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Research Article

Enhancing Hybrid Course Recommendation with Weighted Voting Ensemble Learning

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Abstract: Course recommendation aims to find suitable and attractive courses for students based on their needs, playing a significant role in the curricula-variable system. However, with the abundant available courses, students often face cognitive overload when selecting the most appropriate ones. This research proposes a course recommendation system called the Enhanced Hybrid Course Recommender to address this challenge. This system uses an ensemble learning approach to combine and leverage the power of multiple machine learning classifiers, including Random Forest, Naive Bayes, and Support Vector Machine. By utilizing TF-IDF vectorization for text data transformation and label encoding for target label compatibility, this experiment significantly enhances recommendation precision and relevance, easing students' decision-making process and improving the overall quality of course recommendations. A hybrid approach is applied to improve the recommendation quality by combining predictions from all three classifiers through weighted voting. This ensemble method improves overall robustness and accuracy. This approach not only mitigates the cognitive overload faced by students but also significantly improves the quality of recommendations. Our hybrid model represents a substantial advancement in personalized course recommendation technology by demonstrating superior performance across key evaluation metrics such as accuracy, precision, recall, F1-score, ARHR, and NDCG.

Keywords: Course Recommendation; Ensemble Learning; Hybrid Approach; ARHR; NDCG.

1. Introduction

Recommendation systems in courses are a critical feature of modern learning paradigms, attempting to overcome the problem of the abundance of courses offered to students. They help find one's way in today's wealth of educational opportunities and suggest adequate options based on learning preferences and academic achievements. One important benefit is that these systems can minimize the effect of cognitive load, which occurs when students are offered too many options – the outcome known as the paradox of choice[1]–[3]. Because these systems exclude many irrelevant choices, they help minimize the overwhelming decision-making tasks. Furthermore, course recommendation systems increase the level of satisfaction and learning activity to provide students with courses according to their preferences[4]. Consequently, this alignment enhances the total learning encounter while at the same time boosting the learning achievement. Literature has proven that when students follow hints provided by an AI system, they perform better than those who choose their courses individually[5]–[7]. In addition, these systems promote learner customization by identifying students' preferences and learning patterns to facilitate effective customization of instructional methods and course content.

However, several critical challenges are inevitable in implementing a proactive course recommendation system. One of the challenges is data scarcity, where there is not enough data to predict the student's course preferences from historical data. Likewise, the cold-start problem when working with new students or courses makes it hard to generate stable

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recommendations since there will be little data at one's disposal. Another important consideration is scalability because the traditional algorithm may fail to meet computational requirements when the number of students and courses grows.

Standard recommendation techniques are traditional approaches like collaborative filtering or content-based filtering, which are restricting [8]. Collaborative filtering uses similarity between the students' preferences to forecast their choices but is best constrained by the sparse data and the start-up issue. On the other hand, however, content-based filtering considers course descriptions and keywords to suggest the courses. However, its effectiveness decreases if the descriptions of courses within the sub-areas are not consistent or informative enough. In projects, these challenges show the need for new approaches to address these problems and offer better and much more reliable recommendations.

To this end, the Enhanced Hybrid Course Recommender is presented based upon ensemble-learning techniques. Our proposed solution integrates Random Forest, Naive Bayes, and SVM classifiers all of which have been confirmed to offer unique features in different aspects of handling text classification and recommendation tasks. In this way, the proposed approach combines those classifiers, providing a balanced and stable result that increases the precision and information value of the offered courses.

Using TF-IDF vectorization to convert course descriptions to other textual features, the data used in the proposed model is format-friendly for machine learning (ML) algorithms[9]. The target labels, symbols of the names of the courses, are further transformed using the label encoder to improve their discriminant ability. The assessment criteria used are accuracy, precision, recall, F1 score, Average Reciprocal Hit Rate (ARHR), and Normalized Discounted Cumulative Gain (NDCG), giving an overall system efficiency measure.

2. Related Work

In recent years, various approaches have been developed to address challenges in course recommendation systems. For example, DORIS, a system based on DeepFM, uses student information and course details to make accurate recommendations[10]. DORIS effectively models feature interactions by combining deep neural networks and factorization machines. However, while DORIS performs well, it relies heavily on computationally intensive deep-learning models and does not directly address data sparsity or cold-start problems. Similarly, DECOR integrates deep learning to infer user behaviors and course attributes, demonstrating improved accuracy and robustness in recommendations[11]. Despite its strengths, DECOR's high-dimensional feature modeling requires significant resources, limiting its applicability in smaller-scale settings or environments with limited data.

Hybrid systems, such as the one proposed by Deepak et al. [12], use LSTMs and spectral clustering to improve sequential recommendations. Their approach outperforms traditional clustering techniques like K-means but is primarily tailored for sequence-based recommendations, limiting its generalizability to other scenarios. Another notable system by Tran Thanh et al. [13] leverages MLP networks for recommendations, showing improved performance by including specific features like English marks. However, this model's reliance on large datasets raises concerns about scalability in data-constrained environments.

Research by Subha et al. [14] introduces a hybrid framework combining CNNs and LSTMs to capture both feature extraction and temporal dependencies. However, this approach's complexity and resource requirements make it less practical for broader adoption. A related study[15] emphasizes the importance of collecting the right data and applying feature extraction methods to improve the relevance of course recommendations. The study evaluates Fuzzy Logic and K-nearest neighbors (KNN) for accuracy, highlighting that objective judgments without individual preference considerations can hinder recommendation effectiveness. Furthermore, a study by [16] employs deep reinforcement learning (DRL) and multi-agent systems to provide adaptive, personalized recommendations. Despite its advanced capabilities, this method remains resource-intensive and may not be suitable for smaller institutions or datasets.

Traditional ML methods, such as collaborative filtering and content-based filtering, also have limitations. Collaborative filtering relies on user similarity but struggles with sparse or new data[17]. Content-based filtering, while leveraging course attributes, often fails when course descriptions are inconsistent or incomplete. These challenges highlight the need for approaches that balance efficiency, scalability, and effectiveness[18]. While DORIS, DECOR,

and DRL-based methods demonstrate significant advancements, they often depend on computationally intensive deep learning models that are impractical for small-scale or resource-limited settings. Additionally, traditional methods fail to adequately address data sparsity, cold-start problems, and inconsistencies in feature representations. Table 1 below summarizes the existing work and contrasts with the proposed recommendation system with regards to the research aims, modeling approaches, performance measurements, and results.

Table 1. Comparative analysis of the existing work and proposed recommendation system.

Feature/ Aspect	Proposed Research Work	Ref [10] DORIS	Ref [15]	Ref [11] DÉ-COR	Ref [12] Hybrid RNN	Ref [13] MLP-based System
Methodology	Ensemble of Random Forest, Naive Bayes, SVM	Deep Factorization Machine (DeepFM)	KNN and Fuzzy Logic with TF-IDF and N-gram	Deep learning with RNNs	A hybrid of content-based and collaborative filtering using RNNs and LSTMs	Deep learning using Multi-Layer Perceptron (MLP)
Data Transformation	TF-IDF vectorization, label encoding	Embeddings for deep learning	TF-IDF and N-gram	High-level feature extraction with deep learning	Sequential modeling using RNNs/LSTMs	Pre-processing, including feature analysis
Handling of Sequential Data	Not designed for sequential data	Not specifically designed for sequential data	Not designed for sequential data	Specifically designed for sequential recommendations	Treats recommendations as a sequential problem	Not explicitly designed for sequential data
Feature Interaction	Limited to interactions captured by individual classifiers	High-order feature interaction with DeepFM	Uses TF-IDF and N-gram for feature extraction	Captures high-level feature interactions	Utilizes LSTMs for capturing sequential patterns	Detailed feature engineering, e.g., English skill marks
Performance Metrics	Accuracy, Precision, recall , F1-score , ARHR, NDCG	Outperforms other methods in recommendation quality	Accuracy, precision with TF-IDF and sentiment analysis	HR and NDCG, showing consistent improvements	Precision, recall, accuracy, F-measure	RMSE, MAE
Experimental Results	Relatively high arhr and ndcg scores	Demonstrates superior performance over BPR, LR, FM	Improved accuracy with TF-IDF and N-gram	Better and more robust performance compared to traditional methods	Outperforms other recommender systems, especially with LSTMs	Promising results, improved with English skill marks
Scalability	Scalable with additional classifiers	Requires significant computational resources	Feature extraction methods can be computationally intensive	Requires significant resources for deep learning	Requires resources for RNN/LSTMs and clustering	Requires resources for deep learning

This research proposes the Enhanced Hybrid Course Recommender to address these gaps, integrating ensemble learning techniques with Random Forest, Naïve Bayes, and SVM classifiers. This approach combines the strengths of each classifier, ensuring robust performance while remaining computationally efficient. By employing TF-IDF vectorization and label encoding, the proposed system effectively mitigates issues of data sparsity and variability in course descriptions. The model's performance is evaluated using comprehensive metrics, including accuracy, precision, recall, F1-score, ARHR, and NDCG, providing a thorough assessment of its effectiveness. In summary, the Enhanced Hybrid Course Recommender aims

to bridge the gap between traditional and deep learning methods, offering a scalable, efficient, and reliable solution for course recommendation systems.

3. Materials and Methods

3.1. Dataset

This dataset [19] combines tabular and textual data, detailing a list of programs offered at an autonomous college. This publication also includes a detailed description of the dataset; the information can be viewed in the Table 2. It includes information on various subjects and specifies the developmental needs addressed upon completion of each subject's syllabus. The developmental needs are categorized into Local, Regional, National, and Global levels. The dataset comprises 905 entries and contains six features.

Table 2. Course Dataset.

Feature	Description
SrNo	Serial Number
Name Of the Program	Graduation or Post Graduation Program
Type of Course	Subject Name within selected program
Code	Subject Code
Need	Type of Developmental Need the subject is catering to
Description of the need	Description of Developmental Need associated to the subject

Regarding the dataset, each entry represents a subject within a particular program, with information regarding developmental needs covered by the subject. In the dataset used in the current study. Here is a detailed description of each feature:

1. SrNo: This feature is essential in uniquely identifying every record in the dataset. It is a running number placed on each record that helps to identify it.
2. Name Of the Program: This feature, required, provides information whether the educational program is graduation or post-graduation by giving its name. They are usually in the format "BSc Computer Science" or "MSc Data Science".
3. Type of Course: This feature corresponds with the subject/ Major/ Course category within a chosen program. For example, "Programming Fundamentals" or "Advanced AI Machine Learning".
4. Code: This feature holds the subject's identification code as a unique identifier. It is useful in accurately identifying each course and providing a way of referring to courses in the program. Such as "CS101" for "An Overview to Programming".
5. Need: It also shows the type of developmental need the subject caters to. Developmental needs are categorized as Local, Regional, National and Global. This classification is useful in appreciating the topicality and significance of the subject matter more.

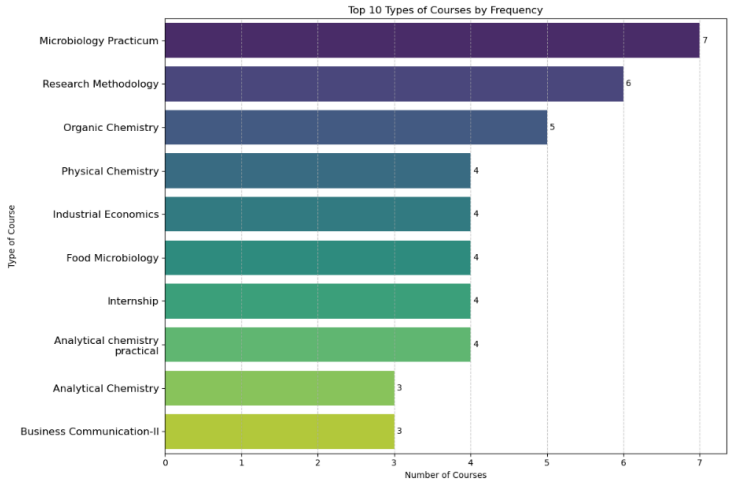

Figure 1. Top 10 Types of Courses by Frequency

6. Description of the need: This feature elaborates the development need linked with the subject. It goes further, explaining how the subject helps to meet certain needs, for instance, to develop employment openings locally, fill a void in technological development in a given territory, boost the nation's economic condition, or build international competencies.

By leveraging this comprehensive dataset, the proposed Enhanced course recommender system can analyze the interplay between subjects and developmental needs, leading to more personalized and contextually relevant course recommendations. This approach ensures that students receive guidance that aligns with their academic goals and broader developmental objectives. Figure 1. illustrates the frequency of the top 10 types of courses available in the dataset. Each bar represents the number of courses for a specific type of course, providing a clear comparison of their prevalence.

3.2. Random Forest Classifier

Random Forest (RF) is a type of ensemble learning algorithms that build n decision trees during the learning phase and gives the mode of the classes as the output in classification problems. It is one of the Ensemble learning methods that build many decision trees during the training phase. Each tree in the forest is constructed heuristically from a different bootstrap sample of the actual data. The decision is based on the decision that most such trees have made. It incorporates randomness in selecting the features to split at any node of the decision tree, and it makes it better than the others by preventing overfitting [20].

Many studies acknowledge RF's performance in terms of large samples and high dimensionality[21]. In recommendation systems, RF has been used to increase the system's performance; this has been done by combining the decisions taken by many decision trees to minimize overfitting.

The TF-IDF vectorizer numerical results from the textual descriptions of courses by identifying the significance of words in the text data. The Random Forest classifier is then built from the TF-IDF transformed data to predict the encoded labels of the courses from their textual descriptions. In the last stage, the recommendation stage, the model applies the decision-making of multiple trees to decide on the proper action for an input.

3.1. Naïve Bayes

Naive Bayes (NB) classifiers rely on Bayes' theorem to make their predictions, assuming that the features are independent of each other. Nevertheless, quite unexpectedly, this assumption can prove to be very useful in practice and Naive Bayes works rather well in numerous applications. Commonly NB calculate using Equation (1).

$$P(y \mid x) = \frac{P(x \mid y) \cdot P(y)}{P(x)} \tag{1}$$

Where $P(y \mid x)$ is the posterior probability of class y given features x; $P(x \mid y)$ is the likelihood of observing features x given class y; $P(y)$ is the prior probability of class y; $P(x)$ is the marginal likelihood of features x.

NB is quite effective in classifying textual descriptions, so it may be effectively used in real-time course recommendations [22]–[24]. In the same way as RF, the TF-IDF vectorizer transforms course descriptions for the model into numerical characteristics. The Multinomial NB classifier is applied to these TF-IDF features and calculates how likely any word would appear in the text of the class labels. In case of a new course description for which we would like to make a prediction, the model computes the probabilities for each class and assigns the class with the highest probability to that course

3.3. Support Vector Machine (SVM)

SVM classifiers are highly effective for binary classification problems. They operate based on two principles: identifying the hyperplane that optimally defines the data in the different classes. SVM intends to achieve the maximum margin of the decision hyperplane between the classes of the data points[25]. It uses kernel functions where the data is non-separable in the required linear form in a two or three-dimensional space. It brings them in a higher dimensional space where a linear separator can be easily employed.

SVM is ideal for working with the intricate feature matrices often characteristic of educational data sets. SVM is trained from the TF-IDF-transformed data so that it may learn to classify the courses by using the appropriate hyperplane that shall separate the classes. SVM for a new course description sets out its class/decision by pointing to which side of the decision hyperplane the data point is on.

3.4. Enhanced Hybrid Course Recommender

The Enhanced Hybrid Course Recommender system aims to provide accurate course recommendations using multiple ML classifiers. This pipeline diagram, as shown in Figure 2, displays the entire functioning of this research work, beginning with data preprocessing.

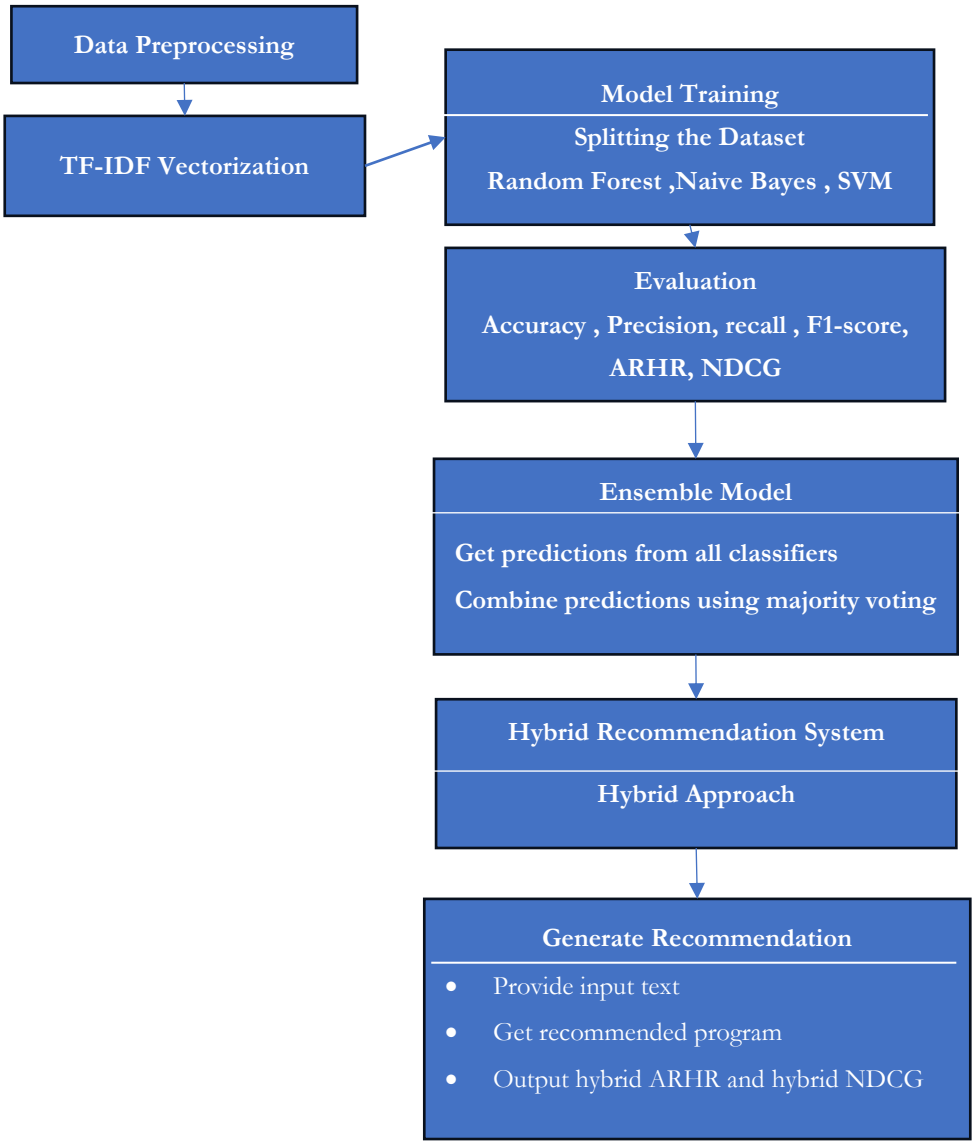

Figure 2. Workflow of the Proposed Enhanced Hybrid Course Recommender System

In the first stage, tabular-text datasets with program specifications and subject requirements are gathered, preprocessed, and wrangled. Among them, textual features of related fields are integrated into one feature, and the target labels are transferred to numerical values of the label encoding method. The next stage involves a feature extraction process where the textual data obtained is converted to numerical feature form through TF-IDF vectorization for models usable for ML. The next is the model training; the dataset is divided into the training (80%) and testing (20%) sets. Three individual classifiers (RF, NB, and SVM) are then trained. The parameter configurations of each classifier are presented in Table 3.

The ensemble modeling stage is to make predictions on the test set about each classifier that has been trained. To develop a recommendation, the forecast occurring from each model is summarized using a weighted voting system. Weights for each model are determined based on its evaluation on a validation set, in this case the F1-score[26]. The weights are calculated using a linear normalization approach from these metrics (see Equation (2).

Table 3. Parameter settings for each classifier.

Random Forest	SVM	Naive Bayes
Number of Trees: 100	Kernel: Radial Basis Function	Smoothing: 1e-9
Max Depth: 10	C (Regularization Parameter): 1	
Minimum Samples Split: 2	Gamma: 0.01	

$$Wi = \frac{F1\ \text{Score}\ i}{\sum F1\ \text{Score}\ i} \tag{2}$$

Where Wi is the weight given to the classifier i.

The performances of each classifier and the integrated classifier system are measured with accuracy, precision, recall, F1-score, Average Reciprocal Hit Rate (ARHR), and Normalized Discounted Cumulative Gain (NDCG), for more details, see Section 3.5.

3.5. Evaluation Metrics

Regarding evaluation, several measures that exist to help scale recommendation systems are used. The other classification performance measures include accuracy, precision, recall, and F1- score. However, for recommendation systems, the ARHR and NDCG are also essential[9]. These indicate the position and importance of the recommendation lists that are superior to the mere success rates of the system.

- The accuracy of each model is calculated by comparing the predicted labels with the actual labels.
- Precision, recall, and f1-score are used to assess the model performance regarding relevance and completeness[27].
- Average Reciprocal Hit Rank (ARHR) $@k$ is used to evaluate the quality of recommendation ranking by considering the reciprocal ranking of correct recommendations. It can be calculated by Equation (3).

$$ARHR@k = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\text{rank}_i} \tag{3}$$

Where rank_i is the rank position of the first relevant item in the top-k list for the i-th instance

- Normalized Discounted Cumulative Gain (NDCG) $@k$ is used to measure the relevance of the top-k recommended items, taking into account the order of recommendations. It reflects how well the top recommendations align with user preferences, see Equation (4).

$$NDCG@k = \frac{DCG@k}{IDCG@k} \tag{4}$$

Where $DCG@k$ is discounted cumulative gain is calculated as $NDCG@k = \frac{\Sigma\,(2^{\text{relevance}\,-\,1})}{\log2(\text{rank}+1)}$; relevance is the relevance score of the item at position rank; rank is the position of the item in the list, starting from 1; $IDCG@k$ (Ideal DCG) is the DCG of the ideal ranking.

4. Results and Discussion

4.1. Results

The proposed ensemble learning-based hybrid approach significantly improves the quality of course recommendations. Analysis using ARHR and NDCG metrics highlights the superiority of this system in prioritizing relevant courses at the top of the recommendation list.

The hybrid system achieved an ARHR score of 0.333 and an NDCG of 1.0, reflecting perfect relevance between the recommendations provided and the user's needs, see Figure 3. In this context, it is important to understand the difference between classification and recommendation processes. The classification process focuses on grouping course data into specific categories based on their characteristics. This is done by RF, NB, and SVM algorithms that predict course labels based on features extracted from course descriptions. However, the recommendation process requires not only correct predictions but also prioritizing the recommendation results to be relevant to the user's needs. This is why metrics such as ARHR and NDCG are crucial, as they both evaluate the quality of the recommendation sequence[28], [29].

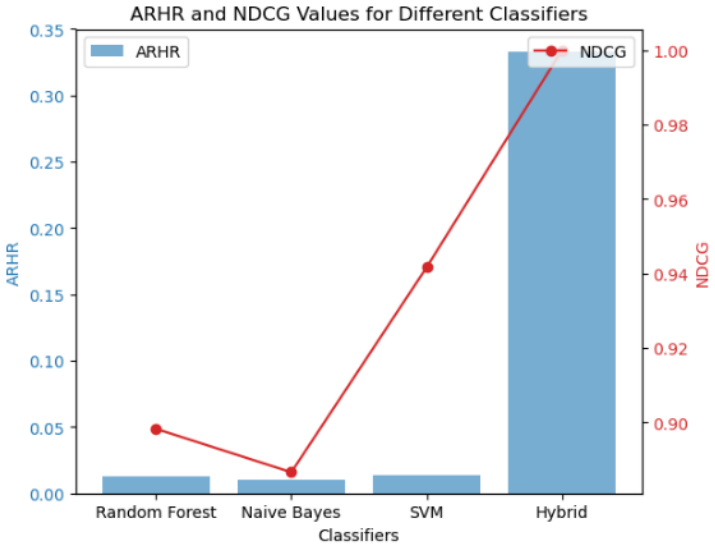

Figure 3. Comparison of ARHR and NDCG Scores.

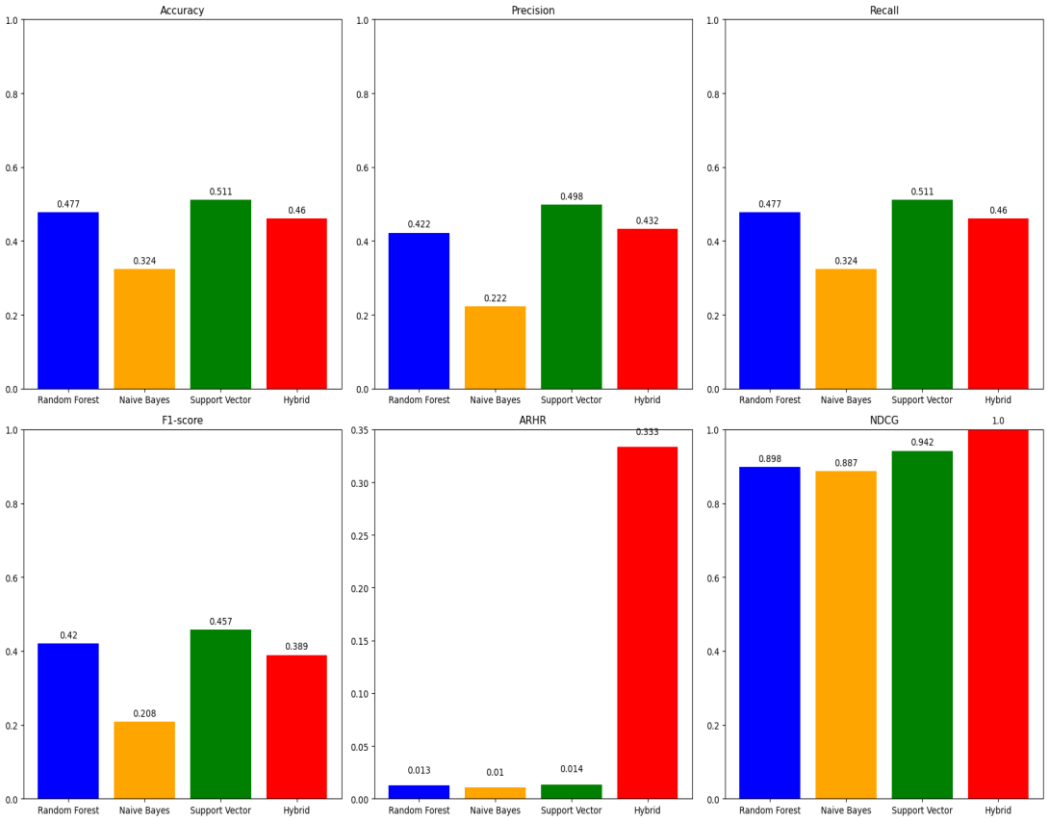

Figure 4. Scores for Random Forest, Naive Bayes, SVM, and Hybrid.

Next, when highlighting the classification results, it appears that SVM has the highest classification accuracy of 51.1%, followed by RF (47.7%) and NB (32.4%), see Figure 4. Although NB has the lowest individual performance in terms of accuracy, this algorithm still contributes to improving the results of the hybrid system. Which, with its ability to analyze text, helps enrich the diversity of predictions. In contrast, SVM shows the best performance among the individual algorithms with an accuracy of 51.1% and the highest F1 score. RF, although having lower accuracy than SVM, shows good stability in classification. By integrating predictions from the three algorithms through a weighted voting mechanism, the hybrid system successfully combines the advantages of each algorithm and improves their weaknesses.

4.2. Key Findings and Implications

The results of this study reveal that the hybrid approach based on ensemble learning provides an efficient and effective solution to the challenges in course recommendation systems, especially the data sparsity and cold-start issues. The system can generate relevant and organized recommendations by utilizing TF-IDF as the text transformation method and weighted voting as the merging mechanism, even with a limited dataset.

The main advantage of the hybrid system over other methods, such as DORIS and DECOR, is its computational efficiency. Although deep learning models such as DECOR excel at capturing complex feature interactions, they often require large datasets and significant computational resources, making them less suitable for implementation in educational settings with limited infrastructure. In contrast, the hybrid approach shows competitive results with lighter resources, making it a practical and relevant solution.

In the context of recommendation, the success of the hybrid system is measured not only by the prediction accuracy but also by the quality of the recommendation ranking. By placing the most relevant courses at the top, the system effectively reduces users' cognitive load and increases their satisfaction. This is achieved by combining the strengths of each algorithm: stable Random Forest, accurate SVM, and effective NB in text analysis.

Furthermore, ARHR and NDCG metrics confirm the relevance of this approach in real-world situations, where users are more likely to pay attention to recommendations at the top of the list. The system's success in generating relevant recommendation sequences shows great potential for application in modern education systems. With further developments, such as integrating modern embeddings or more sophisticated ensemble methods, this system can potentially become a more comprehensive and adaptive solution in the future.

5. Conclusions

The major goal of this study was to design an improved recommendation system to overcome the limitations of current hybrid course recommender methods and increase the accuracy and relevance of the recommendations to be presented. When the advocated models, namely RF, NB, and SVM, are implemented in an ensemble approach as the proposed model, better results are obtained than with standalone models.

The proposed approach improves the refinement and redundancy of course recommendations by using TF-IDF Vectorization for feature extraction and a weighted voting system. Assessment by key measures, including accuracy, precision, recall, F1-score, ARHR, and NDCG, proves the system can offer quality recommendations. In particular, the improvement in ranking quality is defined quantitatively in terms of ARHR and NDCG, and the increase in classification accuracy proves the applicability of the proposed system in reducing students' cognitive load in learning.

This research work's ensemble learning and feature engineering can effectively address challenges such as data sparsity and cold start. Additionally, using weighted voting in the proposed framework allows for proportional voting from models, in addition to increasing recommendation precision and the ranking of the recommendations. The proposed research work will help the students make appropriate choices about the courses they want to take according to their career interests to be more satisfied with their decisions.

Furthermore, this research filled the gaps detected in the literature by integrating the ML models and using the hybrid approach. Unlike the state-of-the-art approaches, DORIS, DECOR, and other deep learning-based approaches, the proposed research work offers an

optimal combination of the benefits of traditional features and the strengths of different classifiers.

However, as with most works on ensemble methods, future studies may build on this work by using deep learning models in conjunction with ensemble frameworks to capture increasingly complex interactions of the model features and users' behaviors concerning the experimentation with different forms of the model features and users' behaviors. Furthermore, it would be worthwhile to consider the possibility of using domain-specific datasets and real-time feedback procedures to refine the recommendation process.

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