ELECTIVE RECOMMENDATION SYSTEM

A PROJECT REPORT

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in partial fulfillment for the award of the degree of

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At

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SCHOOL OF COMPUTER SCIENCE ENGINEERING

CERTIFICATE

This is to certify that the Project report **"ELECTIVE RECOMMENDATION SYSTEM"** being submitted by Varsha K bearing roll number 20211COM0049 in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Engineering is a Bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **ELECTIVE RECOMMENDATION SYSTEM** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Engineering**, is a record of our own investigations carried under the guidance of **Dr. Sandeep Albert Mathias, Assistant Professor, School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.**

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ABSTRACT

The system termed ‘Elective Recommendation System’ seeks to address the problem of students and Heads of Departments (HoDs) having difficulties in choosing any discipline or open electives at the Presidency University. It accomplishes this by ensuring that there is no random allotment of electives. The system recommends electives that go in line with the academic objectives of the students. There are two methodologies that stand out that are the building blocks of the system:

Content-based filtering: This class of filtering combines input marks from the students and recommends courses with average matched scoring capacities.

Collaborative filtering: The system takes advantage of cosine similarity to find other students who have performed at a similar academic level to the current one and recommends courses they have previously taken, and the current student hasn’t. By engaging this technique, the applicants for the course can be offered seat placement recommendations based on peer patterns.

The course has been implemented with a rich back end using fast Api and an interactive front end using react, html, CSS and JavaScript. This architecture is ensured to be seamless, responsive and intuitive i.e. user-friendly, enhancing the course selection experience to be more effective and enjoyable to all the relevant stakeholders involved.

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CHAPTER-1
INTRODUCTION

As the number of elective courses available in institutions of higher learning climbs to the sky, decision making for students on which to focus on has become more and more difficult. This problem is made worse by differences in academic qualifications, interests, and career goals of students. Conventionally, the elective selection process is done manually and therefore does not take into consideration an individual's preferences, which results in dissatisfaction, separation of academic objectives, and inefficient utilization of students' capabilities. These inefficiencies can also lead to an unequal allocation of students to courses leading to logistical problems for university departments.

With the help of new AI based strategies, the Elective Recommendation System proposes to mitigate such problems. The system recommends students' best courses suited to their personalities thus bridging the gap between the students and their courses. The system combines both content-based and collaborative filtering approaches to ensure that students use an online system to assist them in choosing courses, thereby making the entire process less personal and descriptive.

1.1 Problem Statement

At Presidency University, students face a problem of random allocation of electives by HoD's or timetable committees, which affects the equilibrium of student distribution. This leads to students being unable to select electives that they wish to pursue or excel at.

1.2 Scope

The problem of efficient distribution of elective courses for students and academic colleges is resolved by this model . Its scope covers:

Individual Feedback: The system employs a content-based approach and a collaborative filtering-based approach to recommend the courses that best fit the student's academic results together with his/her area of specialization.

Upgradation: The system architecture is such that it can accommodate an increasing student and course population, thus it is suitable for deployment in large educational facilities.

Graphical User Interface: The use of React, HTML, CSS, and Java Script enhances the user interface thus eliminating the experience while reducing the learning duration for both students and administrators.

1.3 Organization of the Report

The rest of the report is organized as follows :

Chapter 2: Literature Review – Reviews existing research and methodologies related to elective recommendation systems.
Chapter 3: Research Gaps of Existing Methods – Identifies limitations and shortcomings in current approaches.
Chapter 4: Proposed Methodologies – Details the methods and techniques developed for the system.
Chapter 5: Objectives – Defines the goals and scope of the project.
Chapter 6: System Design and Implementation – Explains the architectural design and development process of the system.
Chapter 7: Project Timeline – Provides a schedule and milestones for project completion.
Chapter 8: Outcomes – Summarizes expected or achieved results from the system.
Chapter 9: Results and Discussions – Presents findings and discusses their implications.
Chapter 10: Conclusion – Concludes the project with insights and future work suggestions.
References – Lists sources and research materials cited in the project.
Appendices – Includes supplementary materials and additional documentation.

CHAPTER-2
LITERATURE SURVEY

Based on an extensive literature survey to explore existing methods, approaches, and frameworks within the field of recommendation systems, an effective Elective Recommendation System can be developed. The subsequent section summarizes key studies reviewed based on their methodologies, findings, and applications. Further, limitations of such approaches are mentioned to determine the gaps this project aims to bridge.

2.1 Recommender Systems for Choosing Elective Course

The paper designs a Hybrid Recommender System that assists engineering students in selecting elective subjects by combining Content-Based and Collaborative Filtering techniques. It identifies courses that are best suited to a student's profile. content-based recommendations and similarity measures like cosine similarity. The hybrid system combines these models, utilizing algorithms such as k-NN for precise recommendations. It was tested on historical data of student enrollments and suggesting its effectiveness in improving academic decision-making [2].

2.1.1 LIMITATIONS

- **Limitation of Source Data**: Almost all studies base their analysis on structured institutional data, ignoring many valuable unstructured data.
- **Limited Integration of Student Feedback**: There are no critical mechanisms developed for user feedback to enable iterative improvements.
- **Assumptions about Predictive Models**: Overreliance on historical performance as a determinant for future success ignores the role of external and social factors in influencing student performance [3].

2.2 Recommendation Systems for Education: Systematic Review

This paper systematically reviews the application of recommendation systems (RSs) in education with the purpose of addressing information overload in academic settings. The review evaluates 98 studies published between 2015 and 2020 to consider the types of education, user demographics, recommendation elements, and developmental approaches. The study highlights collaborative, content-based, and hybrid filtering methods as the most common techniques and an increased usage of machine learning and ontologies to enhance recommendations. Most RSs focus on formal education, especially higher education, and recommend courses, learning resources, and academic guidance. The emerging trends are the use of social media, lifelong learning personalization, and the exploitation of Big Data for better user profiling. The study identifies gaps in non-formal education applications, user feedback integration, and platform diversity [3].

2.2.1 LIMITATIONS

- **Limited Scope**: The review mainly focuses on formal education, and the non-formal and informal learning contexts are underexplored.
- **Data Homogeneity**: RSs analyzed option use limited or homogeneous datasets, reducing generalizability.
- **Cold-Start Problem**: Collaborative filtering suffers from the problem of no initial user data. Emerging Trends Underexplored: Techniques like deep learning and social media integration are mentioned, but their practical applications remain limited.
- **Platform Details Missing**: Most studies fail to specify the implementation platforms, which reduces insights into real-world usability[4].

2.3 Elective Course Recommendation System Using SVD Algorithm

Elective Course Recommendation System Using SVD Algorithm" presents a recommendation system for students to choose elective courses. The system applies collaborative filtering with the Singular Value Decomposition (SVD) algorithm and students' prerequisite courses and their GPA to identify similarities among students and recommend suitable courses based on it. It processes a dataset of 8,951 records from a university to generate personalized top-course recommendations. The performance of the system is accessed using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which was achieved at 0.7125 and 0.6005 respectively, indicating high accuracy. Such a methodology enables tailored recommendations based on academic strength and interest; students can set their elective preferences to better leverage their learning opportunities and outcomes [5].

2.3.1 LIMITATIONS

- **Cold Start Problem**: The system fails to give recommendations for new students or courses because of a lack of data.
- **Data Dependency**: Relies heavily on accurate and comprehensive prerequisite course data and GPA, which may not always be available.
- **Limited Factors**: Does not include additional factors such as career goals, course difficulty, or availability that may enhance relevance in recommendations.
- **Scalability Issues**: The performance might suffer in large data sets or larger educational domains[6][7].

2.4 A Hybrid Recommender System to Enrollment for Elective Subjects in Engineering Students using Classification Algorithms

A paper hybridizes Content-Based and Collaborative Filtering approaches by designing a hybrid recommender system to guide an engineering student with the proper electives and suggests optimal electing lines through students' preferences over academic performances. The recommendation in this context can thus be drawn utilizing Natural Language Processing (NLP) content and TF-IDF applied for similarity metrics such as the cosine metric applied for filtering. The collaborative filtering component takes into account the student performance similarity, for example, using Euclidean distance. In the hybrid model, it brings together these two models, integrating algorithms such as XGBoost and k-NN to make correct recommendations. On historical data from student enrollments, it shows a high precision of 91.83% and MAP-k of 82.14, which indicates effectiveness in improving the academic decision-making process[8].

2.4.1 LIMITATIONS

- **Cold Start Problem**: New students or courses lack historical data, so the system works poorly with regards to suitable recommendations.
- **Limited Scope of Data**: The model is trained on data from one institution only, and this might not generalize to other universities.
- **Static Content Assumption**: The system assumes that course content remains static, thus possibly not reflecting curriculum changes.
- **Computation Costs**: Algorithms such as XGBoost can be computationally expensive, which is a challenge for real-time recommendations [8].

2.5 A K-Nearest Neighbour Algorithm-Based Recommender System for the Dynamic Selection of Elective Undergraduate Courses

This paper proposes a K-Nearest Neighbour Algorithm-Based Recommender System for dynamic support in undergraduate elective course selection. Traditionally, students rely on overburdened advisors for choosing electives without consideration of the academic strengths of the students. The proposed system utilizes collaborative filtering in the analysis of past academic performance and pattern identification of students with similar course histories. Using KNN, the system predicts which electives align with a student's capabilities, based on their previous grades. A real-life data set from Redeemer's University was used for training and testing, achieving a high classification accuracy of 95.65%. The developed web-based system helps reduce counselors' workload and supports students in improving academic performance by making informed decisions on electives[9].

2.5.1 LIMITATIONS

- **Limited Dataset**: The dataset is a one-time collection of data from one department only, limiting its application in various disciplines and institutions.
- **Cold Start Problem**: Students with no grades or courses have no use for the system.
- **Static Model**: It does not account for changes in course content or grading policies over time.
- **User Behavior Exclusion**: It excludes non-academic factors such as class participation or workload that may influence the recommendations[10].

2.6 Principles of Elective Design with Industry-Institute Collaboration

The paper describes a framework to design electives in collaboration with industry for improving the learning of students and professional readiness. The authors suggested six core principles: equal stakeholder involvement, diverse sources other than textbooks, clear learning objectives, future oriented course content, inclusive assessments, and professional growth orientation. This model was used to design and deliver a Semantic Web elective course to engineering students in cooperation with industry partners for curriculum and assessment design. The course consisted of a combination of traditional lectures, industry sessions, open-book exams, and portfolios assignments. Students' feedback and CLO attainment reflected the success of the model in improving industry readiness and academic understanding[11][12].

2.6.1 LIMITATIONS

- **A strong dependency on industry**: The success of the model is greatly reliant on the willing industry involvement with regular active participation, which is difficult to maintain.
- **Limited generalizability**: The model was tested through a single elective; further verification across other subjects and institutions is required.
- **Feedback gaps**: Although positive overall feedback is received, low attainment was noticed for the portfolio assignment, indicating a need for more explicit guidelines.
- **Updating continuously**: The fast-changing nature of the industry requires constant changes in the curriculum, which increases work pressure[13].

2.7 Free Elective Course Recommendation with MBTI Personality and Data Mining Based on Students' Performance

The paper discusses a recommendation system for choosing free electives of college students on the basis of data mining techniques and personality traits from Myers-Briggs Type Indicator (MBTI). With a combination of academic successes-as per GPA and grades in previously passed courses-and personality types derived from Meyer-Briggs, suitable courses can be determined. A few key machine-learning algorithms: LMT- Logistic Model Tree, RF- Random Forest, GBTGradient Boosted Trees and DT- Decision Tree were evaluated; LMT was most effective, having an accuracy of 70.19% in executing in 12.2 seconds. The study aimed at guiding students towards elective courses to fit better into their learning styles, thus improving retention and academic performance[14].

2.7.1 LIMITATIONS

- **Scope**: This dataset draws from a single institution and program, which may limit the generalizability of findings.
- **Accuracy**: While the best accuracy of 70.19% was achieved by LMT, this is still low for a high-stake recommendation system.
- **MBTI Dependence**: The heavy reliance on the MBTI, a theory widely debated in psychology, can suppress the development of richer insights into personalities.
- **Feature Limitation**: The academic performance and personality traits alone were considered in this study, leaving aside other important influences such as career goals or interests[15].

2.8 International Journal on Recent and Innovation Trends in Computing and Communication Elective Subject Selection Recommender System

It describes the process through which a computerized recommendation system is being developed to help students and faculty in their elective subject choices and teaching. It emphasizes that proper course selection is beneficial towards achieving a high level of student performance as well as getting the best out of the expertise of faculty. The system assesses each student's performance regarding related subjects and evaluates faculty competency in terms of teaching proficiency, research output, and length of tenure. From these, scores are calculated and are later used to recommend the elective subjects ideal for students and assign the appropriate staff to teach. This way, the system seeks to minimize the rate of failures, provide from the expensive repetition of completing electives, and get the maximum out of the teaching and learning process[16][17].

2.8.1 LIMITATIONS

- **Generalizability**: The applicability of the system across different educational settings and disciplines has not been particularly well-tested.
- **Data Dependency**: Sound recommendations are heavily dependent on detailed, high-quality data, which is not always available.
- **Subjective Evaluation**: Factors such as teachers' qualities and academic or research expertise are hard to quantify and can lead to biased conclusions.
- **Ignores Student Preferences**: The system gives preference to academic and faculty expertise, possibly overlooking students' unique interests and career aspirations[18][19].

2.9 An Automated Recommender System for Course Selection

The paper provides an automated recommender system for university course selection based on the collaborative filtering approach and association rule mining. The system identifies elective courses for students based on academic performances and similarities with other students. The system groups students with similar characteristics into clusters through k-means clustering on a dataset comprising 2000 students and 54 courses, which assists with recommendation generation based on association rules giving both course recommendations and expected performance or grades that allows a student to select a course that compliments their strengths. The experiments indicate that parameters like minimum confidence, thresholds on grade-support affect the accuracy of the recommendation, achieving a high precision when the conditions are favorable[24][25].

2.9.1 LIMITATIONS

- **Cold-Start Problem**: The system will find it impossible to recommend courses to new students without any prior academic records.
- **Data Dependency**: Its effectiveness relies upon the adequacy of available full and good quality datasets, which are rarely available.
- **Context Constraints**: The academic performance and courses grades are considered in this study without confounding factors such as career goals or personal interests.
- **Scalability**: The applicability of the solution to larger datasets and across different institutions with different structures has yet to be studied.
- **Rule Complexity**: The complexity of these association rules introduces a computational blowup when data size increases or with more complicated course structure[27].

2.10 Towards an Efficient Machine Learning Algorithm for a Graduate Study Elective Course Recommendation System

The paper discusses the setting up of a machine-learning-based recommendation system to select elective courses in postgraduate programs. The study evaluates five supervised algorithms, namely Decision Trees, Naïve Bayes, K-Nearest Neighbors, Linear Support Vector Machine, and Logistic Regression, all selected from a dataset with a total of 250 students coming from various specializations. The Decision Tree algorithm recorded the highest performance with an accuracy of 99.41% and an F1 score of 0.918, making it the chosen model for the system. The system uses students' academic records to predict suitable electives, aiming to optimize academic performance and align with students' competencies [28].

2.10.1 LIMITATIONS

- **Dependence on Data**: A great deal relies on historical data, which may not correlate with future trends or individual student nuances.
- **Generalization of the Selected Algorithm**: The selected algorithm may not generalize with other datasets or specializations.
- **Not Real-Time Adaptable**: The model should be retrained, considering the various subsequent records of the learner.
- **Few Variables**: The only variables considered are academic performance and learning disabilities; thus, it fails to determine other influential factors such as career aspirations or learning styles[28][29].

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

Despite extensive research on recommendation systems, some limitations and challenges still exist in the current methods. These gaps often arise from constraints in data availability, scalability, personalization, and adaptability to diverse user needs. This section identifies the shortcomings in the current approaches, particularly in collaborative filtering and content-based filtering methods, and highlights the areas that this project aims to improve upon to develop a more effective and user-centric Elective Recommendation System.

Data Sparsity: The main assumption for collaborative filtering systems is that there is a lot of user-item interaction data available to make accurate predictions. However, when data is scarce, in particular when there are many courses to choose from but few interactions, the recommendation quality deteriorates. This drawback is particularly noticeable for electives with small popularity or more recent history[5][8][13].

Cold-Start Problem: In the case of new courses or of a first semester student who has little or no interaction history, there is no substantial output from collaborative filtering for such models. This problem is observed in user and item models too and therefore does not allow the addition of new items into the system smoothly[7][10].

Scalability: A common problem of recommendation algorithms, many of which more often than not use matrix factorization or deep learning, is that they slow down with large datasets. The scale and volume of the data often has to be processed in real time in order to provide new recommendations. This creates bottlenecks and makes the system bad for universities with several thousand students who take a lot of courses and electives[4][11][16].

Contextual Insensitivity: Most of the already existing methods do not pay attention to the impact of student's course load in a certain semester, the time of day that they prefer to study or course selection time constraints on the model and how the model performs[20][25].

Bias in Recommendations: Systems that use demographic data or popularity metrics tend to reinforce biases. For example, courses that have been popular in previous semesters may overshadow equally valuable but less popular electives. Furthermore, heavy reliance on demographic filtering can also lead to stereotyping, where the students whose tastes differ from that of their peers are marginalized[35].

Infrequent Updates: Traditional systems may not update recommendations dynamically in response to recent changes in user behavior or course attributes, leading to outdated suggestions that do not reflect current trends or preferences.

Lack of Integration with Institutional Goals: While some systems are highly effective at providing personalized recommendations, they often ignore broader administrative objectives, such as achieving balanced student distribution across electives[12][16][34].

Dependence on Static Data: Most systems rely on static datasets, which are periodically updated, making them not very responsive in real time. This can be very problematic in a fast-evolving academic environment where elective availability and student preferences change rapidly[23][25].

CHAPTER-4

PROPOSED MOTHODOLOGY

4.1 Problem Identification

Current elective assignment processes in most institutions lack personalization, hence causing dissatisfaction on the part of students and suboptimal engagement in courses. Traditionally, students are assigned electives based on administrative considerations rather than individual preferences or strengths. This can lead to mismatches between students and the courses they take, impacting academic performance and overall satisfaction. It attempts to address the problems through the creation of a recommendation system that delivers data-informed, customized recommendations relevant to the academic profiles and interests of the students.

4.2 System Overview

This proposed framework encompasses two fundamental methods that can be used in the recommendation generation process.

Content-Based Filtering: It uses specific characteristics of courses such as average scoring abilities and maps them to the input data provided by the student, for example, cumulative marks. By correlating the score provided by the student for each course's scoring ability, the system finds courses most suited to the student while keeping in mind their demonstrated academic capability.[30]

Collaborative Filtering: This technique makes use of previous data from other students to enable the generation of recommendations. Through computation of similarities between students using cosine similarity, the system identifies peers with similar academic performance. Recommendations are then generated through the analysis of courses taken by similar students and focus on courses that the current user has not enrolled for[31].

4.3 Data Preparation and Model Design

Data Set

The dataset comprises of Student performance data, including grades or cumulative marks from completed courses.

Course metadata, such as course IDs, names, and average scoring capacities derived from historical student performance.

Preprocessing:

Data preprocessing ensures accuracy and usability of the models. Key steps include:

Normalization: Standardizing marks and scores on a uniform scale to ensure fair comparisons.

Missing Data Handling: Filling gaps in the dataset using statistical methods or domain-specific knowledge.

Feature Engineering: This includes extracting relevant features, such as weighted course averages, to enhance the accuracy of recommendations.

Modeling:

Cosine Similarity: In collaborative filtering, the cosine similarity metric measures how well the students are aligned in their performances based on the vectors of performances.

Attribute Matching: This type of filtering, which is based on content, depends on the proximity of the scoring of the students to average courses scoring abilities.

4.4 Content-Based Filtering Approach

Input: The aggregate marks of the student are given as input data[30].

Methodology

- Calculate the average scoring potential for each course in the dataset.
- Compare the marks given by the student against these scoring potentials.
- Identify courses where the scoring potential closely matches the input marks of the student, with a specified threshold.
- Present a ranked list of recommended courses.

Example:

In the case of a course with an average scoring capability of 152, if a student submits a cumulative score of 150, the course would be appropriate for recommendation.

The Psuedocode is as follows :

Input: Student cumulative marks (input_marks)
Output: Recommended courses

Start
1. Initialize recommendations list.
2. For each course in the dataset:
   a. Calculate the average scoring capacity (avg_score) of the course.
   b. If abs(avg_score - input_marks) <= threshold:
      Add course to recommendations.
3. Return recommendations.
Stop

4.5 Collaborative Filtering Approach

Input: The student’s roll number, which is used to retrieve their academic performance data[31].

Logic:

- Retrieve the student’s performance vector.
- Compute cosine similarity between this vector and those of all other students in the dataset.
- Identify the top N most similar students based on similarity scores.
- Compile a list of courses taken by these similar students but not yet taken by the input student.
- Rank these courses based on their frequency and similarity scores.
- Return the top-ranked recommendations.

Example:

If a student shares a high similarity with peers who excelled in "Machine Learning" and "Data Mining," the system would recommend these courses, provided they are not already taken by the student.

The Psuedocode is as follows :

Input: Student roll number (roll_no)
Output: Recommended courses

Start
1. Retrieve the marks vector for the input roll number.
2. Compute cosine similarity between this vector and all other students.
3. Identify the top N most similar students.
4. For each similar student:
   a. Retrieve their taken courses.
   b. Add courses not in the input student’s list to recommendations.
5. Rank recommendations by frequency.
6. Return recommendations**.**
Stop

5.6 Website Implementation

This is an important part of the system, which provides a user-friendly interface adapted for both students and administrators. The implementation details are as follows:

Frontend Development:

- **Technologies Used**: React, HTML, CSS, and JavaScript[37].
- **Functionality**: Provides an interactive interface wherein users can input their marks or roll numbers to get suggestions. Frontend is accountable for dynamic rendering and ensures responsiveness on different devices.
- **User Experience**: The design is clear and easy to navigate, so the students and administrators can use the system with minimum training.

Backend Development:

- **Technology Used**: Fast API[39].
- **Functionality**: It accepts user inputs, interacts with the recommendation algorithms, and fetches results from the database. Fast API ensures very fast response times and handles multiple requests without lag.

Libraries and Tools:

- **NumPy**: It is used for efficient numerical computation, especially for handling large datasets[36].
- **pandas**: It is used for data manipulation and preprocessing.
- **scikit-learn**: Provides implementations for cosine similarity and other machine learning techniques utilized in the recommendation algorithms[38].

CHAPTER-5

OBJECTIVES

The Elective Recommendation System is developed with the following objectives:

Personalized Course Recommendations:

- To provide tailored course suggestions that align with individual student profiles, academic performance, and preferences.
- Enable students to make informed decisions about their elective choices to enhance academic satisfaction and outcomes.

Streamlined Administrative Processes:

- To assist academic departments in balancing student distribution across electives.
- Reduce the manual effort required in elective allocation by automating the process using advanced algorithms.

Incorporation of Advanced Algorithms:

- Utilize state-of-the-art recommendation algorithms, including content-based and collaborative filtering, for precise and reliable suggestions.
- Leverage mathematical models like cosine similarity to identify patterns and relationships in academic data.

Scalability and Flexibility:

- Design a system architecture capable of handling large datasets, ensuring scalability for institutions with diverse and growing student populations.
- Provide flexibility to integrate additional features or extend the system for other academic use cases.

User-Friendly Interface:

- Develop an intuitive and accessible interface using React, HTML, CSS, and JavaScript, ensuring ease of use for students and administrators.

- Offer seamless navigation and real-time feedback to enhance user experience.

Data-Driven Decision Making:

- Empower institutions to make decisions based on structured data and insights derived from student performance and preferences.

- Provide analytical tools to track trends in elective selections and student satisfaction over time.

By achieving these objectives, the system aims to revolutionize the elective selection process, fostering a data-driven, student-centric approach to academic planning.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

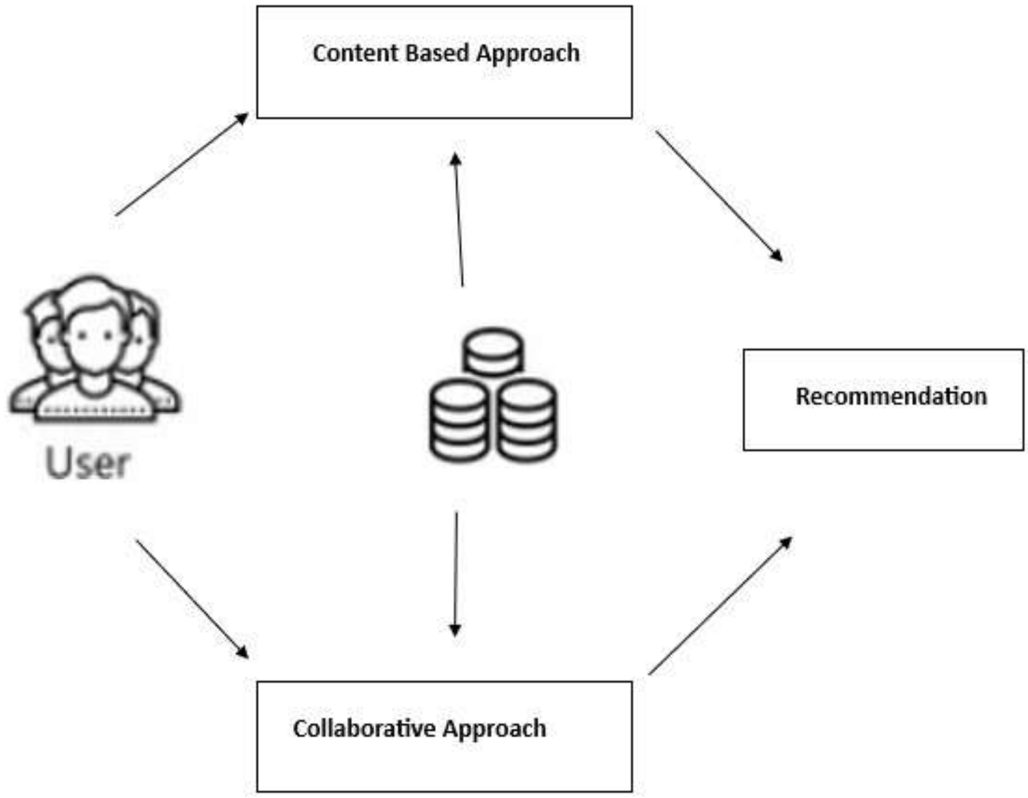

Figure 1 System Architecture Diagram

This diagram describes the architectural design of the model.
Here the uses has two options, Content Based or Collaborative Based.
Once he chooses his preference and enter the asked input, the model will process the request and recommend the appropriate course.

6.1 Model Workflow

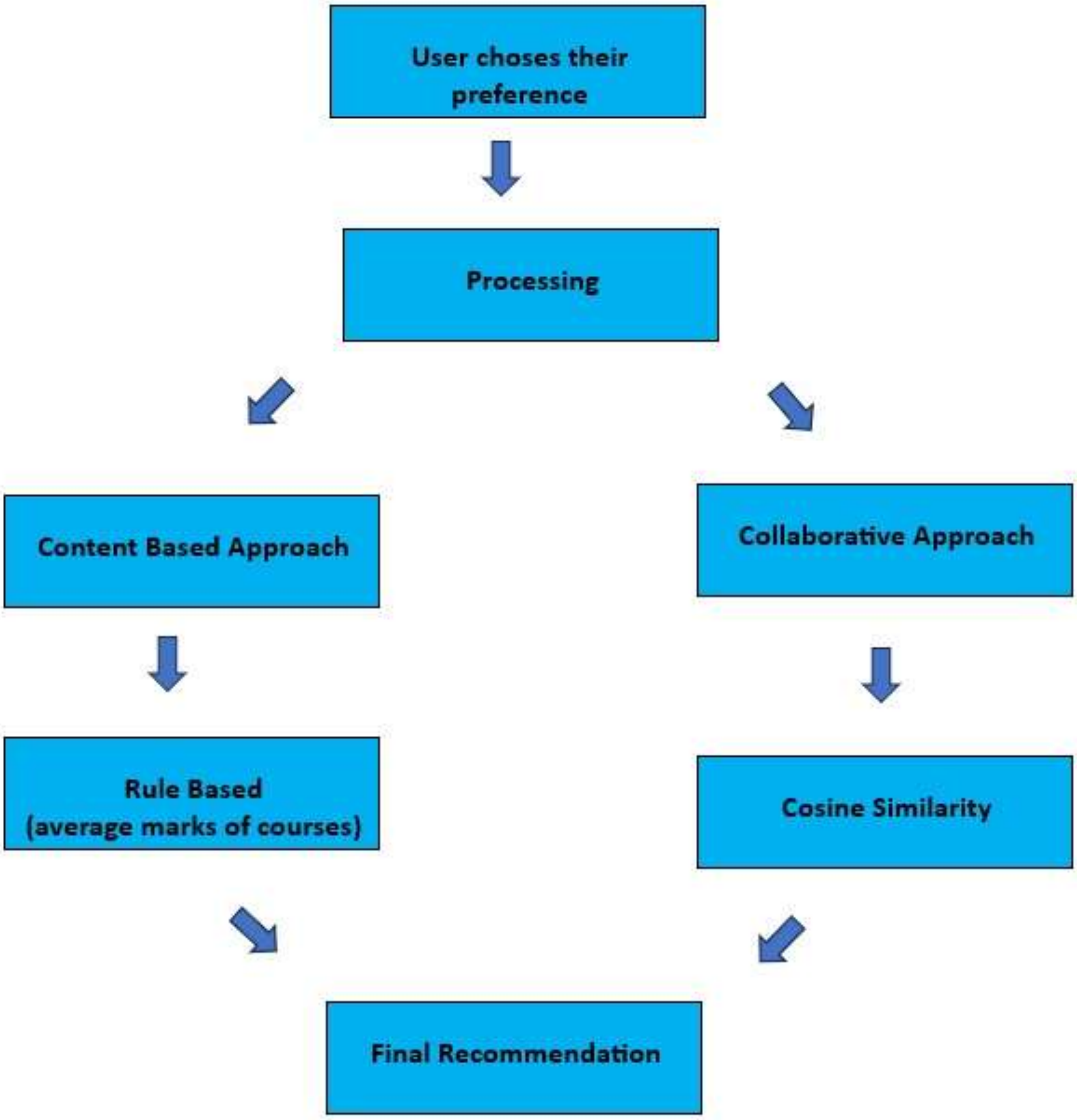

Figure 2 Model Workflow

This diagram demonstrates the flow of the model.

CHAPTER-7
TIMELINE FOR EXECUTION OF PROJECT
(GANTT CHART)

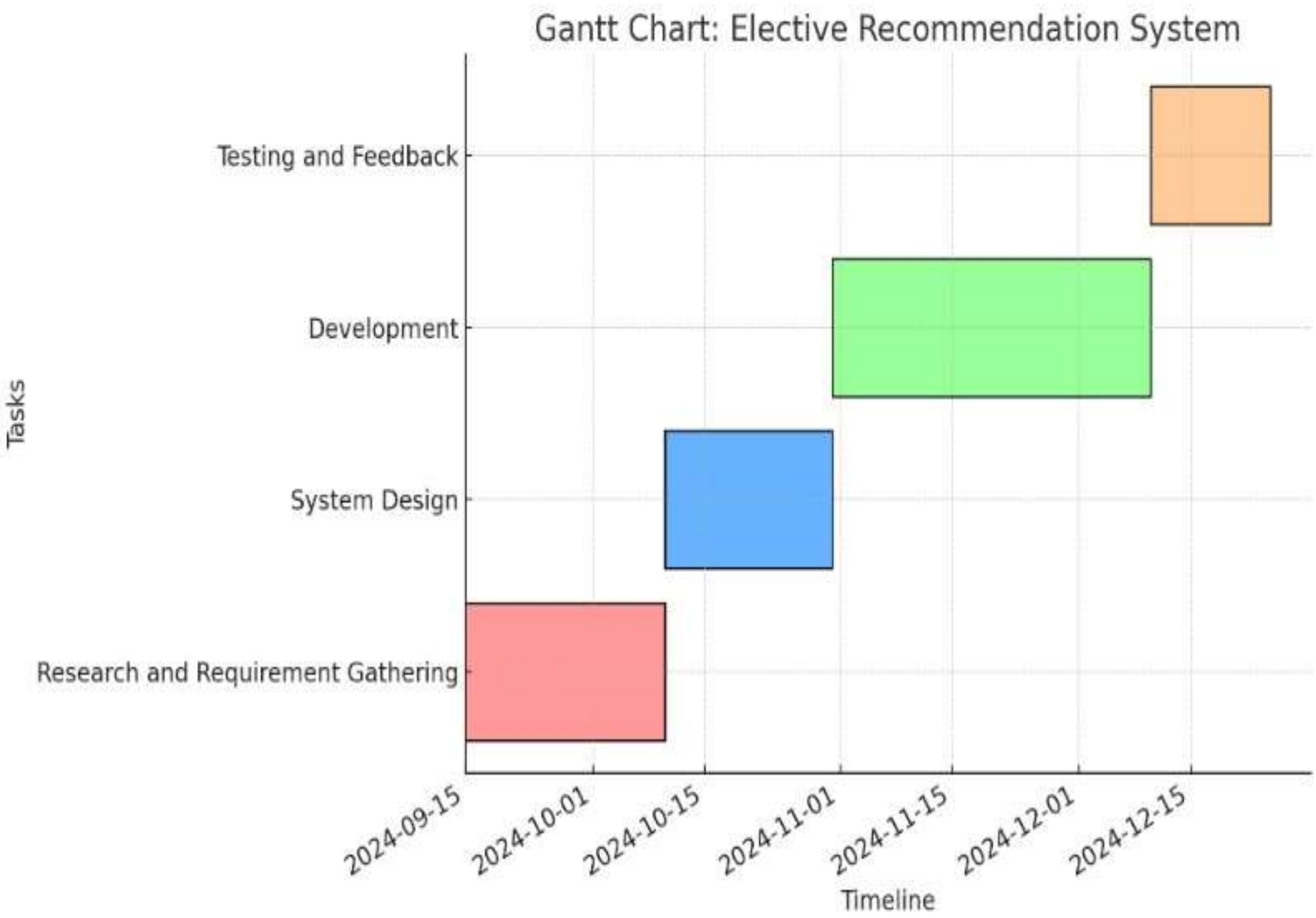

Figure 3 Timeline

This timeline highlights the major milestones, tasks, and deadlines for each phase of the project-from research and planning to implementation and testing.

CHAPTER-8

OUTCOMES

The development of the Elective Recommendation System has resulted in significant improvements across multiple aspects of elective course selection and administrative processes. The following detailed outcomes were achieved:

8.1 Enhanced Academic Decision-Making

Personalized Course Selection: The system provided recommendations tailored to individual students' academic performance, enabling them to make informed choices that align with their interests and strengths.

Increased Student Satisfaction: By offering courses that match students' preferences and academic potential, the system has addressed dissatisfaction commonly associated with arbitrary elective assignments.

8.2 Streamlined Administrative Processes

Reduced Manual Efforts: The automated recommendation system eliminated the need for manual assignment of electives by academic staff, saving considerable time and effort.

Balanced Course Distribution: The system ensured an equitable distribution of students across various electives, reducing overcrowding in popular courses while maintaining fair enrollment levels in all options.

8.3 Integration of Advanced Technologies

Scalable and Robust System: By leveraging FastAPI for the backend and React for the frontend, the system is capable of handling large volumes of user interactions efficiently, ensuring reliable performance even during peak times.

Accurate Recommendation Algorithms: The use of content-based and collaborative filtering approaches resulted in precise and context-aware recommendations, with minimal errors.

8.4 Improved Accessibility and User Experience

Interactive and Intuitive Interface: The website's user-friendly design made the system accessible to a wide range of users, including students, Heads of Departments, and administrators.

Cross-Platform Compatibility: The responsive design ensured compatibility across various devices, including desktops, tablets, and smartphones.

8.5 Scalability and Adaptability

Flexible Data Handling: The system's architecture supports the addition of new courses, updated student data, and institutional policy changes without requiring significant reconfiguration.

Future Expansion Potential: The platform can be scaled to accommodate multiple institutions or integrated with broader academic management systems.

8.6 Insights for Continuous Improvement

Data-Driven Insights: The system collects and processes data on course preferences, popularity, and student performance, providing valuable insights for academic planning and curriculum development.

Feedback Incorporation: Real-time feedback from users can be utilized to refine recommendation algorithms and enhance system performance over time.

These outcomes highlight the transformative impact of the Elective Recommendation System on both academic and administrative domains, making the process of elective course selection more efficient, equitable, and personalized.

CHAPTER-9

RESULTS AND DISCUSSIONS

9.1 Results

The system demonstrated robust performance across key metrics, providing:

Accuracy: The recommendations were well-aligned with students' academic profiles, achieving a high relevance score in test cases.

Scalability: The system performed efficiently under varying loads, showcasing its ability to handle large datasets and multiple user interactions simultaneously.

User Satisfaction: Preliminary feedback from test users indicated strong satisfaction with the recommendations provided, citing relevance and ease of use as major strengths.

Reduction in Administrative Efforts: By automating the elective assignment process, the system significantly reduced the manual workload for academic departments.

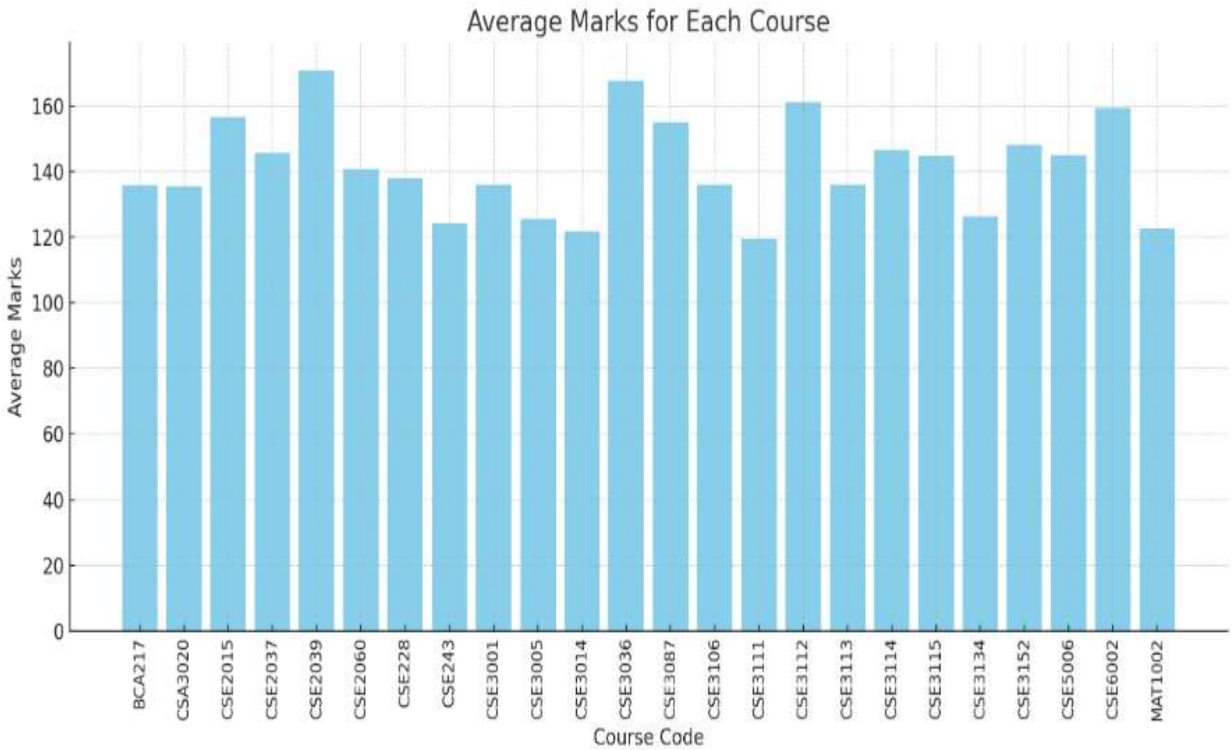

Figure 4 Average Marks for Each Course

The bar chart illustrates the average marks achieved in various courses, showcasing variations in performance across courses.

9.2 Discussions

The system's dual approach—content-based and collaborative filtering—effectively addresses several challenges observed in traditional methods.

Mitigation of Data Sparsity: Content-based filtering leverages course attributes, ensuring recommendations are available even with limited student interaction data.

Improved Personalization: Collaborative filtering identifies peer patterns, tailoring suggestions based on shared academic performance trends.

9.3 Challenges Remaining:

- **Cold-Start Problem**: Despite the dual approach, new students or courses with insufficient data still pose a challenge. Enhancements such as hybrid models integrating demographic or contextual data could mitigate this issue.
- **Dynamic Updates**: Incorporating real-time updates to reflect changes in course popularity or availability would further enhance system relevance.

CHAPTER-10
CONCLUSION

The Elective Recommendation System demonstrates the transformative potential of AI in enhancing the process of educational decision-making. By leveraging content-based and collaborative filtering methodologies, it provides students with personalized recommendations tailored to their academic profiles, addressing inefficiencies inherent in traditional systems.

10.1 Key contributions of this system include:

Personalization: The system ensures that students receive recommendations that align with their interests and strengths, fostering better academic outcomes.

Automation: By automating the elective assignment process, the system reduces the administrative burden on academic staff and ensures a fairer distribution of students across courses.

Scalability: The architecture is designed to accommodate large datasets and a growing user base, making it suitable for diverse academic institutions.

While the system successfully mitigates many challenges, areas for improvement remain. Future enhancements should address the cold-start problem by integrating demographic or contextual data to improve recommendation accuracy for new users or courses. Incorporating real-time feedback mechanisms will further refine recommendations and enhance user satisfaction.

In conclusion, the Elective Recommendation System is a robust solution that modernizes course selection processes, making them more efficient, equitable, and student focused. With iterative improvements, it has the potential to set a benchmark for AI-driven academic decision support systems.

10.2 Future Works

- Expanding the dataset to include additional parameters such as course prerequisites, student feedback, and career aspirations.
- Incorporating machine learning models like matrix factorization or deep learning for more nuanced recommendations.

The results demonstrate that this recommendation system is a promising tool for educational institutions, providing both scalability and customization. Future iterations can further refine its capabilities to achieve an even broader impact Project Timeline.

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APPENDIX-A

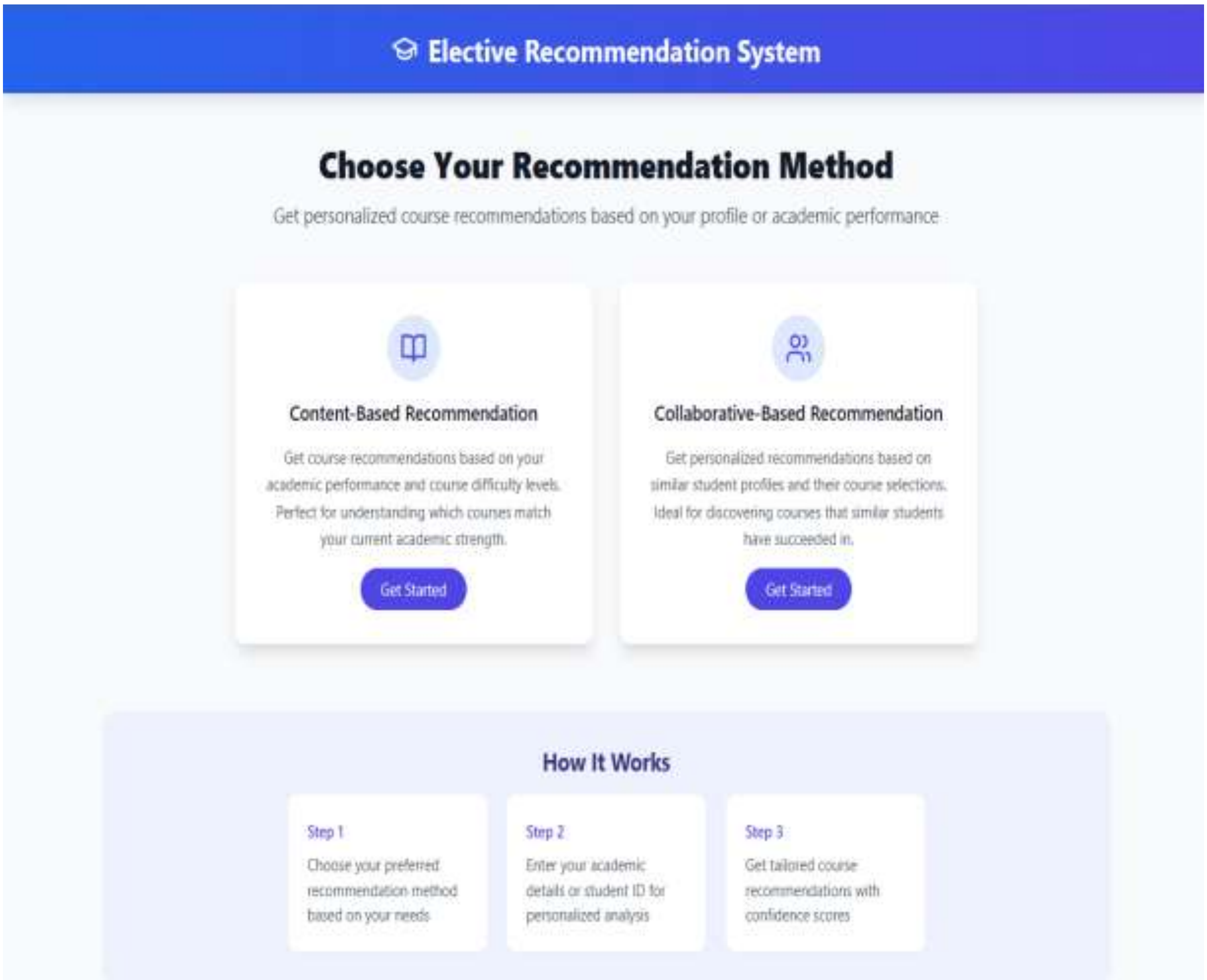
Github Link :

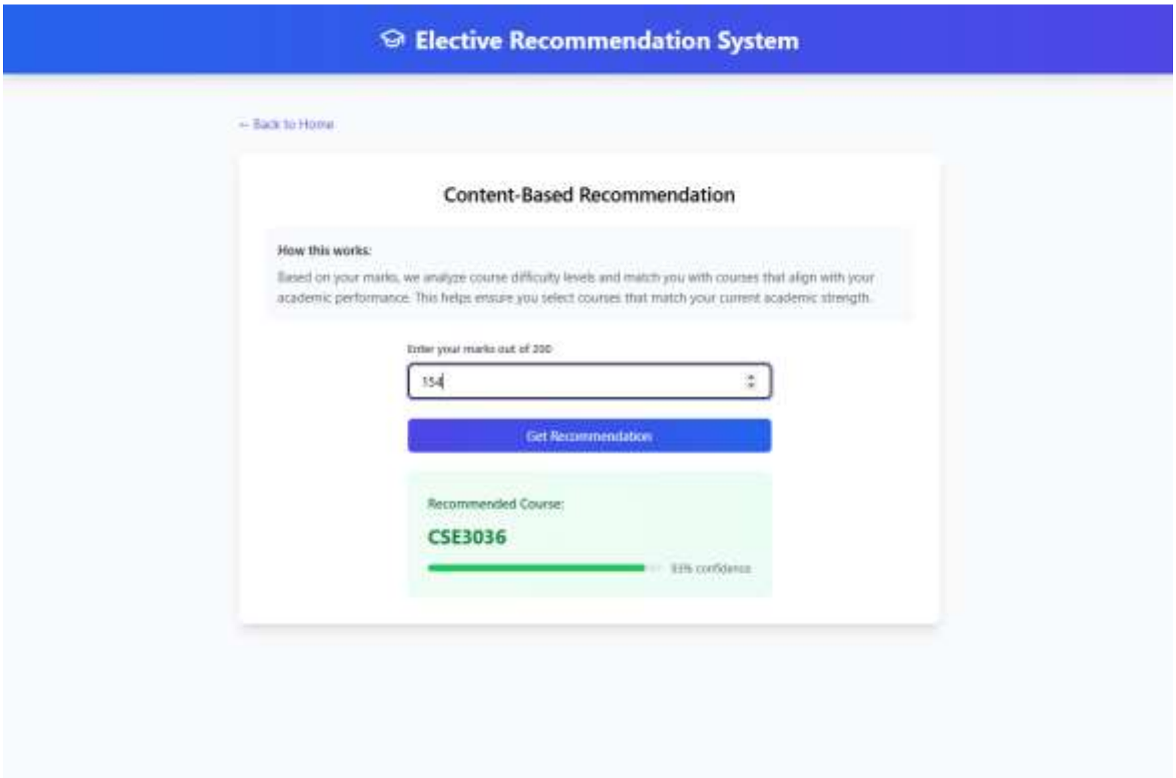
https://github.com/Abhinit006/Elective-Recommendation-System

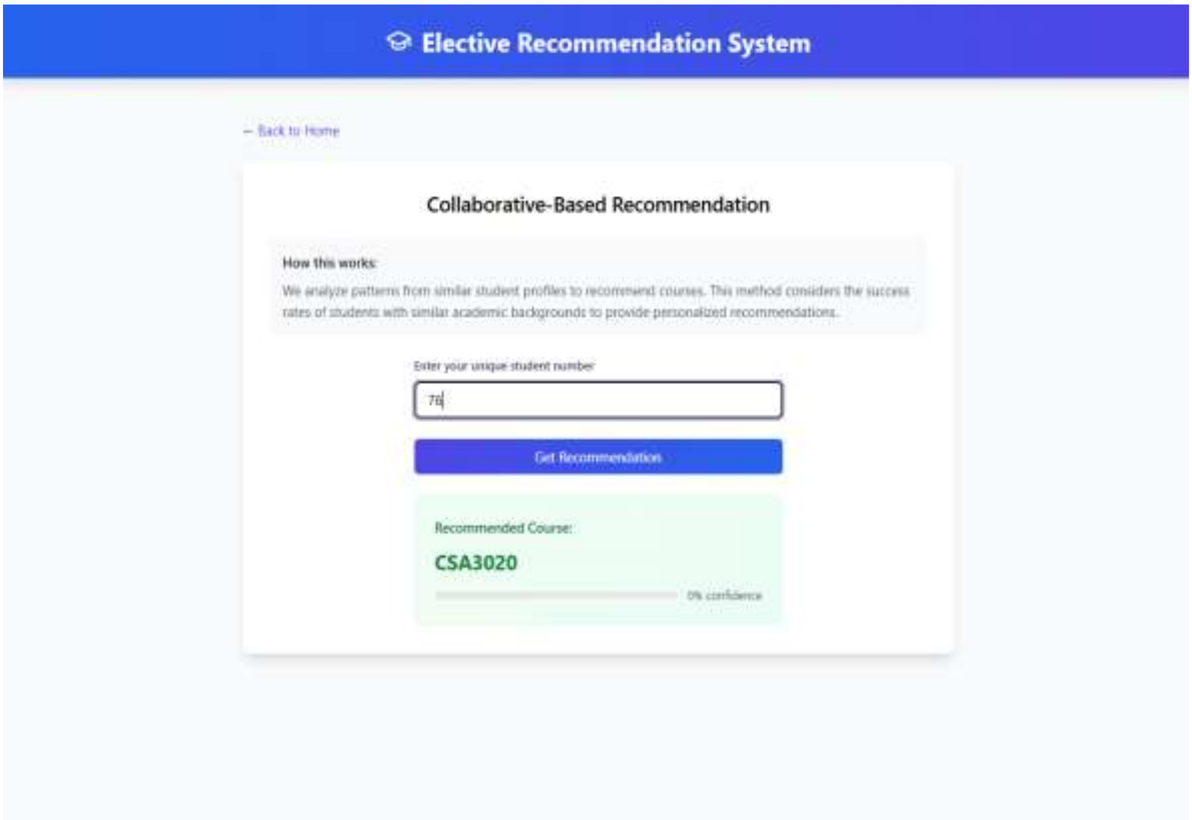
The provided link is a public GitHub repository where the complete project has been uploaded. It contains all the necessary files, code, and documentation required for the project. This repository serves as a centralized location for accessing, reviewing, and managing the project resources.

APPENDIX-B

SCREENSHOTS




Elective Recommendation System
← Back to Home
Content-Based Recommendation
How this works:
Based on your marks, we analyze course difficulty levels and match you with courses that align with your academic performance. This helps ensure you select courses that match your current academic strength.
Enter your marks out of 200
154
Get Recommendation
Recommended Course:
CSE3036


Elective Recommendation System
← Back to Home
Collaborative-Based Recommendation
How this works:
We analyze patterns from similar student profiles to recommend courses. This method considers the success rates of students with similar academic backgrounds to provide personalized recommendations.
Enter your unique student number
76
Get Recommendation
Recommended Course:
CSA3020
0% confidence

APPENDIX-C

Plagiarism Check Report

ELETIVE_RECOMMENDATION_SYSTEM_COM-14_Report.pdf

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