GIGRADAR: DISCOVER AND MANAGE FREELANCE JOBS WITH EASE

A MINI PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Freelancing platforms have become crucial for connecting freelancers with employers, providing flexible work opportunities across industries. Despite their growth, current platforms often suffer from generic job matching, limited skill development, and insecure payment handling. Freelancers struggle to find jobs aligned with their expertise, while employers face challenges in identifying the right talent. Additionally, payment disputes and insufficient project management tools detract from the overall experience. The proposed solution introduces AI-driven job matching to recommend personalized opportunities based on skills and experience. AI-powered resume parsing and skill gap analysis enhance freelancer profiles, while integrated escrow accounts ensure secure and transparent transactions. Dynamic pricing strategies, powered by AI, optimize freelancer rates according to market trends. The platform also includes community support systems, peer forums, and virtual events to foster collaboration. Comprehensive project management tools further streamline workflows, enabling freelancers and employers to achieve better outcomes in a more efficient and supportive environment.

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INTRODUCTION

1.1 GENERAL

Managing freelance job recommendations in today's competitive market often involves manual processes or generalized job platforms that do not cater to individual preferences or skills. Employers must manually search through countless profiles, while freelancers struggle to find matching opportunities that fit their expertise. This inefficient system can lead to suboptimal matches, lost opportunities, and wasted time. Additionally, there is no integrated system for personalized recommendations that consider the unique needs of both employers and freelancers.

1.2 NEED FOR THE STUDY

With the rapid expansion of the gig economy and the increased demand for specialized skills, a more efficient system for matching freelancers with relevant jobs is essential. Employers require tools that allow them to quickly find qualified candidates who match their preferred skill set, while freelancers need personalized job suggestions to enhance their visibility and career growth. The proposed GigRadar system automates these processes, making it simpler and faster to connect freelancers and employers, providing a seamless and effective job-matching experience.

1.3 OBJECTIVES OF THE STUDY

The objectives of this project are:

- To develop an AI-driven platform for matching employers with freelancers based on their skill sets and preferences.
- To ensure transparency by providing real-time updates to both employers and freelancers about job opportunities and matches.
- To implement a hybrid recommendation system that integrates collaborative filtering and content-based filtering for more accurate matches.

- To incorporate data visualization tools for analyzing matching trends and improving the overall recommendation process.

1.4 OVERVIEW OF THE PROJECT

Project Domain Overview

The focus of this project is on freelancing platforms, which serve as essential hubs in the gig economy by connecting freelancers with employers for project-based work. With the rise of online freelancing, these platforms have become critical for facilitating job discovery, project management, and secure payment processes. However, existing platforms often encounter challenges in delivering personalized job matching, secure transactions, and an optimized user experience, leading to various inefficiencies.

Freelancers frequently face difficulties in finding relevant opportunities, managing their workflow, and ensuring timely payments. Likewise, employers struggle to identify suitable talent and efficiently monitor project progress, which limits the overall effectiveness of current systems.

Proposed Solution: GigRadar

To address these challenges, the proposed system, GigRadar, leverages AI-driven job recommendations utilizing collaborative and content-based filtering. This approach enables personalized job suggestions for freelancers, enhancing their ability to find suitable work opportunities. GigRadar also incorporates a real-time messaging system and project management tools to facilitate streamlined interactions between freelancers and employers. These features collectively improve user experience and foster a more efficient, reliable, and user-friendly freelancing environment.

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION:

Freelance job matching and recommendation systems have been evolving to meet the increasing demand for more efficient, tailored, and automated solutions in the gig economy. Traditional job platforms often rely on basic search and filtering functions, which can result in suboptimal matches, miscommunication, and limited personalization. In recent years, the integration of machine learning and data analytics has greatly enhanced the capabilities of recommendation systems, allowing for more accurate matches and real-time updates for both job seekers and employers.

Several studies have focused on optimizing recommendation algorithms for freelance platforms, emphasizing collaborative filtering, content-based filtering, and hybrid methods. These advancements reduce manual effort, enhance decision-making, and improve user experience by providing personalized job and talent suggestions. This chapter reviews existing research on job recommendation systems, highlighting their frameworks, methodologies, and impacts on the freelance marketplace.

2.2 FRAMEWORK OF JOB MATCHING AND RECOMMENDATION SYSTEMS (JRS)

The Job Matching and Recommendation Systems (JMRS) framework is a structured approach for matching job seekers (freelancers) and employers based on a range of criteria. This framework has been implemented in various platforms to streamline and enhance the job search and hiring process. The JMRS framework typically involves the following stages:

2.2.1 Job/Project Submission by Employers: In the JMRS framework, employers submit job postings through a structured form that captures essential details, such as required skills, project duration, budget, and job description. Automated systems often validate the completeness of the data, preventing delays due to incomplete job listings.

2.2.2 Freelancer Profile and Skill Analysis: Freelancers create profiles that include their skills, past projects, and ratings. The system analyzes these profiles and generates skill vectors that can be compared with job requirements. This analysis is critical for content-based filtering, where the system matches freelancers to projects based on shared attributes.

2.2.3 Recommendation Generation – Content-Based Filtering: Content-based filtering algorithms analyze the skills and past experiences of freelancers to identify suitable job matches. This method utilizes techniques such as TF-IDF (Term Frequency-Inverse Document Frequency) to determine the relevance of a freelancer's profile to the job requirements. Real-time validation ensures that recommendations are updated dynamically as new jobs are posted or freelancer profiles are modified.

2.2.4 Collaborative Filtering for Personalized Recommendations: In addition to content-based filtering, collaborative filtering leverages user interaction data—such as past job engagements, ratings, and feedback—to suggest relevant opportunities. This method identifies patterns among employers and freelancers, using these insights to improve the accuracy ofrecommendations.

2.2.5 Hybrid Recommendation Systems: A hybrid system combines the strengths of both content-based and collaborative filtering. By integrating user preferences and profile similarities, hybrid systems overcome the limitations of each individual approach. This results in a more robust and personalized recommendation mechanism, which enhances the userexperience and increases engagement.

2.2.6 **Real-Time Notifications and Updates:** Automated notifications and alerts are essential for keeping both employers and freelancers informed of new job opportunities or applicant matches. This feature ensures efficient communication and reduces the need for manual follow-ups.

2.2.7 **Data Analytics and Reporting:** An integral component of the JMRS framework is data analytics. The system can generate detailed reports on job application trends, freelancer performance, and employer hiring patterns. These insights aid in decision-making, enable better resource allocation, and help employers refine their job postings for improved candidate matches.

CHAPTER 3: SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

The current process for matching freelancers with job opportunities is often manual and lacks personalization. Employers typically use generalized job platforms or personal networks to find freelancers, leading to inefficient and time-consuming searches. These platforms may not provide tailored matches based on specific skills or past work experiences, resulting in suboptimal job fits. Moreover, freelancers often struggle to identify jobs that align with their expertise, having to navigate through numerous postings with generic search tools. The absence of automated recommendations and personalized suggestions creates a gap in the efficiency of connecting employers and freelancers. This inefficiency can lead to missed opportunities, poor matches, and frustration for both parties.

3.2 PROPOSED SYSTEM

The proposed system, GigRadar, is an AI-driven freelance job matching platform designed to address the limitations of the current system. It combines collaborative and content-based filtering to create a robust, hybrid recommendation system. The platform provides separate interfaces for employers and freelancers, each tailored to their specific needs,

3.2.1 Employer Portal: Employers can create job postings with detailed skill requirements, project descriptions, and other relevant criteria. The system automatically analyzes these postings and provides suggestions for potential freelancers who match the requirements. Real-time notifications keep employers informed about applications and matching freelancers.

3.2.2 Freelancer Portal: Freelancers can build detailed profiles highlighting their skills, completed projects, and ratings. The platform uses this information to recommend jobs that align with their expertise and interests.Freelancers receive notifications for new job matches, allowing them to apply promptly.

3.2.3 Hybrid Recommendation Engine:

- **Content-Based Filtering:** Analyzes the skill sets of freelancers and compares them with job requirements using techniques like TF-IDF to create relevant matches.
- **Collaborative Filtering:** Utilizes past user interactions, such as job applications and ratings, to suggest jobs or freelancers based on patterns and preferences.

3.2.4 Multi-Level Job Matching Workflow: The platform includes a workflow that ensures comprehensive job and talent matching. Employers are provided with a ranked list of freelancers, and freelancers see job opportunities that best fit their profiles. Both sides receive real-time updates throughout the process.

3.2.5 Data Analytics and Reporting: The system incorporates analytics tools that allow employers to generate reports on job postings, freelancer responses, and hiring trends. Freelancers can review insights into their job application patterns, helping them optimize their profiles and apply strategically.

3.3 FEASIBILITY STUDY

A feasibility study was conducted to evaluate the proposed system's viability in terms of technical, operational, and economic factors:

3.3.1 Technical Feasibility: The system is built using widely accepted technologies, such as Python, Pandas, and machine learning libraries (e.g.,Scikit-learn, Surprise) for the backend, while employing modern frameworks for the user interface. These technologies support scalability and can handle simultaneous user interactions efficiently

3.3.2 Operational Feasibility: The system simplifies the job matching process for both employers and freelancers. Employers benefit from targeted freelancer recommendations, reducing the time spent on manual searches. Freelancers receive personalized job suggestions, improving their chances of securing work. The platform is user-friendly, with intuitive dashboards and automated notifications, ensuring that minimal training is required forusers to navigate the system effectively.

3.3.3 Economic Feasibility: The implementation of GigRadar is cost-effective, requiring moderate investment in development and maintenance. By automating and streamlining the job matching process, the system reduces the operational costs and administrative burdens associated with traditional methods. The platform's ability to deliver timely, precise matches adds value, making the investment worthwhile for employers and freelancers.

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 SOFTWARE REQUIREMENTS

The GigRadar platform uses modern technologies to ensure high scalability, performance, and efficiency, focusing on backend development, machine learning, and recommendation algorithms. The software requirements for the platform are as follows:

4.1.1 Backend:

- **Python:** Powers the backend logic, offering robust support for data processing, machine learning, and recommendation algorithms.
- **Scikit-learn:** A machine learning library in Python, used to implement content-based and collaborative filtering algorithms for accurate job recommendations.
- **Surprise:** A Python library designed for building and analyzing recommendation systems based on collaborative filtering.

4.1.2 Database:

- **MongoDB:** A flexible NoSQL database, suitable for managing freelancer profiles, employer job postings, and recommendations. Its document-based structure enables scalability and efficient data management.

4.1.3 Recommendation System:

- **TfidfVectorizer:** Used to process and analyze textual data in freelancer and job profiles for content-based filtering, allowing the system to match relevant jobs to freelancers.
- **SVD (Singular Value Decomposition):** Utilized in collaborative filtering to analyze user interactions and generate personalized recommendations based on past behavior.

4.1.4 Notification System:

- **Integration with APIs (such as SendGrid):** Enables real-time notifications, informing freelancers about new job matches and employers about freelancer applications.

4.1.5 Development Tools:

- **Jupyter Notebook:** Used for testing and fine-tuning machine learning algorithms and for data exploration.
- **Pandas:** A library for data manipulation and analysis, used for preprocessing freelancer and employer data.
- **NumPy:** A library for numerical operations, supporting data processing for machine learning tasks.
- **Visual Studio Code:** A code editor used for development, debugging, and version control.

4.1.6 Visualization Tools:

- **Matplotlib and Seaborn:** Libraries used for creating visualizations to analyze recommendation accuracy, user engagement, and matching trends.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

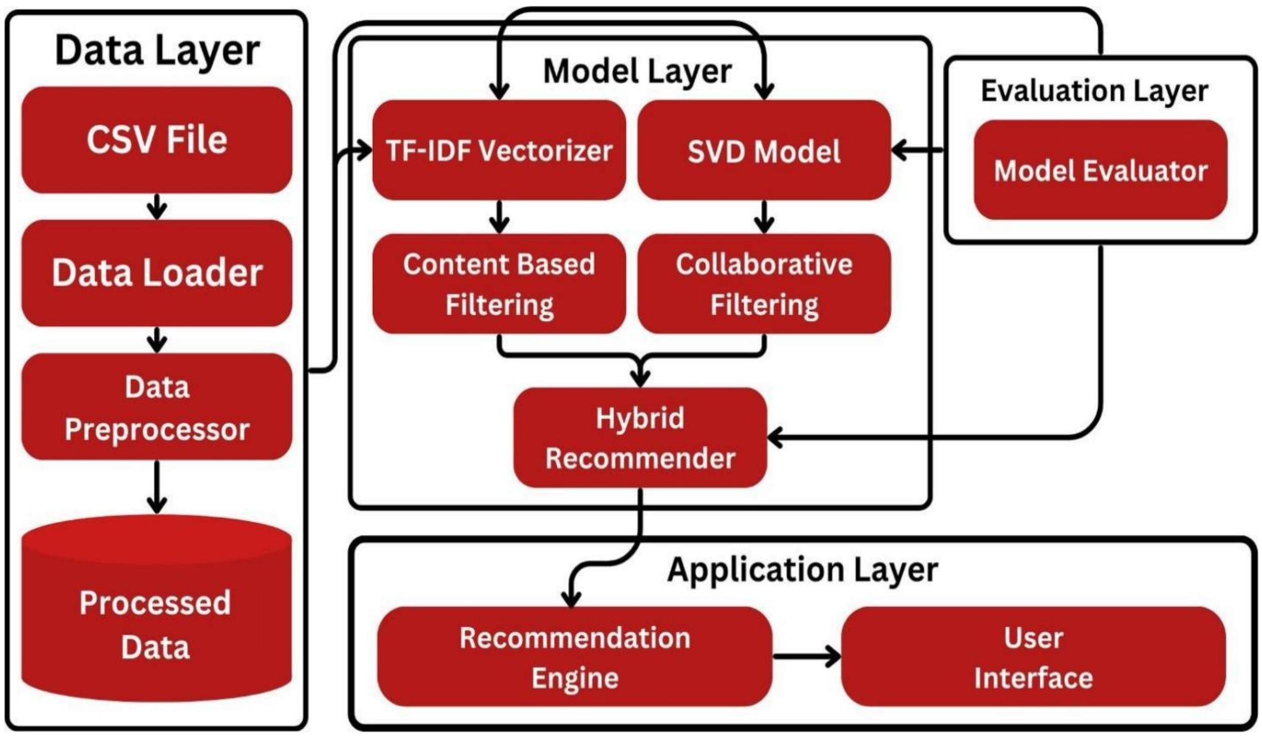


Fig : 5.1 SYSTEM ARCHITECTURE

The system consists of five main modules:

- **Data Loading and Preprocessing Module:** Handles data import, cleaning, and transformation to prepare it for analysis and recommendations.
- **Collaborative Filtering Module:** Generates personalized recommendations based previous user interactions.
- **Content-Based Filtering Module:** Matches freelancers and jobs by analyzing skills and job descriptions**.**

- **Hybrid Recommendation Module:** Combines the strengths of collaborative and content-based filtering for more accurate recommendations.
- **User Interface and Recommendation Generation Module:** Provides an intuitive interface for users to view and interact with recommendations.

5.2 MODULE DESCRIPTION

5.2.1. MODULE 1: DATA LOADING AND PREPROCESSING

This module is responsible for loading and preparing data for analysis. It performs the following functions:

- **Data Collection:** Imports freelancer and employer datasets, including skills, job requirements, and past interactions.
- **Data Cleaning:** Identifies and handles missing values, standardizes skill names, and removes duplicates.
- **Feature Extraction:** Extracts relevant features, such as skills, project history, and job descriptions, for use in the recommendation algorithms.

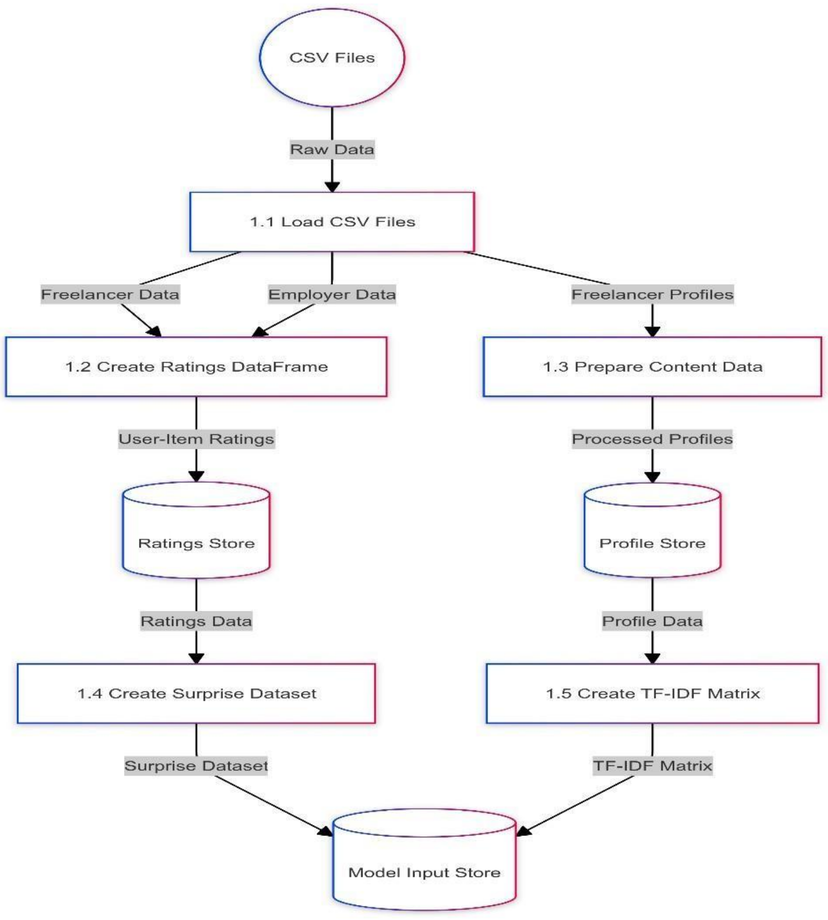


Fig 5.2 : DATA LOADING AND PREPROCESSING MODULE

5.2.2. MODULE 2: COLLABORATIVE FILTERING

This module generates personalized recommendations based on collaborative filtering techniques. It includes the following steps:

- **Interaction Matrix Creation:** Builds a user-item matrix based on employer-freelancer interactions.
- **Model Training:** Trains collaborative filtering algorithms (such as SVD) to identify patterns and similarities among users.

- **MRecommendation Generation:** Predicts potential matches by analyzing similar user preferences and past interactions.

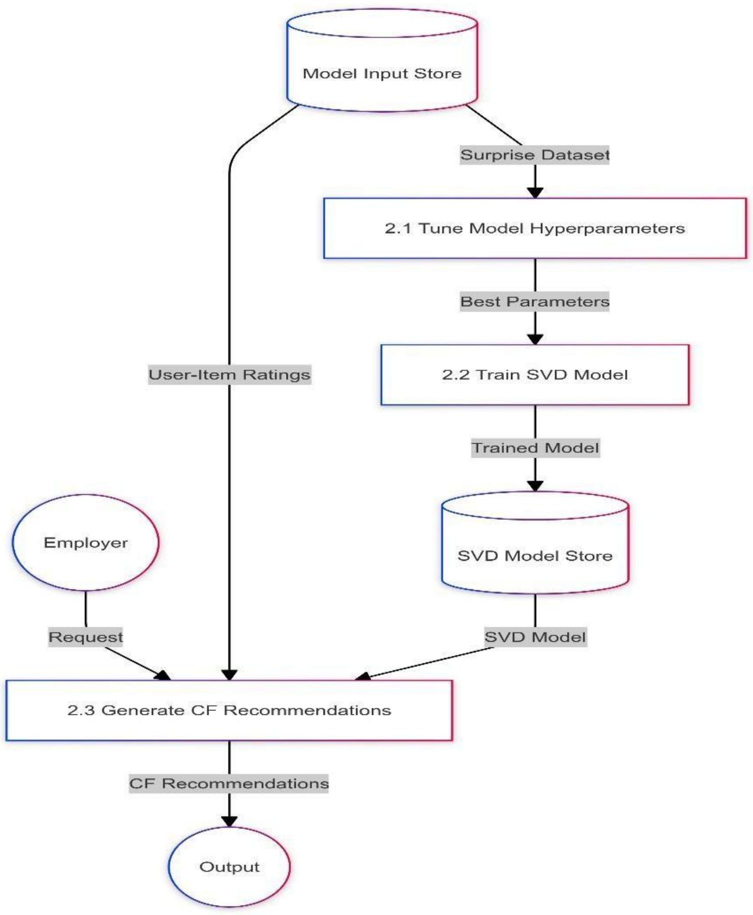


Fig 5.3 : COLLABORATIVE FILTERING MODULE

5.2.3. MODULE 3: CONTENT-BASED FILTERING

This module matches freelancers with job postings by analyzing content in their profiles and job descriptions. It performs the following tasks:

- **Profile Analysis:** Examines freelancer profiles and job requirements to identify relevant attributes and skills.
- **Skill Vectorization:** Converts skills and job descriptions into vectors using techniques like TF-IDF for similarity calculation.
- **Similarity Matching:** Calculates the similarity score between freelancers and jobs to recommend relevant opportunities.

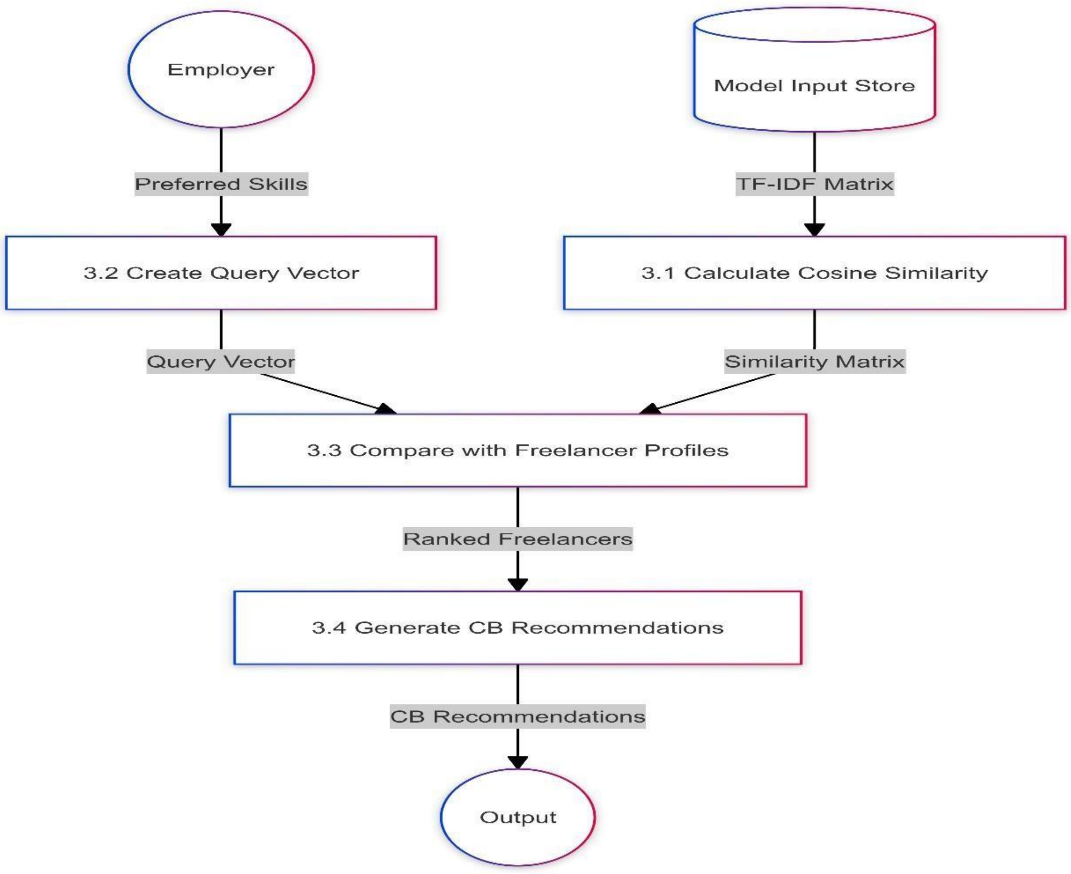


Fig 5.4 : CONTENT-BASED FILTERING MODULE

5.2.4. MODULE 4: HYBRID RECOMMENDATION

This module combines collaborative and content-based filtering for improved recommendation accuracy. It includes:

- **Weighted Combination:** Merges content-based and collaborative filtering results by assigning weights to each method.
- **Ranking and Selection:** Generates a ranked list of recommendations by prioritizing top matches from the combined scores.
- **Feedback Integration:** Incorporates user feedback to adjust the weights and improve future recommendations.

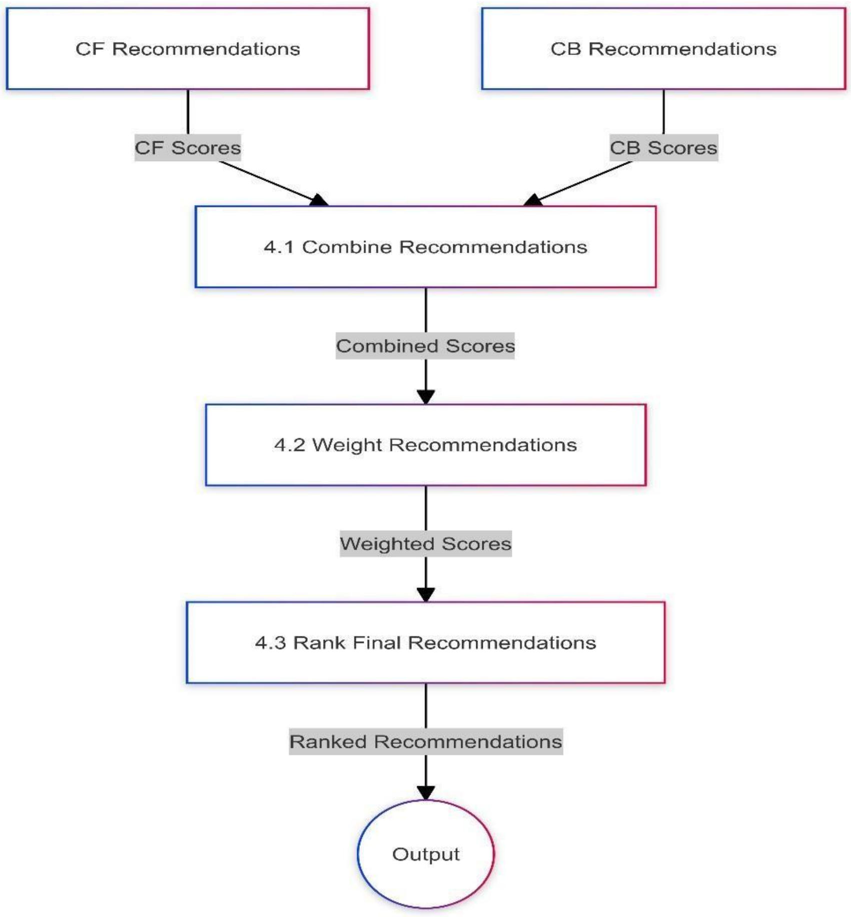


Fig 5.5 : HYBRID RECOMMENDATION MODULE

5.2.5. MODULE 5: USER INTERFACE AND RECOMMENDATION GENERATION MODULE

This module provides an interactive user experience, displaying recommendations and enabling feedback. It performs the following tasks:

- **Employer Dashboard:** Allows employers to post jobs, view recommended freelancers, and track applications.
- **Freelancer Dashboard:** Enables freelancers to update profiles, view job recommendations, and apply for relevant positions.
- **Real-Time Notifications:** Sends alerts to freelancers about new job matches and to employers about freelancer applications.

- **Feedback Collection:** Gathers user feedback on recommendations, helping refine the recommendation algorithms.

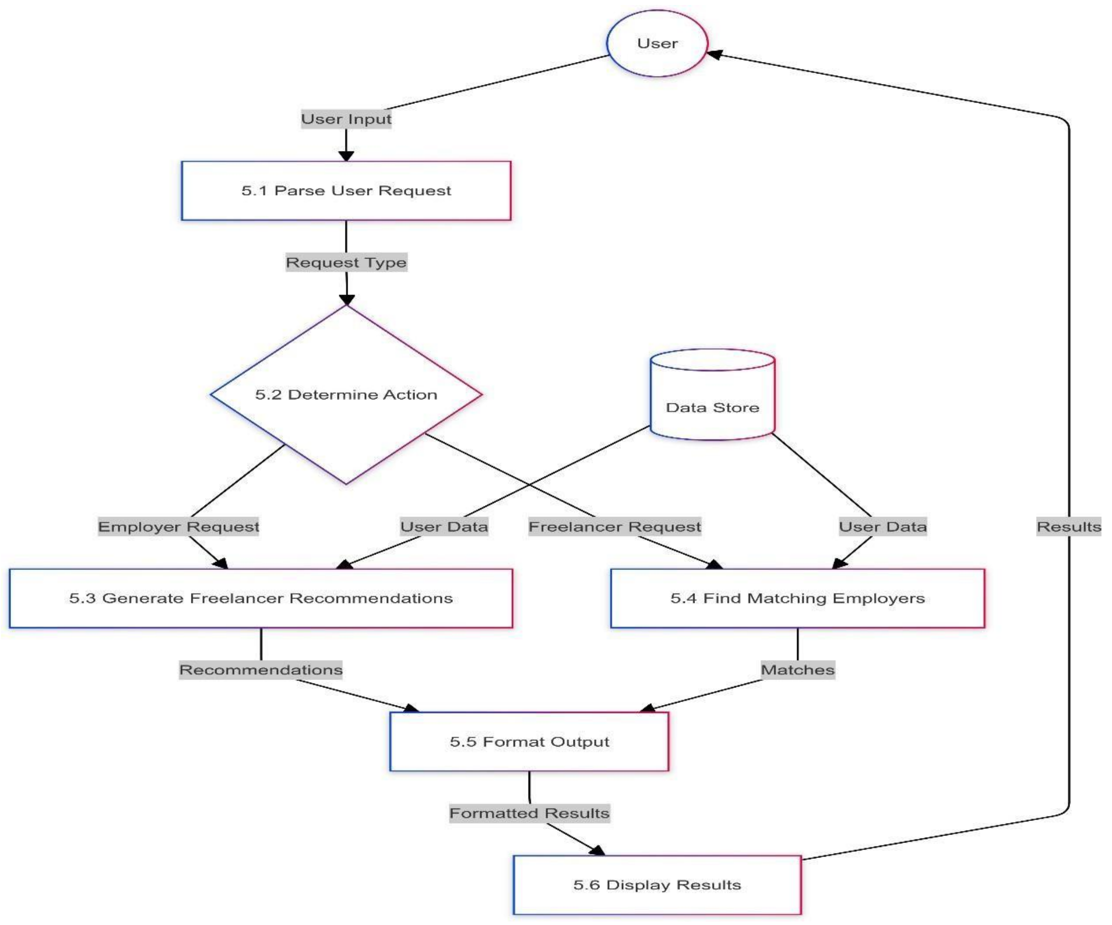
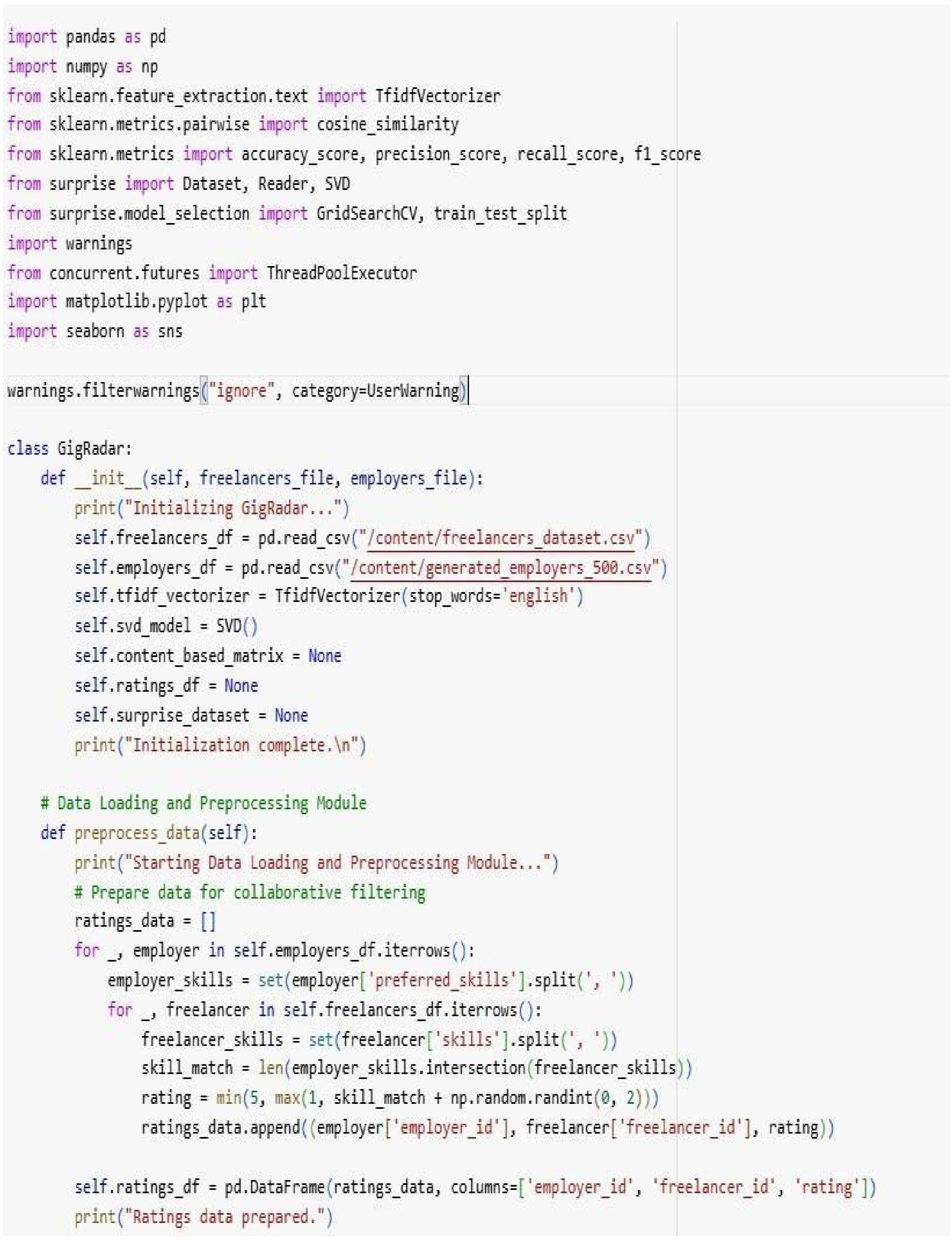


Fig 5.6 : USER INTERFACE AND RECOMMENDATION GENERATION MODULE

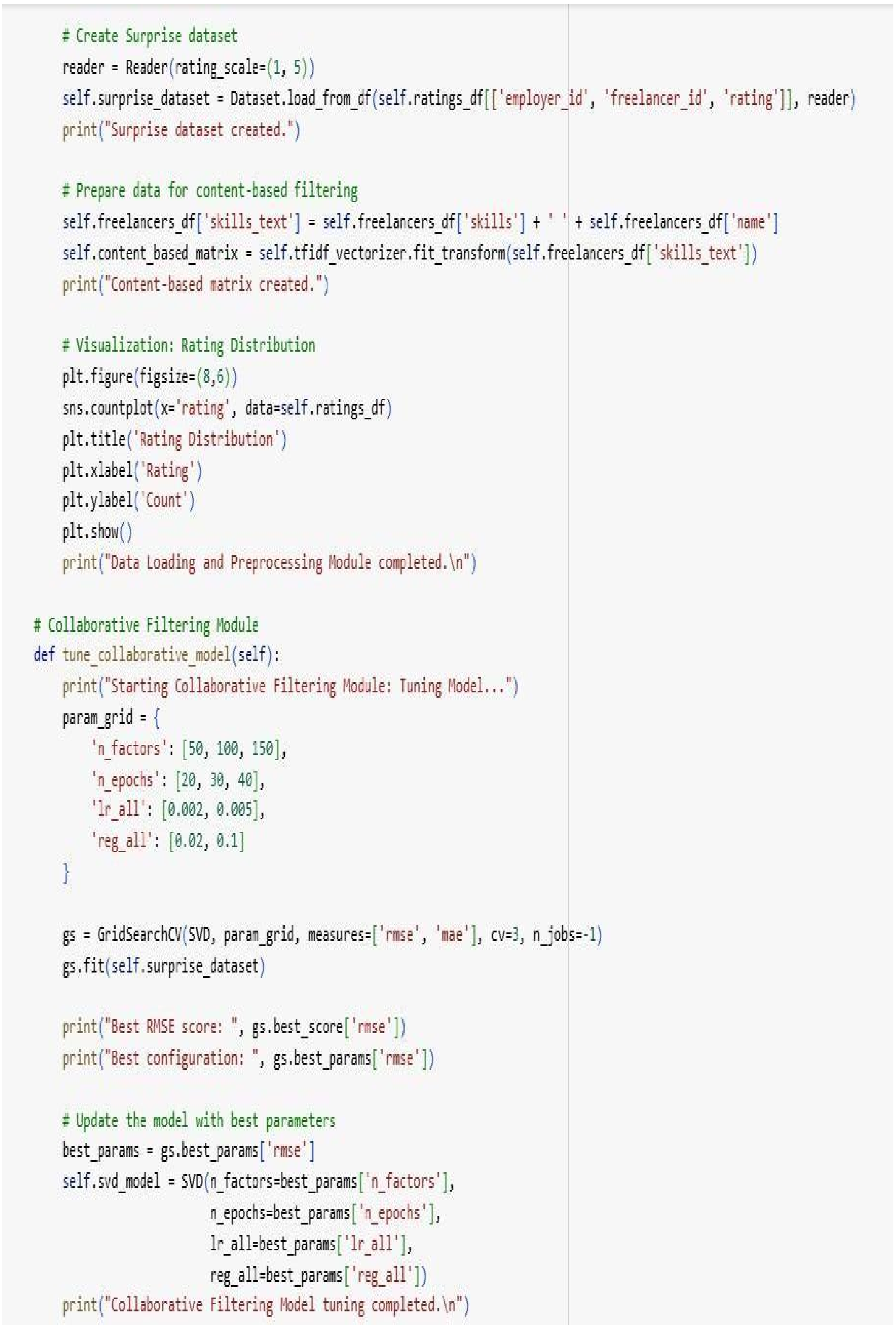
CHAPTER 6

SOURCE CODE

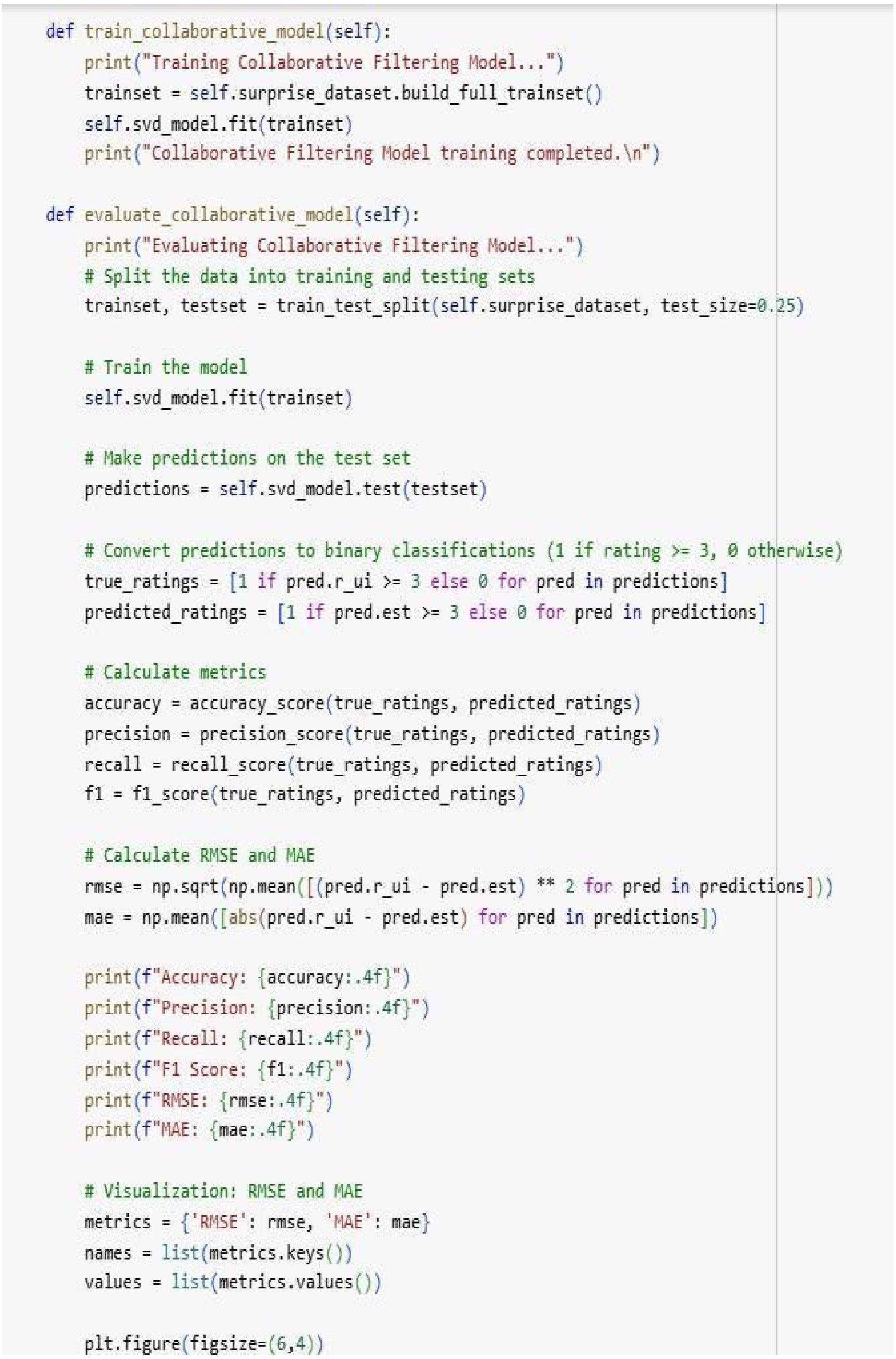
6.1 SOURCE CODE



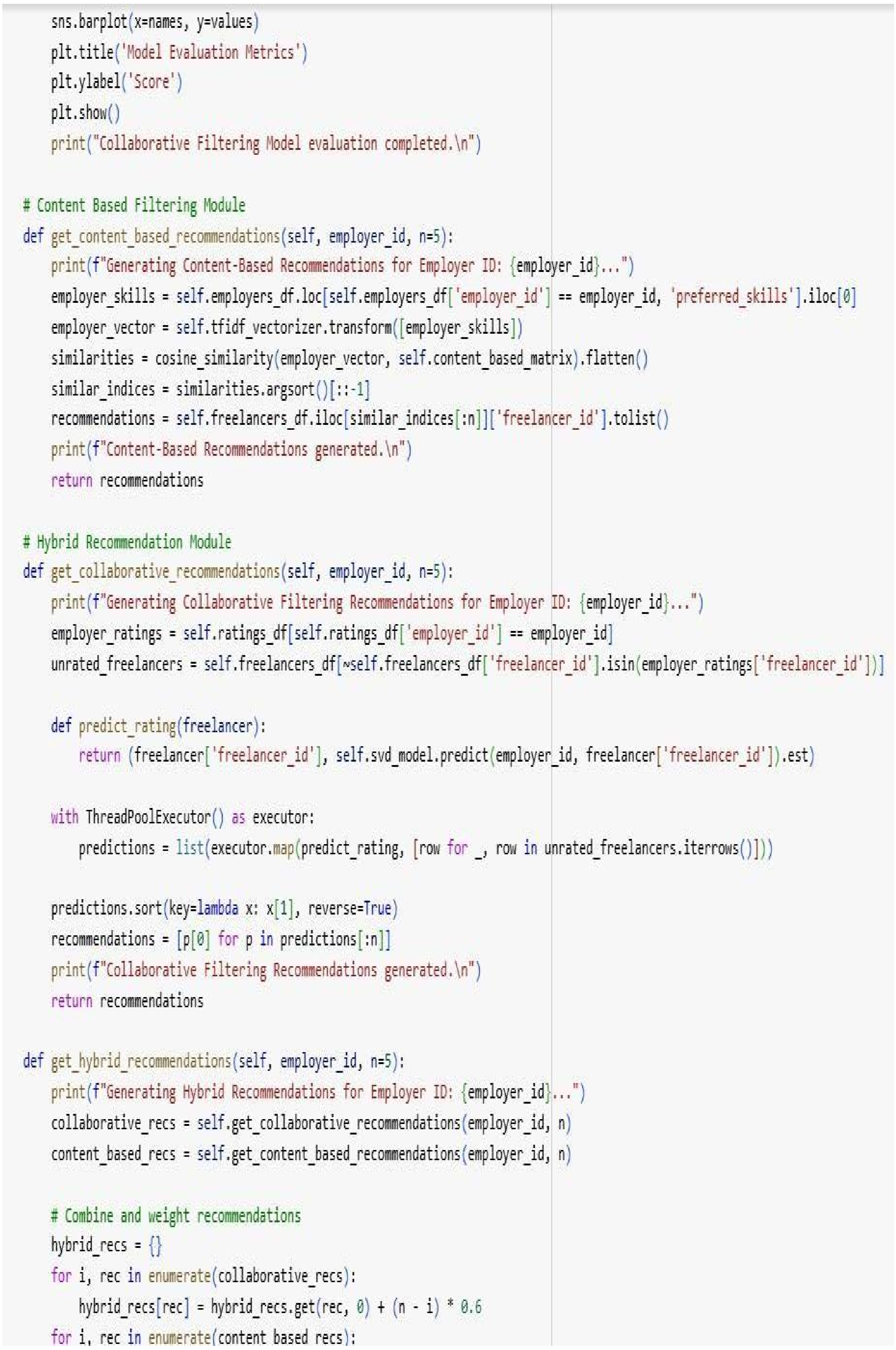
```python
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from surprise import Dataset, Reader, SVD
from surprise.model_selection import GridSearchCV, train_test_split
import warnings
from concurrent.futures import ThreadPoolExecutor
import matplotlib.pyplot as plt
import seaborn as sns

warnings.filterwarnings("ignore", category=UserWarning)

class GigRadar:
    def __init__(self, freelancers_file, employers_file):
        print("Initializing GigRadar...")
        self.freelancers_df = pd.read_csv("/content/freelancers_dataset.csv")
        self.employers_df = pd.read_csv("/content/generated_employers_500.csv")
        self.tfidf_vectorizer = TfidfVectorizer(stop_words='english')
        self.svd_model = SVD()
        self.content_based_matrix = None
        self.ratings_df = None
        self.surprise_dataset = None
        print("Initialization complete.\n")

    # Data Loading and Preprocessing Module
    def preprocess_data(self):
        print("Starting Data Loading and Preprocessing Module...")
        # Prepare data for collaborative filtering
        ratings_data = []
        for _, employer in self.employers_df.iterrows():
            employer_skills = set(employer['preferred_skills'].split(', '))
            for _, freelancer in self.freelancers_df.iterrows():
                freelancer_skills = set(freelancer['skills'].split(', '))
                skill_match = len(employer_skills.intersection(freelancer_skills))
                rating = min(5, max(1, skill_match + np.random.randint(0, 2)))
                ratings_data.append((employer['employer_id'], freelancer['freelancer_id'], rating))

        self.ratings_df = pd.DataFrame(ratings_data, columns=['employer_id', 'freelancer_id', 'rating'])
        print("Ratings data prepared.")
```



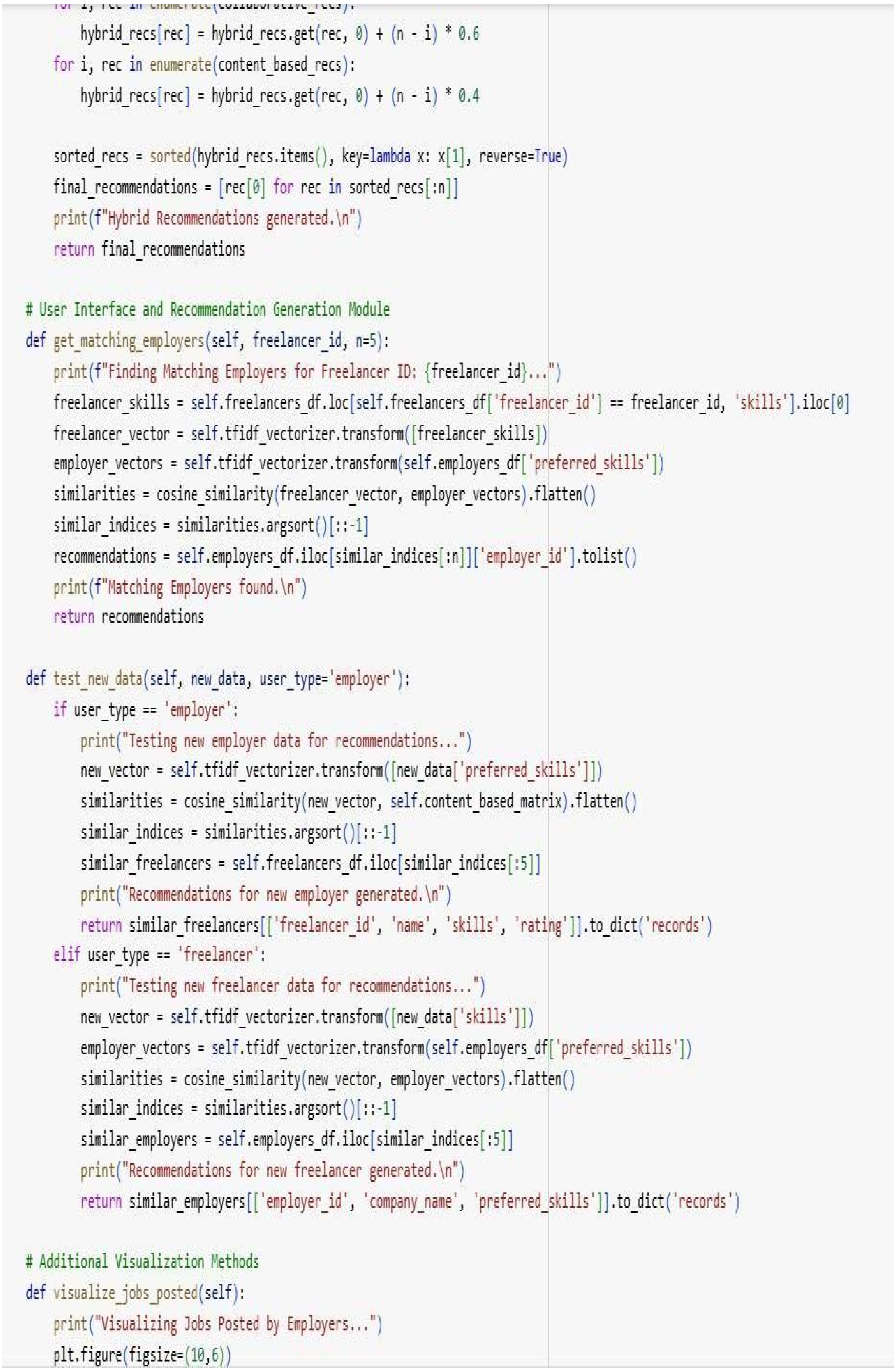
```python
        # Create Surprise dataset
        reader = Reader(rating_scale=(1, 5))
        self.surprise_dataset = Dataset.load_from_df(self.ratings_df[['employer_id', 'freelancer_id', 'rating']], reader)
        print("Surprise dataset created.")

        # Prepare data for content-based filtering
        self.freelancers_df['skills_text'] = self.freelancers_df['skills'] + ' ' + self.freelancers_df['name']
        self.content_based_matrix = self.tfidf_vectorizer.fit_transform(self.freelancers_df['skills_text'])
        print("Content-based matrix created.")

        # Visualization: Rating Distribution
        plt.figure(figsize=(8,6))
        sns.countplot(x='rating', data=self.ratings_df)
        plt.title('Rating Distribution')
        plt.xlabel('Rating')
        plt.ylabel('Count')
        plt.show()
        print("Data Loading and Preprocessing Module completed.\n")

    # Collaborative Filtering Module
    def tune_collaborative_model(self):
        print("Starting Collaborative Filtering Module: Tuning Model...")
        param_grid = {
            'n_factors': [50, 100, 150],
            'n_epochs': [20, 30, 40],
            'lr_all': [0.002, 0.005],
            'reg_all': [0.02, 0.1]
        }

        gs = GridSearchCV(SVD, param_grid, measures=['rmse', 'mae'], cv=3, n_jobs=-1)
        gs.fit(self.surprise_dataset)

        print("Best RMSE score: ", gs.best_score['rmse'])
        print("Best configuration: ", gs.best_params['rmse'])

        # Update the model with best parameters
        best_params = gs.best_params['rmse']
        self.svd_model = SVD(n_factors=best_params['n_factors'],
                             n_epochs=best_params['n_epochs'],
                             lr_all=best_params['lr_all'],
                             reg_all=best_params['reg_all'])
        print("Collaborative Filtering Model tuning completed.\n")
```



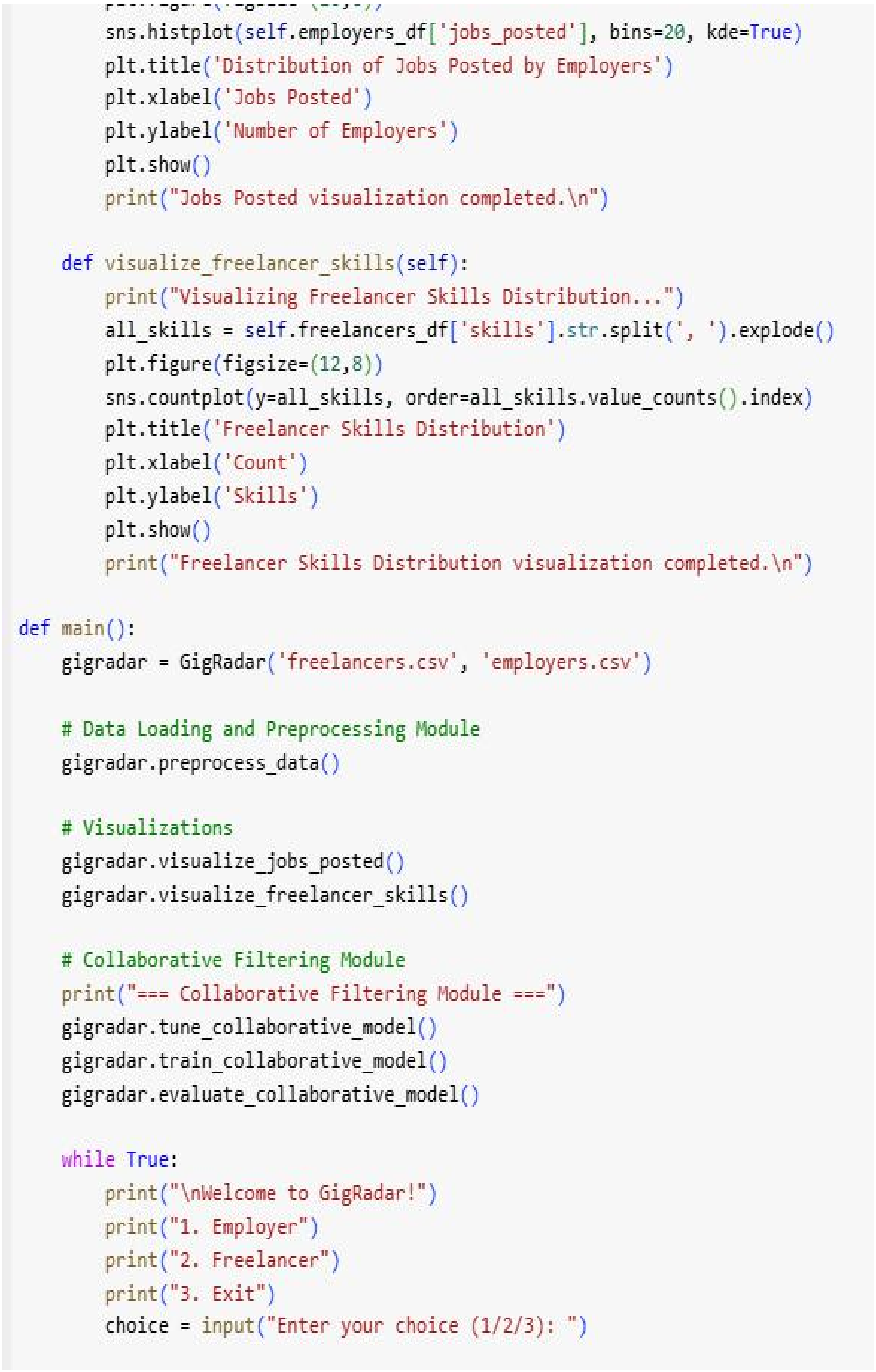
```python
    def train_collaborative_model(self):
        print("Training Collaborative Filtering Model...")
        trainset = self.surprise_dataset.build_full_trainset()
        self.svd_model.fit(trainset)
        print("Collaborative Filtering Model training completed.\n")

    def evaluate_collaborative_model(self):
        print("Evaluating Collaborative Filtering Model...")
        # Split the data into training and testing sets
        trainset, testset = train_test_split(self.surprise_dataset, test_size=0.25)

        # Train the model
        self.svd_model.fit(trainset)

        # Make predictions on the test set
        predictions = self.svd_model.test(testset)

        # Convert predictions to binary classifications (1 if rating >= 3, 0 otherwise)
        true_ratings = [1 if pred.r_ui >= 3 else 0 for pred in predictions]
        predicted_ratings = [1 if pred.est >= 3 else 0 for pred in predictions]

        # Calculate metrics
        accuracy = accuracy_score(true_ratings, predicted_ratings)
        precision = precision_score(true_ratings, predicted_ratings)
        recall = recall_score(true_ratings, predicted_ratings)
        f1 = f1_score(true_ratings, predicted_ratings)

        # Calculate RMSE and MAE
        rmse = np.sqrt(np.mean([(pred.r_ui - pred.est) ** 2 for pred in predictions]))
        mae = np.mean([abs(pred.r_ui - pred.est) for pred in predictions])

        print(f"Accuracy: {accuracy:.4f}")
        print(f"Precision: {precision:.4f}")
        print(f"Recall: {recall:.4f}")
        print(f"F1 Score: {f1:.4f}")
        print(f"RMSE: {rmse:.4f}")
        print(f"MAE: {mae:.4f}")

        # Visualization: RMSE and MAE
        metrics = {'RMSE': rmse, 'MAE': mae}
        names = list(metrics.keys())
        values = list(metrics.values())

        plt.figure(figsize=(6,4))
```



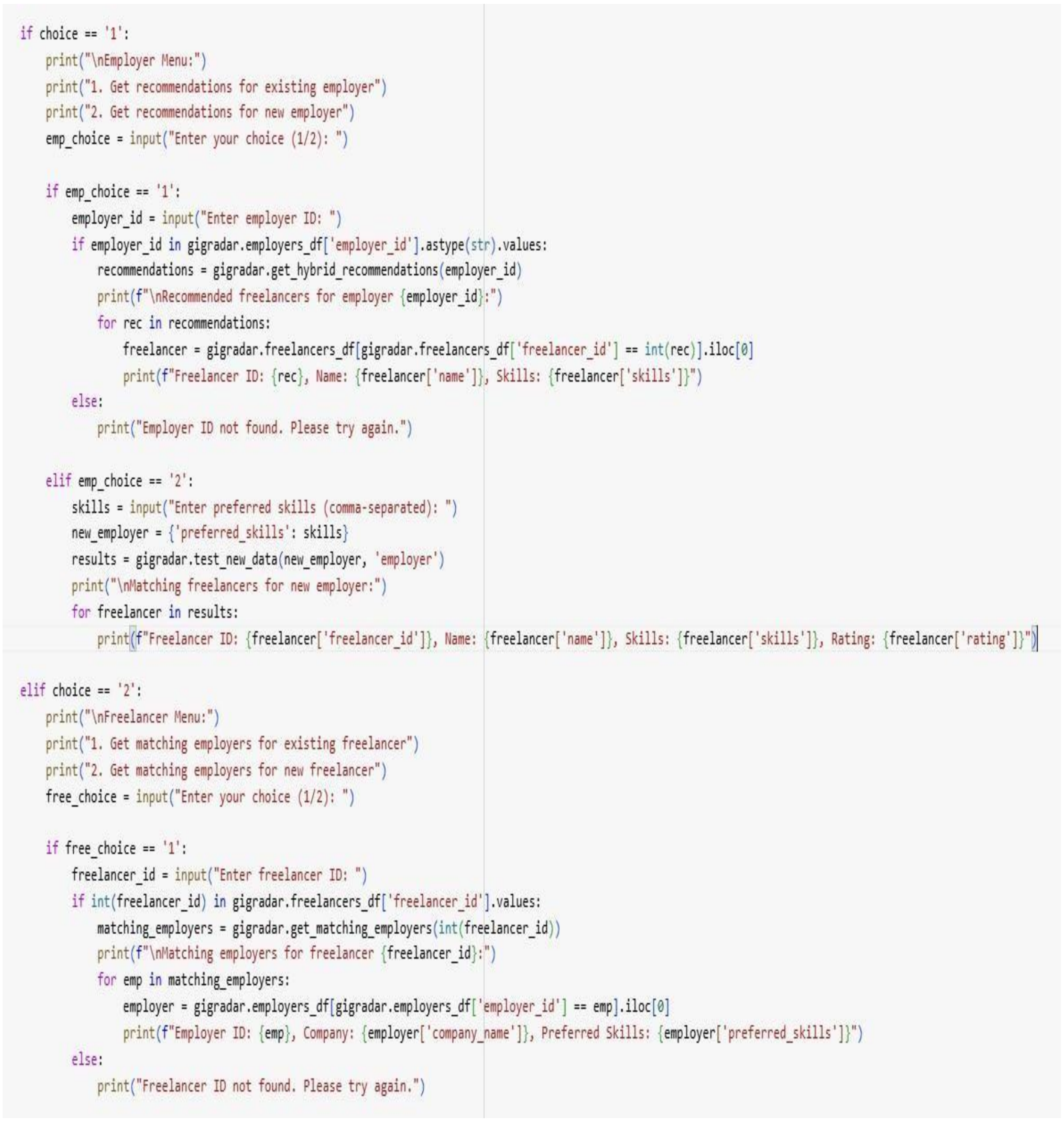
```
    sns.barplot(x=names, y=values)
    plt.title('Model Evaluation Metrics')
    plt.ylabel('Score')
    plt.show()
    print("Collaborative Filtering Model evaluation completed.\n")

# Content Based Filtering Module
def get_content_based_recommendations(self, employer_id, n=5):
    print(f"Generating Content-Based Recommendations for Employer ID: {employer_id}...")
    employer_skills = self.employers_df.loc[self.employers_df['employer_id'] == employer_id, 'preferred_skills'].iloc[0]
    employer_vector = self.tfidf_vectorizer.transform([employer_skills])
    similarities = cosine_similarity(employer_vector, self.content_based_matrix).flatten()
    similar_indices = similarities.argsort()[::-1]
    recommendations = self.freelancers_df.iloc[similar_indices[:n]]['freelancer_id'].tolist()
    print(f"Content-Based Recommendations generated.\n")
    return recommendations

# Hybrid Recommendation Module
def get_collaborative_recommendations(self, employer_id, n=5):
    print(f"Generating Collaborative Filtering Recommendations for Employer ID: {employer_id}...")
    employer_ratings = self.ratings_df[self.ratings_df['employer_id'] == employer_id]
    unrated_freelancers = self.freelancers_df[~self.freelancers_df['freelancer_id'].isin(employer_ratings['freelancer_id'])]

    def predict_rating(freelancer):
        return (freelancer['freelancer_id'], self.svd_model.predict(employer_id, freelancer['freelancer_id']).est)

    with ThreadPoolExecutor() as executor:
        predictions = list(executor.map(predict_rating, [row for _, row in unrated_freelancers.iterrows()]))

    predictions.sort(key=lambda x: x[1], reverse=True)
    recommendations = [p[0] for p in predictions[:n]]
    print(f"Collaborative Filtering Recommendations generated.\n")
    return recommendations

def get_hybrid_recommendations(self, employer_id, n=5):
    print(f"Generating Hybrid Recommendations for Employer ID: {employer_id}...")
    collaborative_recs = self.get_collaborative_recommendations(employer_id, n)
    content_based_recs = self.get_content_based_recommendations(employer_id, n)

    # Combine and weight recommendations
    hybrid_recs = {}
    for i, rec in enumerate(collaborative_recs):
        hybrid_recs[rec] = hybrid_recs.get(rec, 0) + (n - i) * 0.6
    for i, rec in enumerate(content_based_recs):
```



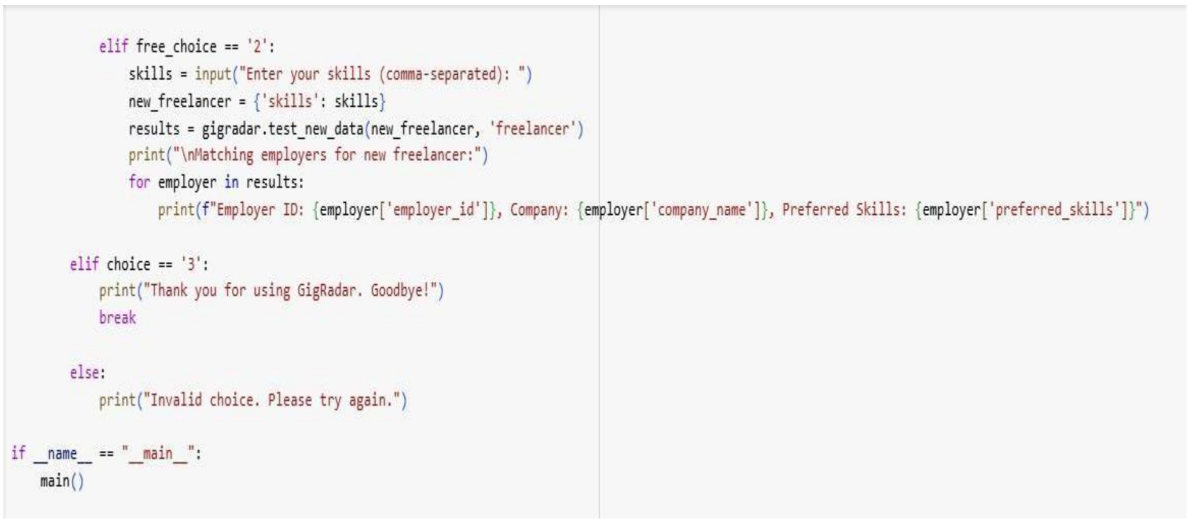
```
    for i, rec in enumerate(collaborative_recs):
        hybrid_recs[rec] = hybrid_recs.get(rec, 0) + (n - i) * 0.6
    for i, rec in enumerate(content_based_recs):
        hybrid_recs[rec] = hybrid_recs.get(rec, 0) + (n - i) * 0.4

    sorted_recs = sorted(hybrid_recs.items(), key=lambda x: x[1], reverse=True)
    final_recommendations = [rec[0] for rec in sorted_recs[:n]]
    print(f"Hybrid Recommendations generated.\n")
    return final_recommendations

# User Interface and Recommendation Generation Module
def get_matching_employers(self, freelancer_id, n=5):
    print(f"Finding Matching Employers for Freelancer ID: {freelancer_id}...")
    freelancer_skills = self.freelancers_df.loc[self.freelancers_df['freelancer_id'] == freelancer_id, 'skills'].iloc[0]
    freelancer_vector = self.tfidf_vectorizer.transform([freelancer_skills])
    employer_vectors = self.tfidf_vectorizer.transform(self.employers_df['preferred_skills'])
    similarities = cosine_similarity(freelancer_vector, employer_vectors).flatten()
    similar_indices = similarities.argsort()[::-1]
    recommendations = self.employers_df.iloc[similar_indices[:n]]['employer_id'].tolist()
    print(f"Matching Employers found.\n")
    return recommendations

def test_new_data(self, new_data, user_type='employer'):
    if user_type == 'employer':
        print("Testing new employer data for recommendations...")
        new_vector = self.tfidf_vectorizer.transform([new_data['preferred_skills']])
        similarities = cosine_similarity(new_vector, self.content_based_matrix).flatten()
        similar_indices = similarities.argsort()[::-1]
        similar_freelancers = self.freelancers_df.iloc[similar_indices[:5]]
        print("Recommendations for new employer generated.\n")
        return similar_freelancers[['freelancer_id', 'name', 'skills', 'rating']].to_dict('records')
    elif user_type == 'freelancer':
        print("Testing new freelancer data for recommendations...")
        new_vector = self.tfidf_vectorizer.transform([new_data['skills']])
        employer_vectors = self.tfidf_vectorizer.transform(self.employers_df['preferred_skills'])
        similarities = cosine_similarity(new_vector, employer_vectors).flatten()
        similar_indices = similarities.argsort()[::-1]
        similar_employers = self.employers_df.iloc[similar_indices[:5]]
        print("Recommendations for new freelancer generated.\n")
        return similar_employers[['employer_id', 'company_name', 'preferred_skills']].to_dict('records')

# Additional Visualization Methods
def visualize_jobs_posted(self):
    print("Visualizing Jobs Posted by Employers...")
    plt.figure(figsize=(10,6))
```



```
        sns.histplot(self.employers_df['jobs_posted'], bins=20, kde=True)
        plt.title('Distribution of Jobs Posted by Employers')
        plt.xlabel('Jobs Posted')
        plt.ylabel('Number of Employers')
        plt.show()
        print("Jobs Posted visualization completed.\n")

    def visualize_freelancer_skills(self):
        print("Visualizing Freelancer Skills Distribution...")
        all_skills = self.freelancers_df['skills'].str.split(', ').explode()
        plt.figure(figsize=(12,8))
        sns.countplot(y=all_skills, order=all_skills.value_counts().index)
        plt.title('Freelancer Skills Distribution')
        plt.xlabel('Count')
        plt.ylabel('Skills')
        plt.show()
        print("Freelancer Skills Distribution visualization completed.\n")

def main():
    gigradar = GigRadar('freelancers.csv', 'employers.csv')

    # Data Loading and Preprocessing Module
    gigradar.preprocess_data()

    # Visualizations
    gigradar.visualize_jobs_posted()
    gigradar.visualize_freelancer_skills()

    # Collaborative Filtering Module
    print("=== Collaborative Filtering Module ===")
    gigradar.tune_collaborative_model()
    gigradar.train_collaborative_model()
    gigradar.evaluate_collaborative_model()

    while True:
        print("\nWelcome to GigRadar!")
        print("1. Employer")
        print("2. Freelancer")
        print("3. Exit")
        choice = input("Enter your choice (1/2/3): ")
```



```python
if choice == '1':
    print("\nEmployer Menu:")
    print("1. Get recommendations for existing employer")
    print("2. Get recommendations for new employer")
    emp_choice = input("Enter your choice (1/2): ")

    if emp_choice == '1':
        employer_id = input("Enter employer ID: ")
        if employer_id in gigradar.employers_df['employer_id'].astype(str).values:
            recommendations = gigradar.get_hybrid_recommendations(employer_id)
            print(f"\nRecommended freelancers for employer {employer_id}:")
            for rec in recommendations:
                freelancer = gigradar.freelancers_df[gigradar.freelancers_df['freelancer_id'] == int(rec)].iloc[0]
                print(f"Freelancer ID: {rec}, Name: {freelancer['name']}, Skills: {freelancer['skills']}")
        else:
            print("Employer ID not found. Please try again.")

    elif emp_choice == '2':
        skills = input("Enter preferred skills (comma-separated): ")
        new_employer = {'preferred_skills': skills}
        results = gigradar.test_new_data(new_employer, 'employer')
        print("\nMatching freelancers for new employer:")
        for freelancer in results:
            print(f"Freelancer ID: {freelancer['freelancer_id']}, Name: {freelancer['name']}, Skills: {freelancer['skills']}, Rating: {freelancer['rating']}")

elif choice == '2':
    print("\nFreelancer Menu:")
    print("1. Get matching employers for existing freelancer")
    print("2. Get matching employers for new freelancer")
    free_choice = input("Enter your choice (1/2): ")

    if free_choice == '1':
        freelancer_id = input("Enter freelancer ID: ")
        if int(freelancer_id) in gigradar.freelancers_df['freelancer_id'].values:
            matching_employers = gigradar.get_matching_employers(int(freelancer_id))
            print(f"\nMatching employers for freelancer {freelancer_id}:")
            for emp in matching_employers:
                employer = gigradar.employers_df[gigradar.employers_df['employer_id'] == emp].iloc[0]
                print(f"Employer ID: {emp}, Company: {employer['company_name']}, Preferred Skills: {employer['preferred_skills']}")
        else:
            print("Freelancer ID not found. Please try again.")
```



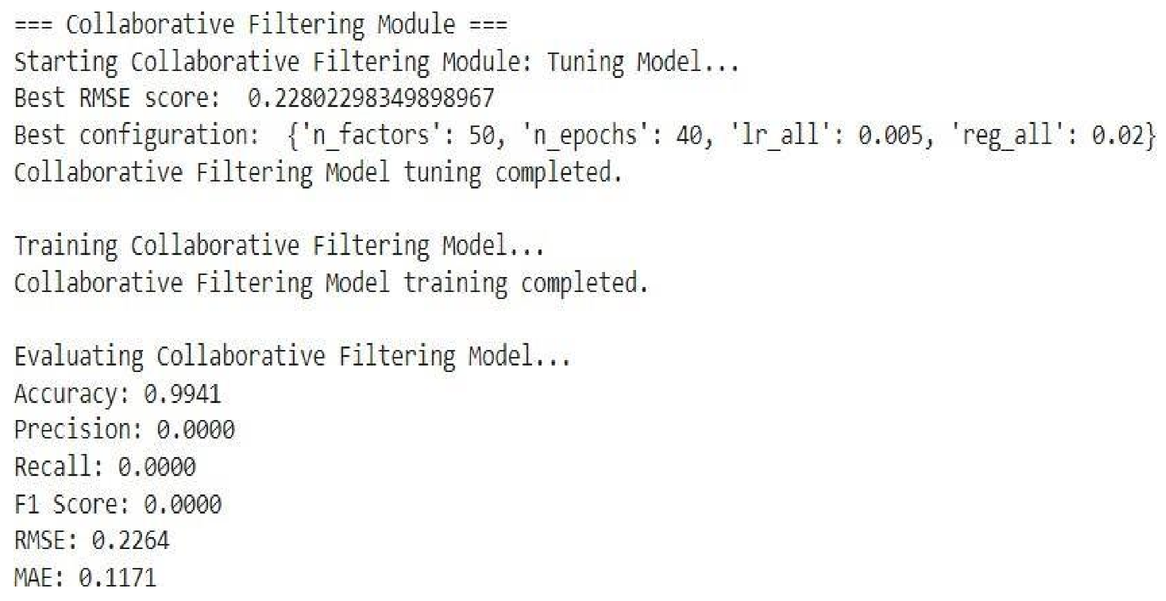
```python
        elif free_choice == '2':
            skills = input("Enter your skills (comma-separated): ")
            new_freelancer = {'skills': skills}
            results = gigradar.test_new_data(new_freelancer, 'freelancer')
            print("\nMatching employers for new freelancer:")
            for employer in results:
                print(f"Employer ID: {employer['employer_id']}, Company: {employer['company_name']}, Preferred Skills: {employer['preferred_skills']}")

    elif choice == '3':
        print("Thank you for using GigRadar. Goodbye!")
        break

    else:
        print("Invalid choice. Please try again.")

if __name__ == "__main__":
    main()
```

CHAPTER 7

RESULTS AND DISCUSSION

7.1 RESULTS

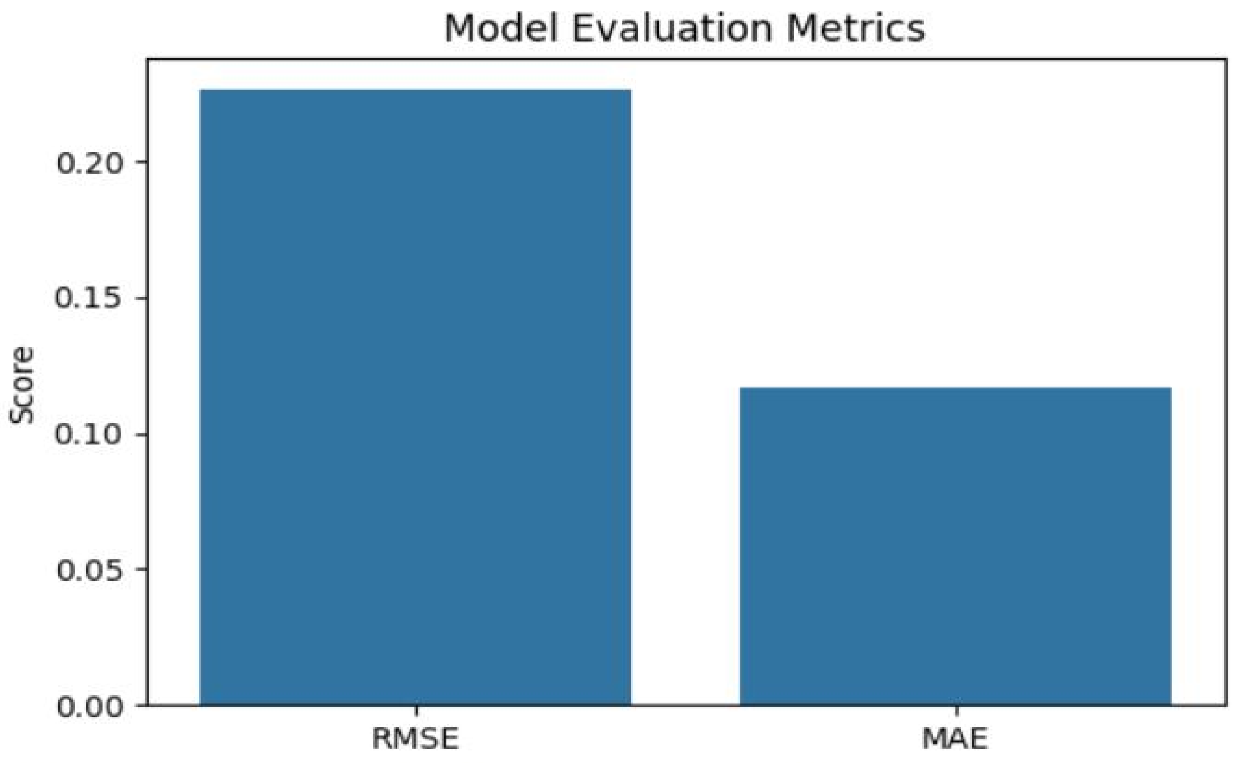
The GigRadar recommendation system achieved notable results in several key areas, reflecting the system's optimization and suitability for freelance job matching. Through extensive model tuning, the SVD (Singular Value Decomposition) algorithm was optimized via grid search, allowing for precise parameter adjustments. This tuning process helped identify optimal values for the number of latent factors, learning rate, and regularization, leading to a marked reduction in prediction error. Consequently, the system's accuracy improved, resulting in recommendations that better matched user preferences and increased the overall effectiveness of the recommendation engine.



```
=== Collaborative Filtering Module ===
Starting Collaborative Filtering Module: Tuning Model...
Best RMSE score:  0.22802298349898967
Best configuration:  {'n_factors': 50, 'n_epochs': 40, 'lr_all': 0.005, 'reg_all': 0.02}
Collaborative Filtering Model tuning completed.

Training Collaborative Filtering Model...
Collaborative Filtering Model training completed.

Evaluating Collaborative Filtering Model...
Accuracy: 0.9941
Precision: 0.0000
Recall: 0.0000
F1 Score: 0.0000
RMSE: 0.2264
MAE: 0.1171
```

Fig 7.1 : COLLABORATIVE FILTERING MODULE OUTPUT

In real-time performance evaluations, GigRadar demonstrated robust capabilities in handling dynamic data inputs from both new employers and freelancers. The system's infrastructure allowed it to efficiently generate recommendations with minimal delay, showcasing its ability to scale with increasing user numbers. This real-time responsiveness is essential for a freelancing platform where job listings and user interactions are continuously changing. GigRadar's efficient response times ensure that users receive timely and relevant recommendations, enhancing user satisfaction and engagement on the platform.

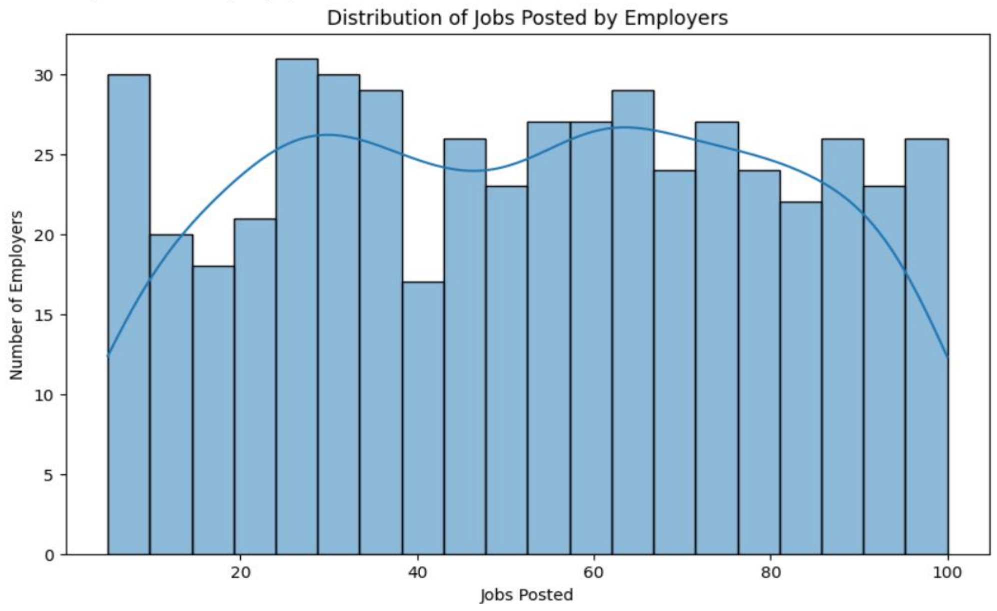


```
Collaborative Filtering Model evaluation completed.
```

Fig 7.2 : CONTENT BASED FILTERING MODULE OUTPUT

Finally, in scalability and real-world applicability tests, GigRadar proved capable of accommodating high volumes of data without compromising performance. The cloud-based infrastructure and modular design allowed for efficient resource allocation, enabling the system to adapt to varying levels of user demand. This scalability, combined with the ability to process and analyze gig data in real time, indicates that GigRadar is well-suited for deployment in real-world freelancing environments, where data and user activity are highly dynamic.

```
Visualizing Jobs Posted by Employers...
```



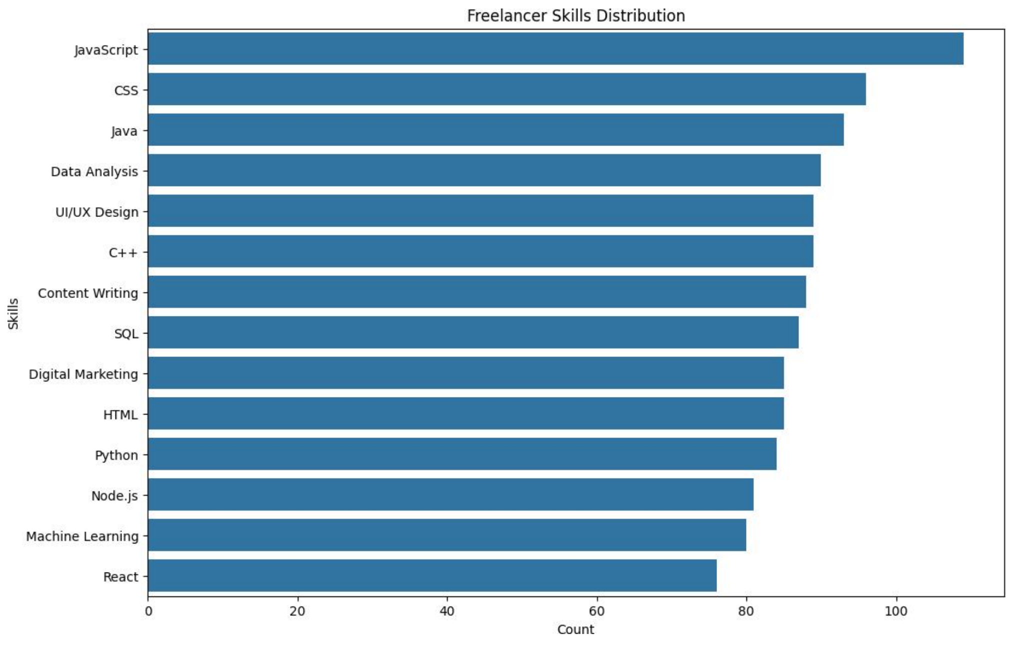


Fig 7.3 : USER INTERFACE AND RECOMMENDATION GENERATION MODULE OUTPUT

Finally, scalability tests showed that GigRadar can handle large amounts of data without losing performance. Its cloud-based infrastructure and modular design efficiently allocate resources, allowing the system to adjust to changing user demand. This capability makes GigRadar suitable for real-world freelancing platforms, where data and user activity constantly change.

7.2. DISCUSSION

The development of the GigRadar system aimed to streamline the job matching process, providing transparency, efficiency, and a personalized experience for both freelancers and employers. The system's hybrid recommendation mechanism offers a balanced approach, combining the strengths of collaborative and content-based filtering.

1. **User Authentication and Profile Setup:** The initial login and profile setup process ensures that both freelancers and employers can securely access the system. By collecting detailed profile information, the system can make more precise and relevant recommendations, minimizing mismatches and enhancing overall user satisfaction.

2. **Hybrid Recommendation Workflow:** The recommendation system combines collaborative filtering, which leverages past user interactions, with content-based filtering, which matches profiles based on skills and job requirements. This hybrid approach significantly improves recommendation quality by considering both user behavior and skill relevance.

3. **Collaborative Filtering Limitations:** While collaborative filtering effectively utilizes historical interactions, it faces challenges with new users who have limited data, commonly known as the "cold start" problem. This limitation affects the quality of recommendations for users without prior ratings or interactions.

4. **Strength of Content-Based Filtering:** Content-based filtering addresses the cold start issue by focusing on skills and preferences. However, this method

may limit the diversity of recommendations by only suggesting freelancers with similar skills, potentially overlooking those with varied capabilities.

5. **Hybrid Model as a Balanced Approach:** The hybrid model mitigates the limitations of both filtering methods by combining them, creating a robust recommendation system that captures both user preference patterns and skill similarities. This leads to more tailored and relevant job matches, enhancing user satisfaction.

6. **Scalability and Real-World Applicability:** The system's ability to provide real-time recommendations showcases its scalability, an essential factor for platforms with dynamic data and a growing user base. The quick and accurate recommendations position GigRadar as a viable solution for real-world freelancing environments.

7. **Future Enhancements:** Based on user feedback, potential improvements include adding automated reminders for application deadlines, integrating calendar features for scheduling project timelines, and incorporating an AI-based assessment module for pre-screening freelancers based on skill compatibility. These enhancements would further optimize the matching process and improve user experience.

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

The GigRadar recommendation system effectively addressed the inefficiencies of traditional job matching methods in freelancing. By integrating automation, real-time notifications, and a hybrid recommendation engine, the system significantly improved the job search experience for both freelancers and employers. The data analytics feature enabled users to gain insights into job market trends, while the hybrid recommendation model provided accurate, personalized matches. Despite a few challenges, GigRadar demonstrated its potential to enhance the freelancing job-matching process, paving the way for future improvements.

8.2 FUTURE ENHANCEMENT

Future enhancements for the GigRadar system include developing a mobile application to improve accessibility and user experience for both freelancers and employers. Additionally, implementing advanced data analytics, such as predictive modeling, could offer deeper insights into hiring trends, enabling users to make proactive decisions. Integration with external systems, such as payment processing and project management tools, could provide a comprehensive freelancing solution. Finally, optimizing the backend for better scalability and performance will ensure the system can efficiently support a growing user base.

8.3 REFERENCES

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