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ANALYZING HYBRID MACHINE LEARNING APPROACHES FOR PREDICTING STUDENT PERFORMANCE IN HIGHER EDUCATION

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Abstract

Higher education has undergone a transformation in recent years due to the incorporation of blended learning models, which combine traditional classroom approaches with online educational resources. This study analyzes and predicts student performance in higher education through the implementation of a hybrid machine-learning approach. Since student learning incorporate various educational and behavioral patterns which needs to be analyzed through appropriate method. First, it implements cluster analysis, infer cluster labels, and apply hybrid classifiers. Through the use of several machine learning techniques, such as ensemble methods, this study hopes to improve performance forecasts over time relative to single algorithms. There are several features were used that includes academic records, online activity logs, discussion forum posts and views. The findings present a comparative analysis of various hybrid techniques and demonstrate that combining models enables more efficient analysis of the different factors influencing student performance.
Keywords: Online learning, Blended Learning, Hybrid Classifiers, LR(Logistic Regression), Clustering Technique(k-means), Classification techniques(RF(Random Forest), KNN(K-Nearest Neighbors)SVM(Support vector Machine), NB(Naïve Bayes).

1. Introduction

In learning Analytics several clustering and classifier algorithms are used to obtained better accuracy result for predicting students' academic performance. Blend-ed learning data of IT stream students consists of both offline and online learning activities. Previous studies use datasets that are readily available and preprocessed, which do have an impact on model accuracy [8][9]. The Gnomio Moodle dataset then replaces it to uncover the different patterns within blended learning data (MTech(PG-1) and MCA(PG-2)). Through clustering techniques we can un-cover the learning patterns hidden within the dataset and through extracting these labels we can then use this dataset to forecast student performance. The Hybrid models can achieve higher accuracy by using the strengths of different algorithms, reducing their individual weaknesses. By using multiple methods, hybrid models can provide more stable and reliable predictions, especially in varying and complex scenarios. Hybrid models can help mitigate overfitting by combining algorithms that complement each other. By adding cluster-based features, the model can capture additional learning patterns in the data. A hybrid model that combines classification and clustering can be an effective technique for enhancing prediction accuracy and learning more about the data. To analyze student performance through hybrid models this study considers academic details, forum views, posts, previous grades, etc. for cluster analysis then it will use the cluster label data to test hybrid classifier models. The role of Information and Communication Technology (ICT) tools in enhancing online learning environments and supporting quality higher education in alignment with NEP-2020 has been discussed in [10]. Section 2 discuss the literature review that specifies the gap that exists and section 3 discusses the methodology implemented to process hybrid models. The details of the dataset (PG-1 and PG-2) have been discussed in section 4. Sections 5 and 6 discuss the cluster analysis and label extraction for further model

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training. Section 7 describes the details of each classification model and the consecutive sections discuss the hybrid model with voting and stacking mechanisms that are

- Random Forest (RF) and Logistic Regression (LR)(Majority Voting)
- Decision Tree (DT), SVM and KNN (Majority Voting)
- Naïve Bayes (NB), Logistic Regression (LR) (Average Voting)
- Naïve Bayes (NB), Logistic Regression (LR), DT (Decision Tree) as a Base classifier, and Logistic Regression as a Meta classifier. (Stacking hybrid model).

At last, models will be compared on the basis of Accuracy, Precision, Recall, and F1 score values.

2. Related Work

Numerous studies have been done on predicting student success in an online learning environment, analyzing their learning style, analyzing course outcomes, influencing aspects, etc. These studies take into account data from multiple sources, including personalized e-learning platforms, Moodle, MOOC, LMS, and Kaggle. Table I lists relevant research in the areas of learning analytics, influencing features, and student performance analysis. Classification Models, Clustering techniques, and several hybrid techniques were implemented in this area.

TABLE I. RELATED WORK

References	***Objective***	***Method Used***	***Dataset***	***Features Used***	***Observations***
[1]	Prediction of at-risk students in a course using standards-based grading.	Single Models: Decision tree, Logistic regression, SVM, MLP, NBC, KNN. Hybrid model: NBC+KNN+SVM	Private Dataset, USA San Jose State University (2973 UG students).	Semester data is used to predict grades.	One dataset of a single course is used to test the Hybrid model (KNN+SVM+NBC). Precision: 86.2%
[2]	Using Hybrid models for predicting student performance.	Classification (NB, DT, NN, SVM)+Clustering(k-means)	Higher Educational Institution.	Demographic, Academic, Behavioral, and Extra features.	The hybrid approach shows a strong relationship between behavioral features and academic success. The accuracy of the hybrid model is 0.75
[3]	Predicting Student performance through a	K-means clustering for segregating students into	North America University, Open	NAU dataset features grades, logs, logins,	Results showed the clustered approach improved

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	hybrid approach.	groups. Hybrid method: Feedforward Dense Network, Random Forest, Decision Tree.	University Learning Analytics Dataset. (Undergraduate Science Course)	content, forum interaction, and quiz review. OULAD: behavioral logs, final result.	prediction, especially clustered FDN, which best identified at-risk students.
[4]	Prediction of Student's performance by modelling small dataset size	Five Model Explored: ANN, SVM, KNN, LDA(Learning Discriminant Analysis), NB	Emirates, British university in Dubai, private dataset(50 PG students)	Id, age, BSc degree, BSc grade, Course name, course grades.	Key features for a small dataset were identified. The best feature was identified through the heat map.
[5]	Predicting student performance using family expenditure and students' personal information.	SVM, c4.5, CART, Bayes Network, and Naïve Bayes.	Private dataset (776 Students).	Students' personal information and family expenditures (total 23 features).	This study predicts the success and failure of students where the proposed model yields 86% accuracy.
[6]	Predicting student performance using MLR and PCA analysis.	MLR	Taiwan University dataset.(58 UG students.)	Student Activity logs, Quiz grades, exercise practice data.	This study implemented PCA with MLR to improve accuracy. pMSE = 198.62. pMAPC=0.81.
[7]	Effect of Question Level on Student Performance in Online Learning	Vector Space Modeling	Higher Educational dataset of IT Stream.	Online Score and Offline Score.	Advantages of e-assessment.
[8]	Comparative analysis of clustering algorithms.	K-means, Hierarchical and Farthest first.	Kaggle dataset.	Behavioral patterns, demographic factors, parent participation along with academic	The k-means algorithm has the highest accuracy.

				details	

All these discussed studies highlights the importance of a hybrid model in order to increase the accuracy and robustness in models. When Clustering combined with classification models it improves the prediction performance of the model, and also gives additional patterns and relationships in data.

3. Modelling Of System

The following phases were implemented to analyze students' performance using the hybrid model.

a) **Phase 1. Data Collection and Pre-processing:** This study considered the IT stream student academic dataset of MCA and MTech students. Teaching learning activities were held both in online as well as offline mode (blended learning mode). Gnomio Moodle was used to conduct online activities such as quizzes, forum discussions, question attempts etc. The complete experimental details of data collection have been discussed in the study [13], where each phase of the data collection phase is described.
b) **Phase 2. Cluster Analysis:** As the dataset is of blended mode, Clustering techniques were used to find students' learning patterns and group similar patterns. This phase applies the k-means clustering technique to both the dataset. The visualization and characteristics of clusters will be discussed in this phase. Along with k-means clustering, Hierarchical and GMM (Gaussian Mixture Model) have also been applied to this dataset [14]. This phase groups the students according to their learning pattern and later on, these clusters will be utilized to test the predictive model.
c) **Phase 3. Feature Extraction from Cluster:** In this phase, cluster labels will be extracted for each instance/student as a new feature and will be added to the existing datasets (PG-1 and PG-2). These datasets will then be used for classification models.
d) **Phase 4. Hybrid Classifiers:** Classification Models will use original as well as new feature cluster label for classifying students through classification models. In this study, Decision Tree (DT- J48), Logistic Regression (LR), Random Forest (RF), MLP(Multilayer Perceptron), SVM (Support Vector Machine), NB (Naïve Bayes) will be used in different combinations to analyze student performance prediction through hybrid models. A hybrid model that combines classification and clustering can be an effective technique for enhancing prediction accuracy and learning more about the data. We can successfully include clustering results into hybrid model to improve its accuracy and robustness by following the above-described methods. In this study, Voting, Stacking and combine clustering and classification hybrid model be analyze.
e) **Phase 5. Evaluating Hybrid Model:** For evaluating the model we will analyze confusion matrix. Figure 1 describes the complete process of this study.

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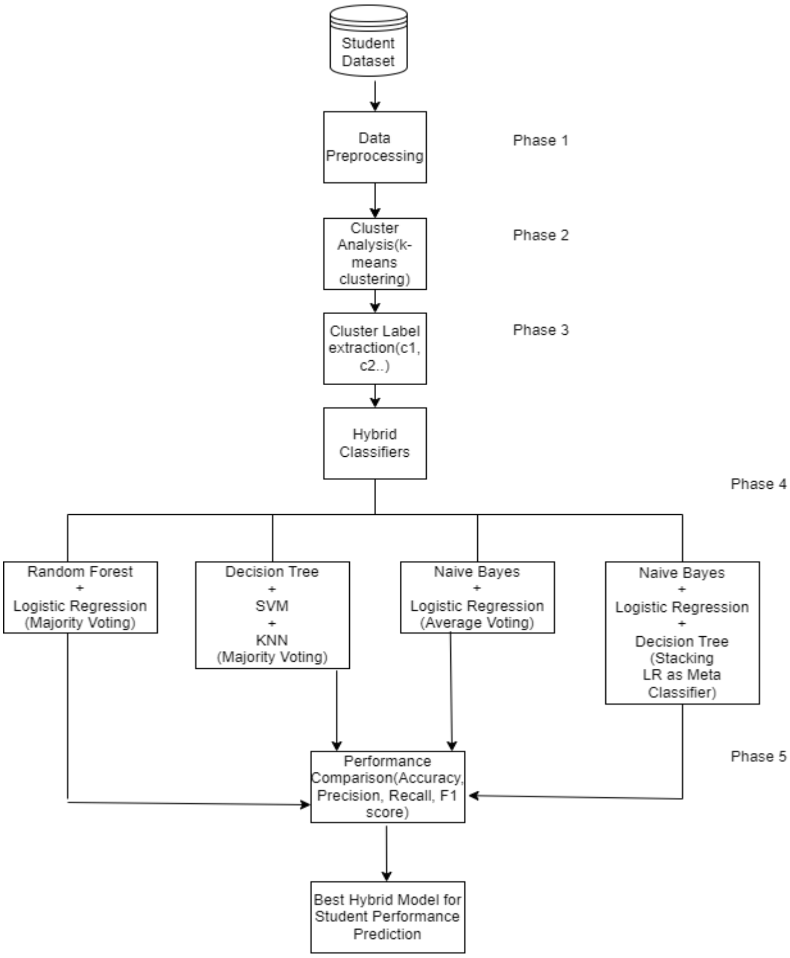

Figure 1. Methodology Phases

4. Data Description and Preprocessing

The dataset used in this study is collected from blended learning courses, namely Data Mining and Warehousing (DMW) and Theory of Computation (TOC), offered to MTech and MCA students. The Gnomio Moodle platform provides detailed information, including student IDs, quiz details, student participation during quizzes, discussion forum posts, number of replies submitted, and individual question-wise grading. For both courses, questions are posted on the discussion forum after the quizzes.

Data preprocessing is a critical step for handling missing values and improving overall data quality, which in turn enhances model performance and ensures dataset accuracy. As a result of missing information, 10 out of 130 student records were removed from the final dataset. The remaining dataset consists of 120 students, with 57 students in PG-1 and 63 students in PG-2.

Records containing duplicate event records , null values, and student records without a single quiz are eliminated throughout the data-cleaning process.

5. Cluster Analysis

The Hybrid Machine Learning approach discussed in this paper first apply k-mean clustering on both datasets (PG-1 and PG-2) for labeling the instances according to the cluster. Then

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this label features data for the classification task. Previous studies have performed comparative analysis using a single classification model [12].
To choose an optimal number of k, a Silhouette analysis has been applied. A high silhouette score indicates well-defined clusters, while a low score suggests poorly defined or overlapping clusters. A well-clustered data point is indicated by a Silhouette value of +1. It signifies that the data point is assigned to the incorrect cluster when it is -1, and it will be at the border when it is 0. For the given dataset the k-means method's highest Silhouette score for the PG-1 is 0.379 at k=2. The k-means method's highest Silhouette score for the PG-2 Dataset is 0.303 at k=3 [14].

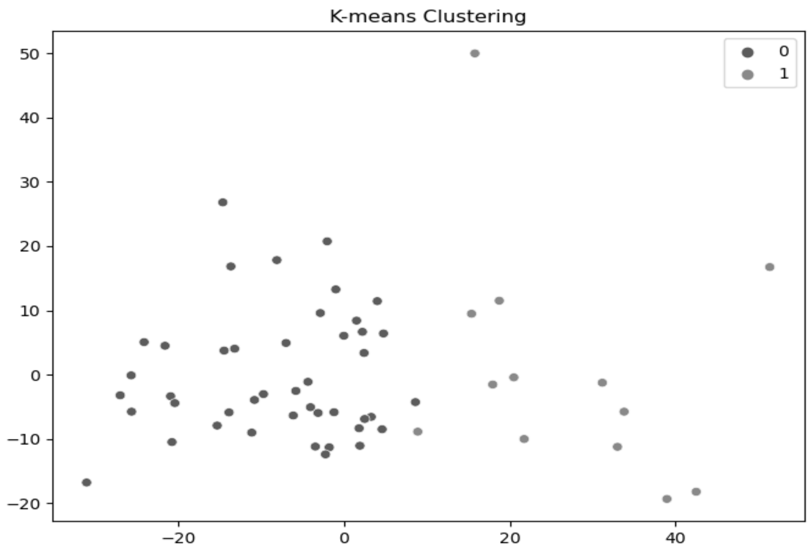

Figure 2. Visualization of PG-1 dataset using k-means [14]

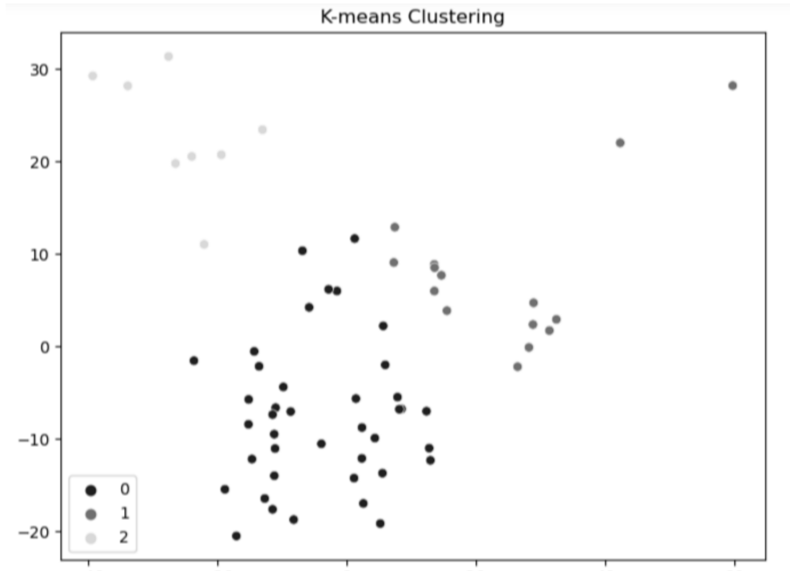

Figure 3. Visualization of PG-2 dataset using k-means [14]

Cluster visualization for the PG-1 dataset is shown in Figure 2, with 44 students in first group and 13 in second group. Figure 3 shows cluster visualization for the PG-2 dataset, in which c1 cluster has 40 students, c2 cluster has 15 students and c3 Cluster has 8 students. The above cluster analysis gives c1 and c2 labels for PG-1 dataset instances and c1, c2, and c3 labels for PG-2 dataset instances[14].

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6. Feature Extraction from Cluster

After cluster development, we extract the cluster labels and add them as new features to the original dataset. In PG-1 there are 2 cluster labels c1 and c2.
c1: High score and high forum interaction.
c2: Low score and low forum interaction.
In PG-2 there are 3 cluster labels c1,c2, and c3.
c1: High grades and a moderate degree of forum participation.
c2: Minimal forum interaction and low grades.
c3: High grades and a lot of forum participation.

7. Model Description (Data Interpretation and Inference of Outcome)

7.1 Random Forest

Multiple decision trees are combined in Random Forest to improve model performance[3]. Figure 4 describes the working architecture of Random Forest. Different student decisions have been created that will yield specific classes. Then through voting mechanism final prediction will be made.

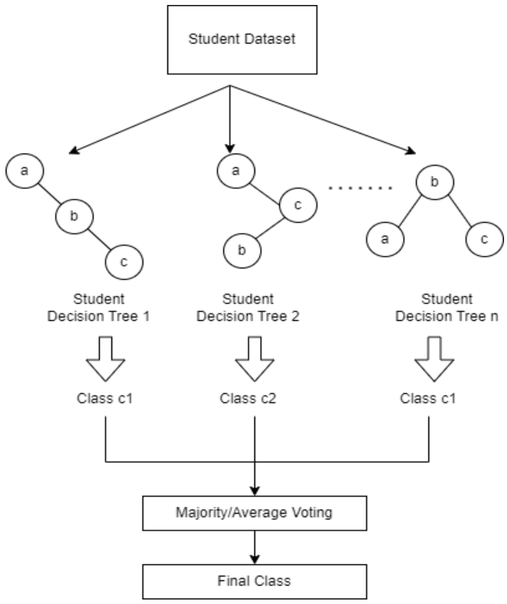

Figure 4. Random Forest Architecture

7.2 Logistic Regression

Logistic Regression is a classification technique used to predict whether a target variable is true or false (1 or 0) depending on input features[1]. After initializing the model parameters, logistic regression computes the linear combination of the input features and weight, applies the sigmoid function, and calculates the probability that the outcome will be as shown in Figure 5. It makes use of the binary cross entropy loss function to calculate the error between the actual labels and the expected likelihood. Then it predicts the label.

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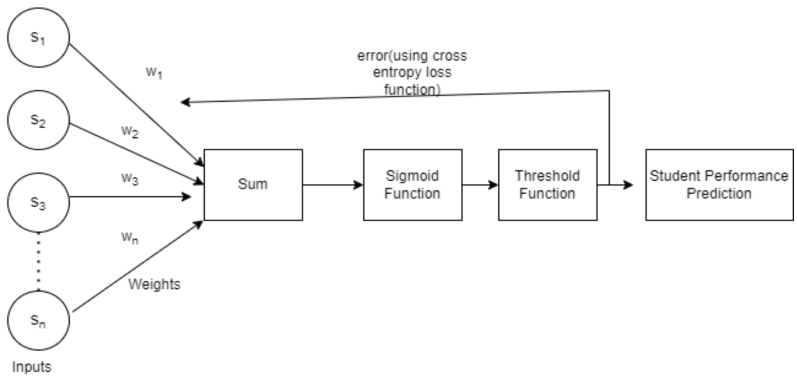

Figure 5. Logistic Regression Working

7.3 Decision Tree

The figure 6 illustrates a decision tree model used for student performance prediction. The process begins at the Root Node, which contains the complete student dataset (PG-1 and PG-2). The decision tree breaks down the student dataset step-by-step based on different educational and behavioral features (attendance, grades, forum activity). Each split creates more homogeneous groups, helping identify patterns related to student performance. The final leaf nodes represent the smallest groups categorized by specific feature values[2][3].

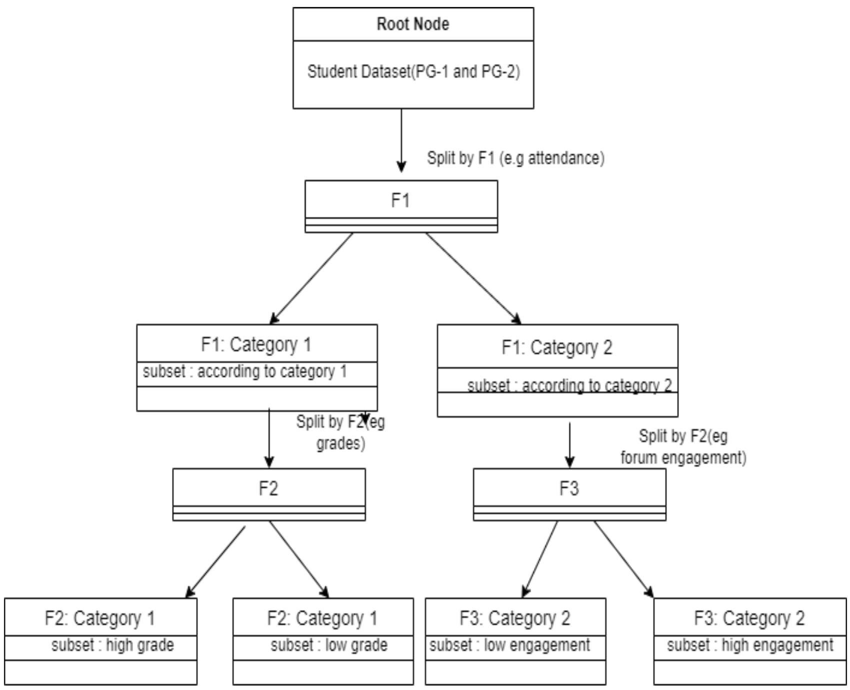

Figure 6. Decision Tree

7.4 SVM

As shown in Figure 7, SVM uses the kernel function to handle data that is not linearly separable in its original feature space then after the weighted sum it makes predictions[15].

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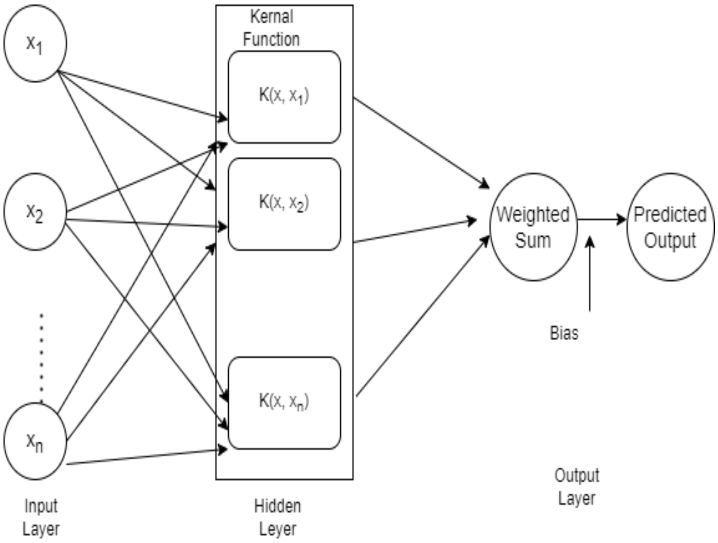

Figure 7. General Architecture of SVM referred

7.5 KNN (K Nearest Neighbor)

The working of KNN is shown in Figure 8, where it first initializes the dataset then calculate the distance between the data points. It determine how many data points there are in each category among these k neighbors. Then it puts the additional data points in the category where the neighbor count is at its highest[1][4].

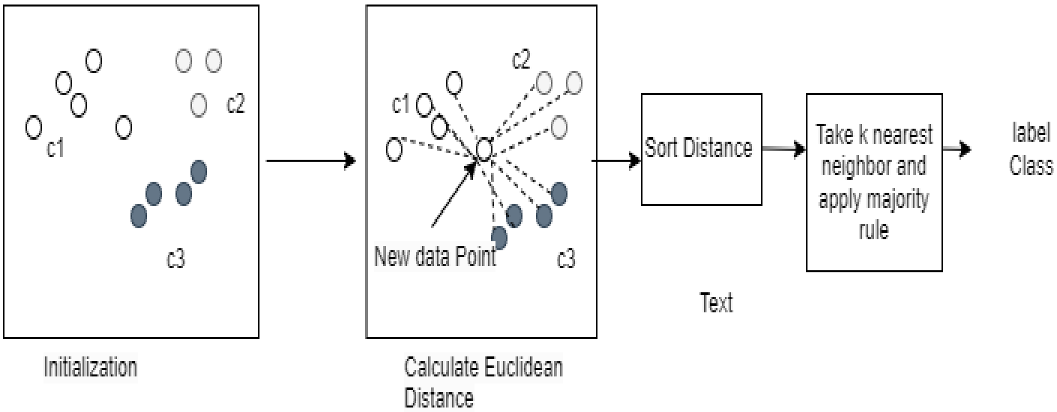

Figure 8. K- Nearest Neighbor Architecture

7.6 Naïve Bayes

The Naïve Bayes algorithm is a supervised learning technique that solves classification issues. It is based on the Bayes theorem[2]. Figure 9 shows the complete working of it.

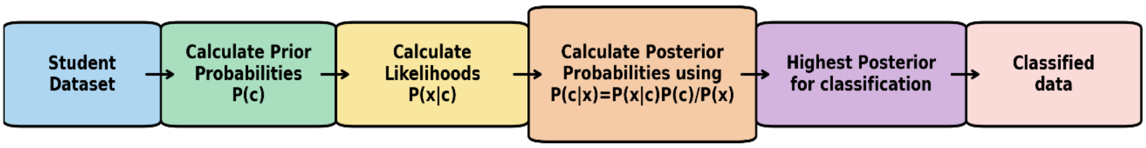

Figure 9. Naïve Bayes Working

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8. Hybrid Classifiers Training and Evaluation

The hybrid models in this work are trained and assessed using 5-fold cross-validation. Cross-validation offers a more precise and trustworthy evaluation of the model's performance by utilizing the complete dataset for both training and testing across many folds. It lowers variance in performance evaluation by averaging findings over multiple folds. Every dataset instance is guaranteed to be used for training and testing through cross-validation. Combining diverse classifiers that complement each other's strengths and weaknesses can lead to a more robust and accurate ensemble model. The following hybrid Classifier was tested on both datasets given in following Table.

TABLE II. HYBRID MODELS

Model Combination	***Technique Used***	***Description***
RF + LR	Majority Voting	Random Forest and Logistic Regression combined using majority voting.
DT + SVM + KNN	Majority Voting	Decision Tree, Support Vector Machine, and K-Nearest Neighbours combined through majority voting.
NB + LR	Average Voting	Naïve Bayes and Logistic Regression integrated using average (soft) voting.
NB + LR + DT → LR	Stacking	NB, LR, and DT act as base classifiers, while Logistic Regression is used as the meta-classifier in the stacking model.

8.1 Hybrid Model with Random Forest and Logistic Regression

- In this case, a Majority voting mechanism is used in which each classifier votes for the class, and the class with the maximum vote will make the final prediction. The Matrix generated through this hybrid model is given in Table III.

TABLE. III CONFUSION MATRIX THROUGH RF AND LR

x	*y*	*z*	
37	2	1	x=c1
5	10	0	y=c2
4	0	4	z=c3

For given model the computed measures are as follows:
Precision Score: 81%
Recall Score: 81%
F1 Measure: 80%
Accuracy Score: 81%
Correctly Classified Instances: 51
Incorrectly Classified Instances: 12

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8.2 Hybrid Model with DT, SVM, KNN

- The majority Voting Ensemble technique was used to build this model. By combining DT, SVM, and KNN, the hybrid model can utilize the interpretability of DTs, the robustness and margin maximization of SVMs, and the instance-based adaptability of KNNs.

The matrix generated through this is given in Table IV.

TABLE IV. CONFUSION MATRIX THROUGH DT, SVM, KNN FOR PG_2 DATASET

x	*y*	*z*	
37	2	1	x=c1
5	10	0	y=c2
4	0	4	z=c3

For a given hybrid classifier, computed measures are:

Accuracy Score: 89%
Precision Score: 89%
Recall Score: 89%
F1 Measure: 89%
Correctly Classified Instances: 56
Incorrectly Classified Instances: 7

8.3 Hybrid model with NB, LR

The average voting technique was used to build this model. These classifiers can all provide probability estimates, making them suitable for average probability voting. Naïve Bayes and Logistic Regression are both particularly suitable for small datasets. By integrating LR and NB, the hybrid model is able to reconcile the more flexible, linear relationships modelled by LR with the strict independence assumptions of NB. On datasets where certain features are independent, this may result in better performance. The matrix generated by NB(Naïve Bayes) and LR(Logistic Regression) Hybrid model is given in Table V.

TABLE. V CONFUSION MATRIX THROUGH NB AND LR FOR PG_2 DATASET

x	*y*	*z*	
37	2	1	x=c1
2	13	0	y=c2
3	0	5	z=c3

For a given model, computed measures are:

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Accuracy Score: 87.30%
Precision Score: 87.2%
Recall Score: 87.3%
F1 Measure: 87.0%
Correctly Classified Instances: 55
Incorrectly Classified Instances: 8

8.4 Stacking Hybrid model with NB, DT, LR

This mix of linear, non-linear, and probabilistic models ensures that the stacking ensemble can capture a wide range of patterns in the data, making it robust to different types of relationships within the small educational dataset. This stacking model configuration balances simplicity, diversity, and resilience, making it ideal for short educational datasets. It uses logistic regression as the meta-model and decision trees, naive Bayes, and logistic regression as base models. While preserving the interpretability and generalisability required for small, potentially noisy datasets, it makes use of the complementing characteristics of the underlying models. It is imperative in educational environments to have a model that is both powerful and intelligible, and this strategy can effectively handle the bias-variance trade-off while lowering the danger of overfitting. The matrix generated through this hybrid model is given in Table VI.

TABLE VI. CONFUSION MATRIX THROUGH NB, LR, DT STACKING MODEL FOR PG_2 DATASET

x	**y**	**z**	
35	2	3	x=c1
2	13	0	y=c2
2	0	6	z=c3

For a given model, computed measures are:
Accuracy Score: 86%
Precision Score: 86.1%
Recall Score: 86%
F1 Measure: 86%
Correctly Classified Instances: 54
Incorrectly Classified Instances: 9

9. Result Discussion

Table VII describes the complete evaluation of the given hybrid models. DT+SVM+KNN is the top performer with the highest accuracy (89%), precision, recall, and F1 score. It also has the fewest incorrectly classified instances, making it the most reliable model for the PG-2 dataset. Figure 10 and 11 shows the comparative analysis of hybrid models using standard performance metrics.

The Naïve Bayes and Logistic Regression model works as the second-best model with 87.3% accuracy, 87.2% Precision, 87.3% Recall, and 87% F1 score value.

TABLE VII. Hybrid Classifier model performance for PG-2 dataset

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Hybrid Models	*Accuracy Score*	*Precision score*	*Recall Score*	*F1 measure*
RF+LR	81%	81%	81%	80%
DT+SVM+KNN	89%	89%	89%	89%
NB+LR	87.30%	87.2%	87.3%	87%
LR+DT+NB	86%	86%	86%	86%

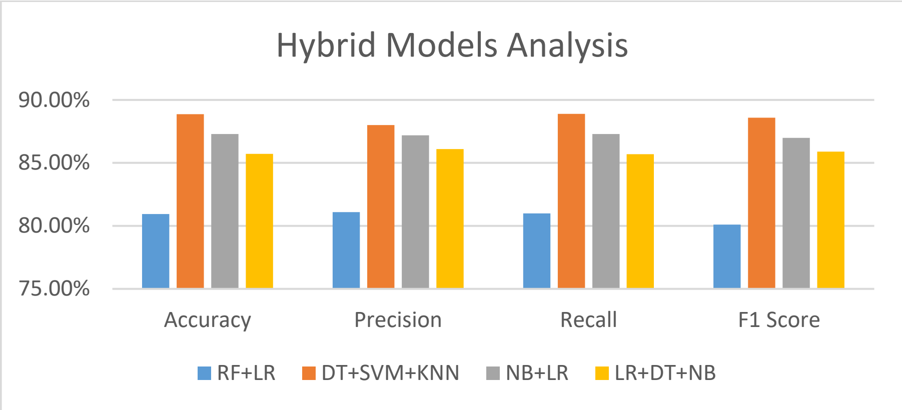

Figure 10. Hybrid Model Analysis PG-2

PG-1 dataset also uses 5-fold cross-validation to evaluate models. The dataset is clustered into 3 classes c1, c2, and c3. The results from the hybrid models are depicted in Table VIII.

TABLE VIII. Hybrid Classifier model performance for PG-1 dataset

Hybrid Models	*Accuracy Score*	*Precision score*	*Recall Score*	*F1 measure*
RF+LR	94.7%	94.9%	94.7%	94.8%
DT+SVM+KNN	94.7%	94.7%	94.7%	94.7%
NB+LR	92.9%	93.6%	93%	93.2%
LR+DT+NB	92.2%	92.9%	93%	92.8%

Through the outcome it appears that RF and LR are the most effective model, offering the best balance between precision and recall, leading to the highest F1 score. DT, SVM, and KNN hybrid models also perform nearly the same as RF and LR.

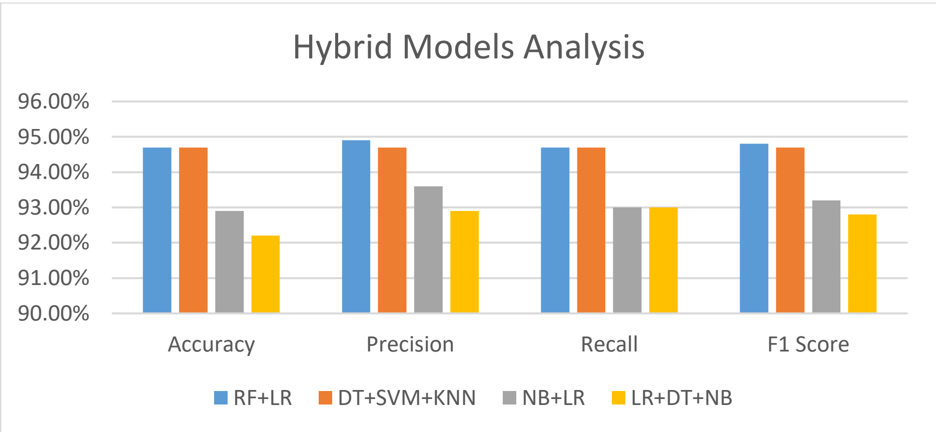

Figure 11. Hybrid Model Analysis PG-1

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10. Conclusion

By combining Clustering techniques with classification techniques this study leverages the strength of each and produces a more robust and accurate model. This study implements both voting and stacking ensemble techniques to analyze model performance and student performance. Both voting and stacking are ensemble methods used to improve the performance of machine-learning models by combining multiple classifiers. However, they are suited to different scenarios and have distinct characteristics.

The majority voting mechanism applies with RF and LR, which yield 94.7% accuracy for PG-1 dataset. The stacking mechanism applies with DT (Decision Tree), LR (Logistic Regression), and NB (Naïve Bayes) classifiers where LR is taken as meta classifiers. It yields 85.71 % accuracy for the PG-2 dataset. The combination of these models, particularly with LR as the meta-classifier, ensures that the model remains interpretable and doesn't become too complex, which is important for small datasets where data scarcity can easily lead to overfitting. The voting mechanism has been applied with 3 hybrid models. The first hybrid model is RF and LR which yield 80.95% accuracy, the second is DT, SVM, and KNN which yield 88.88% accuracy, the third is NB and LR which yield 87.30 % accuracy. A prototype system for enhancing learner community engagement in dynamic online learning environments has been proposed in [11][13].

By using hybrid techniques, the strengths of multiple algorithms can be combined to produce more efficient and accurate results. Since learning patterns in student datasets are often complex, hybrid models provide an effective approach for analyzing these patterns and generating reliable insights.

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