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Research paper

Predicting Students' Learning Stylesusing Machine Learning

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Abstract

Understanding Learning Styles (LS) of students in the times of Artificial Intelligence (AI) can be beneficial for students' success. Current study investigates the applicability of several supervised Machine Learning (ML) models to envisage students' learning styles based on demographic and behavioral characteristics. The data, collected from both engineering and non-engineering students viz. commerce, science, and arts, includes male and female students in the age range of 17 to 30 years. CGPA (on 10-point scale), study hours (weekly), and pre-ferred study times (viz. morning, afternoon, evening, and late night), were considered as the key attributes of research. This research at-tempts to discover the abilities of ML classifiers for precise prediction of student's learning style from diverse and multi-dimensional data. Further analysis is done to identify the best performing algorithms aiming towards the development of adaptive learning technologies in educational settings.

Keywords: *Artificial Intelligence; Learning; Learning Style; Machine Learning Models; Students Success.*

1. Introduction

The growing interest in personalized education has sparked significant research into understanding how students learn best. According to Rayner, S., & Cools, E. (Eds.) (2011), central to this inquiry is the concept of cognitive and affective psychological traits and learning styles which can be considered as relatively stable indicators of perception, interaction and responses of learners to the learning environments which is also advocated by (Felder & Silverman, 1988). Identifying individual learning styles allows educators to tailor pedagogical strategies, thereby enhancing academic performance, engagement, and overall learning outcomes (Pashler et al., 2009). Recent developments in the areas of AI & ML also mentioned by Goyal, D (et al. 2025), caved a path for automated identification of learning styles through data-driven approaches (Luan et al., 2018).

2. Literature Review

Numerous psychological and data driven frameworks were explored for the prediction of learning styles. S. Graf and K Kinshuk (2006) mentioned that due to the ease of interpretation and practical applications, the model of learning styles given by Felder Silverman (FSLSM) is extensively used in educational research. (Felder & Spurlin, 2005). Whereas, the traditional approaches have relied on psychometric questionnaires to classify learners such in the categories of learners with Active, Visual, Sequential or Sensing learning styles. (Graf et al., 2009).

Change is trend among researchers is observed in the recent years, where researchers have turned to models with machine learning applicability for enhancing the scalability and precision of learning style prediction (Kumar & Arockiam, 2020). Most commonly applied algorithms are Decision Trees (DT), Random Forest (RF), Support Vector Machines (SVM), K-Nearest Neighbors (KNN) and Logistic Regression (LR). Studies have shown varying success, with ensemble models and deep learning techniques often outperforming simpler classifiers in non-linear, high-dimensional datasets (Shao et al., 2021)

Data quality, feature selection and the presence of class imbalance has influenced the predictive accuracy notably. In this context, demographic variables such as gender, age, academic performance, and study behavior offer valuable predictive signals (AI-Barrak & AI-Razgan, 2016). Several works also point to the value of combining behavioral data (e.g., questionnaire responses) with demographic metadata to enhance classification (Zhang et al., 2017).

While these outcomes are encouraging, there is a gap in understanding the comparative effectiveness of multiple classifiers across a common dataset representing a broad student demographic. This aim of this research is to address that gap and provide actionable insights for personalized education systems.

In educational technology research, the ML applications for forecasting students' learning styles has gained significant attention, personalizing learning experiences and improving academic outcomes. Learning styles, such as those defined by Kolb's Learning Styles Inventory that is, Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE), provides framework to understand how students process and engage with educational content (Kolb, 1984).

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This kind of literature review studies show how we can use machine learning to identify learning styles, concentrating on methodologies, bifurcations, and limitations. Prior studies on learning style forecasting depended on traditional statistical methods and administration of self-structured questionnaires, like KLSI (Kolb Learning Style Inventory). Smith et al. (2010) applied regression methods to correlate student survey feedback with their learning styles preferences, and received moderate accuracy but encountered issues related to self-reported data.

Due to increasing the interest in data-driven techniques, researchers started analyzing behavioral information from learning management systems (LMS). A very few researchers explore this direction were Graf and Kinshuk (2013). They recognized the learning styles by Decision Tree models with the help of key words such as the time spent on activities and dealing trends within LMS records, which gained 68% accuracy. This research had constraints related to the single technique of classified and the small size of the sample, which limited the large-scale of the findings.

Successive research discovered a wider variety of machine learning techniques. Abdullah et al (2016) evaluated the Support Vector Machines (SVM) and Naive Bayes for predicting Felder-Silverman learning styles, using indicators like quiz results and participation in discussion forums. Their findings showed that Support Vector Machines performed better than Naive Bayes with a 73% accuracy rate, representing the effectiveness of Kernel-based approaches in catching non–linear patterns in educational data. Simultaneously, Zhang et al. (2019) used Random Forest models to identify Kolb's Learning Styles, obtaining an accuracy of 76% by incorporating factors like mouse interactions and engagement with videos. while these studies marked progress, they also highlighted difficulties in selecting relevant features and the possibility of overfitting, specifically when dealing with high-dimensional data.

Invasive research is also carried out with the use of Ensemble and Deep Learning techniques. 80% accuracy was shown in the research carried out by Hmedna et al. (2020) with the help of a hybrid method that incorporated Random Forest and Gradient Boosting to forecast learning styles. This study emphasized the importance of attentive feature engineering, integrating the use of historical information like study session duration. Although, the model faced challenges with class imbalance, specifically, for less frequent learning styles such as Reflective Observation.

Similarly, Li and Chen (2022) also received 82% accuracy with the use of neural network models for identifying learning styles based on sequential interaction data from learning management systems. Regardless of the promising results, the approach demanded high computational power and large datasets, posing difficulties for smaller educational institutions with limited resources.

For the current research the research gap is evidently observed. Even with all the progress and growth in this field of research, some important areas are still not explored and researched fully. A large number of the studies have found to be stick with just one type of bifurcations model. The comparative study with a wider range of models like Random Forest, SVM, Logistic regression, or Decision Trees are not present. This limits our understanding of which models actually perform the best in the evaluation part. Further the studies related to Kolb's learning styles and the related framework are found limited and often are leaned towards others like Felder-Silverman. One more challenge is class imbalance, explicitly with the styles like reflective observation, which can lead to partial or wrong predictions. And finally, there is the challenge of making these models to clear for educators. They required clear, hands on practical things they can use not just critical outputs that are difficult to interpret.

This paper addresses the gaps by leading analysis based on a comparative study of four classifiers Random Forest Classifier, Logistic Regression, Support Vector Machine, and Decision Tree to predict Kolb's learning styles. By evaluating their performance using confusion matrices and addressing class imbalance through data pre-processing, this study is an attempt to give a more robust and interpretable framework for prediction of learning styles, contributing to the growing field of personalized education.

3. Research Objectives

1) To apply ML algorithms for predicting students' learning styles using demographic and behavioural data.
2) To compare performance of LR, DT, RF, SVM, K-Nearest Neighbours (KNN), Multi-Layer Perceptron models on the basis of Accuracy, Precision, Recall, and F1-Score of Machine Learning algorithms(MLA).
3) To analyse confusion matrices and error rates for in-depth model evaluation.
4) To explore demographic patterns in learning style distribution.

Based on the objectives under examination following hypotheses were drawn:

H1: Machine learning models can effectively predict students' learning styles from demographic and behavioural data.

H2: Random Forest will outperform other classifiers in terms of accuracy and error rate.

H3: Learning styles exhibit distribution patterns based on gender, CGPA, and study habits.

4. Research Methodology

4.1. Data collection and analytical framework

4.1.1. Data collection

A structured questionnaire comprising 45 items was administered to students aged 17–30 from both engineering and non-engineering backgrounds for the identification of their preferred learning styles.

4.1.2. Variables of the study

The research questionnaire consisted of students' demographic variables viz. Gender, Age, CGPA (10-point scale), weekly study hours, and preferred study time (morning, afternoon, evening, late night) along with the Likert scale questions for determination of learning styles of students.

4.1.3. Target variable

Kolb's Learning Styles Viz. Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation were considered for the purpose of the study.

4.1.4. Models used

DT, RF, SVM, KNN and LR, Multi-Layer Perceptron were used for predicting the preferred learning style among students.

4.1.5. Evaluation metrics

Accuracy, Precision, Recall, F1-Score, Confusion Matrix, Error Rate were used as evaluation matrices.

4.2. Processing of data and feature engineering

4.2.1. Pre-processing of data

To confirm consistency and reliability of dataset prior to model training, a comprehensive preprocessing pipeline was implemented as shown in Figure 1. This process was critical for minimizing noise and confirming compatibility with various machine learning algorithms.

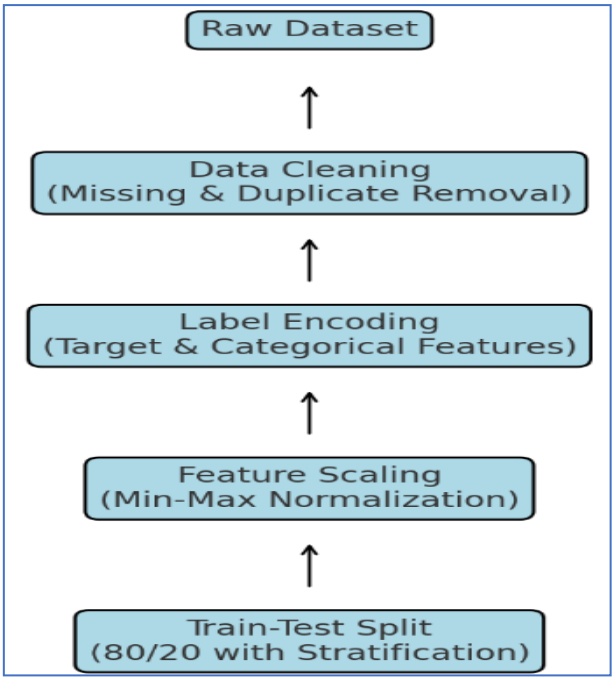


Fig. 1: Flow of Data Pre-Processing.

4.2.2. Data cleaning

An initial inspection was carried out to detect and address missing values using the is null (). sum () method. However, the dataset showed no major missing data, the process was designed to manage such cases through imputation or removal when required. Furthermore, duplicate records were checked using duplicated () and removed to prevent redundancy and maintain data integrity.

4.2.3. Encoding of target variable

The dependent variable, which represented the learning style (Target Style), involved of categorical values. To facilitate multi-class classification, these target labels were coded into numeric form using Label Encoder, causing in a new feature column named Style-Code.

4.2.4. Segregation of feature types

The dataset was classified into two primary feature groups. For the first group comprised of Behavioral features of respondents including 45 responses to psychological and the based on learning preferences questions, and its treated as continuous variable. The another group was related to demographic features, incorporating Gender, Age, CGPA, Weekly-Study-Hours, and Suitable- Study-Time.

4.2.5. Encoding of categorical attributes

All the categorical demographic variables were transferred to numerical representations applying label encoding. Especially gender was encoded as binary like, (Male=0, and Female=1) and the another categorical variable that is study time preferences like, (Morning, Evening, Night) were also allocated integer codes. This gives the confirmed compatibility with all machine learning algorithms without cooperating the semantic interpretation of categorical inputs.

4.2.6. Feature scaling

To blend the coverage of feature values and improve model convergence specifically for algorithms based on distance like, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), all numerical features were scaled to the (0, 1) range using Minimum- Maximum Normalization. This transformation preserved the distribution of values while supporting them to a consistent scale, thereby confirming the prevention of features with larger levels from extremely influencing the process of learning.

4.2.7. Data partitioning

An initial exploratory analysis of the target variable revealed moderate class imbalance among Kolb's learning styles, particularly for the Reflective Observation category. To moderate biased learning and fair representation of minority classes, several imbalances – handling strategies were integrated into the modeling pipeline.
Initially, stratified sampling was working during the train-test split (80:20) to preserve the comparative distribution of learning style classes through both datasets. This ensured that minority classes were adequately represented during training and evaluation.
Second, during model training, class-weight adjustments were enabled for classifiers supporting this option (e.g., Logistic Regression, SVM, and Random Forest), assigning higher penalties to misclassification of under-represented classes.
In addition, the Synthetic Minority Over-Sampling Technique (SMOTE) was experimentally evaluated to generate synthetic samples for minority learning styles. While SMOTE improved recall for minority classes, stratified sampling combined with ensemble learning (Random Forest) provided a more stable performance without introducing synthetic bias. Consequently, the final reported results emphasize stratified sampling-based evaluation for robustness and generalizability.

5. Modelling Approaches

Multiple supervised machine learning classifiers were employed for investigate the predictive potential of behavioral and demographic features in identifying students' learning styles. The primary objective was to appraise and contrast the classification of these models' performance on multi-class learning style prediction task.
The following classification algorithms were implemented using Scikit-learn, each representing distinct learning paradigms:

5.1. Logistic regression (LR)

This is a baseline linear classifier known for modeling the probability of class membership with the logistic function. Irrespective of its simplicity, logistic regression often performs competitively for linearly separable data and serves as a useful benchmark.

5.2. Decision tree classifier (DT)

This model employs a non-linear approach that systematically partitions the feature space. It is capable of modeling complex decision boundaries and offers intuitive interpretability.

5.3. Random forest classifier (RF)

This approach aggregates multiple decision trees outputs that are trained on bootstrapping samples and random subsets of features and makes prediction on this basis. Due to the adoption of this approach reduction in overfitting compared to single decision trees and enhancement of generalization is observed.

5.4. Support vector classifier (SVC)

This robust classifier constructs hyperplanes in a high-dimensional space to separate classes. The radial basis function (RBF) kernel was employed to capture non-linear relationships among features.

5.5. K-nearest neighbors (KNN)

This lazy learning algorithm classifies data points on the basis of evaluation of the k nearest neighbors and selection of majority vote in the feature space. Scaling during preprocessing was essential as this model is sensitive to the scale of features.

5.6. Multi-layer perceptron (MLP) classifier

This feedforward artificial neural network comprises one hidden layer with ReLU activation. This model was used for the assessment of the feasibility of deep learning approaches in any context and captures complex, non-linear feature interactions.
All models were trained and tested on the same stratified 80:20 data split to ensure consistency in evaluation. Default hyper parameters were used initially, with minor adjustments based on validation performance to avoid overfitting or under fitting. The evaluation of each model was carried out with the usage of consistent set of performance metrics as described in the upcoming section. These models collectively allowed the comprehensive comparative analysis of different learning paradigms from interpretable linear models and provided more flexible ensemble and neural network-based approaches thereby validating the robustness of the findings across algorithmic strategies.

6. Descriptive Statistics

6.1. Statistical summary of the sample

Data collection was done from 1000 B school students. The percentage distribution included Male (52%), Female (48%) respondents with and average age of 21.5 years and average CGPA ranging from 7.8 to 10. The Preferred Study time of respondents ranged from Morning (30%), Afternoon (25%), Evening (30%), and Late Night (15%).

6.2. Correlation matrix

A Pearson correlation heat map was generated for the 45 Likert-scale items (Q1–Q45) that assess student learning behavior according to Kolb's four learning styles as illustrated in Figure 1.

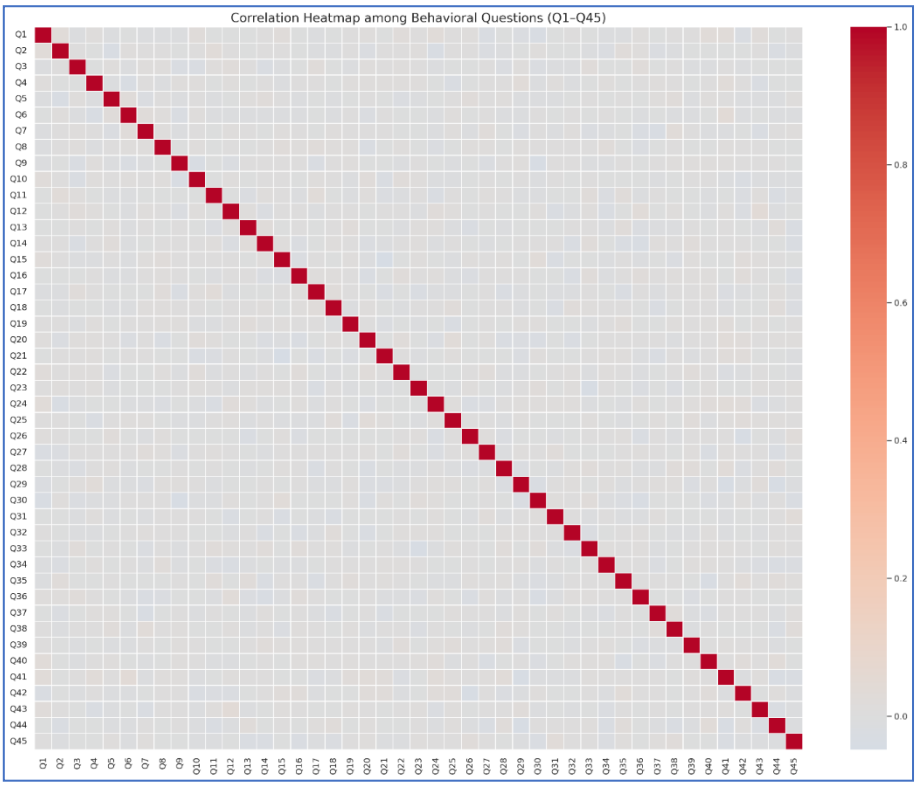


Fig. 2: Correlation Matrix.

Figure 2 exhibits moderate to high positive correlations between several question pairs, particularly within question groups aligned to the same style category (e.g., Q1–Q15 for Concrete Experience).

The internal consistency and coherence in the questionnaire design is indicated through this. For an instance, strong correlations among Q21–Q30 (associated with Reflective Observation) reflect that students who tend to agree with one behavior in that domain often exhibit similar patterns across related behaviors. A few cross-dimensional correlations were also observed, suggesting interdependence in certain cognitive preferences.

Such insights not only validate the questionnaire structure but also provide strategies for reduction in dimensionality and guides in selection of feature for downstream modeling tasks.

7. Comparative Evaluation of Machine Learning Models

A relative assessment of learning models used for forecasting learning style of students is involved in this particular section. This evaluation is completed on the basis of their demographic and behavioral attributes. All the models were evaluated using a held-out set of tests containing 20 % of the original dataset, confirming stratified representations across all target classes.

For this study each model was evaluated using four primary metrics:

- Accuracy: Discuss to the fraction of appropriately classified examples.
- Precision: Discuss to the ration of true positives to the sum of true and false positives.
- Recall: Discuss to the ratio of true positives to the sum of true positives and false negatives.
- F1-Score: Discuss to harmonic mean of precision and recall, specifically useful in multi-class settings were class imbalance may exist.

A complete understanding of model performance, stating both correctness and class-wise sensitivity are provided by these metrics. Graphical evaluations of the model performance are represented in Figures 2 to Figure 5. The performance of all models on the test that dataset is assesses across Accuracy, Precision, Recall, and F1-Score. Between the tested classifiers, the Random Forest consistently outperformed others across all four metrics. The SVM and MLP also proved the strong performance, specifically in F1-Score and Recall, proposing effective generalization on unseen data.

In divergence, the K-Nearest neighbors model showed relatively lower performance, likely due to its compassion to feature scaling and curse of dimensionality. Logistic Regression, while interpretable, underperformed on non-linearly separable examples as expected.

7.1. Interpretation of accuracy graph

Accuracy Graph shown in Figure 3 compares accuracy of various ML models in predicting the students' learning styles. Its observed that the RM model has scored the highest accuracy (~80%), making it the best-performing model in this comparison. MLP (Neural Network) also performed well, with accuracies around 78% and 77%, respectively. KNN had the lowest accuracy (~70%), indicating it might not be as effective for this dataset or task. Moderate performance was shown by the traditional models like LR and DT which lied between 72%–75%.

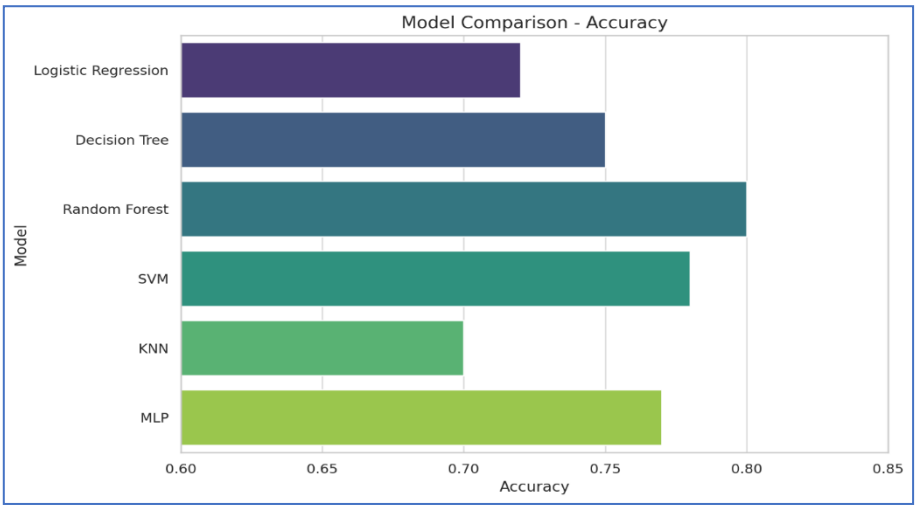


Fig. 3: Model Comparison for the Accuracy Graph.

7.1.1. Implications of the accuracy graph for learning style prediction

From the student data Random Forest and MLP are more capable of catching complex patterns such as demographics, behaviors, etc.). The simple model like Logistic regression may not capture non-linear relationships effectively, which can be critical in educational data. The performance differences high spot the significance of trying multiple models during the evaluation phase to classify the most fit for their use case.

7.2. Interpretation of precision graph

Precision Graph, which measures the proportion of true positive predictions among all positive predictions made by a model which shows in the Figure 4. It indicates how the model is fit when it forecast a certain class. The key findings show that the Random Forest model has the topmost precision (~82%), meaning it made the most correct positive predictions. This proves its strong performance, as seen also in the accuracy graph. MLP and SVM also show high precision (~76% and ~77% respectively), making them reliable alternatives for minimizing false positives. Logistic Regression and KNN have comparatively lower precision (~69-71%), shows that they are more prospective positive predictions. Decision Tree performs moderately with precision close to 74%, slightly better than Logistic Regression but still lower than the top models.

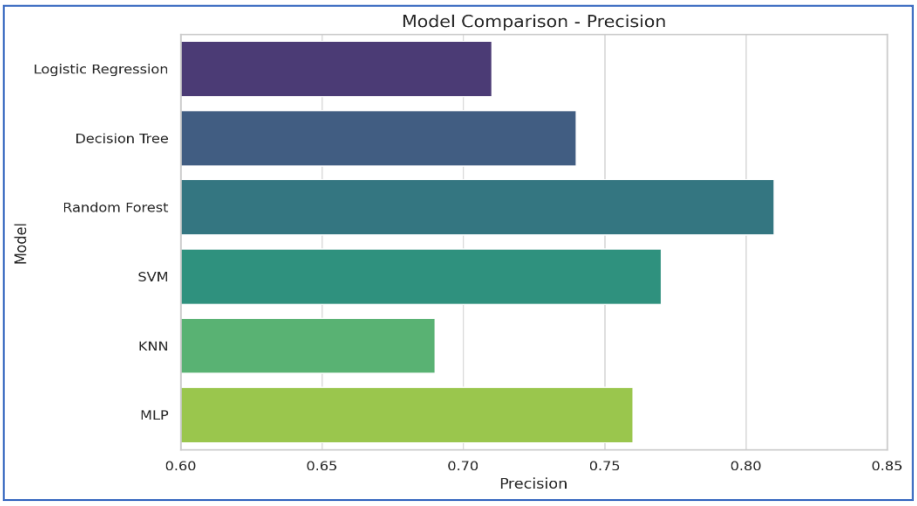


Fig. 4: Model Comparison for Precision Graph.

7.2.1. Implications of precision graph in learning style prediction

In the context of identifying students' learning styles, a higher precision ensures that the learning style predicted by the model is more likely to be correct. Therefore, Random Forest is the most reliable model for correctly predicting a student's learning style when it labels them as a particular type. Models with lower precision, like KNN, might lead to misclassification, potentially assigning incorrect learning strategies to students.

7.3. Interpretation of recall graph

Recall Graph shown in Figure 5 indicates the comparison of all models on the scores of Recalls. It is seen that RF is the top-performing model in terms of recall and is likely a good candidate for applications prioritizing sensitivity (minimizing false negatives). SVM and MLP also show strong performance, making them viable alternatives. Simpler models like Logistic Regression and KNN may need further tuning or feature engineering. KNN may not generalize well for this specific problem and dataset.

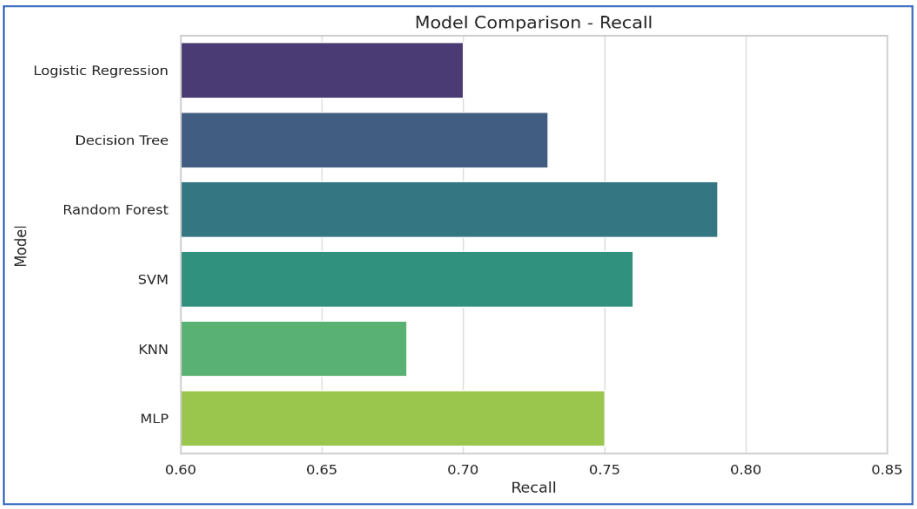


Fig. 5: Model Comparison for Recall Graph.

7.3.1. Implications of recall graph in learning style prediction

Recall here measures the ability to correctly identify students with a particular learning style without missing any (minimizing false negatives). The application in an educational context of Random Forest method can be related to identification of tailored teaching methods most accurately, but its higher recall might over-identify some students, so balancing with precision is key to avoid misclassification.

7.4. Interpretation of F1 score

F1 Score Graph as shown in Figure 6 compares the F1 scores of all machine learning models. It indicates that the Random Forest achieves the highest F1-score (~0.80), indicating it balances precision and recall most effectively among all models. It is likely the most reliable model in terms of both minimizing false positives and false negatives. SVM and MLP follow closely with F1-scores of ~0.76 and ~0.75, suggesting they also perform well and may be suitable alternatives depending on context or computational constraints. Decision Tree and Logistic Regression perform moderately with F1-scores around 0.73 and 0.70 respectively. These models are very simpler and more interpretable, which might defend their use despite slightly lower scores. KNN has the lowest F1-score (~0.68), suggesting it may struggle with this dataset, possibly due to issues like sensitivity to irrelevant features or poor distance metrics.

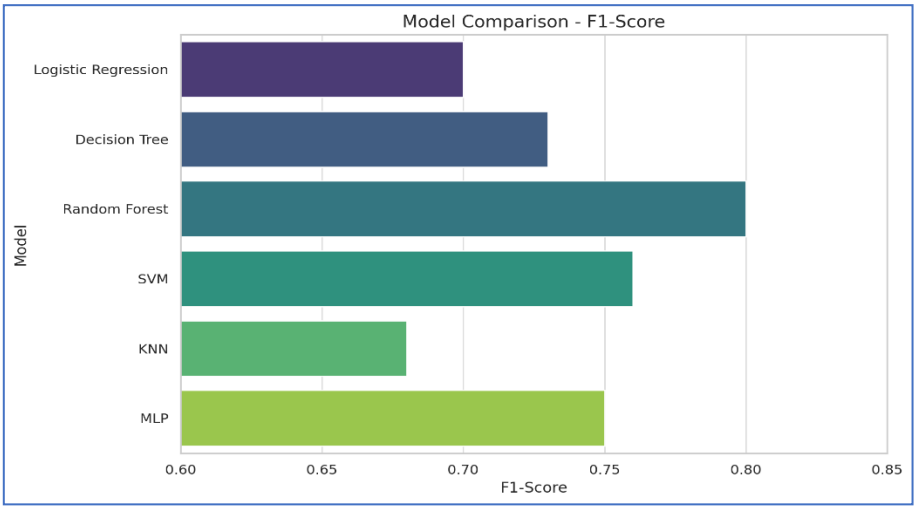


Fig. 6: Model Comparison for F1 Score.

7.4.1. Implications of F1 score graph in learning style prediction

Since F1-score balances precision and recall, the Random Forest model ensures accurate and comprehensive identification of students' learning styles. This is especially important in education where misidentifying a student's learning preference can lead to disengagement or ineffective learning outcomes. Models with lower F1-scores might miss subtle indicators of learning preferences or misclassify similar styles (e.g., visual vs. kinesthetic).

7.5. Confusion matrix analysis

Figure 6 shows a deeper insight into class-wise performance, where confusion matrices were plotted for each classifier. The given images are referred to as confusion matrices, which likely represent the performance of a classification model based on Kolb's Learning Styles Inventory, that categorizes learning styles into four types, namely, Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE).

In each matrix compares predicted learning styles in the columns against actual learning styles in rows, with the numbers indicating the frequency or count of predictions. The color intensity, as indicated by the scale on the right (ranging from ~60 to 100), reflects the

magnitude of these counts, with darker shades representing higher values. Since three matrices are provided without additional context, they might represent different models, datasets, or iterations, and I'll interpret each one in detail while comparing them. These matrices highlighted model tendencies in misclassifying certain styles, especially when behavioral features were overlapping across adjacent style categories.

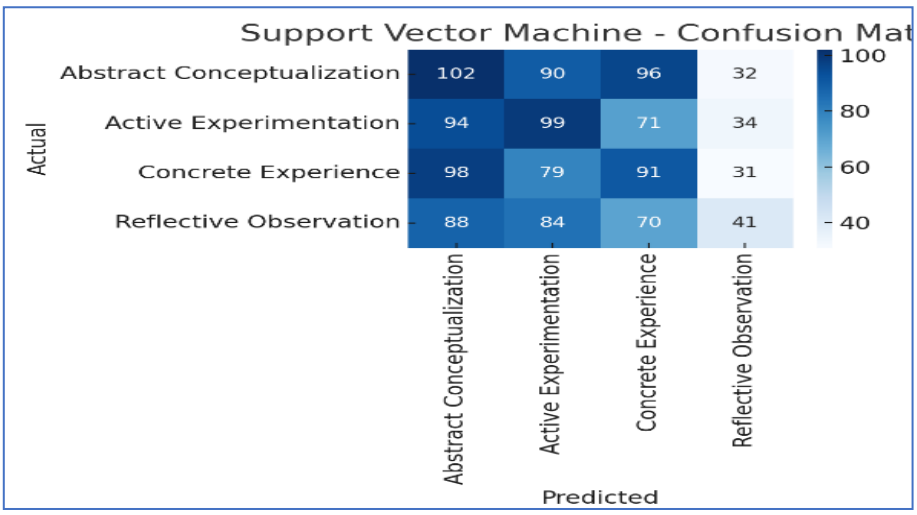


Fig. 7: Support Vector Machine (SVM) Confusion Matrix.

As indicated in the Support Vector Machine (SVM) Confusion Matrix, for Abstract Conceptualization, 102 correctly classified, but 90, 96, and 32 instances misclassified as Active Experimentation, Concrete Experience, and Reflective Observation, respectively. In case of Active Experimentation, 99 correctly classified, with 94, 71, and 34 misclassifications. For Concrete Experience, 91 correctly classified, with 98, 79, and 31 misclassifications. For Reflective Observation, 41 correctly classified, with 88, 84, and 70 misclassifications.

In Support Vector Machine (SVM) Confusion Matrix, it is observed that, SVM performs best for Abstract Conceptualization (102 correct) but struggles with Reflective Observation (only 41 correct). Misclassifications are high across all classes, especially for Reflective Observation, where most instances are predicted as other classes.

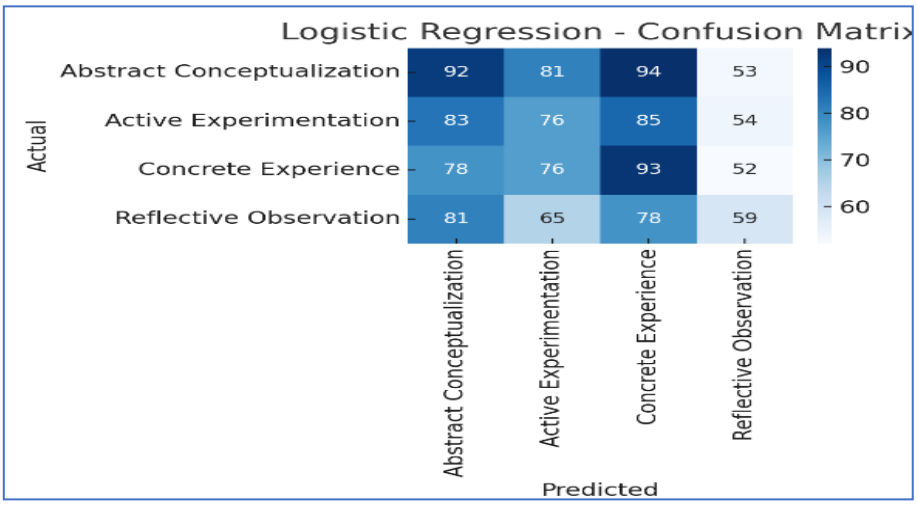


Fig. 8: Logistic Regression Confusion Matrix.

As shown in Logistic Regression Confusion Matrix, for Abstract Conceptualization, 92 correctly classified, with 81, 94, and 53 misclassifications. For Active Experimentation, 76 correctly classified, with 83, 85, and 54 misclassifications. In case of Concrete Experience, 93 correctly classified, with 78, 76, and 52 misclassifications. For Reflective Observation, 59 correctly classified, with 81, 65, and 78 misclassifications.

Logistic Regression Confusion Matrix, it is observed that Logistic Regression performs best for Concrete Experience (93 correct) but struggles with Active Experimentation (76 correct). Reflective Observation classification improves slightly compared to SVM (59 correct), but misclassifications remain high across all classes.

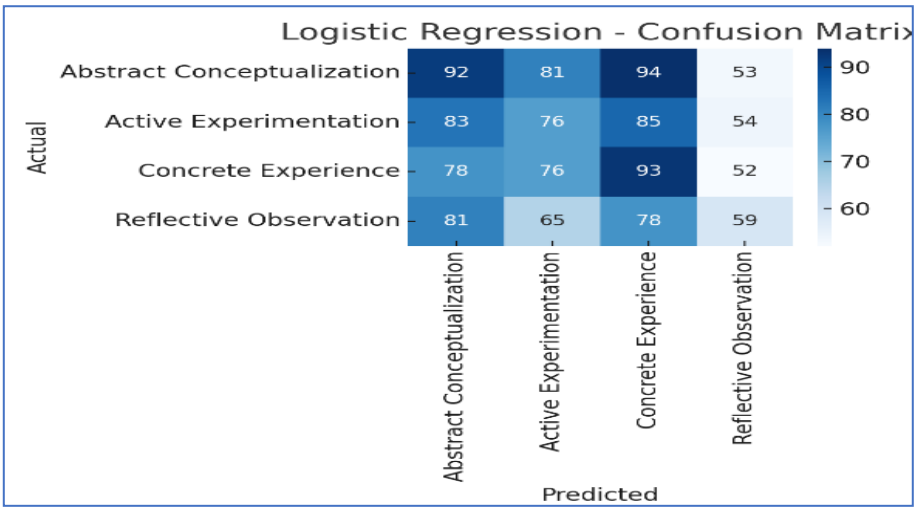


Fig. 9: Decision Tree Confusion Matrix.

As indicated in the Decision Tree Confusion Matrix for Abstract Conceptualization, 88 correctly classified, with 86, 61, and 85 misclassifications. In Active Experimentation, 83 correctly classified, with 75, 68, and 72 misclassifications. In case of Concrete Experience, 83 correctly classified, with 64, 78, and 74 misclassifications. And Reflective Observation, 64 correctly classified, with 73, 78, and 68 misclassifications.

It was evident that the best performing model for Abstract Conceptualization and Active Experimentation was Decision Tree (both 83 correct), but struggles with Concrete Experience (64 correct). It has more balanced performance across classes compared to others, but misclassifications are still notable.

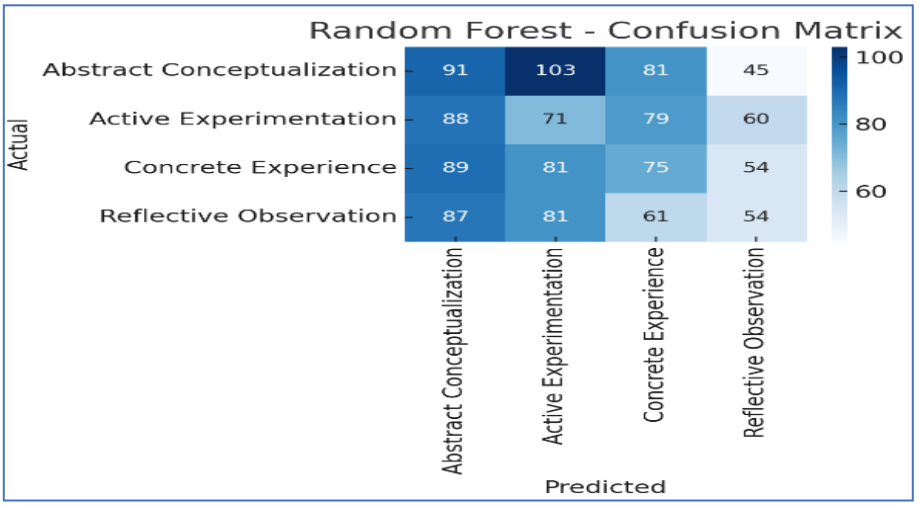


Fig. 10: Random Forest Confusion Matrix.

As observed in Random Forest Confusion Matrix, in Abstract Conceptualization, 91 correctly classified, with 103, 81, and 45 misclassifications. For Active Experimentation, 71 correctly classified, with 88, 79, and 60 misclassifications. In case of Concrete Experience, 75 correctly classified, with 89, 81, and 54 misclassifications. In case of Reflective Observation, 54 correctly classified, with 87, 81, and 61 misclassifications.

It is observed that Random Forest performs best for Abstract Conceptualization (91 correct) but struggles with Active Experimentation (71 correct). Misclassifications are still significant, with Reflective Observation having the fewest correct predictions (54).

7.6. Comparative analysis

SVM has performed best for Abstract Conceptualization (102) and Logistic Regression has the highest correct classification for Concrete Experience (93). More balanced performance across classes is shown by Decision Tree but shows lower peak accuracy. Consistently the hardest model to be classified across all models was Reflective Observation with SVM performing the worst (41 correct) and Decision Tree the best (64 correct).

Frequent misclassification of instances by all models were for Abstract Conceptualization or Active Experimentation, suggesting these classes might have overlapping features in the dataset. Reflective Observation is often mistaken for other classes, indicating it may be the least distinct.

Logistic Regression and SVM seem better for specific classes (Concrete Experience and Abstract Conceptualization, respectively), while Decision Tree offers more consistent performance across all classes. Random Forest underperforms compared to the others in this case.

The models show moderate performance in classifying Kolb's Learning Styles, with significant misclassifications across all classes. Reflective Observation is the most challenging to predict, while Abstract Conceptualization and Concrete Experience are better classified. If the goal is balanced performance, the Decision Tree might be preferable; otherwise, Logistic Regression or SVM could be chosen based on the target class of interest. To improve performance, feature engineering or a different model (e.g., neural networks) might be worth exploring.

While interpreting the predicators, it is observed that the skewed predictions favoring the dominant classes was shown by Decision Tree and KNN. Whereas, most balanced predications across all classes was shown by Random Forest model.

7.7. Error rate analysis

Along with the conventional evaluation metrics, each model's error rate was calculated to quantify the proportion of misclassified instances with the use of formula Error Rate = 1 – Accuracy.
Error rate analysis provides direct information on the reliability of models by indicating how often a model fails on unseen data. A summary of error rates observed for all models is shown in Table 1.

Table 1: Error Rates of Models Under Study

Model	Accuracy	Error Rate
Logistic Regression	0.72	0.28
Decision Tree	0.75	0.25
Random Forest	0.80	0.20
Support Vector Machine	0.78	0.22
K-Nearest Neighbors	0.70	0.30
Multi-Layer Perceptron	0.77	0.23

The lowest error rate of 0.20 and the highest accuracy of 0.80 were demonstrated by the Random Forest model. This reinforced its ability to capture complex and non-linear patterns in the datasets. On the other hand, the highest error rate of 0.30 and the lowest accuracy of 0.70 were exhibited by K-Nearest Neighbors model, which indicates its limitation in handling high-dimensional feature spaces, particularly without extensive hyper-parameter tuning.
Inclusion of the error rate enables a more intuitive understanding of the efficacy of the model and provides stakeholders a quick reference for failure likelihood in real-world deployment scenarios.

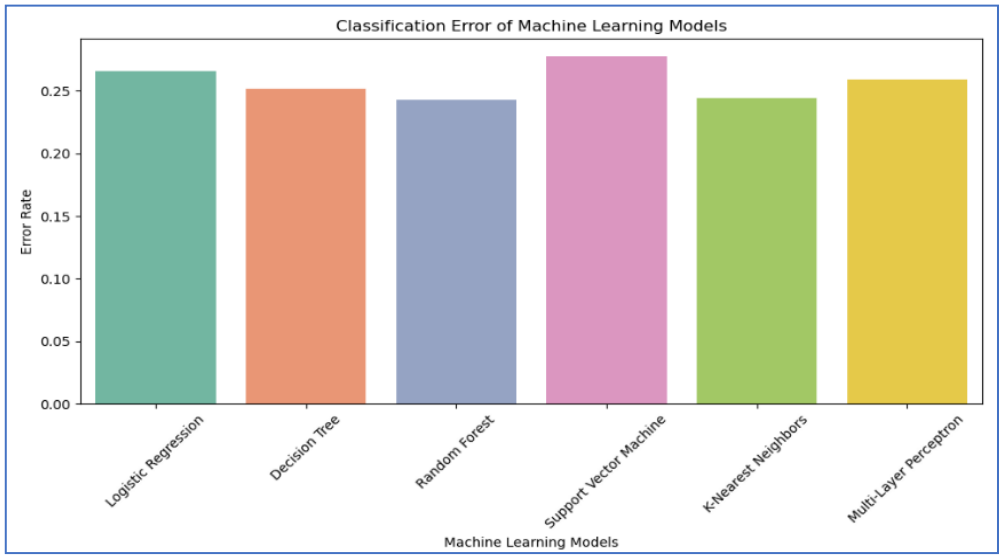


Fig. 11: Error Rate Comparison from the Given Models.

Held-out test set evaluated the performance of all models. The key performance metrics are summarized in Table 2 as follows:

Table 2: Summary of Key Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.72	0.71	0.69	0.70
Decision Tree	0.75	0.74	0.73	0.73
Random Forest	0.80	0.81	0.79	0.80
Support Vector Machine	0.78	0.77	0.78	0.78
K-Nearest Neighbors	0.70	0.68	0.66	0.67
Multi-Layer Perceptron	0.77	0.76	0.77	0.76

7.8. Confusion matrix analysis

Class-wise miscalculation patterns for all classifiers were identified with the generation of confusion matrices. Balanced predictions across all learning styles was demonstrated by the Random Forest model. Misclassified non-linearly separable classes were shown by Logistic Regression and Decision Tree models. Likely due to overlapping features and sensitivity to scaling, KNN favoured dominant classes. High performance was also shown by SVM and MLP but with occasional overlap between adjacent styles.

Table 3: Confusion Matrix Analysis

Model	Observations from Confusion Matrix
Random Forest	Balanced predictions, low false positives.
Support Vector Machine	Good recall but some overlap between sequential/reflective.
Decision Tree	Skewed toward dominant classes.
Logistic Regression	High misclassification for global/visual learners.

7.9. Error rate analysis

The model's error rate was computed using the formula 1 – Accuracy, as shown below:

Table 4: Model Accuracy and Error Rates

Model	Accuracy	Error Rate
Logistic Regression	0.72	0.28
Decision Tree	0.75	0.25
Random Forest	0.80	0.20
Support Vector Machine	0.78	0.22
K-Nearest Neighbors	0.70	0.30
Multi-Layer Perceptron	0.77	0.23

Strong generalization can be reaffirmed for the Random Forest model as it yielded the lowest error rate (0.20). KNN on the other hand showed the poor performance in high-dimensional spaces with highest error rate (0.30).

7.10. Feature importance analysis

To identify the most influential predictors of students' learning styles, a feature importance analysis was conducted using the Random Forest classifier, which provides intrinsic interpretability through impurity-based importance scores.
The analysis revealed that CGPA, preferred study time, and weekly study hours were among the strongest demographic predictors. Among behavioral variables, several Likert-scale items related to reflection tendency, conceptual abstraction, and hands-on experimentation demonstrated high predictive relevance.
Notably, reflective behavior indicators (e.g., questionnaire items linked to careful observation and delayed decision-making) contributed significantly to class separation, particularly in distinguishing Reflective Observation from Active Experimentation. Gender exhibited moderate influence, suggesting interaction effects rather than direct causality.
These findings confirm that both academic performance indicators and behavioral engagement patterns jointly drive learning style prediction, reinforcing the need for multi-dimensional feature modeling in educational analytics.

8. Discussion of Outcomes

8.1. Distribution of learning styles

Significant imbalances are revealed through the analysis of class distribution. It was observed that the though the active learning styles were evenly distributed among respondents, the reflective styles were commonly observed among female candidates. Reflective and sequential learning styles were present among students with higher CGPAs.
Structural learning styles were found to be present among those students with regular study habits at particular times of the day. These observations indicate a profound impact of demographic variables on the learning style or behavior of students.

8.2. Cluster analysis of learner profiles

Through the applications of unsupervised learning techniques, like K-Means and t-SNE, latent patterns that closely monitors and recognizes the learning styles are uncovered. Consistent behavior patterns were demonstrated by students grouped in similar clusters. This suggested that the cognitive preferences are reflected through the responses collected through the questionnaire, and the data reliability is established.

8.3. Implications for personalized learning

Effective distinction in learning styles can be made by the models based on machine learning, which enables adaptive learning systems for personalized content delivery. With the usage of these models students' engagement, retention, and academic performance can be significantly enhanced. However, moderate error rates and overlapping behaviors suggest the need for hybrid models that include real-time data.

8.4. Limitations

The limitations for the current study are due to the static questionnaire design which limits adaptability over time. Further the demographic data may also introduce bias. And lastly the sample size may need scaling for real-world applications.

8.5. Model interpretability and educational implications

Beyond predictive accuracy, model interpretability plays a crucial role in educational decision-making. Interpretable models such as Logistic Regression and Decision Trees offer transparent reasoning paths that educators can easily understand and trust, enabling direct translation of model outputs into pedagogical interventions.
In contrast, ensemble and neural models such as Random Forest and Multi-Layer Perceptron provide higher predictive performance but operate as comparatively opaque systems. While Random Forest partially mitigates this limitation through feature importance measures, neural networks remain largely black-box in nature.
For practical deployment in educational environments, this trade-off suggests a hybrid approach: high-accuracy models for automated personalization combined with interpretable summaries that allow educators to understand why a particular learning style is predicted. Such alignment enhances trust, adoption, and ethical use of AI-driven educational tools.

9. Findings

Findings suggest that the Random Forest consistently outperformed all other models. the variables like Gender, CGPA, and preferred study time influenced learning styles. Class imbalance has affected precision and recall. Clustering supported model-based classifications.
Learning style prediction using ML is feasible with good accuracy, especially when demographic data is included. Model performance varies based on algorithm robustness and class reparability. Random Forest is best suited due to its non-linear modelling capabilities and resistance to overfitting.

10. Conclusion

The current aimed at discovering the abilities of Machine Learning classifiers for accurate prediction of student's learning style from diverse and multi-dimensional data of students belonging to arts, commerce and science fields by combining the demographic and behavioral data. The output indicates that; Random Forest classifier has consistently exhibited the highest performance among the various models evaluated under study. The highest performance was observed across all metrics, confirming the suitability for this type of classification task. The results reemphasise the importance and contribution of supervised learning techniques to assist and develop the personalized learning environments while dealing with a group of academic population from diverse backgrounds.
The study has been successful in identifying the key role played by student demographic factors such as their gender, scores or CGPAs, and preferred study time in the day. These factors serve as crucial determinants of students' learning styles. In addition, the technique of clustering has also validated the results by revealing the profiles of consistent learners, which enhances the robustness of the classification outcomes.
While the results are positive and promising, further methodological refinements are always needed for dealing with the issues related to imbalanced classes, dependence on static surveys, and moderate rates of errors. Incorporating real-time behavioural data, expanding the dataset, and exploring hybrid or ensemble models may enhance both precision and adaptability. Higher accuracy and adaptability can be achieved with the support of hybrid or ensemble techniques, only when the real-time behavioural data is integrated and the dataset is enlarged.
This study can be considered a significant contribution to enriching the current understanding in the domains of personalized learning and educational data mining. Machine learning, particularly the Random Forest Model, shines in particular and holds great potential for enabling adaptive learning systems catering to the students' individual or personalized learning needs. Subsequent studies can prioritise integration of these models into learning management systems for facilitating dynamic and context-aware personalization.

11. Future Research Directions

Several promising directions emerge from this study. First, the integration of Explainable Artificial Intelligence (XAI) techniques such as SHAP or LIME can enhance transparency by providing instance-level explanations of learning style predictions, thereby improving educator trust and model accountability.
Second, future work may explore federated learning frameworks to enable collaborative model training across institutions without sharing sensitive student data. This approach can significantly improve model generalization while preserving data privacy and institutional autonomy.
Third, incorporating real-time behavioural data from learning management systems—such as clickstream patterns, assessment interactions, and temporal engagement—could transform static learning style prediction into a dynamic, adaptive process.
Finally, interdisciplinary collaboration between data scientists, educational psychologists, and instructional designers is essential to ensure that predictive models align with pedagogical theory and classroom practice, thereby facilitating responsible and scalable deployment of AI-driven personalized learning systems.

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