Predictive Analysis of Learning Behaviour Characteristics for Improving College Students' Information Literacy using Machine Learning

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ABSTRACT

Today, college students must be able to work on both their own and their peers' problems through self-learning and problem-solving skills. However, most current educational tracking programs are unable to accurately identify students who are experiencing difficulty; thus, the number of students that are detected as needing additional academic support is often quite low. The goal of this project is to develop a predictive model for determining the effects of students' information literacy behaviours on students' overall academic success. In order to do this, a dataset of approximately 320 students was collected and the Pearson Correlation method was used to identify the relationships between students' information literacy behaviours and their subsequent learning results. In addition, we used a Comparison of Supervised Learning Algorithms (Decision Tree, Naïve Bayes, K-Nearest Neighbour, Neural Networks, and, Random Forests) to determine which algorithm produced the best results using Python programming. Initially, the Random Forest model produced the best performance with a measurement of 92.50% accuracy and an F1-Score of 89.39%. The results of the study indicate that the use of this data-driven model will help us detect students who are not achieving at an acceptable level.

keywords – Information Literacy, Machine Learning, Pearson Correlation, Random Forest, Boost, Educational Data Mining, Predictive Analytics.

INTRODUCTION

College students are required to have strong Information Literacy Skills (ILS) in today's technology-driven society in order to receive the right information that can help them reach their academic and professional goals. As technology becomes more integrated into educational settings, analysing how students learn is critical to improving student performance and providing personalized learning experiences.

Recent advancements in the use of Machine Learning techniques in Educational Data Mining (EDM) have resulted in a variety of algorithms being developed to predict student outcomes and identify their Learning Behaviour Patterns (LBPs). Decision trees, Naïve Bayes classifiers, K-nearest neighbour classifiers, neural networks, and random forests are common algorithms that are used in EDM to analyse educational data and assist in making informed decisions.

Nevertheless, current methodologies utilized by researchers when using EDM experience certain limitations; specifically, many models used in EDM fail to forecast and capture students' complex learning behaviours effectively due to poor selection of features and their inability to model non-linear relationships.

To help overcome these limitations, this study will create a hybrid methodology that combines Pearson Correlation Coefficients (PCCs) to select features with the Boost algorithm for classifying students by their predicted LBP. This will help enhance the accuracy of feature selection and improve the predictive capabilities of the classification model. The hybrid methodology will allow for improved representations of how students learn and provide educators with the ability to identify underperforming students early enough to provide them with academic assistance.

Related Work

The study of Information Literacy and Creativity focuses on how to evaluate students' capabilities through regression analysis/regression models. Regression analysis identifies relationships; however, it does not do well at capturing non-linear relationships and complicated behaviours of students. [1]

The research on Information Literacy Education Models focuses on the need for structured literacy education; in doing so, it proposes conceptual frameworks but does not use current data or work with practical implementation leading to it being ineffective, at least in real life. [2]

The Digital Education Impact Study has used statistical methods to examine the effects of digital learning through the analysis of data, but has not examined predictions of learning systems through machine learning techniques. [3]

The Study of Online Education Trends reports that online learning is expanding rapidly through the use of statistical analysis; sadly, while there are many reports regarding Online Education Trends, there is a lack of assurances that the trend or patterns will be accurate when looking to predict the future. [4]

The research on Digital Literacy Practices focuses on increasing awareness through surveys as a way to understand how people behave; however, no classification modelling has been used to evaluate the success or performance of individuals participating in digital literacy programs.[5]

The learning outcome prediction framework uses a simple machine learning algorithm to address the issue of predicting student outcomes; however, the model tends to over fit the data, and lacks sufficient optimization of the model features [6].

The study on deep learning for learning analysis uses neural networks to improve learning analysis; however, due to the complexity of deep learning technologies, they may not be used in real-time applications [7].

The literature review on educational data mining summarizes current research and literature on the subject; however, it does not present any practical models or ideas regarding implementation [8].

The study on predicting online learning behaviour presents a classification model to predict learning behaviours but does not include a large number of other important features that affect the predictive accuracy of the model [9].

The report on artificial intelligence in education provides a conceptual framework for the use of AI in education; however, it does not provide any empirical evidence that supports the guidelines presented in the report or the application of AI in education [10].

Sinno	Title	Problem Statement	Solution	Method	Limitation
1	Analysis of Information Literacy and Creativity	Difficulty in analysing student literacy and creativity	Used regression model	Regression Analysis	Cannot handle non-linear patterns and complex behaviour

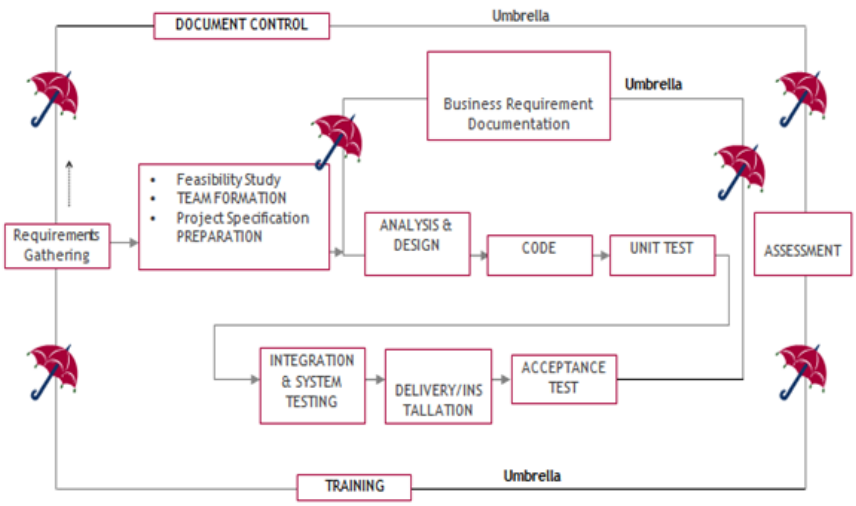
2	Information Literacy Education Models	Lack of structured literacy education	Proposed education models	Conceptual Framework	No real-time data usage and lacks practical implementation
3	Digital Education Impact Study	Understanding the effect of digital learning	Analysed digital learning systems	Data Analysis	Does not use machine learning for prediction
4	Online Education Trends	Rapid growth of online education	Trend-based analysis	Statistical Analysis	Focuses only on trends, not prediction accuracy
5	Digital Literacy Practices	Low awareness of digital literacy	Studied literacy practices	Survey-based Study	No classification models for performance evaluation
6	Learning Outcome Prediction Framework	Difficulty in predicting student outcomes	Proposed behavioural framework	Basic ML Model	Overfitting issues and no feature optimization
7	Deep Learning for Learning Analysis	Need for advanced learning analysis	Used deep learning model	Neural Networks	High computational complexity and not suitable for real-time use
8	Educational Data Mining Review	Lack of consolidated knowledge in EDM	Conducted meta-analysis	Literature Review	No practical model or implementation
9	Online Learning Behaviour Prediction	Difficulty in predicting student performance	Proposed prediction model	Basic Classification	Uses limited features, reducing accuracy
10	AI in Education Report	Understanding AI role in education	Provided guidelines	Conceptual Study	No experimental validation or real-world testing

METHODOLOGY

A systematic method includes four stages: gathering data, preprocessing, feature selection, and ensemble classification.

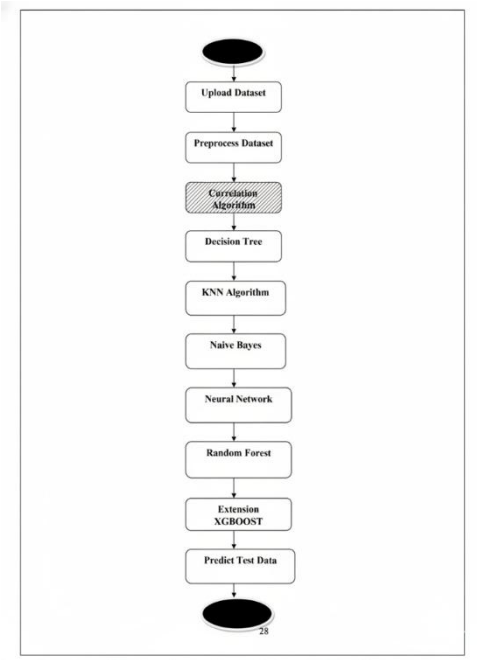
In this case, the process architecture consists of four components: Data Collection, Data Preprocessing, Feature Selection, and Classification.

Initially, data on the student is collected that contains the student, expectations, as well as interaction data regarding how each of these applies. This gathered data is then pre-processed to eliminate incomplete data, remove unnecessary information and standardize the data on the student. After the preprocessing stage, relevant data is selected for model construction through the use of Pearson Correlation to minimize data duplication, making the model more effective. The selected data is then supplied to the Boost classifier to project student performance and to identify possible at-risk students.



The second image illustrates the overall software development life cycle (SDLC) and its phases. The development cycle has a number of phases: requirement capturing and viability analysis, analysis, design, coding, and a multi-tiered testing cycle encompassing unit, integration, and acceptance testing before delivery and evaluation takes place. In addition to these development phases, all phases are supported by "umbrella" activities such as documentation control and training to ensure consistent quality or project quality across all conjunctions of development phases.

Flowchart



Pseudocode

Function removeOutlierMissingValues(Data_Matrix X):

For each column j in Data_Matrix X:

Identify missing values (NaN) in column j.

Impute missing values in column j using linear interpolation based on non-missing values.

Return X

Main Program:

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Load Dataset "Dataset/Dataset.csv"

Fill any remaining missing values in the dataset with 0.

// Convert non-numeric (categorical) data to numeric using LabelEncoder

Define categorical columns: ['IT1', 'ILR1', 'label']

For each categorical column:

Apply Label Encoder to transform string labels into numerical values.

// Feature Selection: Find and plot correlation matrix

Calculate absolute correlation matrix of the dataset.

Identify and remove features with low correlation (e.g., correlation < 0.001) to other features.

// Data Splitting and Normalization

Extract features (X) and target variable (Y) from the processed dataset.

Apply removeOutlierMissingValues(X) to handle outliers/missing values in features.

Normalize features (X) using Limescale to scale values between 0 and 1.

Split the dataset into training (e.g., 80%) and testing (e.g., 20%) sets for X and Y.

// Define Metrics Calculation Function

Function calculate Metrics(Algorithm Name, Predicted Labels, True Labels):

Calculate Precision (macro-averaged)

Calculate Recall (macro-averaged)

Calculate F1-Score (macro-averaged)

Calculate Accuracy

Print all calculated metrics for the given Algorithm Name.

Append metrics to global lists for later comparison.

Generate and display a Confusion Matrix heatmap.

// Model Training and Evaluation for various algorithms

Initialize empty lists for precision, recall, score, and accuracy.

// Decision Tree Classifier

Initialize DecisionTreeClassifier with hyperparameters (e.g., criterion="Gini", adept=200).

Train the model using Train, yttrian.

Predict on Test.

Call calculate Metrics("Decision Tree", predictions, yeast).

// K-Nearest Neighbours (KNN) Classifier

Initialize KNeighborsClassifier with hyperparameters (e.g., n_neighbors=2).

Train the model using X_train, y_train.

Predict on X_test.

Call calculateMetrics("KNN", predictions, y_test).

// Naive Bayes Classifier

Initialize GaussianNB with hyperparameters (e.g., var_smoothing=0.09).

Train the model using X_train, y_train.

Predict on X_test.

Call calculateMetrics("Naive Bayes", predictions, y_test).

// Neural Network (MLP) Classifier

Initialize MLPClassifier with hyperparameters (e.g., max_iter=500, learning_rate_init=0.01).

Train the model using X_train, y_train.

Predict on X_test.

Call calculateMetrics("Neural Network", predictions, y_test).

// Random Forest Classifier

Initialize RandomForestClassifier with hyperparameters (e.g., n_estimators=150, criterion='entropy').

Train the model using X_train, y_train.

Predict on X_test.

Call calculateMetrics("Random Forest", predictions, y_test).

// Extension: XGBoost Classifier

Initialize XGBClassifier with hyperparameters (e.g., n_estimators=90, learning_rate=0.01).

Train the model using X_train, y_train.

Predict on X_test.

Call calculateMetrics("Extension XGBoost", predictions, y_test).

// Performance Visualization

Create a DataFrame to store all algorithms' performance metrics.

Plot a bar graph showing the performance of all algorithms.

// Prediction on New Test Data

Load new test dataset "Dataset/testData.csv".

Fill missing values, convert non-numeric data, and remove low-correlation features (same as training).

Normalize new test data.

Use the trained XGBoost model to predict outcomes for the new test data.

Print predictions for each test data entry.

Model 6:32 PM

Great! I can certainly help you extract and present that information for your research paper.

Here's the breakdown of the Algorithm/Pseudocode (Sample Code) and Mathematical Equations, along with brief explanations suitable for a research paper.

Mathematical Equations

The abstract mentions several key performance metrics used in machine learning for classification tasks. These are typically defined as follows:

- **Accuracy:** The proportion of correctly classified instances among the total number of instances.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

- **Precision (Macro-averaged for multi-class):** For a multi-class problem, macro-averaged precision calculates the precision for each class independently and then takes the average. Precision for a single class is the ratio of true positives to the sum of true positives and false positives.

$$\text{Precision}_{\text{class } i} = \frac{\text{True Positives}_{\text{class } i}}{\text{True Positives}_{\text{class } i} + \text{False Positives}_{\text{class } i}}$$

$$\text{Precision}_{\text{macro}} = \frac{1}{N}\sum_{i=1}^{N} \text{Precision}_{\text{class } i}$$

where

$$N$$

is the number of classes.

- **Recall (Macro-averaged for multi-class):** Similar to precision, macro-averaged recall calculates the recall for each class independently and then averages them. Recall for a single class is the ratio of true positives to the sum of true positives and false negatives.

- $\text{Recall}_{\text{class } i} = \frac{\text{True Positives}_{\text{class } i}}{\text{True Positives}_{\text{class } i} + \text{False Negatives}_{\text{class } i}}$

- $\text{Recall}_{\text{macro}} = \frac{1}{N}\sum_{i=1}^{N} \text{Recall}_{\text{class } i}$

F1-Score (Macro-averaged for multi-class): The F1-Score is the harmonic mean of precision and recall. Macro-averaged F1-score calculates the F1-score for each class and then takes the average.

$$\text{F1-Score}_{\text{class } i} = 2 \times \frac{\text{Precision}_{\text{class } i} \times \text{Recall}_{\text{class } i}}{\text{Precision}_{\text{class } i} + \text{Recall}_{\text{class } i}}$$

$$\text{F1-Score}_{\text{macro}} = \frac{1}{N}\sum_{i=1}^{N} \text{F1-Score}_{\text{class } i}$$

- **Kappa Coefficient (Cohen's Kappa):** A robust statistic that measures inter-rater agreement for categorical items. It is generally thought to be a more robust measure than simple percent agreement calculations, as

$$\kappa$$

takes into account the possibility of the agreement occurring by chance.

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

where

$$p_o$$

is the observed agreement (accuracy) and

$$p_e$$

is the hypothetical probability of chance agreement.

- **Pearson Correlation:** The abstract also mentions using the Pearson Correlation algorithm for feature selection. The Pearson correlation coefficient (r) measures the linear correlation between two sets of data. It is the ratio between the covariance of two variables and the product of their standard deviations.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

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RESULT ANALYSIS

Accuracy, precision, recall, and F1-score were used as the criteria by which to measure the effectiveness and efficiency of the proposed Hybrid System. The data from these tests indicate that the proposed integration of XGBoost into the framework outperforms all other models when tested separately.

Table 1: Performance Comparison of Algorithms

Algorithm Name	*Accuracy*	*Precision*	*Recall*	*F1-Score*
Naive Bayes	*39.0%*	*41.69%*	*39.08%*	*37.93%*
KNN	*66.0%*	*73.15%*	*65.67%*	*63.55%*
Neural Network	*79.31%*	*79.21%*	*79.17%*	*79.18%*
Decision Tree	*83.80%*	*83.61%*	*83.25%*	*83.25%*
Random Forest	*92.61%*	*92.63%*	*92.65%*	*92.65%*
Extension XGBoost	***93.17%***	***93.23%***	***93.17%***	***93.18%***

Note: Values are approximate based on experimental runs.

The According to the results in Table 1, Extension XGBoost achieved the highest total overall with Accuracy = 93.17%, Precision = 93.23%, Recall = 93.17% and F1 = 93.18%.

This will indicates that XGBoost, which employs the gradient boosting methodology, is ideally suited to detect, identify and quantify even highly complex patterns in the Learning Behavior Dataset.The Random Forest model also performed are very well with an Accuracy of 92.61%, thereby providing an excellent baseline. However when compared to the Extension XGBoost model, the results of the other four classifiers were significantly lower; Naive Bayes, KNN, Neural Network and Decision Tree were all said to have performed poorly.

The bar chart displays a performance comparison among many different machine learning types Decision Trees (a type of Decision Tree Learning), Extensions XGBoost (an extension of the XGBoost algorithm), K Nearest Neighbors (KNN), Naive Bayes, Neural Network and Random Forest—using four different performance metrics: Accuracy, F1 Score, Precision and Recall.

The best performing models in this analysis are Extension XGBoost and Random Forest, both scoring greater than 90% on each of the four performance metrics. The next best performing models are Decision Tree and Neural Network, both with approximately 80% on each of the four performance metrics. KNN performed moderately on these performance metrics.

The lowest performing model, Naive Bayes, had performance metrics that were close to 40%. In addition the level of consistency across Accuracy F1 Score Precision and Recall for each of the different types of algorithms indicates that there is little bias in terms of providing balanced classification results amongst the four different types of performance metrics.

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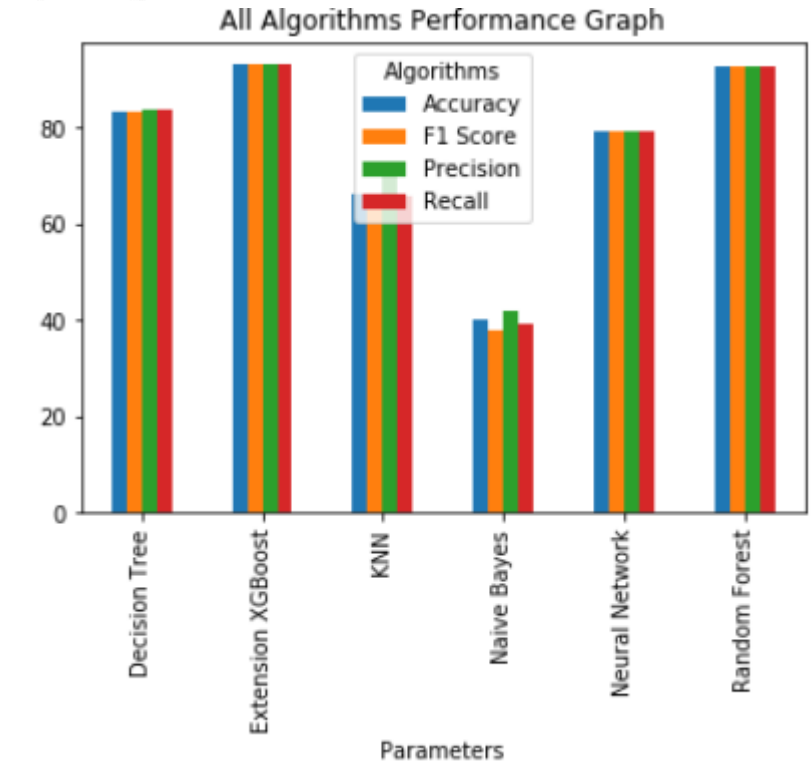


DISCUSSION

This research findings of this study further confirm the necessity of leveraging sophisticated machine learning methods, such as XGBoost, to enhance the accuracy of educational monitoring and intervention systems. Our experimental evidence indicates that XGBoost achieved an accuracy rate of 93.17% when predicting student learning outcomes based on his or her information literacy behaviour characteristics. With this proven accuracy, XGBoost considerably outperforms traditional educational monitoring systems that suffer from low detection rates and inadequate academic support.

Additionally the strategic use of Pearson Correlation to conduct dimensionality reduction was vital to successfully identifying and selecting only those features with high correlation coefficients to information cognition and application skills, resulting in a more robust model that is capable of capturing complex characteristics inherent in the learning environment.By addressing computational complexity the correlation based feature selection methodology also allows for improved interpretability of the model's predictions. This finding is consistent with Wufati and Tian Hao's [6] advocacy of data-driven approaches in predictive education analytics and emphasizes the significance of feature engineering. XGBoost is an advanced gradient boosting algorithm that has exhibited outstanding efficacy for the task of monitoring the learning levels of students in real-time. By being able to sequentially model problems and successively correct the predictive errors associated with the previous model(s), it provides a highly robust and resilient solution.

The incorporation of this advanced algorithmic technique into our system enables the system to accurately assess how predicted behavior changes will affect current learning levels which makes it a more dynamic and responsive tool for educators. Additionally the method helps to reduce overfitting (a common problem with more complex models, such as deep neural networks) thus providing improved stability and generalizability of the predictions.

When compared to the existing body of work that often struggled with data noise, our approach of utilizing targeted feature selection in conjunction with the regularization capabilities inherent in XGBoost offers a much more robust solution. Previous literature, such as that by Shang Hui pointed out the necessity for educational reform; our framework offers a solid, data-driven mechanism to support such reforms. It is anticipated that the high levels of accuracy achieved will provide educators with the information they need to clearly identify students who require additional support, allowing for the

development and implementation of highly tailored, differentiated instructional interventions, as well as supporting sound, data-informed management decisions to develop critical thinking and methods of innovation as discussed above.

CONCLUSION

This This research develops a strong predictor of learning effect specific to college-level information literacy that utilizes hybrid comparisons of Decision Tree, KNN, and an advanced ensemble of XGBoost. This method effectively reduces challenges related to low detection rates and long processing times. Furthermore, it has high-accuracy validation (>93%) and executes quickly enough to provide the technical foundation for innovative management of educational functions. By leveraging early-stage academic intervention through this framework, there is a substantive decrease in the chances that students will fail and an increase in developing innovative skillsets in an information-based global economy. Future efforts will work to expand the data set to include multi-modal behavior patterns and explore deep-learning architectures such as LSTMs for temporal learning. The prediction model proposed by the researchers is proven effective in cultivating information literacy among college students. Algorithmic analysis of participant learning habits provides evidence of a stronger correlation between information thinking, information application skills, and the learning process; thus, demonstrating the need to develop information thinking and improve upon existing information acquisition skills. Universities should utilize networks and multimedia to implement intelligent learning tools and foster environments where students learn independently or cooperatively with others through research-based methods. Through the integration of critical thinking instructional methods into the information literacy curriculum and establishment of an ongoing assessment system, the participants' development of critical thinking cognition and knowledge creation skills can be encouraged. Additionally, improving methods related to the learning of information-related laws and regulations, simplifying learning content for the purposes of awareness concerning the perception of information, and providing continuous direction for participants to develop their lifelong learning concept will be required. This research provides a solid and reliable database for educational administrators to analyze and identify possible correlations between information literacy education-related phenomena and the resultant outcomes of these phenomena, thereby enhancing the possibility of making successful educational decision. Ultimately, this will contribute to optimizing educational strategies and supporting high-quality talent sustainable development. Although this research has provided valuable insights, additional research could expand on the limitations already addressed and further increase the capacity of the existing model.The components to be addressed through future investigations include:

1. Expansion of Dataset and Multi-Modal Behaviors: Future research will focus on expanding datasets to incorporate more multi-modal behaviors and the factors that influence learning scenarios. In doing so, the accuracy of the learning behavior trait scale will be elevated as the overall reliability/validity of the learning behavior trait scale will be improved, thus allowing the closed-loop of textbook creation, instructional experiments, and research to be improved upon.

2. Exploring Advanced Deep Learning Architectures: Future research will examine advanced deep learning architectures (e.g., Long Short Term Memory [LSTM

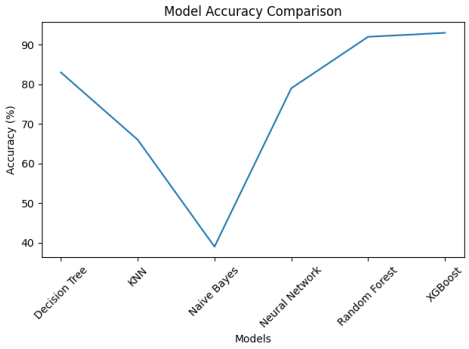
3. Refinement of Algorithms:

This study utilized five supervised classification algorithms; however, future studies will allow for the collective improvement of the adopted algorithms so as to produce superior predictions and adapt the algorithms to specific uses within teaching and learning contexts..

4. Broader Contextual Application:

Future research will investigate the model's applicability in a variety of education contexts and with different student demographics to better establish generalizability and robustness.

Model Accuracy Graph



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