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A Machine Learning Approach for Personalized Elective Recommendation in Engineering Education

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***Abstract*— In modern engineering education, students often struggle to select suitable open electives and core courses that align with their academic performance, personal interests, and long-term career goals. To address this issue, we present a hybrid recommendation framework grounded in machine learning, designed to aid academic curriculum planning in engineering institutions. The proposed system integrates both content and collaborative based filtering approaches, effectively utilizing student academic records, stated preferences, and detailed course metadata. Content-based filtering enables the system to analyze individual learner attributes and course features, while collaborative filtering predicts course ratings. This dual strategy enhances the accuracy and personalization of course recommendations. Experimental evaluations on real-world academic datasets demonstrated that the proposed system significantly improves elective selection accuracy and student engagement. This framework can serve as a valuable decision-support tool for both students and academic advisors, ultimately facilitating more informed curriculum planning and improved academic outcomes.**

***Index Terms*— Course Recommendation System, Engineering Education, Machine Learning, Personalized Learning.**

I. INTRODUCTION

In today's data-driven academic environment, engineering students are often faced with a complex set of choices when it comes to selecting open electives and courses that align with their individual learning trajectories and career aspirations. Choosing the right elective or course has always been a critical aspect of a student's academic journey, especially in engineering education, where curriculum choices can significantly impact both learning outcomes and career paths [1]. With the increasing number of available electives and specialization options, students often find it difficult to make informed decisions that align with their interests, academic strengths, and long-term goals. The challenge lies not in the lack of options but in the overwhelming number of them, often offered without tailored guidance. As a result, students may end up selecting courses based on peer suggestions or superficial interests, rather than informed academic alignment or skill development relevance [2-3].
Traditional methods of academic advising, while valuable, are increasingly strained due to growing student populations and limited one-on-one counselling time. To address this issue, educational institutions are beginning to explore intelligent Recommendation Systems (i-RS) that can offer timely, personalized course suggestions [4-5]. Inspired by the widespread success of recommendation systems in domains such as retail and media streaming, this study explores how similar methodologies can be effectively adapted for academic course recommendation within engineering education.

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Specifically, this research proposes a hybrid recommendation framework that combines content-based filtering using cosine similarity with collaborative filtering based on predicted course ratings to suggest open electives and core courses aligned with a student's academic background, preferences, and interests. The content-based component of the system analyzes course attributes, such as domain, prerequisites, and learning outcomes, and compares them against a student's academic history using cosine similarity, identifying courses with the highest semantic relevance. Simultaneously, the collaborative filtering module utilizes historical enrollment and rating patterns of courses from similar students to predict personalized course ratings using Machine Learning (ML), thereby enhancing the recommendation quality through peer-informed insights. This study makes the following key contributions:

- Collected real-time academic data from students and integrated course information sourced from the NPTEL platform, reflecting actual offerings in the engineering curriculum.
- Developed a hybrid recommendation framework that leverages both content similarity and collaborative behavior to generate more accurate and personalized open elective and course suggestions.
- Evaluated the system on real-world academic data to demonstrate the system's effectiveness in improving course selection accuracy and student satisfaction.

The remainder of this paper is structured into five sections. The existing literature on course recommendation systems is reviewed in section 2, focusing on filtering techniques and their applications in education. Section 3 discusses the design and methodology of the recommendation framework. The experimental result evaluation and system performance using standard metrics is presented. And finally, the paper is concluded in last section.

II. Related Work

Numerous studies have explored recommendation systems, each aiming to enhance academic decision-making through personalized suggestions, discussed further. In recent years, a wide range of intelligent RS approaches have emerged within e-learning systems, each aiming to create more tailored learning experiences. One such approach applies collaborative filtering in combination with ML to refine the way learners engage with digital platforms, ultimately improving the overall user experience [6]. Another notable solution involves course RS specifically crafted for students, where algorithmic learning models are employed to support better academic performance [7]. To address the limitations posed by the cold-start problem, a hybrid RS framework was proposed that blends attribute-based techniques with sophisticated filtering mechanisms [8]. Efforts have also been made to construct predictive systems that utilize various ML algorithms to recommend academic pathways and streamline instructional processes [9]. Refined LSTM neural networks, which allow for dynamically adapting to a learner's preferences and providing deeper levels of personalization [10]. In higher education, the PERKC model was developed, integrating a personalized kNN algorithm alongside a CPT to offer smarter academic course suggestions [11]. A dedicated framework was developed for e-learning environments, specifically focused on enhancing study efficiency through individually customized recommendations [12]. Additionally, combining educational knowledge graphs with collaborative filtering was proven effective in both forecasting student performance and generating content that aligns with their learning trajectories [13]. When addressing younger learners in K-12 settings, scholars were introduced to a conceptual design that outlines essential features for building personalized recommendation tools suited to foundational education levels [14]. A cross-domain meta-learning approach was introduced to further overcome the challenge of limited data in new or underrepresented domains, enabling improved adaptability and robust recommendations despite sparse user interactions [15]. Lastly, the integration of ML within IoT-driven smart learning environments developed a personalized RS in MOOCs and e-learning platforms, offering learners curated content that aligns with their educational goals and preferences [16].

The hybrid deep learning-based model was developed tailored for online course RS, aiming to support improved learner outcomes by aligning suggestions with individual learning paths [17]. In a related approach, an e-learning RS was built using autoencoder networks, enabling more accurate and personalized content delivery by capturing latent user preferences [18]. Another contribution introduced a RS framework centered around optimizing QoE, targeting higher satisfaction among learners when interacting with digital learning materials [19]. A deep learning-driven system has also been implemented to model user profiles and generate course suggestions based on rating predictions, enriching the personalization experience on e-learning platforms [20]. To further address learner diversity in MOOCs, a hybrid filtering approach was proposed that emphasizes user-centric personalization, tailoring RS based on both content features and user interactions [21]. In addition, a smart learning environment leveraging reinforcement learning was designed to offer adaptive learning paths and sequential recommendations, making learning more dynamic and responsive [22]. Collaborative filtering techniques continue to be widely adopted, as seen in systems developed to assist learners in choosing suitable courses through data-driven modeling of peer selections and preferences [23]. Similarly, personalized RS engines utilizing ML algorithms have been applied to refine the overall e-learning journey by adapting suggestions to individual learners' educational needs and goals [24]. For supporting academic planning, a system based on ML has been proposed to recommend appropriate course enrollments, enabling students to make more informed decisions during registration periods [25]. In another innovative design, agent-based systems have been employed within e-learning platforms, combining ML with knowledge discovery to provide intelligent and adaptive course suggestions [26]. Lastly, a hybrid RS architecture has been crafted to deliver personalized learning recommendations, emphasizing improved learning efficiency and greater alignment with user capabilities and objectives [27].

One such system integrated deep Flamingo search techniques with reinforcement learning, leveraging social media data to generate context-aware learning suggestions tailored to users' online behavior patterns [28]. In another study, artificial neural networks were applied to forecast students' final outcomes, thereby providing valuable insights for customizing educational support [29]. Efforts to align technology with sustainability in education have led to the development of a deep learning-based course RS framework aimed at promoting long-term academic growth and relevance [30]. Combining the strengths of knowledge graphs and collaborative filtering, researchers have built a course RS model capable of offering more precise and relevant suggestions by incorporating relational and preference-based information [31]. To further enrich the e-learning experience, ML-driven RS was introduced, focusing on enhancing user engagement and supporting diverse learning needs [32]. For learners who prefer greater autonomy, a personalized self-directed RS model has been proposed to empower individuals in navigating their own learning paths effectively [33].

While course recommendation systems have become more common in academic settings, many of the existing models fall short in practice. A major issue is that a lot of them rely on collaborative filtering, which tends to perform poorly when there's not enough data—especially for first-year students or newly introduced courses. Some systems also don't take into account important academic factors like a student's strengths, the complexity of the course, or how it fits into their overall curriculum. This often leads to suggestions that feel disconnected from what the student actually needs or is prepared for. On top of that, many models depend on user ratings or reviews, which aren't always available or reliable in a university context. All of this points to a gap: there's a clear need for recommendation systems that can work well even when data is limited, and that truly consider both the student's background and the nature of the courses being recommended.

III. Methodology

Figure 1 shows the proposed hybrid framework to deliver personalized elective and course recommendations to engineering students considering the academic profiles and interests of students.

A. Data Collection

The dataset used in this study was collected from different prestigious Colleges of Engineering and Technology, in Maharashtra. The data comprises academic records of students from the Information Technology (IT) stream, specifically from third to seventh semesters (III, IV, V, VI, and VII).

The student dataset includes academic performance indicators such as course completion history, grades, and subject-wise proficiency levels. Additionally, the course dataset was curated from NPTEL (National Programme on Technology Enhanced Learning), which offers a rich repository of engineering-related courses with detailed content descriptions, domains, prerequisites, and difficulty levels.

The comprehensive set of attributes was collected and structured for both student and course profiles. These attributes are summarized in Table 1, which includes student identifiers, enrolled courses, grades, interest domains, course metadata, and relevant prerequisites.

TABLE I: STUDENT AND COURSE DATA ATTRIBUTES

Entity	Attributes
Student's Data	Timestamp, Enrollment ID, Email, Full Name, Gender (M/F), Region(District), Skills, Carrier Objective, Device to be Used (Mobile, Laptop), Previous Attended Course
Course Data	Open Elective, Course Title, Instructor, Institution, Focus Summary, Rating

B. Data Preprocessing

To ensure consistency and improve the quality of input for the recommendation model, several preprocessing operations were applied to both student and course datasets. Initially, all textual data fields—including course titles, descriptions, and student-declared interests—were converted to lowercase to maintain uniformity and prevent mismatches due to case sensitivity. Next, any parentheses along with their enclosed content were removed to eliminate supplementary information that might introduce noise rather than value. Special characters, except for commas (which were retained for their semantic importance in separating tags or keywords), were also removed. This step helped in reducing irrelevant symbols that could interfere with feature extraction. Finally, extra spaces resulting from the previous cleaning operations were removed to streamline the data and ensure clean tokenization in subsequent stages such as vectorization and similarity computation. These preprocessing steps were crucial in preparing the data for accurate and meaningful comparison using cosine similarity.

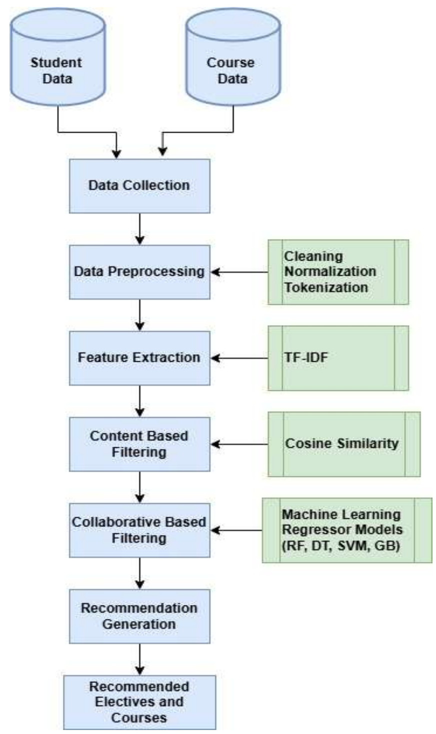


Figure 1: Hybrid Framework for Elective and Course Recommendation Framework

C. Feature Extraction

To effectively represent course content in a numerical format suitable for similarity computation, feature extraction was performed using the Term Frequency–Inverse Document Frequency (TF-IDF) technique, applied to the textual attributes of the course data, specifically the fields 'Open Elective', 'Course Title', 'Focus', and 'Summary'. These fields collectively provide critical insights into the thematic and academic orientation of each course. The TF-IDF approach captures the importance of words not just based on their frequency within a specific course entry but also considering how uniquely they appear across all course descriptions. This ensures that commonly occurring but less informative terms are down-weighted, while more distinctive terms receive higher importance. The resulting TF-IDF vectors encapsulate the semantic structure of each course and serve as the foundation for computing similarity scores with student profiles. This textual feature representation plays a crucial role in accurately identifying and recommending courses that align with individual student interests and academic background.

TF-IDF for a term *t* in a course data *d* within entire course dataset *D* is computed as follows:

$$TF - IDF(t, d, D) = TF(t, d)\ x\ IDF(t, D)$$

Where:

- TF quantifies the frequency with which a phrase *t* appears in a document *d*:

$$TF(t, d) = \frac{f_{t,d}}{\sum_k f_{k,d}}$$

Here, $f_{t,d}$ represents frequency of term t in d, and the denominator represents the total number of terms in d.

- IDF measures how distinct or informative a phrase is across all documents in the corpus:

$$IDF(t, D) = \log\left(\frac{N}{1 + n_t}\right)$$

Where:

- N is the corpus's total number of courses,
- n_t is the documents numbers that contain term t,
- A smoothing term +1 is added to avoid division by zero.

The final TF-IDF vector for each course is formed by computing the TF-IDF values for all terms across the combined textual fields, *Open Elective, Course Title, Focus,* and *Summary*. These vectors are then used to represent courses in a high-dimensional vector space for similarity analysis.

D. Content based Filtering

Content-based filtering is a personalized RS approach that recommends items—such as open electives or courses by interpreting the characteristics of the items and corresponding them to a user's individual profile. In the context of academic course selection, this technique utilizes the content features of available courses and compares them with a student's academic background, skills, and declared career interests.

For instance, a student with a strong foundation in programming and a career objective in artificial intelligence would be recommended courses that emphasize AI, machine learning, or data science. This is achieved by converting both student profiles and course descriptions into feature vectors, often using techniques like TF-IDF to quantify textual information. Cosine similarity is then applied to measure how closely each course aligns with the student's profile. The higher the similarity score, the more relevant the course is considered for recommendation. With this approach, the suggestions are guaranteed to be independent of what others decide, but rather tailored to the student's own goals and strengths, resulting in more meaningful and goal-oriented academic planning.

Consider, S = student profile vector (based on skills, past courses, career goals), Ci = feature vector of the *ith* course

Each vector is constructed using TF-IDF or other feature encoding methods. The similarity score between a student and a course is computed using cosine similarity:

$$Similarity(S, C_i) = \cos(\theta) = \frac{S.C_i}{||S||\,.\,||C_i||}$$

Where:

- $S{\cdot}Ci$ is the dot product of the vectors & ‖S‖ and ‖Ci‖ are their magnitudes

The top-N courses with the highest similarity scores are selected as recommended electives for the student:

$$Recommended\ Courses = \underset{i \in \{1, \ldots.. n\}}{TopN} Similarity(S, C_i)$$

E. Collaborative based Filtering based on Machine Learning

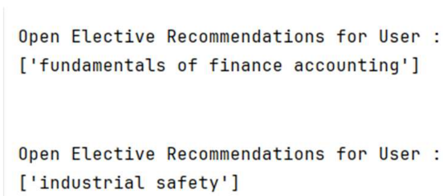
Collaborative based filtering (CF) is a powerful RS technique. The two main categories are Memory and Model-based techniques. Memory-based CF relies directly on the entire user-item interaction data to make recommendations without building an abstract model. But it performs poorly with large datasets and fails when many users haven't rated many items. Hence, Model-based CF is used in the proposed approach that utilizes machine learning or statistical models to predict user rating preferences. It learns patterns from the user-item interaction data and builds a intelligent model. To enhance the accuracy and personalization of the course recommendation system, a machine learning-based regression approach was employed to predict the potential rating a student might give to a course. The objective was to model the relationship between student profile attributes and course features to estimate how well a course would align with a particular student.

Several regression models were trained and evaluated for this task, including Decision Tree Regressor (DT), Random Forest Regressor (RF), Support Vector Regressor (SVR), and Gradient Boosting Regressor (GBR). Each model was trained on a labeled dataset where the target variable was either actual student-provided ratings or proxy ratings derived from academic feedback and course outcome alignment. The predicted ratings were then integrated into the recommendation framework, allowing the system to prioritize not only content similarity but also the expected satisfaction or usefulness of the course for the student.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed hybrid recommendation system was developed using Python within the PyCharm Integrated Development Environment (IDE). To ensure realistic modeling and practical relevance, the system was trained and tested using a collected real-world dataset. The development and experimentation were carried out on a Windows 11 OS equipped with an Intel i5 processor, 16GB RAM, and a 4GB GPU, providing adequate computational resources for model evaluation. Standard assessment measures including Mean Squared Error (MSE), Mean Absolute Error (MAE), and the R-squared (R^2) Score were used to evaluate the performance of the regression models utilized in the system. These metrics provide information about the accuracy and dependability of the predictions. The dataset was split 80:20 across training and testing subsets to provide a fair and accurate assessment of model performance. To achieve optimal accuracy, both the machine learning model hyperparameters and the dimensionality of the TF-IDF matrix were carefully fine-tuned through iterative experimentation.

Figures 2 and 3 illustrate the functional output of the recommendation engine. Figure 2 displays the recommended open electives generated based on the student's academic and interest profile, while Figure 3 presents the top 3 course recommendations, personalized for the user. These outcomes show that the algorithm can rank relevant courses according to anticipated user satisfaction in addition to filtering them based on content similarity.



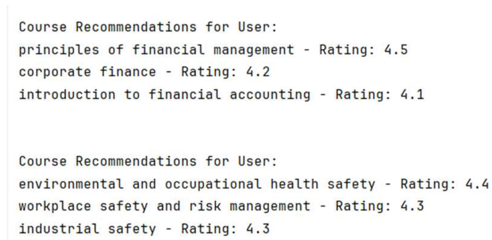


Figure 2: Recommended Output for Open Elective for users   Figure 3: Recommended Output for Course Recommendation for users

The quantitative performance evaluation is shown in Table 2, specifically for third-semester (III sem) students, where various ML regression models, DT, RF, SVR, and GB regressors were used to predict the expected rating of each course. The models were evaluated using MAE, MSE, and R^2 score.

TABLE II: DIFFERENT MODELS EVALUATION FOR COURSE RATING PREDICTIONS FOR III SEMESTER

Regressor Model	MAE	MSE	R2 Score
Random Forest	0.2023	0.0569	0.3458
Decision Tree	0.1666	0.0366	0.5769
Support Vector	0.2498	0.0729	0.1586
Gradient Boosting	0.1586	0.0324	0.6257

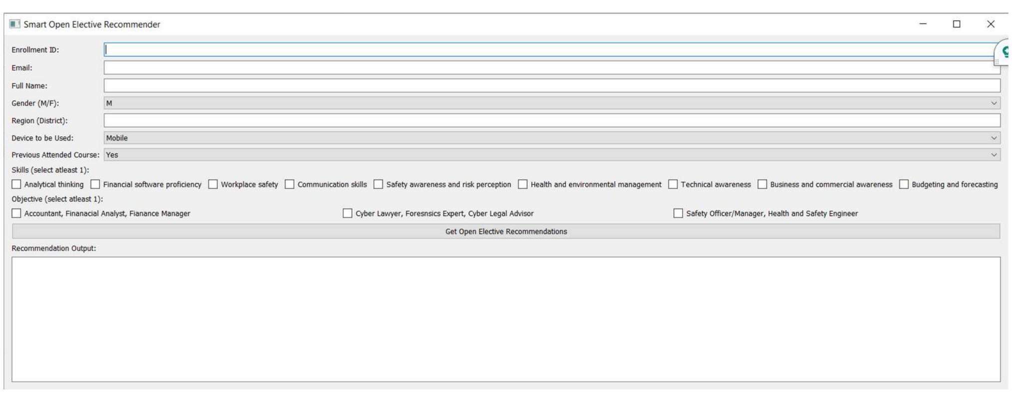


Figure 4: Smart Elective Recommender GUI

The models that fared the best were the RF and GB regressors, which had the lowest MSE and MAE and higher R^2 values, demonstrating resilience and excellent prediction accuracy. A lower MSE score indicates that the model's accuracy in predicting course suitability was confirmed, since the predicted and actual student ratings closely matched. The ensemble approaches were also substantially better at capturing the intricate links between student characteristics and course material, as evidenced by their significantly higher R2 score, which quantifies the percentage of variation explained by the model. This evaluation was further extended to students from other semesters (IV to VII), following the same methodology. Similar performance trends were observed, reinforcing the generalizability of the system across different academic levels. Additionally, Figure 4 presents the Graphical User Interface (GUI) designed for this system, offering a user-friendly platform where students can input their academic profiles and receive tailored course recommendations in real-time. The GUI effectively bridges the technical backend with an accessible frontend, enabling broader usability in academic environments.

In summary, the results affirm that the integration of content-based filtering with machine learning regression yields a highly accurate and personalized course recommendation system. The system not only enhances elective selection for engineering students but also supports informed academic planning based on individual career goals and interests.

V. CONCLUSION

This paper presented a personalized course recommendation framework designed to assist engineering students in selecting suitable open electives. The proposed system adopts a hybrid filtering approach, combining content-based filtering using cosine similarity with collaborative filtering techniques based on machine learning models to deliver highly personalized recommendations. Course content vectors were generated using TF-IDF applied to descriptive course attributes, while student profiles—including academic records, interests, and learning goals—were used to assess relevance. Furthermore, ML regression models were utilized to predict personalized course ratings, leveraging historical student-course interaction data. The proposed system improved recommendation accuracy, adaptability, and overall user satisfaction. Experimental evaluation using a real-world dataset demonstrated that the proposed framework is capable of producing relevant and accurate course suggestions. Among the machine learning models tested, ensemble-based methods showed strong predictive performance as measured by MAE, MSE, and R^2 metrics. This research highlights the potential of combining semantic content analysis with predictive modelling in the academic domain, particularly for assisting students in making informed elective choices.

Future work may focus on enhancing the hybrid recommendation system by integrating more advanced techniques with Big Data, incorporating real-time student feedback for dynamic personalization, and scaling the framework to support diverse academic programs across multiple institutions and their streams.

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