Research Square

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Implementation of Recommendation System using Content Based Approach for Course Selection of University Students

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Abstract

Modern higher education institutions focus on flexibility and interdisciplinary courses which changed the dynamics of course planning for their students. Today, course structures include a wide range of electives, allowing students to choose what they want to learn. However, with so much variety comes with complexity of choosing courses. A student can feel uncertain, overwhelmed by information, and exhausted by the process of choosing courses that meet their strengths and career aspirations. In this context, there is an evident need to develop and intelligent recommendation system to support learners in making informed, confident decision about their academic courses. The primary objective of this research is develop a personalized recommendation system for a student which suggest a suitable course based on their academic performance and their preferences. This research presents a student-centric, content-based course recommendation framework, which combines academic performance, learner preferences and advanced ensemble learning to facilitate smart course selection in higher education. To solve the problem of cold-start, the proposed model is not rely on historical data or past data which used only directly available learner inputs. To improve the model performance, bagging and stacking techniques is used on ensemble learning model. The study evaluates the model's effectiveness using various metrics for classification, including accuracy, precision, recall, F1-score and an evaluation of the confusion matrix. The result reflects smooth and balanced performance on training, validation and testing etc. which is an indicator of the model's ability to generalize.

1. Introduction

In India before NEP 2020 implementation, most of the universities offered fix curriculum and if it is offered the course selection is limited which is from the same stream or a discipline. After the implementation of NEP2020 scenario changed; now course selection in higher education become student-centric, flexible, credit-based and multidisciplinary. Now students can make combination of different courses in the form of core, major, minor, skill enhancement, vocational, value added course from across various disciplines [1,2].

Modern higher education system has flexibility and diversity in course selection which make it highly complex to the students. Because of wide range of electives, interdisciplinary courses, and skilled-based module students struggles to identify courses that aligned with their academic strengths and personal interest. For this reason, majority of the students uses traditional approach of asking and taking suggestion of others while other students uses internet [3].

The students who use traditional methodology for choosing their course take help of their teachers or elder members of the family or their friends which again rely on incomplete or limited data. Their subjective assessment could not accurately assess student's learning preferences or ability which can lead to poor academic performance [1].

The students who use internet are again facing problem in selecting courses because in today's information edge thousands of courses and multidisciplinary pathways are available on internet they

suggest courses to the students on the basis of current trends and employability available. Students often select courses based on the market trends and ignore their capability and interest [4].

As education system shift from a traditional model to flexible and dynamic, it is important to consider the mindset of students. While NEP2020 offers numerous advantages, it also introduces challenges for the students, particularly in the selecting appropriate courses. Here Recommendation system play an important role for the students while they are selecting course. Recommendation system is an intelligent algorithm which analyze various factor like student's academic history, interest, carrier goal, preferences, etc. to suggest personalized and relevant courses. The recommendation systems give intelligent decision support system to the student that guide them in making their academic choice. It reduces the complexity and improve student decision in flexible and multidisciplinary higher education environment [5].

The recommendation system have been extensively studied and successfully deploy in different domain like e-commerce, social media, Over-The-Top (OTT) platform, health care but the adoption for course selection in higher education remain limited because the use of recommendation system in other domain industry make money in the business while the usage recommendation system in higher education will increase the success ration of the students there is no direct profit. There are other factors also added of limited adoption of recommendation system like trust, data privacy concern, institutional constraints, etc. [5].

The main factor which gives motivation of this research is to make skilled and industry ready students. The research says that Indian industry is not consistently getting skilled people. This mismatch between education and industry demand recommendation system for course selection in education.

2. Literature Review

Recommendation System is an intelligent algorithm which is designed to reduce overloaded information generated through the internet by giving personalized suggestion. It uses user behavior, preferences and historical data. Nabila et al.[5] says that initially recommendation system was developed for commercial domain such as e-commerce in which it gives successful result after that its applications grow significantly in entertainment, healthcare and education. In the context of education, Bushra et al. [6] emphasis that recommendation system aims is not only improve user satisfaction but it allows students to make decision effectively, it improve user satisfaction, also support learning outcomes and success in academics.

Educational Recommender System have been widely used to recommended learning material, academic programs, career pathways. Dhar and Jodder [7] proposed machine learning base system to predict suitable educational programme by analyzing students data. It also demonstrate that predictive modeling can enhance academic performance. Likewise, Ismail et al.[8] developed an autonomus course recommender system for undergraduate programme which highlights the need of automated recommending system in higher education.

In Educational Recommender System, Content-Based Filtering, Collaborative Filtering and Hybrid Approach are the most popular method. Among all Content-Based Filtering is most useful as it matches students profile with course attribute to recommend course. Morsomme et al.[9] represent the importance of students preferences and subject characteristics for using content-based filtering. Further Kruthika and Divakar [10], demonstrate that machine learning content based models can significantly improve accuracy in course recommendation when model use students academic performance.

Despites of number of techniques used in educational recommendation system several challenges are remain. Urdaneta-Ponte et.al. [11], recognized the issue in educational recommendation system such as cold-start problem, data sparsity, privacy concerns which is a major problem in adopting it in a real world. Likewise Lynn and Emanuel [12], stated that most of the proposed research are in experimental stage, they also highlights a significant gap between theoretical concept and practical implementation.

Elahi et. al. [13] said that the methodology use in educational recommender system should be transparent and understandable so student can trust on the result given by recommendation model. This requirement make a difference between commercial application with educational application as a decision taken for education may have long term significances.

Table 1
Comparative analysis of Educational Recommendation Techniques Used

Recommendation Techniques	Machine Learning Algorithm	Advantages	Disadvantages	References
Content-Based Filtering	Cosine Similarity, TF-IDF, KNN	Highly personalized, handle cold start	Overspecialization, Limited diversity	10,11,16
Collaborative Filtering	Matrix Factorization, KNN	Capture peer behavior, diverse suggestions	Cold-start problem, Data sparsity	13,16,17
Hybrid Recommendation	Combination of CBF and CF	Improved accuracy, balanced personalization	Higher complexity, Costly computation	12,13,17,18
Graph-Based Recommendation	Graph Clustering	Improve Diversity	Scalability issue	14,16,17
Reinforcement Learning Based Recommendation	Q-Learning and Policy Gradients	Dynamic Adaption	Needs large data, slow convergence	15,16,17

While creating a model data quality and selection of appropriate algorithm is a crucial and important part. There are so many techniques available for handling and improving data quality. Likewise, so many machine learning algorithms are available for the educational recommendation system but still it is

difficult to choose the most suitable algorithm for an application. Some of them which are majorly used are describe below [14].

K-Nearest Neighbor

It is a supervised learning technique which is widely used in recommendation technique. It measure the distance to analyze the labels of it nearest neighbor in order to identify a new data instance. In the context of education, KNN make cluster of students whose academic profile, interest, learning patterns or recommend course are similar. This approach is useful to identify similar students for giving personalized course guidance [15,16].

Decision Tree

Decision Tree is also supervised learning techniques which use hierarchical tree structure for representing decision making process. In education, decision trees are useful because of it interpretability and rule-based learning. It allows students and academic advisor to understand the logic behind the recommendation [14,17,18].

Linear Regression

Linear regression is a predictive modeling approach that assumes a linear relationship between the input variables and the output variable. In the context of educational recommendation systems, linear regression is often employed to predict continuous values such as expected educational performance or course appropriateness scores[19,20]. The goal of linear regression is to reduce the difference between the predicted and actual values by fitting a best-fit straight line. While linear regression is computationally efficient and simple to implement, it has limitations in modeling complex nonlinear learning behaviors[21].

Apriori Association Rule Mining

Apriori Association is a data mining technique which is used to discover hidden patterns and relationship between items in a dataset [17,22]. It is also used to identify frequent item sets based on minimum support threshold and also generate association rules based on confidence values. In education, it can be applied to determine frequently used subject combinations, skill dependencies and learning behavior trends. Although, it is very effective to identify pattern discovery it finds error in the training data easily[23,24].

K-Means Clustering

K-Means clustering in an unsupervised learning technique which is used to make a group of a data points into predefined number of clusters based on similarity. In education recommendation system, It is used to divide students into group which have a similar characteristics. K-Mean is iterative in nature which is required to specify number of clusters in advance[22,25].

3. Research Methodology

From the literature reviews, mainly three major gaps are found and that are:

1. Mostly the content-based course recommendation technique depend on single predictive models, hence it gives inaccurate result when students have variety of attribute in the dataset.
2. To improve the reliability, focus is given to the feature -driven personalization, but ensemble learning techniques are not explored.
3. Existing studies highlight the importance of explainability but it is not integrated conceptually into the design of content-based system.

This gap motivates the proposed research, whose aims is to design a model which use ensemble technique along with bagging and stacking in content-based recommendation for suggesting course to the university students.

For doing this research I study and examine various research paper of recommendation and finalize below recommendation model which have five key steps like collection of student data, preparing data and selecting proper feature from data, division into training and testing and implementation.

With the help of working flow which is explained in above diagram, I prepare a novel and improved version of recommendation model for university course selection which have five key features like Load Dataset, Preprocessing Data, Calculating Cosine Similarity, Features Selection, Split Data for Training and Validation, Training the Model and Give Recommendation to the Student.

3.1 Data Collection and Load Data set

In machine learning, data collection is an important task. It is the process of gathering relevant information to train, validate and test the models. This data must be relevant to the specific objective and must represent real world data because it enables models to learn meaningful patterns and relationship which are essential for reliable prediction and intelligent decision making. In the context of educational recommender system, for training and evaluating the model different data of a student like academic grade, course preferences, rating, learning history are required. These data is the foundation for personalized recommendation models that are usually obtain from institutional database, learning management system, student feedback mechanism, etc.

3.2 Data Preprocessing and Creating Clusters

Data preprocessing is an important step after data collection because it behaves like a crucial bridge between data collection and model training. It gives surety that data which are feed to the model will represent the problem properly and it is compatible with learning model. Proper preprocessing significantly improves the model performance. It involved collection of methods like cleaning, transforming and structuring raw data for improving data quality, accuracy. It helps in reducing noise and

bias in machine learning models and makes machine learning models more interpretable and trustworthy.

In the research no of steps involved in data preprocessing like Grade and Numeric Mapping, Create Clusters of Subject, Handling Null Value and Apply Encoding on Offered Subjects and Priority.

Creating of a cluster of a subject is an important step for research because it helps in organizing a large and different set of subjects into meaningful groups based on similarity. It improves recommendation efficiency, accuracy and also improve scalability because model need not required to match student profile with individual subject instead of it, model identify appropriate clusters. It also helps to handle cold-start problem for a new subject because it directly added to the cluster which characteristics match.

Cosine similarity is a mathematical measurement which is used to determine similarity of two vectors by calculating the cosine of the angle between them where the range of the value is 0 and 1. The value 1 represents similarity whereas the value 0 represents no similarity. To identify the perfect academic path, cosine similarity helps the model by giving the closeness of student choice with the perfect academic path. When selected subjects differ across students, cosine similarity helps by normalizing the measurement of similarity. It gives surety of the fair comparison across different profiles. It also helps by giving personalized and goal-oriented recommendations. When a student's binary vector closely matches with the ideal vector, it gives higher similarity score which represent the strong alignment with recommended priority.

3.3 Feature Selection

Feature selection is the process of selecting and creating meaningful input variables from raw data which will be used by machine learning models to learn the patterns effectively. In feature selection two variables, independent and dependent are selected. To give recommendation a single factor is not selected, instead the overall characteristics of the students are selected like how well students perform in their exam, their liking etc. which will improve personalization, it also reduces mismatches and gives proper clarity and reduces cold-start problem.

In the proposed model independent variables are core1, core2, core3, core4, number of fail, average grade, cosine similarity score, priority where dependent variable is offered subject.

3.4 Split Data into Training and Testing

Data splitting is the process of dividing data set into training, validation and testing data so that machine learning model can train and evaluate properly. Each subset serves a different purpose in the model development life cycle. Training set is used to train the model, validation is used to tune model parameters and select best model configuration and testing is used to evaluate the model performance. Splitting the data give surety that model is not evaluated on the same data set. In the proposed model

approximately, training data is divided into 66%, testing data is divided into 10% and validating data is 24%.

3.5 Train the Model using Bagging and Stacking Techniques

After completion of data collection, preprocessing, calculation of cosine similarity, feature selection and splitting the data next step is training the model. Training the model is a step where algorithm recognize meaningful patterns from the dataset, it also learns how to use data for making accurate recommendation.

In the proposed research, supervised learning technique along with content-based recommendation is used because the student dataset is labeled and literature review suggest that content-based is more appropriate for educational recommendation system. Each algorithm works differently like K-Nearest Neighbor (KNN) work on similarity-based learning, Decision Tree (DT) make rule-based decision, Support Vector Machine (SVM) handle high dimensional features, XGBoost represent non-linear relationship. When we evaluate these algorithms, it makes a reliable baseline performance which highlights their strength and weakness.

After implementing algorithms individually, bagging technique is implemented on selected algorithms like bagging of K-Nearest Neighbor and Support Vector Machine, Bagging of K-Nearest Neighbor and Decision Tree, Bagging of K-Nearest Neighbor, Support Vector Machine and Decision Tree to find out how much model reduce the variance and give stability in prediction. The accuracy of different implemented algorithms is as below:

Table 2
Accuracy Matrix of Machine Learning Algorithm

Algorithm Name	Training Accuracy	Validation Accuracy	Testing Accuracy
K-Nearest Neighbors (KNN)	51.47%	32.87%	38.69%
Decision Tree (DT)	69.66%	31.47%	34.17%
Support Vector Machine (SVM)	43.23%	33.80%	37.19%
Random Forest (RF)	90.65%	35.90%	33.67%
XGBoost	89.32%	35.20%	34.67%
Bagged KNN and DT	56.41%	33.57%	36.68%
Bagged KNN and SVM	45.88%	32.63%	38.69%
Bagged KNN, SVM and DT	57.00%	34.27%	41.21%

The above analysis illustrates that in compare to individual machine learning model, ensemble-based learning approach give improved and consistent result across training, validation and testing datasets because aggregation of model reduces variance and noisy records, it also helps to minimize the impact

of various learning patterns which commonly found in student educational records. Hence, implementation of ensemble method is more suitable than the single learning approach in this research.

The above implemented algorithm shows that Random Forest and XGBoost classifier give decent accuracy on training data but it does not give proper accuracy on validation and testing. There are so many reasons of not performing well on validation and testing like overfitting, imbalance class, feature selection is poor, not able to generalize unseen data or used model is too complex for the problem. To solve this issue bagging technique is used because it reduces the variance with the help of combining the prediction of different model which trained on different bootstrap samples.

Bagging have advantages like it reduce the variance and make model stable but on the other hand it also has a drawback like it treat all base learner as same. To solve this issue stacking technique is used because it improves the generalization by combining optimal prediction of multiple bagged model which use meta learning approach. Hence, the proposed model use the technique of bagging and stacking to improve the performance of proposed model. Which will be illustrate in below figure:

As describe in the model bagging and stacking technique is applied. Bagging is applied to multiple base classifier. In the proposed model used random forest and XGBoost model which will be trained independently on the dataset. In the bagging process, models which are bagged, learn different features from the data and the combine result generated by the model are not used during bagging process, so it minimizes the variance and overfitting. Stacking is applied to integrate the prediction of first level which is a bagged model. The prediction which is given by the bagging model is collected and use as an input for the meta-learner. Here meta-learner is XGBoost, which use the prediction of the bagging model, then based on the reliability of the prediction the value of the learner contribution is calculated and ideal combination is find out for the student.

3.6 Give Recommendation of a Course

In the final stage, the trained model generates personalized course recommendation for students based on the provided input, the trained model processes this information and give appropriate recommendation. The below image illustrates the step where students enter subject grade of Basics of Programming, Advanced Programming Concepts, Object Oriented Programming, Web Technology, Basic Mathematics, Statistical Methods, Basic Microcomputer, Basic Computer Concepts and Operating System and three priorities of subject.

4. Result

To know how the proposed model give the performance and to give the surety of the comprehensive assessment various classification metrics are used. To evaluate the quality and reliability of the recommendation precision, recall, F1-score and confusion matrix are used.

Table 3
Model Evaluation Matrix

Model Overall Accuracy: 88%		
Precision	88.59%	Represent less inaccurate recommendation
Recall	88.44%	Model successfully identify most of the suitable courses.
F1-Score	88.45%	Represent consistency and reliability of the model.

Overall accuracy of the model is 88% which prove strong predictive performance on unseen data. Precision measure the correctness of the recommended course by measuring the fraction of the recommended courses that are actually relevant. A high precision value indicates that there are fewer incorrect or irrelevant recommendation. The weighted precision is 88.59% says that model minimize the number of inaccurate recommendations by giving appropriate suggested course. On the other hand, recall measure the model's capability to identify all relevant courses for a student by showing how well the system recommends appropriate courses. A high recall value ensures that model is not missing out on good academic choices. The weighted recall is 88.44% which says that the model successfully identifies most of the suitable courses for a student. The weighted F1-score is 88.45% which says about balanced trade-off between precision and recall and represent the consistency and reliability of the model.

Further class-wise evaluation supports above finding. Web development has the best performance with precision 94% and F1-score of 91% which indicates strong and stable result. Introduction to cyber security and Artificial intelligence have a good and balances precision and recall while mobile development has lower recall and is less confused with neighboring classed but still has a good F1-score, which indicates that the model handles the minority or more complex classes decently. The below table represent the classification report of the model.

The macro-average result shows that the model is working well on all classes, and the weighted average shows that the class imbalance problem is being handled correctly. This is an indication that the ensemble learning strategy is effective in maintain fairness and stability with respect to the varying distribution of courses.

Table 4
Classification Report

Course Name	Precision	Recall	F1-Score
Artificial Intelligence (AI)	84%	92%	88%
Introduction of Cyber Security (ISC)	89%	88%	89%
Mobile Development (MD)	82%	78%	80%
Web Development (WD)	94%	89%	91%
Macro Average	87%	87%	87%
Weighted Average	89%	88%	88%

From the results, it is clear that the proposed bagging and stacking ensemble learning approach is accurate, stable for all classes and has a good precision-recall. This approach is suitable for recommending the courses to students in higher education.

5. Discussion

This study tackles how students pick courses in college by improving outdated methods that schools often use. Instead of just copying what others like or following fixed rules, it builds something more personal. Academic records matter here, along with clear input from learners about what they want. A mix of smart algorithms helps weigh these pieces together. What makes it stand out is not fancy tech but how it brings different learning factors into one view. The result gives a clearer path when deciding which courses to take.

A fresh approach works well when new students arrive, a common scene in college settings. Because decisions come from what learners share now, not old records of who joined before. This study also leans on cosine math to spot how near a learner’s traits sit beside the target shaped by course rules and goals.

One more thing - the research suggests a setup with two layers. At the start, there’s a method called bagging, cutting down on noise and too much sensitivity. Then comes stacking, linking that earlier result with another model to shape suggestions. When it comes to recommending things in education, blending similarity-focused parts into this kind of combined structure brings something new to the table.

What stands out in this work is how it builds a clear, reliable way to suggest courses - helping learners choose wisely in college settings. Instead of guessing, the approach fits recommendations to each person's goals while keeping learning paths sound. By fitting into guidance tools, the method eases pressure when picking courses. It lowers chances for wrong picks. Getting through university becomes smoother, less overwhelming, because support feels more personal. Decisions gain clarity without extra weight.

6. Conclusion and Future Work

Selecting courses now feels different because colleges keep changing how they teach - more freedom, mixed subjects, learning built around each person. This new setup lets students shape their own journey - but too much choice can feel messy, unclear, even heavy on the mind. Facing dozens of classes across fields, learners must decide without enough personal support guiding them through. Old-style advising still leans on fixed rules or paper-heavy methods - not sharp enough for real student needs. Instead of sticking to outdated systems, this effort aimed at building something smarter, roomy enough for growth, focused squarely on the learner. A tool helping students choose college paths with clearer eyes, better results, less stress.

A new kind of guidance tool came together in this work. Built around what students learn, like, value, and how they compare to others, it uses a fresh mix of learning methods. Instead of just looking at test scores, the idea here is to suggest courses shaped by more personal details. Helping meet required levels matters, yet so does matching what excites one learner over another. Starting with what students care about, then layering in their actual performance, the approach manages to mirror not just ability but also drive. Because of this mix, suggestions feel grounded, meaningful, and shaped around each person's reality.

This research pushes tech forward while quietly showing why learning tools must center on students first. Because guidance fits now and stretches toward future goals, choices gain clarity. Decisions breathe easier under this approach. Course picks turn surer. Education feels better lived through it. The mix changes how people move through options.

Built to shift size and shape depending on a university's needs, this tech might slide quietly into current guidance setups. Universities could guide way more students one-on-one, helping each pick courses that actually fit. Choices get clearer. Wrong turns become less likely. One thing that is definitely concluding is that adding content-based filtering to college course suggestions really boosts how well they work

Declarations

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Data Availability: Student’s data and code are available from the corresponding author upon reasonable request.

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Figures

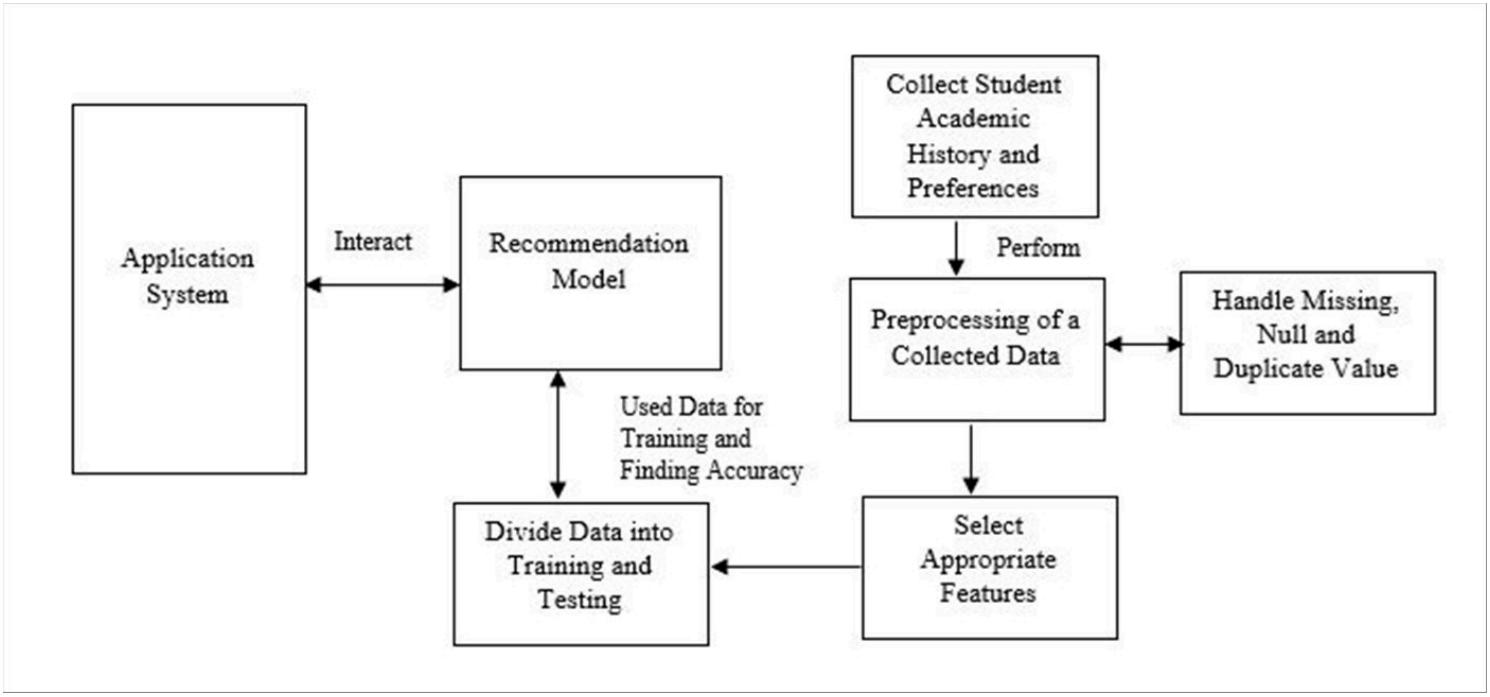


Figure 1

Working Flow of the Recommendation Model

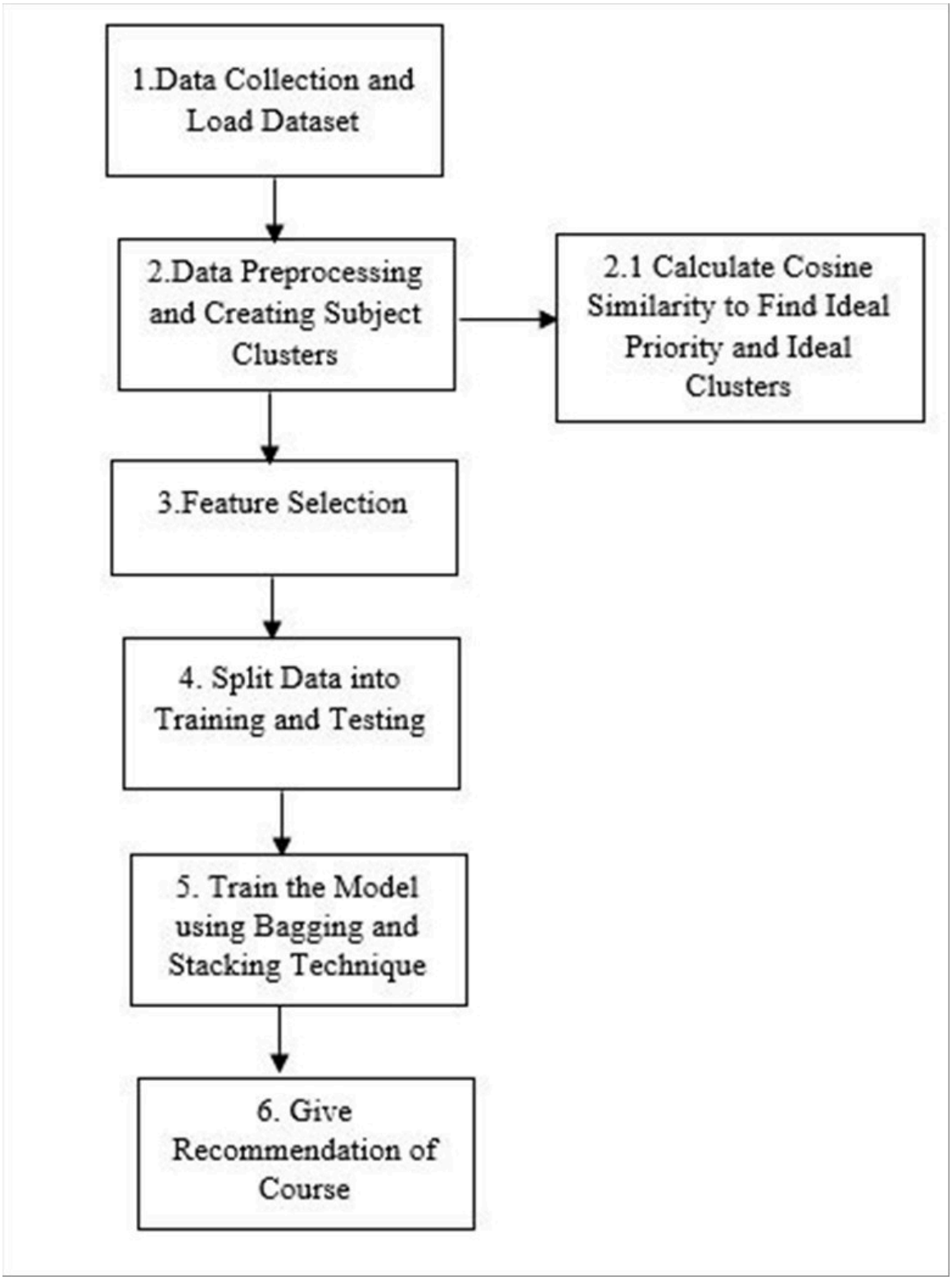


Figure 2

Workflow of Proposed Model

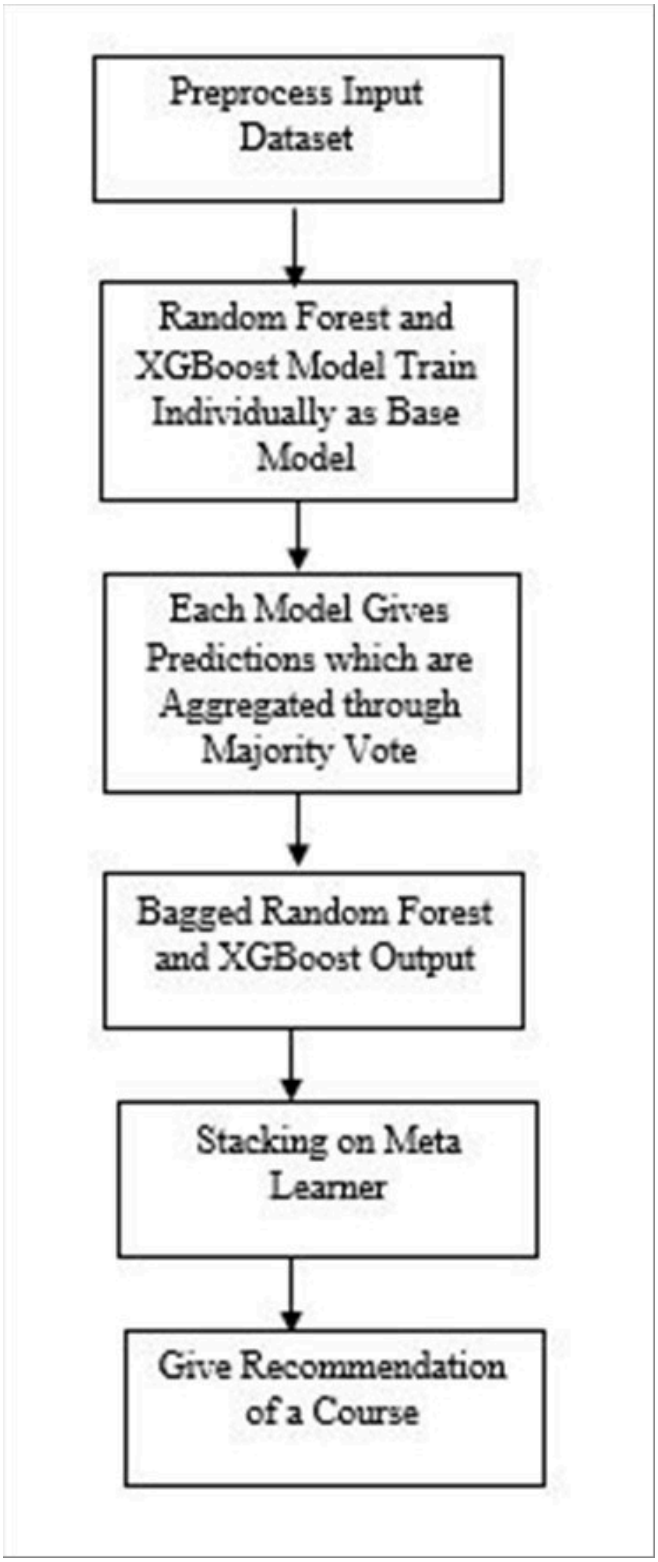


Figure 3

Workflow of Proposed Model

```
Enter subject grades (O, A, B, C, D, F) and your 3 elective preferences:

Basics of Programming (O/A/B/C/D/F): f
Advanced Programming Concepts (O/A/B/C/D/F): d
Object Oriented Programming(JAVA) (O/A/B/C/D/F): d
Web Technology - I (O/A/B/C/D/F): c
Fundamental of DBMS (O/A/B/C/D/F): d
Web Technology - II (O/A/B/C/D/F): c
Basic Mathematics (O/A/B/C/D/F): d
Statistical Methods (O/A/B/C/D/F): c
Basic Microcomputer Application (O/A/B/C/D/F): c
Basic Computer Concepts (O/A/B/C/D/F): c
Operating Systems (O/A/B/C/D/F): c
Priority 1: ai
Priority 2: wd
Priority 3: isc

 Recommended Elective Subject: ISC
```

Figure 4

User Input and Prediction of the Model