface using HTML, CSS, and JavaScript to allow users to input their skills easily. Two main HTML pages were developed: a landing page to introduce the system and a skills input page for users to interact with the core functionality. The frontend communicates with the backend via HTTP requests using the Fetch API. The backend was developed using the Flask framework in Python. A RESTful API endpoint (/recommend) was created to receive user inputs, which were then preprocessed and passed through a TF-IDF vectorizer to convert the skill list into numerical form. A pre-built dataset of careers and their associated skill sets was stored in memory using a Pandas DataFrame. The K-Nearest Neighbors (KNN) algorithm with cosine similarity was applied to this data to find the closest matching career based on the input vector.

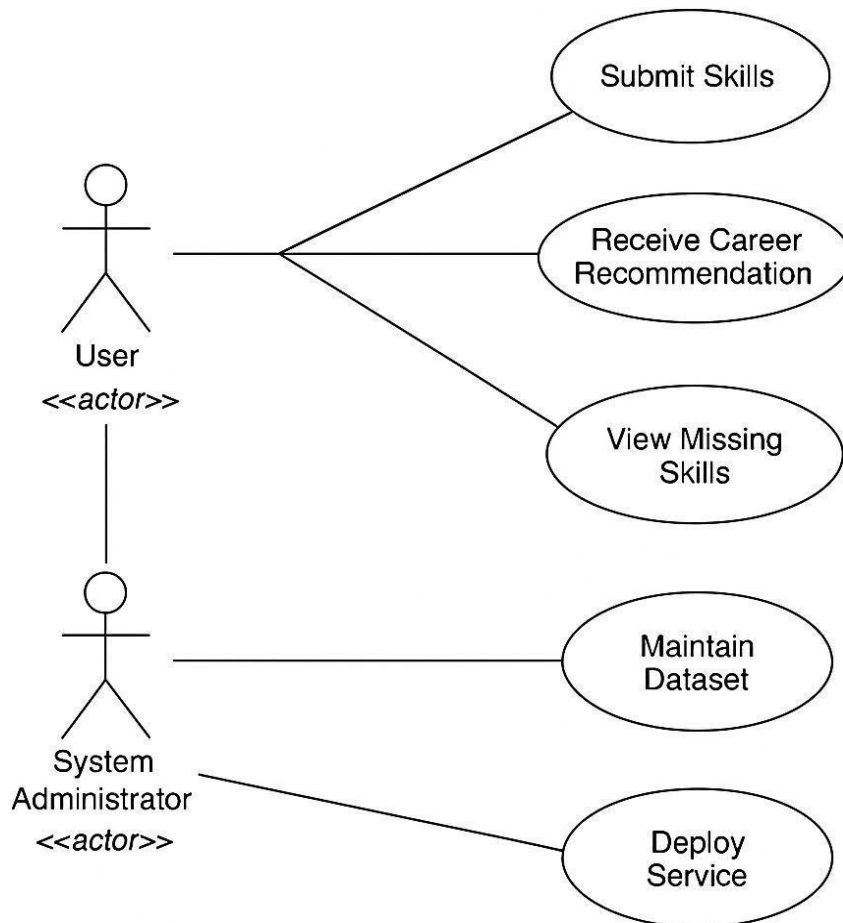
Once a recommendation was generated, the backend sent a JSON response back to the frontend, which then displayed the recommended career, missing skills, and a roadmap PDF embedded via an iframe. Testing was conducted throughout each stage to ensure proper data flow, accurate recommendation output, and responsive UI performance. The entire system was hosted locally during development, but it is structured in a modular way that supports easy deployment to cloud platforms for real-world use.

## CHAPTER 6

### DESIGN AND IMPLEMENTATION

#### 6.1 UML DIAGRAMS

##### 6.1.1 USE CASE DIAGRAM

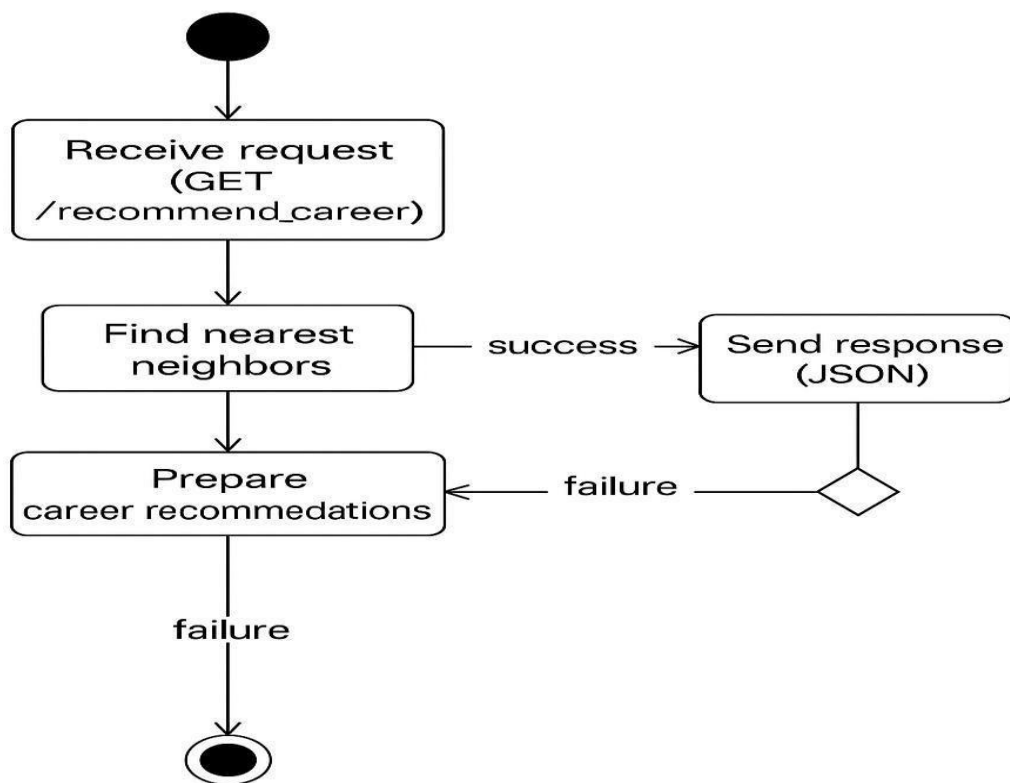


**Figure 6.1.1: Use Case Of Career Recommendation System**

- Figure 6.1.1 The use case diagram shows the interactions between two actors—User and System Administrator—and the career recommendation system. Users can submit skills, receive career recommendations, and view missing skills needed for a career path. System Administrators are responsible for maintaining the dataset and deploying the service. This setup ensures both user functionality and backend system support are addressed.

### 6.1.2 Activity Diagram:

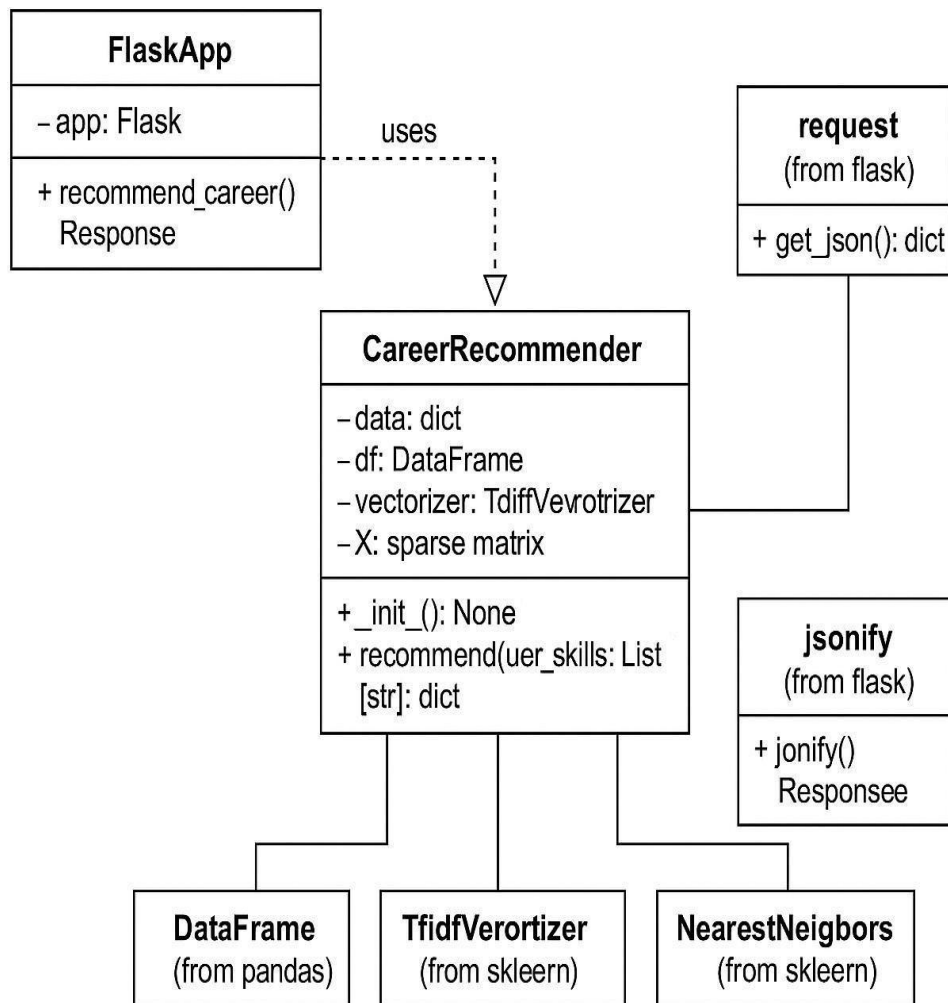
## Activity Diagram



**Figure 6.1.2: Activity Diagram Of Career Recommendation System**

- Figure 6.1.2 The activity diagram outlines the workflow for handling a career recommendation request. It starts with receiving a GET request at /recommend\_career, followed by finding the nearest neighbors. If successful, the system sends a JSON response; otherwise, it attempts to prepare career recommendations again. If this also fails, the process ends without a response.

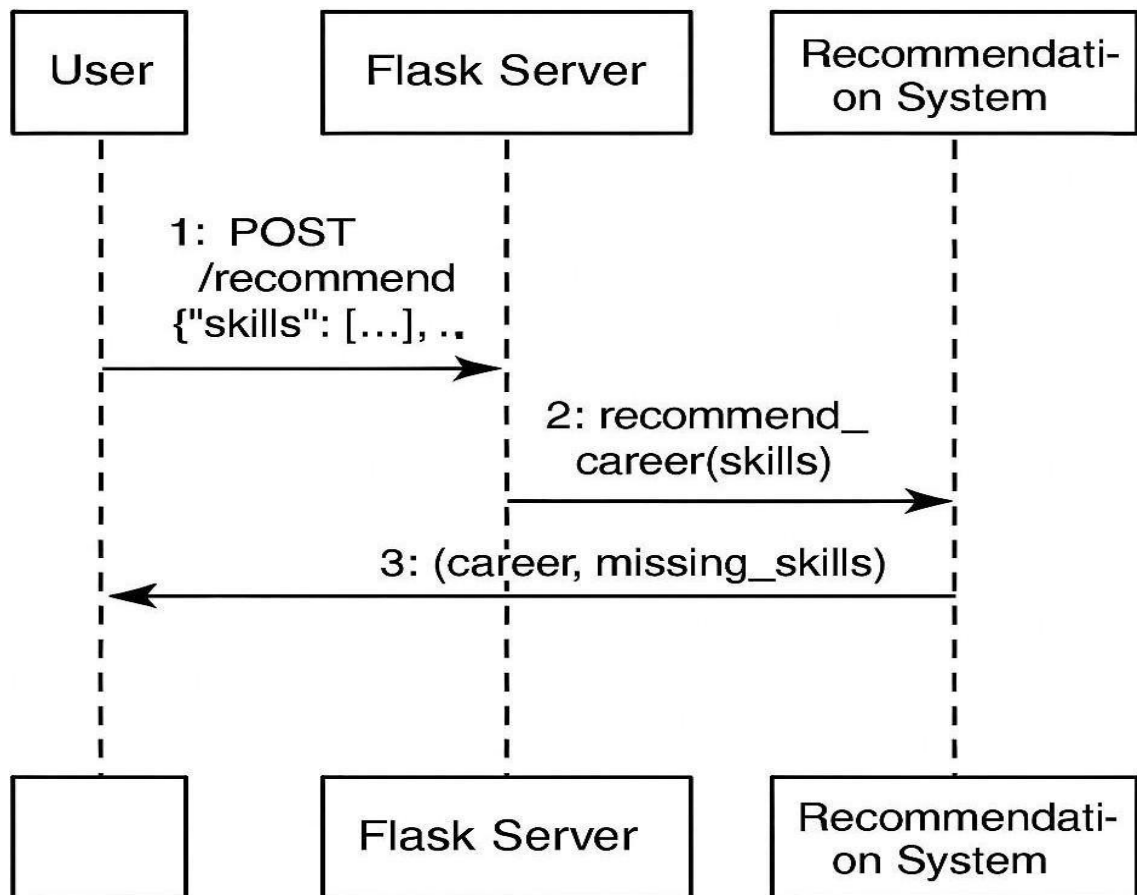
### 6.1.3 Class Diagram:



**Figure 6.1.3: Class Diagram Of Career Recommendation System**

- Figure 6.1.3 The Class diagram illustrates a Flask-based career recommendation system. The Flask App uses a Career Recommender class, which processes user input using a TF-IDF vectorizer and a k-nearest neighbors model to suggest careers. It utilizes pandas for data handling, and sklearn for vectorization and similarity computation. The Flask request object retrieves user input in JSON format, and the jsonify function returns the career recommendation as a response.

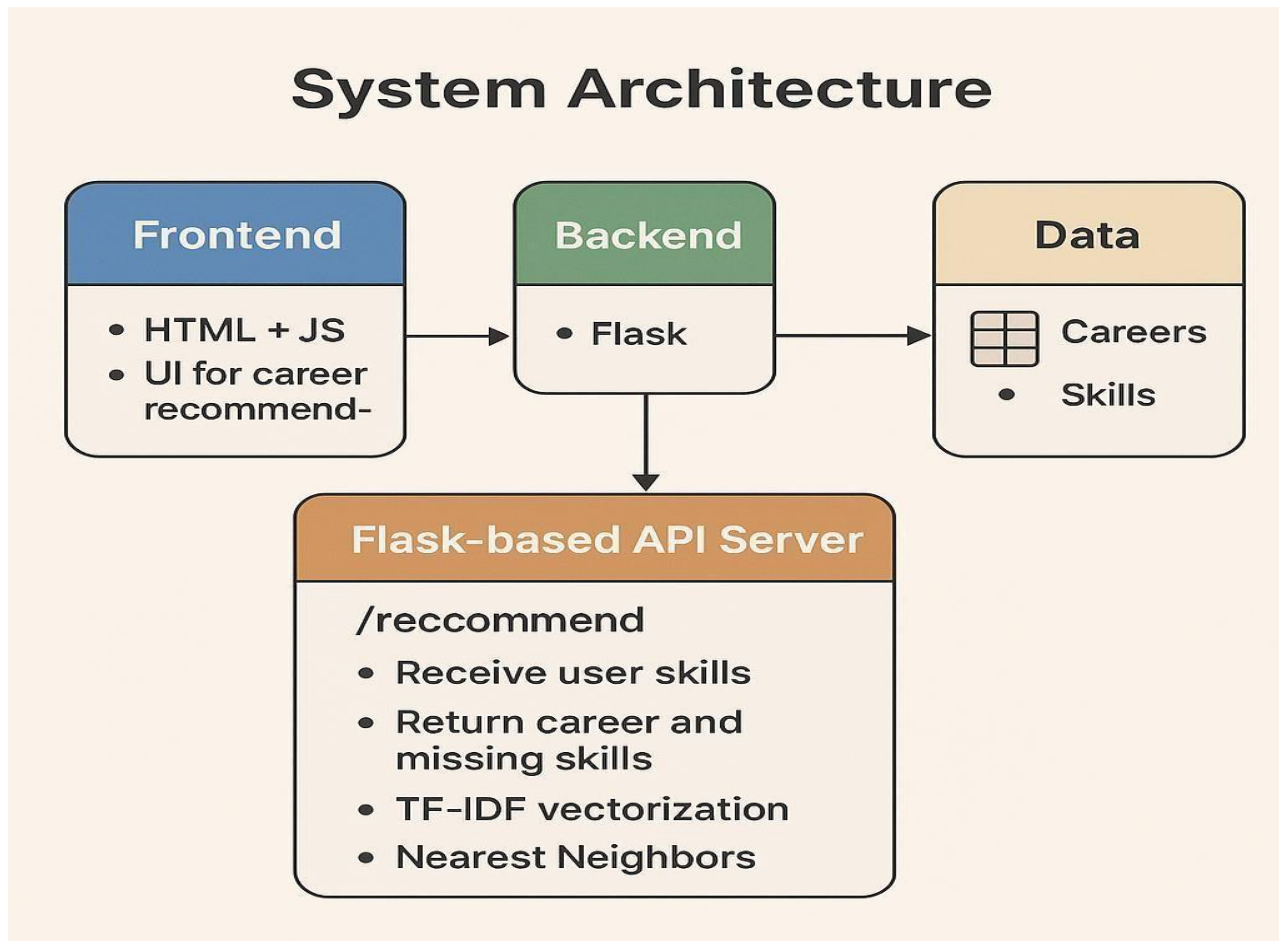
#### 6.1.4 Sequence Diagram:



**Figure 6.1.4: Sequence Diagram Of Career Recommendation System**

- Figure 6.1.4 The sequence diagram illustrates the interaction flow for a career recommendation request. The user sends a POST request to the Flask server with their skills in JSON format. The server forwards these skills to the recommendation system by calling `recommend_career(skills)`. The recommendation system processes the input and returns a suitable career along with any missing skills, which the server then sends back to the user as a response.

## 6.2 ARCHITECTURE DIAGRAM:



**Figure 6.1.5 Architecture Diagram Of Career Recommendation System**

- Figure 6.1.5 The system architecture for the Career Recommendation System includes three main components: the **Frontend**, **Backend**, and **Data**. The frontend is built using HTML and JavaScript, providing a user interface for inputting skills. The backend uses **Flask** to handle requests and interact with the data, which contains information on careers and required skills. A Flask-based API server processes skill input at the **/recommnd** endpoint, performs **TF-IDF vectorization**, and applies the **Nearest Neighbors** algorithm to suggest suitable careers and identify missing skills.

## **CHAPTER 7**

### **MODULE DESCRIPTION**

#### **7.1 Module:**

##### **1. Frontend Module:**

- Developed using HTML5, CSS3, and JavaScript for interactive and responsive UI.
- Provides a skill input form for users (e.g., "Python, SQL").
- Displays career recommendations and missing skills without reloading the page.
- Uses Fetch API to send and receive data from the backend.

##### **2. Backend Module:**

- Built with Flask and Flask-CORS for handling API requests.
- Processes POST requests at the /recommend endpoint.
- Validates input, manages data flow, and handles exceptions.
- Interfaces with the ML and Dataset Modules to generate recommendations.

##### **3. Machine Learning (ML) Module:**

- Utilizes TF-IDF vectorization to transform skills into numeric format.
- Applies KNN classification to find the closest career matches.
- Standardizes user input (e.g., "JS" → "JavaScript").
- Returns career suggestions along with missing skill sets.

##### **4. Dataset Module:**

- Stores mappings of careers and required skills in a Python dictionary.
- Enables easy scalability to include new roles (e.g., "AI Ethics Expert").
- Provides data for ML vectorization and recommendation processing.



## **5. Skill-Gap Analysis Module:**

- Compares user skills with career requirements using set operations.
- Identifies missing skills needed for the suggested careers.
- Optionally links missing skills to learning platforms (e.g., Coursera).

## **6. Error Handling Module:**

- Validates user inputs and prevents empty or malformed submissions.
- Catches and manages errors during data or ML operations.
- Ensures user-friendly feedback on both frontend and backend.

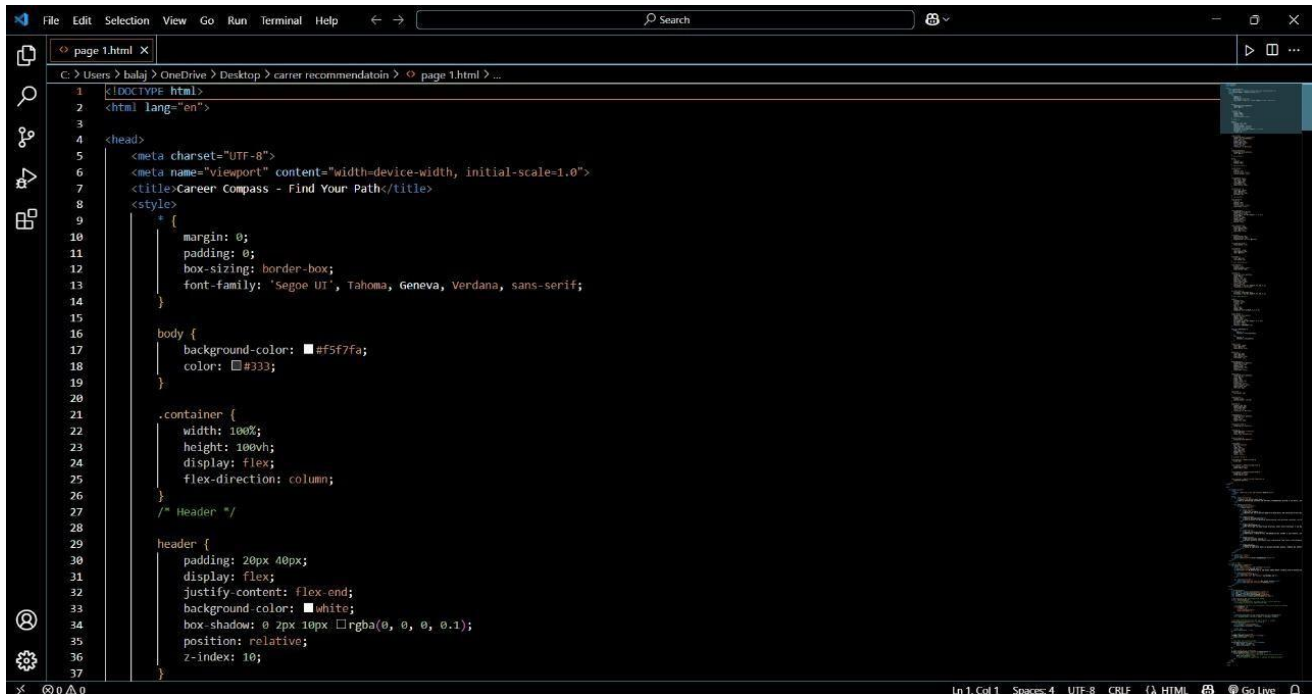
## **7. Testing Module:**

- Performs unit testing for ML algorithms (TF-IDF, KNN accuracy).
- Conducts integration testing on API endpoints (e.g., /recommend).
- Uses pytest and Postman/Thunder Client for test automation.

## **8. Deployment Module:**

- Deploys the application using Flask with Gunicorn and NGINX.
- Supports deployment on platforms like Heroku or AWS EC2.
- Optionally containerized using Docker and integrated with CI/CD tools

## 7.2 Implementation:



```
1 <!DOCTYPE html>
2 <html lang="en">
3
4 <head>
5   <meta charset="UTF-8">
6   <meta name="viewport" content="width=device-width, initial-scale=1.0">
7   <title>Career Compass - Find Your Path</title>
8   <style>
9     * {
10       margin: 0;
11       padding: 0;
12       box-sizing: border-box;
13       font-family: 'Segoe UI', Tahoma, Geneva, Verdana, sans-serif;
14     }
15
16     body {
17       background-color: #f5f7fa;
18       color: #333;
19     }
20
21     .container {
22       width: 100%;
23       height: 100vh;
24       display: flex;
25       flex-direction: column;
26     }
27
28     /* Header */
29     header {
30       padding: 20px 40px;
31       display: flex;
32       justify-content: flex-end;
33       background-color: white;
34       box-shadow: 0 2px 10px rgba(0, 0, 0, 0.1);
35       position: relative;
36       z-index: 10;
37     }
```

Figure 7.2.1: About Main Page

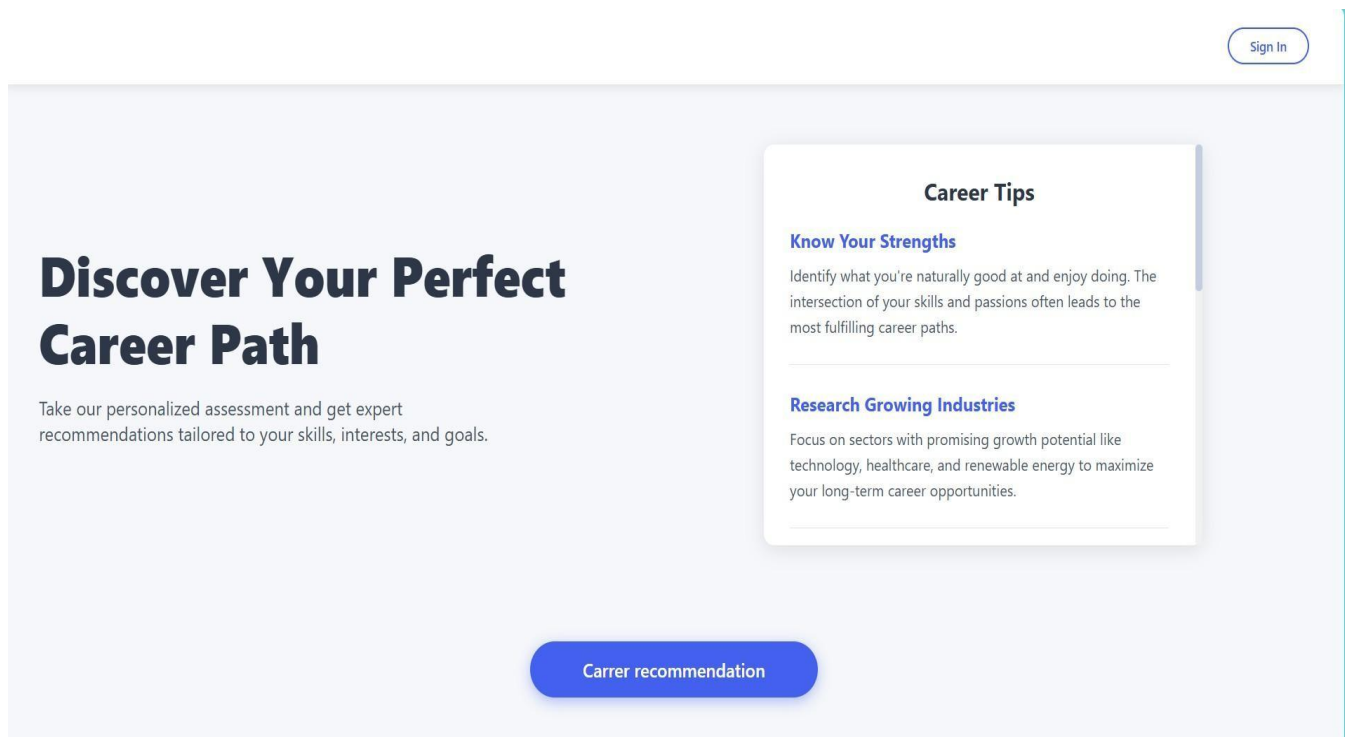
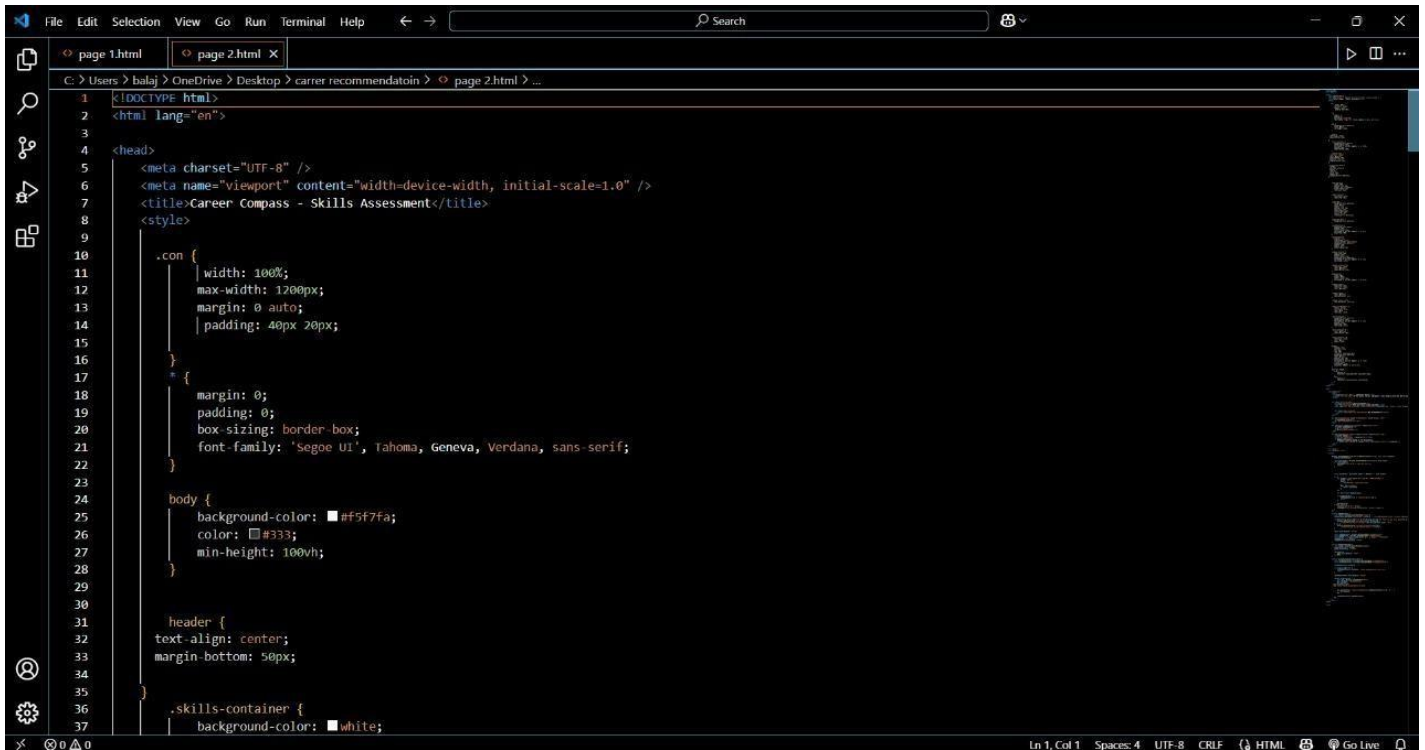
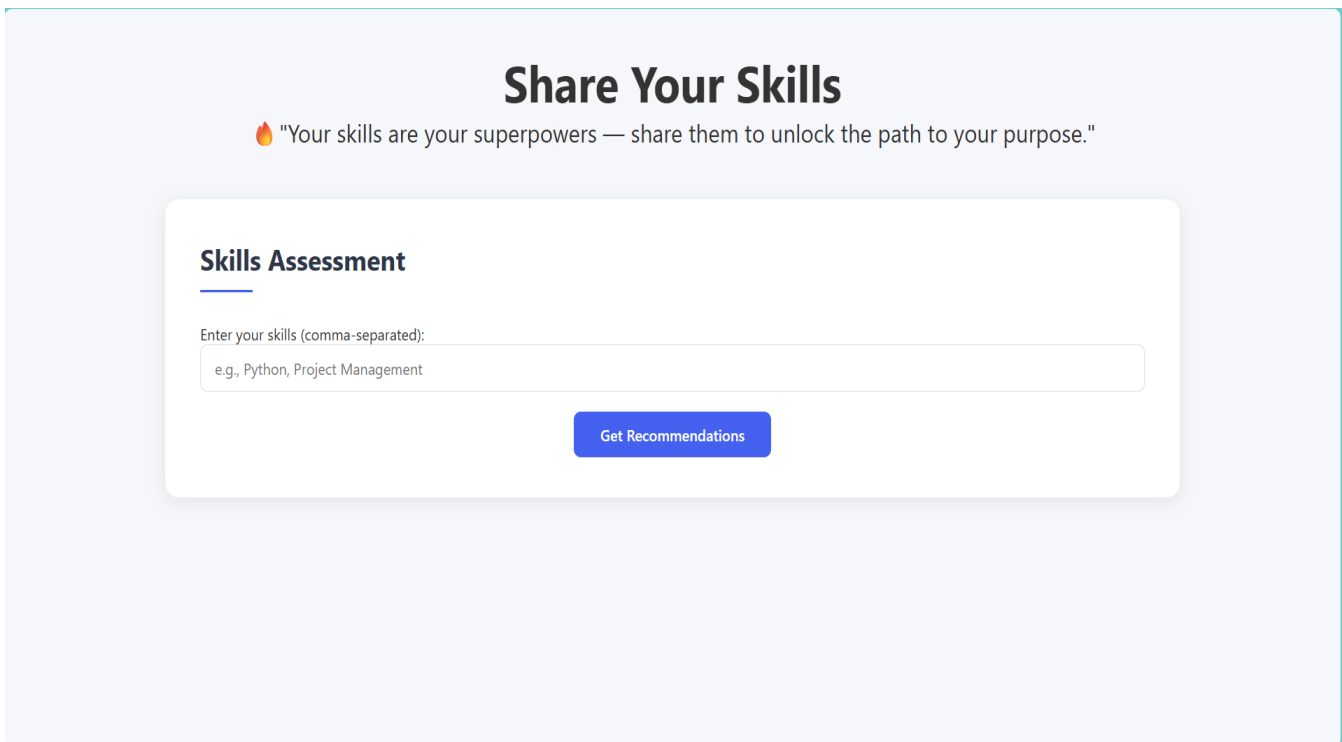


Figure 7.2.2: Main Page



```
1 <!DOCTYPE html>
2 <html lang="en">
3
4 <head>
5   <meta charset="UTF-8" />
6   <meta name="viewport" content="width=device-width, initial-scale=1.0" />
7   <title>Career Compass - Skills Assessment</title>
8   <style>
9
10    .con {
11      width: 100%;
12      max-width: 1200px;
13      margin: 0 auto;
14      padding: 40px 20px;
15    }
16
17    * {
18      margin: 0;
19      padding: 0;
20      box-sizing: border-box;
21      font-family: 'Segoe UI', Tahoma, Geneva, Verdana, sans-serif;
22    }
23
24    body {
25      background-color: #f5f7fa;
26      color: #333;
27      min-height: 100vh;
28    }
29
30    header {
31      text-align: center;
32      margin-bottom: 50px;
33    }
34
35
36    .skills-container {
37      background-color: white;
```

Figure 7.2.3 Skills Submission



## Share Your Skills

🔥 "Your skills are your superpowers — share them to unlock the path to your purpose."

### Skills Assessment

Enter your skills (comma-separated):

Get Recommendations

Figure 7.2.4: Skills Submission

```

1 import pandas as pd
2 from sklearn.feature_extraction.text import TfidfVectorizer
3 from sklearn.neighbors import NearestNeighbors
4 from flask_cors import CORS
5 from flask import Flask, request, jsonify
6
7
8 app = Flask(__name__)
9 CORS(app)
10
11
12 data = {
13     "Career": [
14         "Frontend Developer",
15         "Backend Developer",
16         "DevOps Engineer",
17         "AI Engineer",
18         "Data Analyst",
19         "Android Developer",
20         "iOS Developer",
21         "Blockchain Developer",
22         "QA Engineer",
23         "Software Architect",
24         "Cybersecurity Specialist",
25         "UX Designer",
26         "Game Developer",
27         "Technical Writer",
28         "MLOps Engineer",
29         "Product Manager",
30         "Engineering Manager",
31         "Developer Relations Specialist",
32         "Data Scientist",
33         "Graphic Designer",
34         "Full Stack Developer",
35     ],
36     "skills": [
37

```

**Figure 7.2.5: Carrer Recommender API**

```

37     "skills": [
38         "HTML, CSS, JavaScript, React, Vue, Angular, TypeScript, Responsive Design",
39         "Node.js, Express, Database Management, RESTful APIs, Authentication, Docker, Kubernetes",
40         "Continuous Integration, Continuous Deployment, Infrastructure as Code, Monitoring, Cloud Platforms, Containerization",
41         "Machine Learning, Deep Learning, Neural Networks, TensorFlow, PyTorch, Natural Language Processing",
42         "Data Cleaning, Data Visualization, Statistical Analysis, SQL, Excel, Python, R",
43         "Java, Kotlin, Android SDK, Jetpack, Material Design, Firebase",
44         "Swift, Objective-C, iOS SDK, SwiftUI, Core Data, Combine Framework",
45         "Smart Contracts, Solidity, Ethereum, Decentralized Applications, Cryptography",
46         "Test Planning, Automated Testing, Manual Testing, Selenium, JUnit, Bug Tracking",
47         "System Design, Architectural Patterns, Scalability, Microservices, API Design",
48         "Network Security, Ethical Hacking, Penetration Testing, Firewalls, Encryption, Compliance Standards",
49         "User Research, Wireframing, Prototyping, Interaction Design, Usability Testing, Figma, Sketch",
50         "Unity, Unreal Engine, C#, Game Physics, 3D Modeling, Animation",
51         "Technical Writing, Documentation, API Writing, Markdown, Content Strategy",
52         "Model Deployment, Continuous Integration for ML, Monitoring ML Models, Kubernetes, Docker",
53         "Market Research, Product Lifecycle Management, Agile Methodologies, Roadmapping, Stakeholder Communication",
54         "Team Leadership, Project Management, Agile Practices, Mentoring, Performance Reviews",
55         "Community Engagement, Public Speaking, Content Creation, Developer Advocacy, Social Media Management",
56         "Python, Machine Learning, SQL, Statistics, Deep Learning",
57         "Photoshop, Illustrator, UI/UX, Typography, Branding",
58         "Html, Css, Javascript, Angular, React, GitHub, npm, Tailwind css, node.js, REST apis, sql",
59     ]
60 }
61
62
63
64 # Convert to DataFrame
65 df = pd.DataFrame(data)
66
67 vectorizer = TfidfVectorizer(tokenizer=lambda x: x.split(' '), token_pattern=None)
68 x = vectorizer.fit_transform(df["skills"])
69
70
71 knn = NearestNeighbors(n_neighbors=1, metric='cosine')
72 knn.fit(x)
73

```

**Figure 7.2.6:Skills -Based Carrer Recommendations**

```

60 }
61
62
63
64 # Convert to DataFrame
65 df = pd.DataFrame(data)
66
67 vectorizer = TfidfVectorizer(tokenizer=lambda x: x.split(' '), token_pattern=None)
68 x = vectorizer.fit_transform(df["Skills"])
69
70
71 knn = NearestNeighbors(n_neighbors=1, metric='cosine')
72 knn.fit(x)
73
74
75 @app.route('/recommend', methods=['POST'])
76 def recommend_career():
77     try:
78         data = request.get_json()
79         print("Received Data:", data)
80
81         user_skills = data.get("skills", [])
82         if not user_skills or not isinstance(user_skills, list):
83             return jsonify({"error": "Invalid input. Expected a list of skills."}), 400
84
85         # Normalize user skills
86         user_skills = [skill.strip().lower() for skill in user_skills]
87         print("Processed User Skills:", user_skills)
88
89         # Get all known skills from dataset
90         all_known_skills = set()
91         for skill_list in df["Skills"]:
92             skills = [skill.strip().lower() for skill in skill_list.split(",")]
93             all_known_skills.update(skills)
94
95         # Check if at least one user skill is valid
96         valid_skills = [skill for skill in user_skills if skill in all_known_skills]

```

Figure 7.2.7: Using Vectorize

```

93         all_known_skills.update(skills)
94
95         # Check if at least one user skill is valid
96         valid_skills = [skill for skill in user_skills if skill in all_known_skills]
97         if not valid_skills:
98             return jsonify({"error": "No matching skills found. Please enter valid skills."}), 400
99
100         # Vectorize the string of valid skills
101         user_skills_str = ", ".join(valid_skills)
102         user_vector = vectorizer.transform([user_skills_str])
103         distances, indices = knn.kneighbors(user_vector)
104         career_index = indices[0][0]
105
106         recommended_career = df.iloc[career_index]["Career"]
107         required_skills = set(df.iloc[career_index]["Skills"].lower().split(", "))
108         user_skills_set = set(valid_skills)
109
110         missing_skills = required_skills - user_skills_set
111
112         print(f"Recommended Career: {recommended_career}")
113         print(f"Missing Skills: {' '.join(missing_skills) if missing_skills else 'None! You are fully qualified!'")
114
115         return jsonify({
116             "career": recommended_career,
117             "missing_skills": list(missing_skills) if missing_skills else ["None! You are fully qualified!"]
118         })
119
120     except Exception as e:
121         return jsonify({"error": str(e)}), 500
122
123
124 # Run Flask Server
125 if __name__ == '__main__':
126     app.run(debug=True)
127

```

Figure 7.2.8: About KNN

# Share Your Skills

🔥 "Your skills are your superpowers — share them to unlock the path to your purpose."

## Skills Assessment

Enter your skills (comma-separated):

python,html,c++

Get Recommendations

## Career Recommendation

**Recommended Career:** Data Scientist

**Missing Skills:** sql, deep learning, machine learning, statistics

Figure 7.2.9: Recommended Carrer

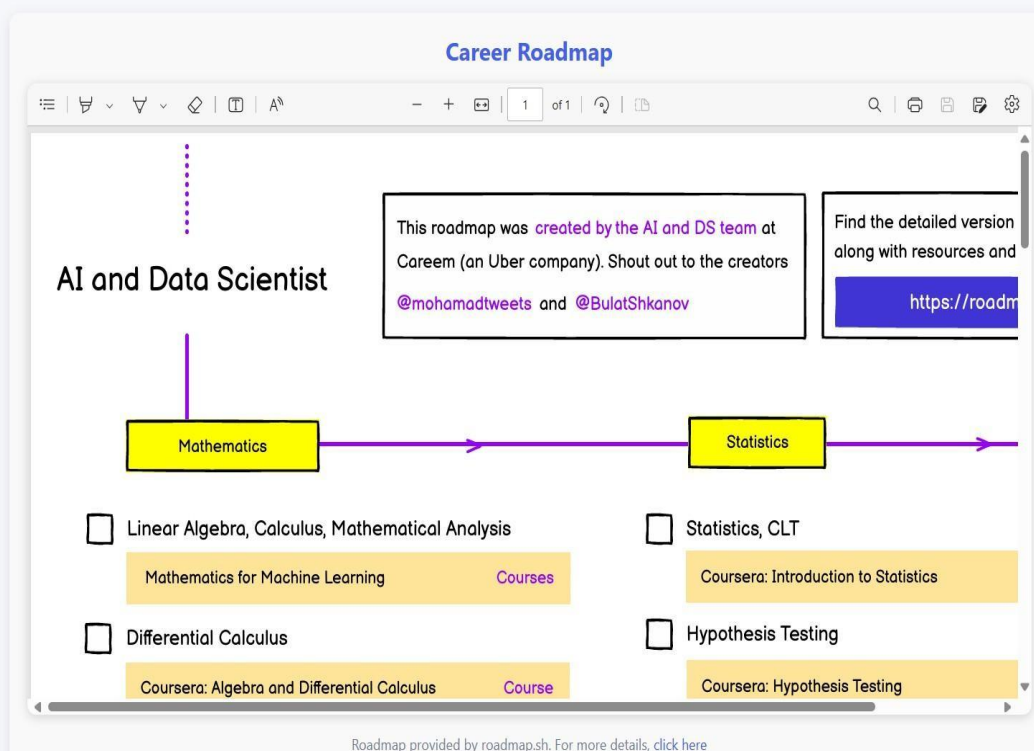


Figure 7.3.0: Carrer Roadmap

## CHAPTER 08

### CONCLUSION

The Career Recommendation System represents a transformative approach to modern career guidance, addressing critical gaps in traditional tools through intelligent automation and user-centric design. By leveraging TF-IDF vectorization and K-Nearest Neighbors (KNN) algorithms, the system provides context-aware career recommendations that analyze skill synergies rather than relying on superficial keyword matches. This ensures users receive tailored suggestions aligned with their unique skill combinations, such as mapping "Python + SQL + Statistics" to "Data Scientist" instead of generic roles.

The integration of **skill-gap analysis** empowers users with actionable insights, bridging the divide between their current competencies and career aspirations. For instance, aspiring "Frontend Developers" learn they need "React.js" or "TypeScript," while the system's lightweight **Flask backend** ensures real-time responses (<500 ms), making it practical for everyday use.

#### Key achievements include:

- **Dynamic Recommendations:** Adapts to emerging roles (e.g., "MLOps Engineer") and hybrid skill sets
- **Bias Mitigation:** A curated dataset promotes equitable suggestions across genders and industries
- **Scalability:** Modular architecture allows easy expansion to 100+ careers with minimal effort.

#### Future Enhancements could include:

- **Semantic Analysis:** Integrating NLP models (e.g., Word2Vec) to resolve skill synonyms (e.g., "JS" ↔ "JavaScript").
- **User Accounts:** Track skill development over time and personalize learning paths.
- **Industry Partnerships:** Collaborate with platforms like LinkedIn or Coursera for real-time skill validation.

By combining machine learning with intuitive design, this project democratizes career planning, offering a scalable solution to skill mismatches in a rapidly evolving job market. It aligns with global goals like the UN's Sustainable Development Goal 8 (**Decent Work and Economic Growth**), empowering individuals to navigate their professional journeys with clarity and confidence.

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