Prediction of Student Outcomes using Machine Learning Algorithms for Dropout and Engagement Analysis

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***Abstract*—In this paper, the primary objective is to apply different machine learning techniques to predict outcomes of students in learning environments. Personalised learning is an integral part of modern education which compels us to tailor strategies suitable for the same. This study predicts dropout likelihood, learning styles and engagement levels of students by performing various ML techniques on the dataset. Decision Trees, K-Nearest Neighbours (KNN) and Support Vector Machines (SVM) are the classification models implemented on the dataset. Besides, Random Forest, Gradient Boosting and Logistic Regression were also performed on the dataset and the results were analyzed. Multiple techniques were used for preparation and pre-processing the data, handling class imbalance, encoding categorical data and extraction of the useful features.**

Keywords—decision tress; random forest; gradient boosting; machine learning; personalized learning dataset; python

I. Introduction

There has been a tremendous increase in online learning models, especially from Covid 19 times and it has seen an increase in its usability since then. So, it becomes crucial to assess student behaviour and performance which are significant for determining academic success [1]. There is a concern regarding higher dropout rates among institutions, facilitating the need for data-driven solutions [2]. This paper provides insights for predicting key educational metrics such as dropout likelihood, engagement level, and learning styles of students using various machine learning techniques.

This study's main aims are:

- To classify pupils according to their chance of dropping out.
- To predict student involvement levels using classification models.
- Using K-Means to cluster students depending on their learning styles.

II. Literature Review

Machine Learning has been extensively used in educational data mining to forecast student outcomes. Several research prospects have investigated predicting models for academic success, engagement levels, and dropout rates [3].

A. Predicting Dropout Likelihood

Various studies have deployed machine learning techniques to predict dropout rates of students. Decision Trees and Neural Networks have demonstrated potential for assessing student retention data [4]. A recent research study has highlighted the use of ensemble approaches, such as Random Forest, to improve accuracy of prediction [5]. Deep Learning techniques, such as recurrent neural networks (RNNs), have also been investigated for sequential dropout prediction [6]. Bayesian networks have been used probabilistically, which improves prediction reliability.

B. Engagement Level Prediction

Student involvement is critical to academic performance, since it influences retention and learning outcomes. Data on behavioral, interactional, and academic performance can be used to assess degrees of engagement [8]. Traditional engagement measurement focused on manual assessments and surveys, while machine learning allows for automatic analysis based on student behaviors and replies [9]. Several categorization algorithms such as Support Vector Machines (SVM), Logistic Regression, and deep learning methods, have been employed to forecast involvement levels. SVM, in particular, have been used in engagement classification due to its capability to handle high dimensional data accurately identify engagement categories [10]. Deep learning techniques, including recurrent neural networks (RNNs) and transformers, have been used to predict sequential engagement patterns in online learning systems [11]. Additionally, reinforcement learning has been used to dynamically tailor student interactions based on engagement levels [12]. Sentiment analysis using natural language processing (NLP) has also been used to evaluate student involvement via textual feedback and discussion forum participation [13]. Recent study indicates that combining behavioral tracking with ML models enhances engagement prediction accuracy and gives actionable insights for instructors [14].

C. Learning Style Clustering

K-Means and hierarchical clustering algorithms have been used to categorize pupils according to their learning patterns [11]. Clustering algorithms have been shown in studies to provide insights for individualized learning tactics [12]. A combination of supervised and unsupervised learning has been tested to improve clustering performance in educational datasets [13]. More recent research has looked on graph-based clustering approaches for understanding complex student interactions and learning paths [14].

D. Machine Learning in Personalized Education

Romero and Ventura [15] provide an extensive analysis of the impact of machine learning in personalized education. AI-powered models have been implemented into intelligent tutoring systems, adaptive learning platforms, and recommendation engines to improve learning outcomes [16]. Reinforcement learning has been used to dynamically customize learning content based on student performance and progress [17].

This study extends previous research by using various classification models and clustering techniques to assess tailored learning tactics.

III. Problem and Dataset Description

Educational institutions face two major challenges: dropout rates and student engagement. Understanding the elements that influence student learning behaviors can assist apply early interventions [18]. Personalized learning solutions can increase retention rates and maximize teaching methods [19].

A. Dataset

The 'Personalized Learning and Adaptive Education Dataset' is authored by Adil Shamim and is publicly available on Kaggle platform [20]. This dataset is intended to aid research into adaptive learning systems, individualized education, and predicting student success models. It collects detailed interaction data from online education systems, such as student involvement, quiz performance, learning preferences and dropout rates. The dataset is preprocessed to handle missing values and categorical encoding [21]. The dataset contains 15 columns and 10000 rows, each row catering to a particular student identified by unique Student_ID.

TABLE I. Dataset Features

Feature	Description
Student_ID	Uniquely identifies each student
Age	Age of student (15-50 years)
Gender	Male, Female or Other
Education_Level	High School, Undergraduate, Postgraduate
Course_Name	Online course student is enrolled: Machine Learning, Python Basics, Data Science
Time_Spent_on_Videos(mins)	Total minutes spent on watching online videos
Quiz_Attempts	Number of attempts in the quiz
Quiz_Scores	Score obtained in quiz (%)
Forum_participation(posts)	Number of forum discussions student was engaged in
Assignment_Completion_Rate	Number of assignments completed by student (%)
Engagement_Level	High, Medium or Low
Final_Exam_Score	Score of student in final exam (%)
Learning_Style	Visual, Auditory, Reading, Writing, Kinethestic
Feedback_Score	Rating of the course by student on a scale of 5 (1-5)
Dropout_Likelihood	Will the student dropout or not (Yes/No)

Use cases of the dataset: Developing AI- driven adaptive learning models, analyze student engagement and performance patterns, predicting dropout rates based on learning behaviors, developing individualized educational content.

IV. Methodology

A. Machine Learning Techniques

1. Decision Tree Classifier:

A decision tree classifier is a rule-based classification technique that divides the dataset recursively depending on feature relevance in order to categorize cases. It works by creating a tree-like model of decisions, with each node representing a feature condition and each branch leading to an outcome. Decision trees are easy to interpret and are good at handling both categorical and numerical data. They are, however, sensitive to overfitting, particularly when dealing with dense woods. Pruning strategies and ensemble approaches, such as Random Forest, can help to alleviate this issue. In this study, Decision Trees are used to estimate dropout chances.

2. Random Forest Classifier:

Random Forest is a machine learning technique that generates numerous decision trees and then averages their predictions using majority voting (for classification) or averaging (for regression). It increases model accuracy and resilience by lowering variance and preventing overfitting when compared to a single decision tree. The relevance of features is evaluated during training, which is useful for feature selection. In this work, Random Forest is employed as an alternative model to estimate dropout chances.

3. Support Vector Machine (SVM):

SVM is a strong supervised learning model that determines the best hyperplane to divide various classes in a high-dimensional space. The fundamental goal of SVM is to maximize the margin between data points from different classes, which improves generalization. The model may capture nonlinear interactions in data using several kernel functions (linear, polynomial, and radial basis function). It is especially useful for engagement level classification due to its ability to handle skewed datasets and high-dimensional feature spaces.

4. Gradient Boosting Classifier:

Gradient Boosting is a strong ensemble learning method that creates decision trees in a sequential manner, with each new tree fixing the faults of the preceding ones. Gradient Boosting, unlike Random Forest, adjusts the loss function iteratively to eliminate bias and increase predictive performance. It performs particularly well with structured data and classification jobs. Gradient Boosting is used in this study as an alternate dropout prediction strategy to improve model accuracy and reduce overfitting.

5. K-Nearest Neighbors (KNN):

KNN is an instance-based learning and non-parametric based, technique that categorizes new data points using the majority class of its k-nearest neighbors. Euclidean distance is commonly used to quantify the similarity between instances. While KNN is simple to understand and implement, it can be computationally expensive for large datasets because it requires storing and searching all training examples during classification. In this study, KNN is used to predict learning styles since students who demonstrate similar behavioral patterns may have comparable learning preferences.

6. Logistic Regression:

Logistic Regression is a popular statistical model that uses the logistic function to calculate the likelihood of class membership. Unlike linear regression, it is specifically developed for classification tasks, using sigmoid activation to limit output values to 0 or 1. The coefficients in the model describe each feature's influence on the likelihood of a specific class. Logistic Regression is used to predict involvement levels in this study because it is efficient at handling binary and multi-class classification problems.

7. K-Means Clustering:

K-Means is an unsupervised machine learning algorithm that divides data points into k separate clusters based on feature similarity. It works iteratively, assigning each data point to the nearest centroid, updating centroids, and reducing intra-cluster variation. The elbow technique or silhouette analysis are common methods for determining the ideal number of clusters. In this study, K-Means is utilized to classify students based on their learning styles, allowing for more individualized instructional tactics.

B. SMOTE Analysis for Class Imbalance:

Class imbalance is a prevalent issue in real-world datasets, with some classes having much fewer instances than others. This mismatch can cause machine learning models to favor the dominant class, resulting in biased predictions and poor generalization for minority groups [22]. In classification issues such as dropout prediction and engagement level estimate, the minority class (i.e., students at high risk of dropping out) is frequently underrepresented, making it difficult for models to acquire meaningful patterns about this class.

SMOTE (Synthetic Minority Over-sampling Technique) is used to overcome this issue. SMOTE is an oversampling approach that generates new samples for the minority class rather than duplicating old ones. It operates by choosing a data point from the minority class, determining its k-nearest neighbors, and generating fresh samples throughout the line segments joining the original data point and its neighbors [23]. It balances the dataset while keeping its structure, avoiding overfitting that can occur with simple random oversampling [24].

C. Model Evaluation:

The performance of classification models is evaluated using accuracy, precision-recall, F1-Score, RMSE and the ROC curve. The silhouette score is used to assess the quality of K-Means clustering.

V. Experimental Setup:

A. Data Pre-Processing:

Data preparation is an important step in ensuring that the dataset is clean, consistent, and ready for machine learning models. Several preprocessing techniques were used to normalize the dataset and deal with missing or category variables.

1. Label Encoding for Categorical Features:

Gender, Education Level, and Course Name were transformed to numerical values using Label Encoding [26]. This transformation enables numerical-based machine learning algorithms to efficiently process categorical features.

2. Standardization of Numerical Features:

StandardScaler was used to standardize numerical features such as age, time spent on videos, quiz scores, and final exam scores, guaranteeing that all features had a mean of zero and a standard deviation of one. This change improves the performance of distance-based algorithms such as SVM and KNN [27].

3. Handling Missing Data:

Mean imputation was used to address missing values, which involved replacing missing entries in numerical features with the mean value of the corresponding column. This method prevents loss of data while maintaining consistency of the dataset [28].

4. Splitting of Data:

The dataset is divided into training and testing segments. 80% of the data is for training the models and 20% data is for testing. Random state is set at 42 so that the models produce same results every time the setup is processed.

B. Selection of Features:

Feature selection is the process of determining the most important attributes in a dataset that adds to the prediction capability of machine learning models. Removing superfluous or duplicated features can increase model efficiency and generalizability [29].

1. Random Forest for Feature Selection:

The Random Forest model was used to determine the relevance of various characteristics by assessing how much each feature contributes to minimizing impurity in splits across decision trees. Features with low significant scores were deleted to improve performance of the model [30].

2. Reduction of Dimensionality

Less important features, as determined by feature significance scores, were removed to avoid overfitting and reduce computational complexity by performing Principal Component Analysis (PCA). This phase guarantees that models learn only from the most relevant qualities while reducing noise in the input.

C. SMOTE Analysis:

In this work, SMOTE was used to balance the dataset, especially for dropout likelihood and engagement level predictions, resulting in enhanced model performance. By using synthetic examples, SMOTE improves the model's capacity to generalize minority class instances, leading in higher recall and F1 scores. The efficacy of SMOTE was assessed by comparing model performance before and after oversampling, which revealed considerable gains in classification accuracy for marginalized groups. Class distribution plots were also inspected before and after the SMOTE application to ensure that the dataset was balanced properly. SMOTE was used to balance the dataset, particularly for dropout and engagement level predictions, resulting in improved performance in minority classes. The following figures describe the results before and after applying SMOTE.

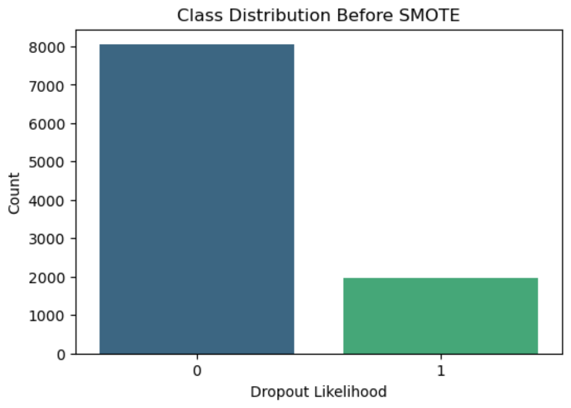

Fig 1: Class Distribution before applying SMOTE

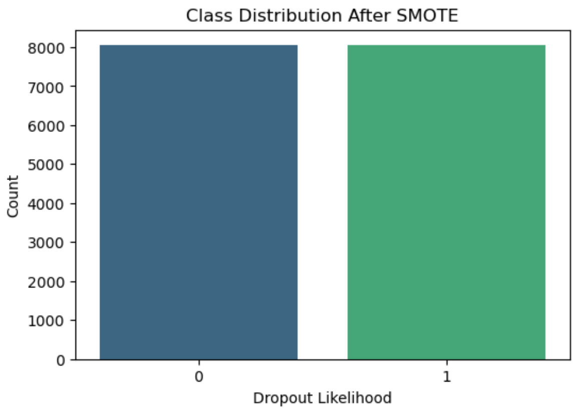

Fig 2: Class Distribution after applying SMOTE

D. Hyperparameter Tuning:

Hyperparameter adjustment is critical for improving machine learning model performance. The precise hyperparameter selection can have a considerable impact on precision, accuracy and generalization ability [31].

1. GridSearchCV for Optimal Parameter Selection:

GridSearchCV was used to fine-tune hyperparameters in SVM and Random Forest. Cross-validation is used in this strategy to conduct an exhaustive search over given hyperparameter values. For example, numerous iterations were used to identify the ideal values for the number of estimators in Random Forest and kernel type in SVM, resulting in improved classification accuracy [32].

2. Cross Validation for KNN:

Cross-validation was used to find the optimal number of neighbors (k) for the K-Nearest Neighbors (KNN) classifier. Various k values were evaluated to determine the best trade-off between model complexity and forecast accuracy. Cross-validation reduces overfitting by guaranteeing that the model works well on previously unknown data [33].

E. CLASSIFICATION AND CLUSTERING PARAMETERS:
To enhance performance, the classification and clustering models in this study were tuned using specified hyperparameters.

1. DECISION TREE:

Criterion	Gini impurity
Max Depth	10 (improved using GridSearchCV)
Min samples split	2

2. RANDOM FOREST:

Estimators	100
Criterion	Gini impurity
Max Depth	12 (improved using GridSearchCV)

3. SUPPORT VECTOR MACHINE (SVM):

Kernel	Linear
C (Regularization parameter)	1.0 (optimized using GridSearchCV)
Scale	Gamma

4. GRADIENT BOOSTING:

Estimators	100
Learning Rate	0.1
Max Depth	3

5. K-NEAREST NEIGHBORS (KNN):

No. of neighbors (k)	5 (using cross-validation)
Distance metric	Euclidean

6. LOGISTIC REGRESSION:

Solver	lbfgs
Max iterations	1000
C (Regularization parameter)	1.0

7. K-MEANS CLUSTERING:

No. of clusters (k)	3
Initialization method	K-Means++
Max iterations	300

Gini impurity: Gini impurity is a statistic used in Decision Trees to determine the level of impurity in a dataset at a specific node. It helps to determine how successfully a split separates data into distinct classes. The node that has a lower Gini impurity is purer. It is given by the following formula:

$$G = 1 - \sum_{i=1}^{C} p_i^2$$

Where,

- G is gini impurity
- C is number of classes
- p_i is the proportion of samples belonging to class *i* in the node

Gini Impurity is more computationally efficient than alternatives such as Entropy, hence it is a frequent choice in Decision Trees and Random Forests [34].

Maximum depth: 'max_depth' of a decision tree controls how many levels it can reach before stopping. It is an important hyperparameter that directly influences model complexity**.**

- Deeper trees have a higher potential to learn patterns but may lead to overfitting.
- Shallower trees result in simpler models that may not capture complicated patterns, perhaps leading to underfitting.

To avoid overfitting, cross-validation or GridSearchCV are commonly used to optimize max_depth for better performance [35]. Table below describes the techniques used in this study and their purpose.

TABLE II

Technique	Usage
Decision Tree	Predict Dropout Likelihood
Support Vector Machine	Predict Engagement Level
K-Nearest Neighbors	Predict Learning Style
Random Forest	Alternative for dropout prediction
Logistic Regression	Alternative for engagement prediction
Principal Component Analysis (PCA)	Dimensionality Reduction
K-Means Clustering	Group students based on features

VI. RESULTS:
The metrics of the techniques used for this research; accuracy, precision, recall, F1-score and RMSE are summarized in the tables below:

TABLE III

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.762275	0.762612	0.762275	0.762187
Random Forest	0.881603	0.900252	0.881603	0.880235
Gradient Boosting	0.837166	0.876884	0.837166	0.832819
SVM	0.655687	0.661251	0.655687	0.652565
KNN	0.736172	0.786459	0.736172	0.723911
Logistic Regression	0.502486	0.502491	0.502486	0.502485

TABLE IV

Model	RMSE
Decision Tree	0.487571
Random Forest	0.344088
Gradient Boosting	0.403527
SVM	0.586782
KNN	0.513642
Logistic Regression	0.705347

From the tables above, it can be observed that the three best performing models are ***Random Forest***, ***Gradient Boosting***, ***Decision Tree*** respectively with KNN and SVM closely following. Logistic Regression performed the worst as compared to other techniques.

The above metrics are calculated as follows:

1. Precision (Positive Predicted Value):

$$Precision = \frac{TP}{TP + FP}$$

2. Recall (True Positive Rate):

$$Recall = \frac{TP}{TP + FN}$$

3. F1-Score (Harmonic Mean of Recall & Precsion):

$$F1 - Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall}$$

4. RMSE (Root Mean Square Error):

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} (Actual\ value - Predicted\ Value)2}$$

Where,
TP: True Positives
FP: False Positives
FN: False Negatives
n: Total number of data points
Lower the RMSE score, the better the model is. Random Forest has an RMSE score of 0.344088 which is the lowest and hence it is the best performing model. Whereas, Logistic Regression has the highest RMSE score and hence, the worst performing model.

The table below depicts the classification report of Decision Tree:

TABLE V

	Precision	Recall	F1-Score	Support
Class 0	0.77	0.74	0.76	1606
Class 1	0.75	0.78	0.77	1612
Accuracy			0.76	3218
Macro avg	0.76	0.76	0.76	3218
Weighted avg	0.76	0.76	0.76	3218

Class 0 and Class 1 in the above classification report are label encoded values for Decision Tree, Yes and No respectively. The Decision Tree model performs reasonably well, with balanced accuracy and class-wise performance. F1-scores for both classes are close (~0.76-0.77), indicating that the model does not favor one class over the other. This makes the model appropriate for balanced datasets in which all classes are equally essential, such as predicting dropouts when both dropouts and non-dropouts are relevant.

The number of trees used for Random Forest technique is 100.

The Confusion matrices for the three best performing techniques:

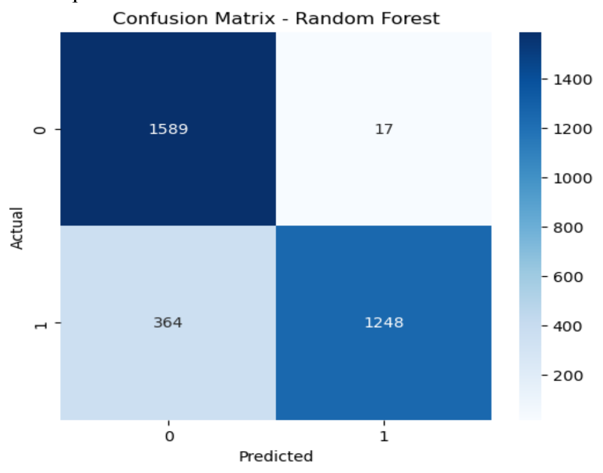

Fig 3: Heatmap for confusion matrix for Random Forest

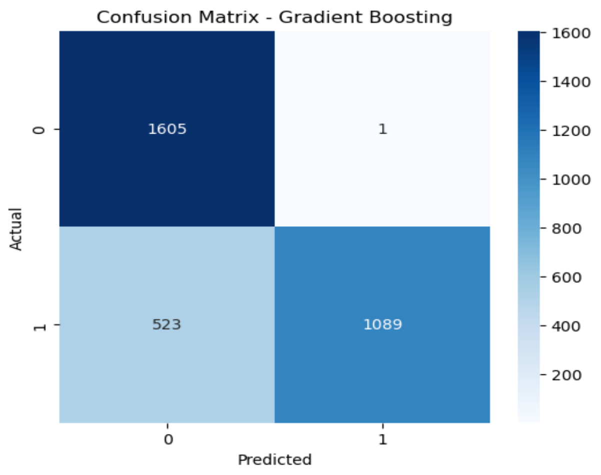

Fig 4: Heatmap for confusion matrix for Gradient Boosting

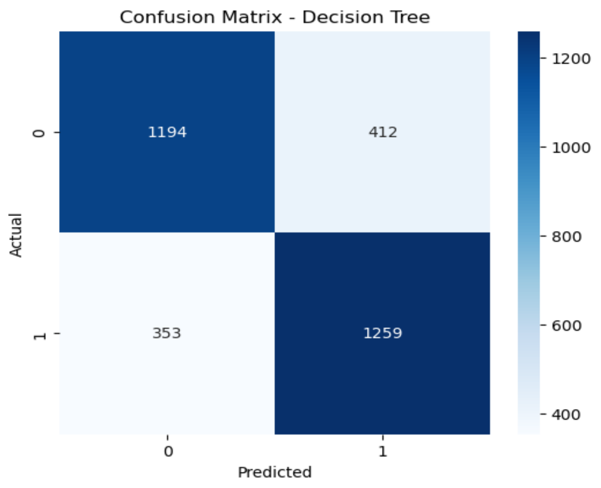

Fig 4: Heatmap for confusion matrix for Decision Tree

The confusion matrix for Random Forest depicts a low rate for False Positive cases (17) meaning the technique is well suited. There are a few False Negative cases (364) as well. True Negative rate is higher meaning the model is excellent at identifying negative cases. The model is very accurate and precise, meaning when it depicts that a student will drop out, its generally correct prediction. The confusion matrix for Gradient Boosting shows extremely high precision as there are hardly any False Positive cases (1). It has more False Negative cases (523) than Random Forest as the model misses more dropout cases hence it has lower accuracy in comparison to Random Forest. Decision Tree has balanced precision and recall but lower than Random Forest. It also depicts higher False Positive cases (412) suggesting that numerous non-dropout students were misclassified.

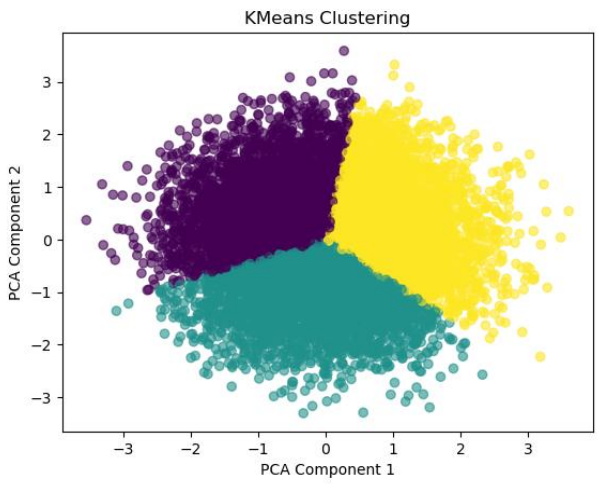

Fig 6: Clustering of groups by learning styles

The scatterplot above depicts the findings of K-Means Clustering using two Principal Components (PCA 1 and 2). The dataset has been clearly divided into three distinct learning styles which are demarcated by three different colors. The clusters appear to be well-defined, yet there is substantial overlapping between them. The Silhouette score is 0.51, meaning that they are well-defined and meaningful clusters. Due to the presence of high variance in the dataset, PCA was deployed to reduce dimensionality. The value of k (Number of clusters) was set to 3 for clustering analysis.

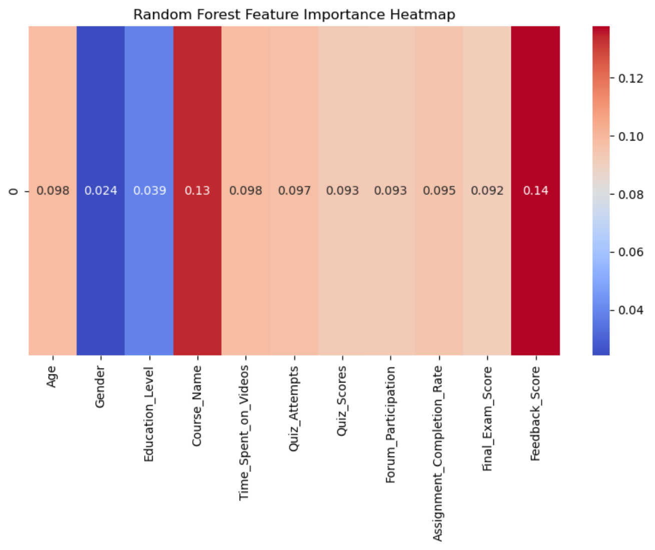

Fig 7. Heatmap for Feature Importance (Random Forest)

From the above heatmap for feature importance, it can be seen that Feedback_Score (0.14) and Course_Name (0.13) are the most important features. This shows that student feedback and the structure of the course have a significant influence on predictions (most likely student success or engagement). The higher values suggest that eliminating or misrepresenting these variables could have a major impact on the model's performance. Features such as Age (0.098), Time_Spent_on_Videos (0.098), Quiz_Attempts (0.097), Assignment_Completion_Rate (0.095) are of moderately significant. This implies that learning behaviors (engagement, assessments, and involvement) have an important role in influencing results. On the other hand, Education_Level (0.039) and Gender (0.024) have lowest significance. This implies that they have very little predictive potential in the model.

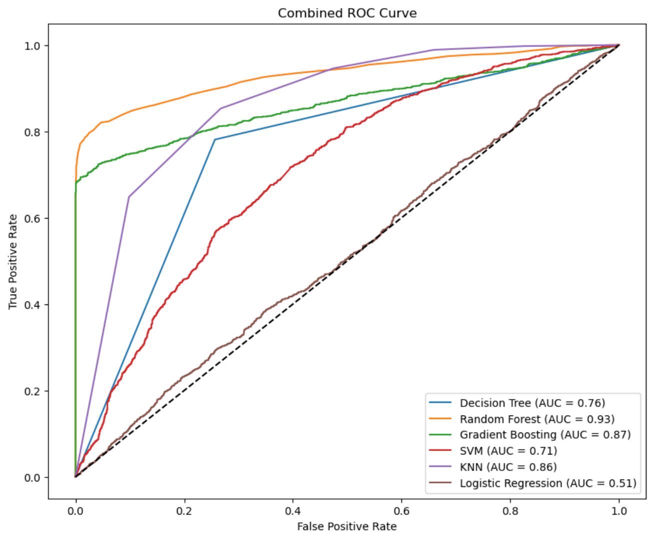

Fig 8: Combined ROC Curve

The Receiver Operating Characteristic (ROC) Curve above shows that the best performing models are Random Forest, Gradient Boosting and K-Nearest Neighbors with AUC (Area Under Curve) values 0.93, 0.87 and 0.86 respectively. Decision Tree (AUC = 0.76) and Support Vector Machine (SVM) (AUC = 0.71) follow closely. Logistic Regression (AUC = 0.51) is the worst performing model indicating very poor predictive power.

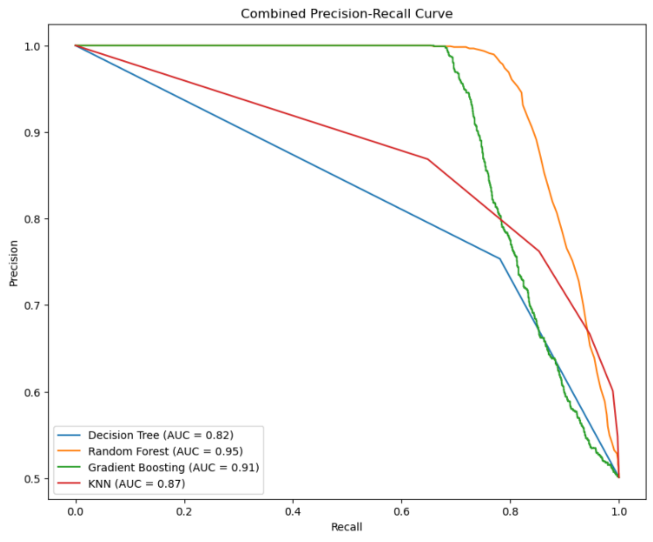

Fig 9: Combined Precision-Recall Curve

The Precision-Recall Curve above shows that Random Forest (AUC = 0.95) and Gradient Boosting (AUC = 0.91) are the most optimal models. Whereas KNN (AUC = 0.87) and Decision Tree (AUC = 0.82) are moderately performing models. Random Forest and Gradient Boosting provide the best balance between Precison and Recall. Logistic Regression and SVM are dropped from Precsion-Recall curve since they are the worst performing models.

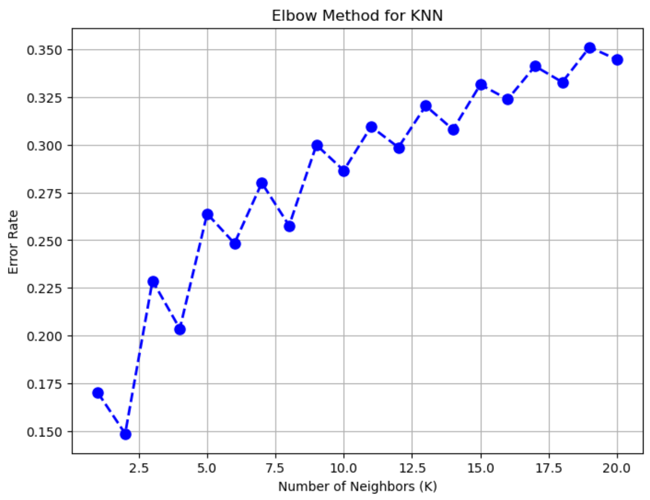

Fig 10: Elbow Method for KNN

The ideal value of K in KNN is determined using the Elbow Method. It detects the point at which increasing K no longer significantly reduces the inaccuracy. This is known as the "elbow point" because the curvature frequently makes an elbow-shaped bend. In the K-Nearest Neighbors (KNN) algorithm, the X-axis indicates the number of neighbors (K). The Y-axis depicts the error rate. The dashed blue line depicts how the error rate varies as K grows. The graph indicates that the error rate is lowest at K = 2. As K exceeds 5 or 6, the error rate rises, indicating poor performance. Normally, the elbow point is where the error stops reducing considerably, however here, the error rate continually grows beyond K = 2. In this scenario, K = 2 or 3 appears to be the best option given the lowest inaccuracy. Higher K values cause underfitting (excessive smoothing). Lower values of K (e.g., K=1) may result in overfitting (sensitivity to noise).

VII. Discussion and Conclusion:

The study found that machine learning can accurately estimate dropout likelihood, engagement level, and learning styles using educational data. The outcomes highlight crucial findings: Random Forest and Gradient Boosting outperform individual classifiers [34] because of their ability to reduce overfitting and capture complicated patterns. SMOTE considerably improved minority class predictions [35]. Prior to using SMOTE, dropout likelihood models had low recall. Oversampling of the minority class increased model balance, resulting in greater classification performance. Logistic Regression and SVM [36] performed well for Engagement Level Classification, distinguishing between low, medium, and high levels of engagement. K-Means Clustering identified significant student groupings [37]. The Silhouette Score of 0.51 suggests well-defined clusters for learning style segmentation, demonstrating the promise of unsupervised learning in personalized education.

1. Confusion Matrices:

Random Forest achieves the optimum blend of precision and recall. Gradient Boosting is overly conservative, resulting in nearly no false positives while missing many true dropouts. Decision Trees exhibit overfitting, with more false positives and less generalization.

2. Feature Importance Heatmap (Random Forest)

Course performance metrics (such as Feedback_Score, Course_Name, and Exam_Scores) have a significant impact, which is understandable given that they directly represent student involvement and outcomes. Demographic characteristics (such as Gender and Education_Level) are the least important, implying that the model does not rely substantially on them for decision making.

3. ROC Curve:

Ensemble models (Random Forest and Gradient Boosting) perform best, as expected, because they mix several trees for higher generalization. KNN works fairly well (AUC = 0.86), implying that the data may contain local clusters where nearest neighbors are informative. SVM and Decision Tree perform moderately, whereas Logistic Regression fails (AUC = 0.51), indicating that linear decision boundaries are ineffective for this dataset.

4. Precision-Recall Curve:

Random Forest and Gradient Boosting outdo others, demonstrating that ensemble models excel at managing precision-recall trade-offs. KNN does quite well, but Decision Tree struggles to maintain high precision as recall increases. A higher AUC-PR indicates that the model successfully detects positive cases without compromising too much precision.

This study effectively used a variety of machine learning techniques to predict dropout rates, engagement levels, and student learning styles. The findings indicate that ensemble models such as Random Forest and Gradient Boosting outperform individual classifiers. SMOTE effectively resolved class imbalance, resulting in higher memory ratings for minority classes. Furthermore, K-Means clustering provides useful insights into student learning styles, allowing for more individualized educational tactics.

VIII. Future Works:

Several areas can be investigated to expand this research:

1. Deep Learning Model Integration: Using Recurrent Neural Networks (RNNs) or Transformers to forecast dropouts and engagement. 2.
2. Time-Series Analysis: Analyzing student engagement patterns across time to detect early dropout signs.
3. Sentiment analysis is being used to extract insights from student comments and discussion forums via Natural Language Processing (NLP).
4. Adaptive Learning Systems: Use Reinforcement Learning (RL) to tailor learning sessions depending on projected engagement levels.
5. Real-time Predictive Analytics: Creating AI-powered dashboards that allow educators to dynamically track and respond to student performance.

By progressing in these areas, AI-powered educational systems will be able to create more tailored learning experiences, increasing retention rates and student performance.

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APPENDIX:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.cluster import KMeans
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report,
precision_recall_curve, roc_curve, auc, f1_score, silhouette_score,
mean_squared_error
from sklearn.multiclass import OneVsRestClassifier
import numpy as np

# Load the dataset
path = "personalized_learning_dataset.csv"
data = pd.read_csv(path)

# Drop unnecessary columns
data.drop(columns=['Student_ID'], inplace=True)

# Encode categorical features
label_maps = {}
categorical_features = ['Gender', 'Education_Level', 'Course_Name',
'Engagement_Level', 'Learning_Style', 'Dropout_Likelihood']
for feature in categorical_features:
    encoder = LabelEncoder()
    data[feature] = encoder.fit_transform(data[feature])
    label_maps[feature] = encoder

# Define inputs and targets
features = data.drop(columns=['Engagement_Level', 'Dropout_Likelihood',
'Learning_Style'])
target_dropout = data['Dropout_Likelihood']
target_engagement = data['Engagement_Level']
target_learning = data['Learning_Style']

# Feature scaling
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

# Balance classes using SMOTE
smote = SMOTE(random_state=42)
X_dropout, y_dropout = smote.fit_resample(features_scaled, target_dropout)
X_engagement, y_engagement = smote.fit_resample(features_scaled, target_engagement)
X_learning, y_learning = smote.fit_resample(features_scaled, target_learning)

# Train-test split
X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_dropout, y_dropout,
test_size=0.2, random_state=42)
X_train_e, X_test_e, y_train_e, y_test_e = train_test_split(X_engagement,
y_engagement, test_size=0.2, random_state=42)
X_train_l, X_test_l, y_train_l, y_test_l = train_test_split(X_learning, y_learning,
test_size=0.2, random_state=42)

# Models for dropout prediction
```

```python
dt_clf = DecisionTreeClassifier(random_state=42)
dt_clf.fit(X_train_d, y_train_d)
y_pred_dt = dt_clf.predict(X_test_d)

# SVM for engagement classification
svm_clf = OneVsRestClassifier(SVC(kernel='linear', probability=True,
random_state=42))
svm_clf.fit(X_train_e, y_train_e)
y_pred_svm = svm_clf.predict(X_test_e)
svm_scores = svm_clf.decision_function(X_test_e)

# KNN for learning style
knn_clf = KNeighborsClassifier(n_neighbors=5)
knn_clf.fit(X_train_l, y_train_l)
y_pred_knn = knn_clf.predict(X_test_l)

# Alternative dropout models
rf_clf = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf.fit(X_train_d, y_train_d)
y_pred_rf = rf_clf.predict(X_test_d)

gb_clf = GradientBoostingClassifier(n_estimators=100, random_state=42)
gb_clf.fit(X_train_d, y_train_d)
y_pred_gb = gb_clf.predict(X_test_d)

# Logistic Regression for engagement
lr_clf = LogisticRegression(max_iter=1000, random_state=42)
lr_clf.fit(X_train_e, y_train_e)
y_pred_lr = lr_clf.predict(X_test_e)

# PCA for visualization
pca = PCA(n_components=2)
pca_components = pca.fit_transform(features_scaled)

# KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
kmeans_labels = kmeans.fit_predict(features_scaled)
kmeans_sil = silhouette_score(features_scaled, kmeans_labels)
print("Silhouette Score for KMeans Clustering:", kmeans_sil)

# Model dictionary and evaluation
classifiers = {
    'Decision Tree': dt_clf,
    'Random Forest': rf_clf,
    'Gradient Boosting': gb_clf,
    'SVM': SVC(probability=True, random_state=42),
    'KNN': KNeighborsClassifier(),
    'Logistic Regression': LogisticRegression(max_iter=1000, random_state=42)
}

results = []
predicted_probs = {}
for model_name, clf in classifiers.items():
    clf.fit(X_train_d, y_train_d)
    preds = clf.predict(X_test_d)
    probs = clf.predict_proba(X_test_d)[:, 1]
    predicted_probs[model_name] = probs

    acc = accuracy_score(y_test_d, preds)
    prec = classification_report(y_test_d, preds, output_dict=True)['weighted
avg']['precision']
    rec = classification_report(y_test_d, preds, output_dict=True)['weighted
avg']['recall']
```

```python
    f1 = f1_score(y_test_d, preds, average='weighted')
    rmse_val = np.sqrt(mean_squared_error(y_test_d, preds))

    results.append([model_name, acc, prec, rec, f1, rmse_val])

    plt.figure(figsize=(6,5))
    sns.heatmap(confusion_matrix(y_test_d, preds), annot=True, fmt='d', cmap='Blues')
    plt.title(f'Confusion Matrix - {model_name}')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

# Show model comparison
results_df = pd.DataFrame(results, columns=['Model', 'Accuracy', 'Precision',
'Recall', 'F1 Score', 'RMSE'])
print(results_df)

# Plot ROC and Precision-Recall curves
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
for model_name, prob in predicted_probs.items():
    fpr, tpr, _ = roc_curve(y_test_d, prob)
    auc_score = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'{model_name} (AUC = {auc_score:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()

plt.subplot(1, 2, 2)
for model_name, prob in predicted_probs.items():
    precision, recall, _ = precision_recall_curve(y_test_d, prob)
    plt.plot(recall, precision, label=model_name)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend()

plt.show()

# Clustering visualization
pca = PCA(n_components=2)
pca_transformed = pca.fit_transform(features_scaled)
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(pca_transformed)
plt.scatter(pca_transformed[:, 0], pca_transformed[:, 1], c=kmeans.labels_,
cmap='viridis', alpha=0.6)
plt.title('KMeans Clustering')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.show()

# Feature importance from Random Forest
rf_importances = rf_clf.feature_importances_
sns.heatmap([rf_importances], cmap='coolwarm', annot=True,
xticklabels=features.columns, yticklabels=['Importance'])
plt.title('Random Forest Feature Importances')
plt.show()

# Elbow method for KNN
e_rate = []
```

```
for k in range(1, 21):
    knn_test = KNeighborsClassifier(n_neighbors=k)
    knn_test.fit(X_train_d, y_train_d)
    pred_k = knn_test.predict(X_test_d)
    e_rate.append(np.mean(pred_k != y_test_d))

plt.figure(figsize=(8, 6))
plt.plot(range(1, 21), e_rate, marker='o', linestyle='dashed', color='blue',
linewidth=2, markersize=8)
plt.title('Elbow Method for KNN')
plt.xlabel('Number of Neighbors')
plt.ylabel('Error Rate')
plt.grid(True)
plt.show()
```