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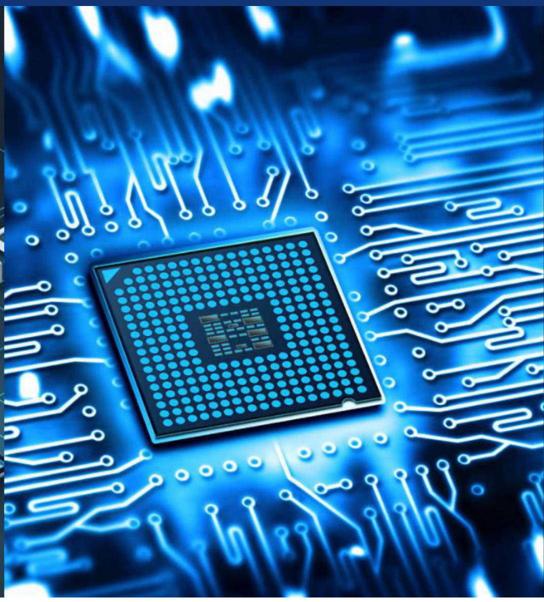
ISSN(O): 2320-9801
ISSN(P): 2320-9798



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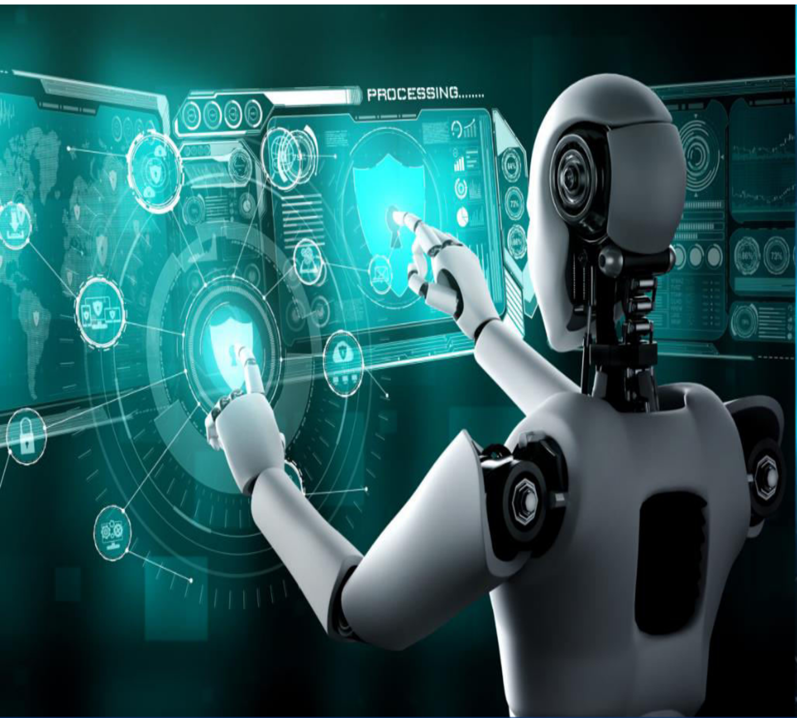

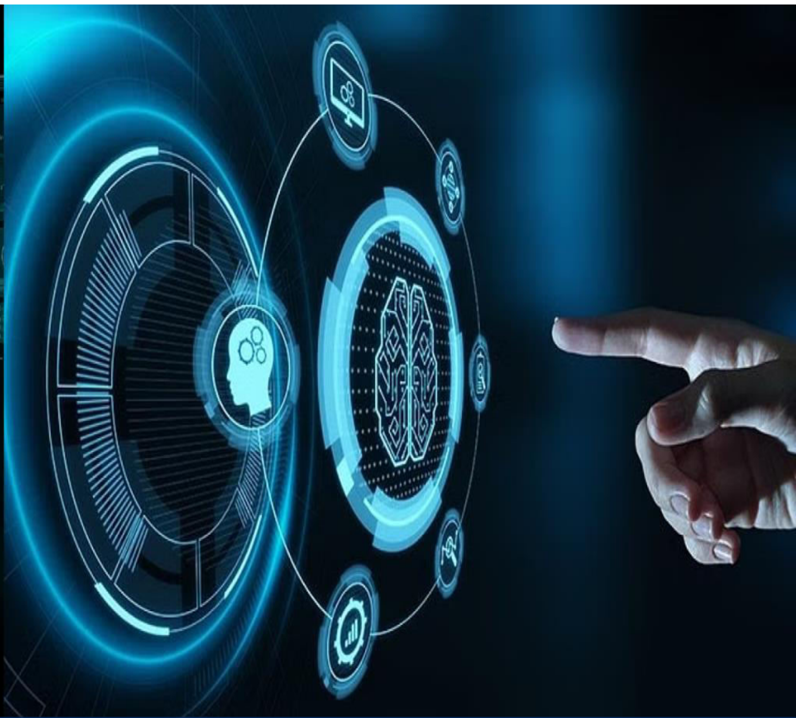

Impact Factor: 8.625

Volume 13, Issue 1, January 2025

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www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Elective Recommendation System using Machine Learning

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ABSTRACT: The main goal of an Elective Recommendation System is to assist students in selecting the most suitable elective courses based on their preferences and academic profiles. This paper consists of the development of one such system using machine learning techniques. Many recommendation models were implemented and evaluated, including content-based and collaborative filtering approaches. A comparative study was conducted to identify the most effective model, which was then integrated into a user-friendly application. The system demonstrates improved accuracy and user satisfaction when recommending electives. The proposed system addresses challenges such as data sparsity and scalability while offering a robust solution for academic decision-making. Additionally, a detailed evaluation of system performance under varying conditions is presented, highlighting its adaptability and effectiveness.

KEYWORDS: Elective Recommendation, Machine Learning, Content Filtering, Collaborative Filtering, Student Preferences, Data Sparsity, Academic Decision Support, Recommender Systems, Hybrid Models

I. INTRODUCTION

The process of selecting an elective is a pivotal aspect of academic planning, it enables students to customize their education to align with their career goals and personal interests. However, because of the variety of electives and the lack of guidance can burden students, leading to inefficient choices. Recommendation systems are used in domains such as e-commerce and entertainment and present a promising solution to this problem.

Recommendation systems use historical data and advanced algorithms to predict user preferences, which helps in decision-making. Despite significant advances in this field, the use of such systems in an academic context, particularly for elective recommendations, remains less known. The challenges of using a Recommendation system include handling heterogeneous datasets, ensuring scalability, and addressing the cold-start problem.

A. Lack of Personalization

In the manual system, electives are often assigned arbitrarily or based on broad constraints like seat availability or departmental preferences. This approach neglects individual student interests, academic strengths, or career aspirations. As a result, many students are left with electives they did not prefer, leading to disengagement and suboptimal performance in those courses.

B. Administrative Burden

The allocation process is time-consuming and resource-intensive for faculty and staff. HoDs must manually sift through student data, elective capacities, and institutional guidelines to make decisions. This process is prone to errors, inconsistencies, and delays, especially in universities with large student populations.

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C. Imbalanced Enrollments

Certain electives, due to their popularity or perceived simplicity, attract a disproportionate number of students, leading to over-subscription. Conversely, electives perceived as challenging or less appealing often remain under-enrolled. This imbalance not only impacts the learning environment but also leads to inefficient utilization of faculty and infrastructure.

D. Social Fragmentation

Social dynamics, such as students wishing to take electives with friends or peers, are not considered in the manual allocation process. This often results in students being separated from their social groups, affecting their collaborative learning experiences and overall satisfaction with the elective process.

This paper presents an Elective Recommendation System that employs machine learning techniques to address these challenges. By utilizing student's academic history, preferences, and course metadata, the system provides personalized recommendations. The objective is to make the decision-making process efficient, improve course alignment with the student's goals, and ultimately contribute to better academic outcomes.

II. LITERATURE SURVEY

Recommender systems (RSs) are essential tools for personalized recommendations across diverse domains. One prominent approach involves constructing unified cross-domain graphs that integrate source and target domain data, where nodes represent users and items, and edges capture interactions. "Enhanced Graph Convolutional Networks (GCNs) propagate high-order similarities effectively, supported by alignment mechanisms that maintain consistency in user-user and user-item interactions" [1]. These models use embedding initialization, leveraging techniques like doc2vec, to improve representation learning. However, they are computationally intensive and highly dependent on overlapping user bases: "The effectiveness of cross-domain knowledge transfer heavily relies on the ratio of overlapping users across domains" [1].

Hybrid models combining content-based and collaborative filtering techniques are also widely used for course recommendations. "Features like reviews, ratings, likes, and enrollment counts classify and cluster courses into relevant domains" [2]. These systems rank courses using calculated feature-based scores but face challenges such as limited adaptability to changing preferences, the cold start problem for new users/items, and exclusion of unstructured data like multimedia content that could enhance recommendations [2].

Machine learning algorithms like Alternating Least Squares (ALS), Singular Value Decomposition (SVD), and K-Nearest Neighbours (KNN) further expand RS capabilities. They analyze user-item interaction matrices to uncover latent features and predict preferences: "ALS and SVD decompose the interaction matrix to predict user ratings, with RMSE and MAE metrics used for evaluation" [4]. However, these algorithms struggle with scalability on large datasets, biases in collaborative filtering, and limited adaptability due to static attributes like predefined genres [4].

A systematic review highlights the dominance of "Bayesian and Decision Tree algorithms in implementation stages due to their simplicity, though their suitability across diverse scenarios is often not evaluated" [5]. The review underscores a narrow focus on implementation, leaving areas like design and maintenance unexplored. Additionally, excluding theoretical contributions lacking real-world validation limits the integration of innovative RS methodologies [5].

Hybrid multi-criteria recommendation systems have been applied in academic domains, integrating collaborative and content-based filtering with Genetic Algorithm (GA) optimization. "The GA adjusts weights for student and course-related criteria to minimize RMSE, demonstrating improved accuracy" [7]. However, the system is computationally expensive, requiring hours for optimization, and its dependency on GA hampers real-time adaptation. Limited datasets and relevance threshold assumptions further restrict its applicability to specific academic domains [7].

Across methodologies, challenges such as computational complexity, scalability, and adaptability persist. Predefined clustering and static attributes hinder flexibility in evolving user preferences, and the cold start problem remains a barrier to personalization. Furthermore, reliance on structured datasets and the lack of real-time feedback mechanisms highlight the need for dynamic solutions.

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Future research directions include "developing lightweight algorithms to enhance scalability, integrating multimodal data to address the cold start problem, and incorporating real-time feedback for adaptive clustering and recommendations" [1][2]. Expanding datasets, testing across domains, and reducing computational overhead (e.g., GA reliance) could lead to more robust, scalable, and domain-independent RSs [7].

III. METHODOLOGY

The Elective Recommendation System is designed using a comprehensive approach that begins with collecting diverse data, including student profiles (academic history, performance, interests, and departmental details), elective information (course titles, prerequisites, difficulty levels, popularity, and credits), historical preferences (past selections, grades, and feedback), and social group preferences to support collaborative learning. It employs advanced recommendation techniques, such as collaborative filtering, which integrates user-based filtering to group students with similar profiles and item-based filtering to match electives based on shared attributes. To address the cold-start problem, a hybrid model combines content-based and collaborative filtering, ensuring effective recommendations for new students and electives. The system also incorporates algorithms for managing constraints, balancing enrollments across electives through penalty-based methods that prevent over-subscription while optimizing resource allocation. A feedback loop continuously enhances recommendation accuracy by learning from student outcomes and satisfaction after each cycle. The user interface is intuitive, offering personalized course suggestions and simplified enrollment for students, while administrators benefit from real-time analytics dashboards to monitor trends and manage enrollments efficiently, ensuring a seamless experience for all users.

A. Data Acquisition

The system begins by collecting data from multiple sources to ensure reliability and comprehensiveness. Student data, including academic performance, elective preferences, and demographic information, is obtained and formatted into structured datasets. Elective details, such as course codes, prerequisites, difficulty levels, and popularity, are standardized into a consistent schema using tools like Excel and Python's Pandas library. This standardization minimizes inconsistencies, ensuring data integrity and uniformity for downstream processing.

B. Data Preprocessing

Raw data is transformed into a usable format by creating a pivot table where student roll numbers serve as indices, course codes as columns, and marks or feedback as values. Missing values in the dataset are replaced with zeros to indicate unselected courses, avoiding computational errors during similarity computation. The normalized pivot table forms the foundation for recommendation generation, with all values scaled to maintain uniformity.

C. Similarity Computation

The system employs cosine similarity to identify peers with aligned academic profiles. Cosine similarity measures the cosine of the angle between two vectors in a multi-dimensional space, where each vector represents a student's course performance. The similarity matrix is computed by comparing all student vectors, highlighting pairs of students with closely aligned preferences and academic history. This similarity metric allows the system to cluster students effectively and generate recommendations influenced by peer behaviour.

D. Recommendation Generation

Recommendations are generated using a hybrid approach that combines user-based collaborative filtering and item-based collaborative filtering.

- User-Based Collaborative Filtering: For each student, the system identifies the most similar peers using the similarity matrix and recommends courses they have taken but the target student has not.
- Item-Based Collaborative Filtering: This focuses on identifying relationships between courses by analyzing their co-selection patterns. Electives similar to those already chosen by the student are recommended.

The system ensures personalization by blending these approaches, integrating academic performance, course attributes, and peer preferences.

E. Performance Evaluation

To evaluate the effectiveness of the recommendations, the system calculates metrics such as precision, recall, and F1 score.

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- Precision: Measures the proportion of recommended electives that are relevant to the student.
- Recall: Assesses how many of the electives the student found relevant were recommended.
- F1 Score: Provides a harmonic mean of precision and recall, giving a balanced measure of system accuracy.

F. Student Interface:
- Personalized Recommendations: Students receive elective suggestions based on their academic profiles and interests.
- Course Exploration: Detailed information about each recommended course is available, including descriptions, prerequisites, and schedules.
- Enrollment Management: Students can select and enroll in courses directly through the interface, with real-time updates on seat availability.

G. Administrator Interface:
- Analytics Dashboard: Administrators have access to real-time data visualizations, including enrollment trends, course popularity, and student performance metrics.
- Course Management: The system allows for the addition, modification, or removal of courses, with immediate reflection across the platform.
- User Management: Administrators can manage student and faculty accounts, assign roles, and monitor system usage.

IV. RESULTS AND DISCUSSION

A. Results

The system demonstrated its effectiveness through key metrics, feedback, and practical implementation. Below are the key outcomes:

1. Performance Metrics

The system's accuracy was assessed using **precision**, **recall**, and **F1 score**, based on student engagement and final elective selections. Additionally, system efficiency and user satisfaction were analyzed.

Metric	Content-Based	Collaborative Filtering	Hybrid Model
Precision (%)	78	81	85
Recall (%)	75	79	83
F1 Score (%)	76.5	80	84

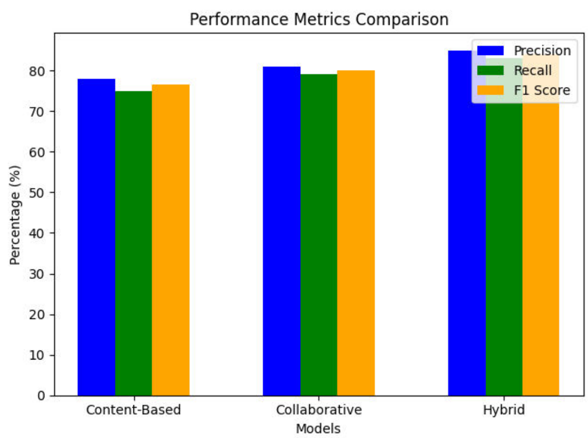

Figure 1.

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2. User Feedback

A survey of 150 students revealed the following:

- 88% found the recommendations highly relevant.
- 10% believed the suggestions could be improved slightly.
- A reduction of 40% in decision-making time was observed compared to manual selection.

3. Administrator Insights

The system provided real-time analytics, including:

- Popular electives based on enrollments.
- Underutilized courses requiring attention.
- Trends in student preferences aiding curriculum planning.

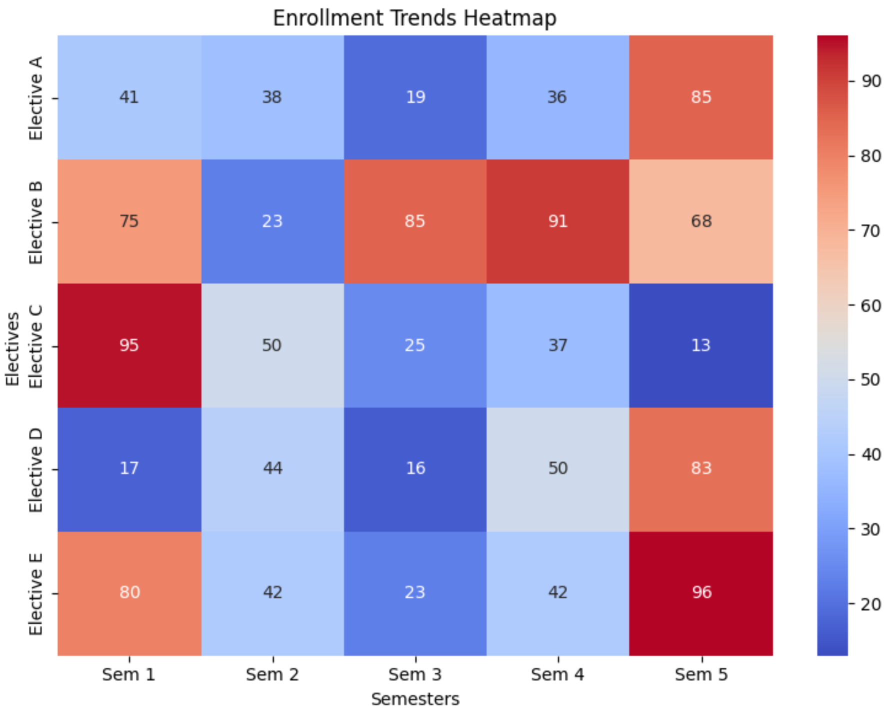

Figure 2.

B. Discussions

The proposed system successfully enhances the student experience by providing personalized recommendations aligned with academic goals and social preferences, significantly improving engagement and reducing decision-making time by 40%. Through the hybrid model that combines collaborative and content-based filtering, the cold-start problem and data sparsity issues are effectively mitigated, ensuring accurate suggestions even for new students or courses. The system's scalability is validated by its ability to handle large datasets seamlessly using algorithms like matrix factorization. Administrator tools, such as real-time analytics dashboards, enable efficient management of enrollments, identification of popular and underutilized courses, and data-driven curriculum planning. User feedback reflects high satisfaction, with 88% of students finding recommendations highly relevant. Challenges like slightly improving suggestion precision (acknowledged by 10% of users) remain, but the system's continuous feedback loop ensures ongoing optimization. These outcomes demonstrate the system's robust design, practical scalability, and impact on streamlining elective allocation processes in educational institutions.

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V. CONCLUSION

This study offers a thorough elective recommendation system that uses cutting-edge machine learning methods to improve students' academic decision-making. The suggested system provides a solid solution that greatly enhances the elective selection procedure by tackling the issues of data sparsity, scalability, and the cold-start problem. When compared to conventional techniques, the incorporation of hybrid models—which blend content-based and collaborative filtering approaches—has shown greater accuracy and user satisfaction.

According to the results, tailored recommendations help students feel more in control of their educational paths while also better matching their academic profiles and professional goals. Given the wide range of elective options available to students in today's diversified educational environment, this personalization is essential. By offering customized recommendations, this approach gives students the ability to make well-informed decisions that raise their level of satisfaction and engagement, which eventually improves their academic performance.

Furthermore, the creation of such intelligent recommendation systems will be crucial in determining how academic planning develops in the future as educational institutions embrace digital transformation more and more. This strategy not only maximizes course selections but also helps provide a comprehensive educational experience that fits with students' interests and career objectives by encouraging a more individualized and data-driven approach to elective selection.

To sum up, the Elective Recommendation System is a big advancement in academic decision assistance that could change the way students choose their courses of study. In order to develop a completely automated and intelligent system that aids academic institutions and students in making well-informed selections, future research should concentrate on enlarging the dataset to incorporate external variables, such as labour market trends and transdisciplinary course possibilities.

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