European Journal of Clinical Pharmacy
Print ISSN: 2385-409X **Online ISSN**: 3105-0409
Website: https://farmclin.com/

Original Research Article

Improving Student Performance through Class Presentations and Part-Time Coaching using Machine Learning

Article History:

Name of Author:
Ghulam Murtaza*[1] and Dr. Amiya Bhaumik[1]

Affiliation: *[1]Department of Psychology, Lincoln University College Malaysia*

Corresponding Author:
Ghulam Murtaza

Received: 01-10-2025
Revised: 10-10-2025
Accepted: 20-11-2025
Published: 28-12-2025

Abstract: This study explores the application of machine learning techniques to enhance student success in class presentations and part-time coaching. As the educational landscape evolves, personalized learning strategies have become essential for addressing individual student needs. By analyzing various factors such as preparation time, presentation quality, coaching feedback, and engagement, this research investigates how machine learning can predict student outcomes and optimize teaching methods. The study employs a range of machine learning algorithms, including Decision Trees, Random Forests, and Support Vector Machines, to analyze the impact of these factors on student performance. Evaluation metrics such as accuracy, precision, recall, and F1 score are used to assess the models' predictive power. The findings suggest that machine learning can significantly improve the personalization of teaching strategies, enabling educators and part-time coaches to intervene proactively and offer tailored support. Furthermore, by identifying patterns in student behavior and performance, machine learning models provide insights into effective coaching techniques and presentation strategies. The research contributes to the growing body of knowledge on personalized learning and demonstrates the practical applications of machine learning in educational settings, providing valuable recommendations for enhancing student performance in both class presentations and part-time coaching sessions.

Keywords: Class presentations, Part-time coaching, Student learning outcomes, Personalized instruction, Communication and critical thinking skills.

INTRODUCTION

Background:

Class presentations and part-time coaching have become integral aspects of modern education, particularly at the collegiate level. Class presentations serve as a key method for students to showcase their understanding of subject material while also improving their public speaking, communication, and critical thinking skills. These activities not only promote active learning but also help students engage with the material in a deeper, more meaningful way. As students present their ideas and solutions, they receive immediate feedback, which helps them refine their knowledge and presentation skills. In many ways, presentations have become an essential tool for measuring a student's ability to synthesize information and communicate it effectively to an audience.

Part-time coaching, on the other hand, has emerged as an important supplemental teaching method. As students face increasing academic demands, many seek additional support through part-time coaching to reinforce classroom lessons, address knowledge gaps, and receive personalized guidance. Part-time coaches often have the flexibility to work with students one-on-one or in small groups, providing tailored instruction that adapts to individual learning styles. This type of coaching helps students stay on track academically, offering them additional resources, strategies, and explanations that are not always possible in traditional classroom settings.

The integration of machine learning into these educational practices can enhance both class presentations and part-time coaching. Machine learning algorithms can analyze student data, such as performance in presentations and study habits in coaching sessions, to uncover patterns and trends. For instance, ML models can predict a student's potential success in a presentation based on past performance, recommend specific improvements in their presentation style, or even suggest personalized coaching strategies. By collecting and analyzing data on factors like time spent studying, engagement during sessions, and presentation feedback, machine learning can provide real-time insights that allow educators and coaches to offer more personalized, effective guidance. In doing so, it transforms both class presentations and part-time coaching from traditional methods into adaptive, data-driven learning experiences that support students' individual needs and help them excel academically.

Problem Statement:

While class presentations and part-time coaching are widely used to enhance students' learning experiences, there is a lack of data-driven methods to effectively assess and optimize their impact. Class presentations primarily focus on evaluating students' communication and understanding of course material, but they do not offer personalized feedback or adaptive learning strategies. Similarly, part-time coaching, though beneficial for reinforcing classroom learning, often lacks structured approaches and tailored interventions. Educators and coaches typically rely on subjective judgments to measure student progress, which may not accurately reflect individual learning needs. With the increasing volume of student data available, machine learning presents an opportunity to bridge this gap by offering predictive models and personalized recommendations. By analyzing patterns in student performance, engagement, and study behaviors, machine learning can provide valuable insights into how class presentations and part-time coaching can be optimized for better learning outcomes (Gollapalli et al., 2023). This research aims to explore the use of machine learning to predict academic success, recommend targeted strategies for both presentations and coaching, and enable educators and coaches to adapt their methods to meet students' specific needs, ultimately enhancing their academic performance.

Objectives of the Study:

This study aims to utilize machine learning to enhance class presentations and part-time coaching by analyzing student performance and engagement. The key objectives of the study are:

- To explore how machine learning can enhance class presentations by analyzing student performance and providing personalized feedback.
- To assess the effectiveness of machine learning in part-time coaching by tracking student progress and recommending tailored strategies.
- To develop machine learning models that predict student success in class presentations and part-time coaching based on factors such as study habits and engagement.
- To compare different machine learning algorithms to determine which model offers the most accurate predictions of student performance.
- To provide actionable, data-driven recommendations for educators and coaches to improve their teaching methods and enhance student outcomes.

Research Questions:

This study seeks to answer key questions regarding the application of machine learning in class presentations and part-time coaching. The research questions are as follows:

1. How can machine learning improve the effectiveness of class presentations by providing personalized feedback and identifying areas for improvement?
2. How can machine learning track and enhance student engagement during part-time coaching sessions to influence academic success?
3. Which machine learning models provide the most accurate predictions of student performance in class presentations and part-time coaching?
4. How can machine learning be used in part-time coaching to recommend the most effective study strategies for individual students?
5. How can machine learning identify at-risk students early based on their performance and engagement in class presentations and part-time coaching sessions?

Motivation and Scope of the Study:

The motivation for this study stems from the growing need to enhance the educational experience for students, particularly in the areas of class presentations and part-time coaching. As educational environments evolve, the traditional methods of assessment and teaching are proving to be limited in addressing the diverse needs of students. While class presentations provide a platform for students to showcase their knowledge, and part-time coaching helps reinforce learning, these methods often lack a structured approach that can address individual learning styles and provide real-time feedback. The integration of machine learning offers an innovative solution, enabling personalized, data-driven insights that can significantly improve both teaching and learning outcomes. By analyzing student data, machine learning can identify patterns in behavior, predict performance, and provide actionable recommendations to enhance the educational process.

The scope of this study focuses specifically on how machine learning can be applied to optimize class presentations and part-time coaching. It will explore how machine learning algorithms can predict student performance, suggest improvements, and recommend effective coaching strategies based on individual needs. The research will not only analyze how student performance can be enhanced through data-driven insights but will also examine how machine learning can provide early identification of students at risk of underperforming (Butt et al., 2025). By narrowing the focus to class presentations and part-time coaching, this study aims to provide a clear framework for incorporating machine learning in these key areas of education. The findings from this research will offer practical solutions for educators and coaches to improve student success and foster a more personalized learning environment.

Structure of the Paper:

This paper is organized into several key sections to provide a comprehensive understanding of the study. The **Introduction** outlines the background, problem statement, objectives, and research questions that guide the study. The **Literature Review** discusses relevant research on machine learning applications in education, particularly in enhancing class presentations and part-time coaching, and explores existing challenges in these areas. In the **Research Methodology**, the study details the data collection process, the machine learning models used, and the evaluation methods applied to assess the effectiveness of the models. The **Results and Discussion** section presents the findings of the study, compares the performance of different models, and analyzes the implications for educators and coaches. Finally, the **Conclusion** summarizes the key findings, offers recommendations for future research, and discusses the practical contributions of the study for improving class presentations and part-time coaching.

LITERATURE REVIEW

Overview of Class Presentations and Part-Time Coaching Using Machine Learning:

Class presentations and part-time coaching play vital roles in enhancing student learning experiences. Class presentations provide students with the opportunity to articulate their understanding of course material in a public setting, improving their communication, critical thinking, and organization skills. These presentations also allow instructors to gauge students' depth of understanding and their ability to express ideas clearly. Part-time coaching complements this by offering students personalized focused support outside of regular class hours. Through one-on-one or small group sessions, part-time coaches can address individual learning gaps, provide additional explanations, and help students apply concepts more effectively. Both methods are important for developing a student's academic skills but often lack a systematic approach to measure and enhance their effectiveness.

Machine learning has the potential to revolutionize both class presentations and part-time coaching by providing data-driven insights into student performance and engagement. In the context of class presentations, machine learning can analyze various data points, such as preparation time, presentation delivery, and audience feedback, to identify which factors contribute to a successful presentation (Basheer & Aslam, 2025). By detecting patterns in the data, machine learning models can predict which presentation techniques or strategies are likely to lead to better outcomes. This allows educators to offer targeted feedback and adjustments to improve student presentations in real time, making the process more dynamic and personalized.

Similarly, machine learning can be applied to part-time coaching to track and optimize the learning process. By collecting data on student progress, engagement, and coaching session interactions, machine learning models can highlight areas where students need additional support or where specific coaching strategies have been most effective (Chen, 2025). This enables coaches to personalize their teaching approaches, providing more tailored instruction and interventions. Ultimately, the use of machine learning in both class presentations and part-time coaching offers a more refined, data-driven approach to teaching, enhancing student outcomes through personalized and actionable insights.

Key Factors Affecting Class Presentations and Part-Time Coaching:

The success of class presentations and part-time coaching is influenced by multiple factors that impact how students engage and perform. These factors are essential to understanding how both methods can be optimized for better learning outcomes. The key factors include:

- **Preparation Time and Content Quality**: The quality of a class presentation depends on the amount of time students dedicate to preparation. Well-researched content, well-organized ideas and clear, concise communication enhance the presentation. The more effort students put into preparing their content, the more likely they are to deliver a successful presentation.
- **Presentation Style**: A student's presentation style, including body language, tone of voice, and use of visual aids, plays a significant role in engaging the audience. Clear articulation, confident delivery, and effective use of supporting materials can make the presentation more impactful and help

students communicate their ideas more effectively.

- **Feedback and Reflection**: Constructive feedback from peers and instructors helps students identify areas for improvement and refine their presentation skills. Reflecting on feedback allows students to adjust their approach for future presentations, ensuring continuous improvement and a more polished delivery with each attempt.
- **Coaching Frequency and Consistency**: The consistency and regularity of part-time coaching sessions greatly influence how effectively students can reinforce their learning. Frequent coaching allows students to address gaps in their understanding, receive continuous feedback, and practice new skills, which ultimately improves their academic performance and understanding of the material.
- **Engagement and Commitment**: Active engagement and commitment from students during part-time coaching sessions are essential. Students who are proactive in applying what they learn, ask questions, and follow through on recommendations tend to make more progress. Their active participation ensures that the coaching sessions lead to meaningful improvements in their learning outcomes.

Importance of Class Presentations in Academic Learning:

Class presentations are an essential part of the learning process as they allow students to actively engage with the material and demonstrate their understanding. Presentations require students to synthesize information, organize their thoughts, and communicate complex ideas in a clear and concise manner. This process not only deepens their understanding of the subject matter but also enhances their critical thinking and problem-solving skills. By articulating their thoughts verbally, students gain a deeper insight into the material, improving their ability to retain and apply the knowledge in future academic tasks.

Figure 0.1: Importance of Class Presentations in Academic Learning

In addition to improving comprehension, class presentations offer students valuable opportunities to develop essential life skills such as public speaking and effective communication. Delivering a presentation in front of an audience, whether peers or instructors, helps students build confidence and overcome public speaking anxiety. The act of presenting allows students to practice articulating ideas, adjusting to audience reactions, and responding to questions, all of which are essential in both academic and professional settings. These communication skills are crucial for success in many fields, making class presentations a key element of academic learning.

Moreover, class presentations provide an opportunity for immediate feedback from instructors and classmates, which plays a significant role in student development. Feedback helps students recognize their strengths and areas for improvement, allowing them to refine their presentation skills over time. This process of self-assessment and continuous improvement is essential for personal and academic growth (Stasolla et al., 2025). The introduction of machine learning in analyzing class presentations can further enhance this process by providing data-driven insights into student performance, such as predicting successful presentation strategies or identifying areas of weakness. By using machine learning, students can receive more personalized and targeted feedback to improve their presentation skills over time.

Role of Machine Learning in Education:

Machine learning (ML) has the potential to transform educational practices, particularly in areas such as class presentations and part-time coaching. By leveraging vast amounts of student data, ML can identify patterns, predict outcomes, and offer personalized learning experiences. In the context of class presentations, machine learning can be used to analyze student performance, feedback, and engagement, identifying key factors that contribute to successful presentations. For example, machine learning models could predict which presentation techniques or preparation strategies are most effective, offering students tailored advice to improve their delivery and content organization. This data-driven approach ensures that feedback is both specific and actionable, ultimately enhancing students' public speaking and communication skills.

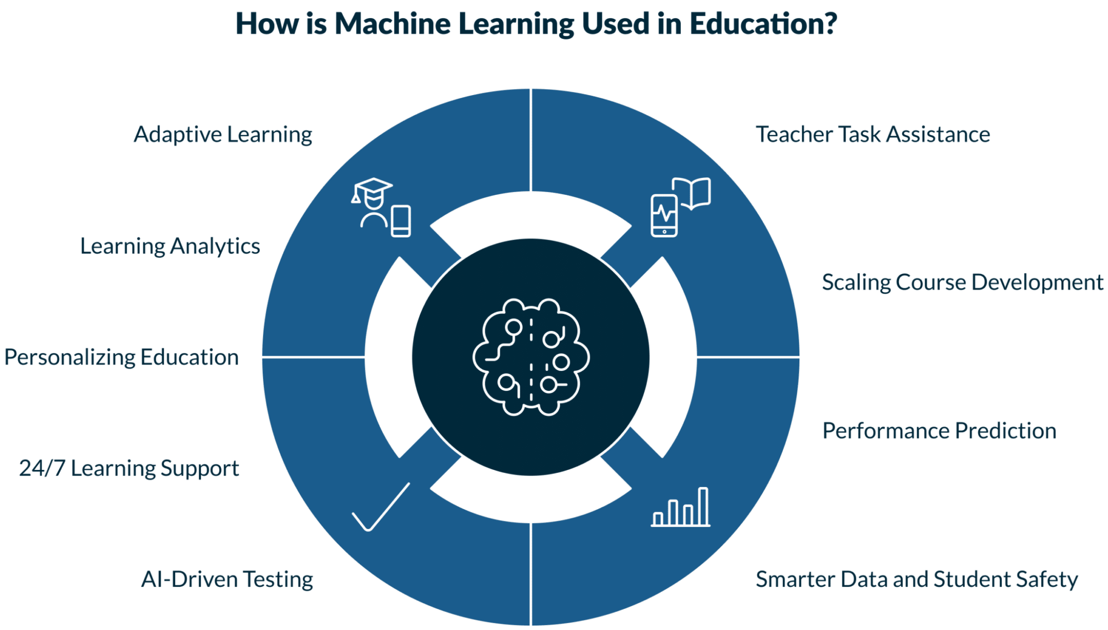


Figure 0.2: Role of Machine Learning in Education

In part-time coaching, machine learning can be utilized to track a student's progress over time, pinpointing areas where additional support is needed. By analyzing data from past coaching sessions, study habits, and engagement levels, machine learning can recommend personalized coaching strategies and even predict when a student may be at risk of falling behind. These predictive insights enable coaches to intervene early, offering support before issues become more significant, and adapting their approach to suit the individual needs of each student (Onker et al., 2025). This helps create a more dynamic and responsive coaching environment that promotes continuous improvement.

Moreover, machine learning can improve educational outcomes by facilitating data-driven decision-making for educators. By analyzing various factors—such as class presentation performance, engagement metrics, study habits, and coaching effectiveness—machine learning can provide educators with real-time insights on how to adjust their teaching methods to best support students. This adaptive approach ensures that class presentations and part-time coaching are not one-size-fits-all, but rather personalized, dynamic, and optimized learning experiences that maximize student success.

Machine Learning Models for Class Presentation and Part-Time Coaching:

Machine learning offers various models that can significantly enhance the effectiveness of class presentations and part-time coaching by providing insights into student performance and predicting outcomes. For class presentations, models like **Decision Trees** and **Random Forests** are particularly effective. These models analyze factors such as presentation preparation, content quality, delivery style, and audience engagement. By examining these variables, machine learning algorithms can identify key features that predict the success of a presentation. For example, the use of visual aids or the time spent rehearsing may correlate with higher audience engagement and clearer communication. Educators can leverage these insights to offer more specific and personalized feedback, helping students refine their presentation skills.

In the context of part-time coaching, **Support Vector Machines (SVM)** and **K-Nearest Neighbors (KNN)** are useful for classifying students based on their engagement, study habits, and coaching participation. SVM can categorize students into different performance levels, identifying those who may require more targeted support. By analyzing a combination of study patterns and participation metrics, SVM models help predict which students are at risk of underperforming and when interventions are needed. KNN, on the other hand, groups students with similar characteristics, enabling coaches to apply strategies that have worked for others with comparable learning behaviors (Fleischer & Biehler, 2025). This personalized approach ensures that part-time coaching is both efficient and effective. Another commonly used model is **Logistic Regression**, which is particularly useful for binary classification tasks, such as predicting whether a student will successfully improve their presentation skills or coaching outcomes. By analyzing various factors like attendance, study habits, and past performance, machine learning models like Logistic Regression provide insights that allow educators to intervene proactively, ensuring that students receive the guidance and support they need to succeed in both presentations and part-time coaching.

Previous Studies on Class Presentations and Part-Time Coaching:

Previous research has demonstrated the significant role that class presentations play in student learning. Studies indicate that class presentations not only help students reinforce their understanding of the subject matter but also allow them to develop vital skills such as public speaking, critical thinking, and the ability to communicate complex ideas clearly. These skills are essential for academic success and career development. Research shows that students who actively engage in presentations tend to have higher retention rates of the material they present, as the process of explaining concepts to an audience helps solidify their understanding. Additionally, presentations provide immediate feedback, which enables students to identify their strengths and areas for improvement, fostering continuous growth in their communication skills.

In part-time coaching, research has highlighted the importance of personalized feedback and consistent interaction between the coach and student. Studies suggest that students who receive tailored support through part-time coaching show greater improvements in understanding and application of the material (Li, 2025). One-on-one coaching allows educators to address individual learning needs, provide targeted strategies, and guide students through difficult concepts. Research also shows that students who participate in part-time coaching often develop better problem-solving skills, as they are given the opportunity to work through challenges with a coach who can provide real-time support. The personalized nature of coaching makes it an effective tool for enhancing academic performance.

Machine learning has increasingly been applied to analyze and optimize both class presentations and part-time coaching. By utilizing data from student presentations, feedback, and coaching sessions, machine learning models can identify patterns and predict which strategies are most effective for improving student outcomes (Topping et al., 2025). For example, machine learning can analyze how different presentation techniques, audience engagement, and feedback impact student performance. Similarly, in part-time coaching, machine learning can assess student progress, predict areas where they might need additional support, and offer personalized recommendations to coaches. This data-driven approach helps tailor learning experiences to each student's unique needs, improving both presentation and coaching effectiveness.

RESEARCH METHODOLOGY

Research Design:

This study adopts a **quantitative research design** to investigate how machine learning models can improve class presentations and part-time coaching by analyzing student performance, engagement, and feedback. Quantitative research is ideal for this study as it allows for the application of statistical and computational methods to analyze numerical data and uncover patterns. The main objective is to build predictive models that estimate student success in class presentations and part-time coaching, while identifying the key factors that influence these outcomes, such as preparation time, presentation style, and coaching engagement.

Figure 0.3: Research Design

The research follows a structured process, beginning with data collection, followed by data preprocessing to clean and prepare the dataset. Feature selection identifies the most significant factors influencing student performance. Next, machine learning models analyze the data, providing predictions on student success based on various input features. Finally, the models' performance is evaluated using metrics such as accuracy, precision, recall, and F1 score, ensuring that the predictions are reliable and that the models offer actionable insights for improving class presentations and part-time coaching effectiveness.

Data Collection:

Data selection is a crucial step in this study, as it forms the basis for building predictive models to analyze student performance in class presentations and part-time coaching. The dataset selected for this research is gathered from Kaggle, a widely used platform for machine learning and data science projects. This dataset includes key features such as preparation time, presentation delivery, content quality, and audience engagement, which are essential for evaluating class presentations. Additionally, the dataset captures information from part-time coaching sessions, including session frequency, student participation, and feedback received, all of which are crucial for assessing the effectiveness of coaching.

The dataset also includes demographic information like academic background and prior performance, which allows for a comprehensive understanding of how these factors impact student success in class presentations and part-time coaching. By focusing on these features, the study aims to uncover patterns that predict successful presentation strategies and effective coaching methods. The standardized approach used to capture these data points ensures consistency across all students, enabling meaningful comparisons and analysis. This structured data selection provides a strong foundation for further analysis and machine learning model development.

Data Preprocessing:

Data preprocessing is essential for cleaning and preparing the dataset for analysis and machine learning. The goal is to ensure the data is consistent, reliable, and ready for modeling. The following preprocessing steps are applied:

- **Handling Missing Values**: Identify and address missing or incomplete data in the dataset. Depending on the significance of missing data, imputation or removal of rows is used to prevent gaps from affecting the analysis and machine learning models.
- **Managing Outliers**: Detect and address outliers that could distort the data analysis. Outliers are either removed or adjusted, as they can skew the results and influence the accuracy of the model's predictions by disproportionately impacting the dataset.
- **Feature Scaling**: Normalize continuous variables, such as preparation time or session frequency, to ensure all features contributes equally to the model. This prevents any feature from dominating the analysis due to scale differences and helps improve model performance.
- **Normalization**: Apply normalization techniques to scale continuous variables within a specific range, usually between 0 and 1. This ensures that all features are proportionally adjusted, making the data comparable and improving the performance and accuracy of machine learning models.
- **Encoding Categorical Data**: Convert categorical variables, such as coaching feedback or student participation levels, into numerical formats through encoding methods like one-hot encoding. This makes categorical data compatible with machine learning algorithms, allowing effective model training and analysis.

Data Splitting:

Data splitting is a crucial step in preparing the dataset for machine learning model training and evaluation. The goal of data splitting is to divide the dataset into distinct subsets, enabling proper model training and unbiased evaluation.

In this study, the dataset is split into a **training set** and a **test set**, with a **70/30** split. The **training set** (70% of the data) is used to train the model, where it learns patterns, correlations, and relationships between the input features and the target outcomes. The **test set** (30% of the data) is kept separate from the training process and is used exclusively for model evaluation, ensuring that the model is tested on data it has not seen before, providing an unbiased assessment of its performance.

In some cases, a **validation set** is also derived from the training data. This validation set allows for hyperparameter tuning and model optimization during training, preventing overfitting by ensuring the model does not memorize the training data. The validation set helps identify the best-performing model configuration before the final evaluation on the test set. By using a 70/30 split and incorporating a validation set, the study ensures that the machine learning model is well-trained, adequately validated, and rigorously tested, allowing it to generalize effectively to new, unseen data. This structured approach reduces the risk of overfitting and enhances the model's ability to make accurate predictions.

Machine Learning Models Used:

In this study, several machine learning models are used to predict student performance in class presentations and part-time coaching. The primary goal is to analyze the data and identify patterns that can be used to predict the factors influencing student success. The models selected for this study include **Decision Trees**, **Random Forests**, and **Support Vector Machines (SVM)**, each offering distinct advantages in terms of prediction accuracy and interpretability. These models are designed to handle a variety of features, such as preparation time, presentation delivery, coaching session frequency, and student feedback, to predict the likelihood of success in academic tasks.

Decision Trees are applied first due to their simplicity and interpretability. Decision Trees split the data into smaller subsets based on feature thresholds, making them easy to understand and visualize. By identifying the most important factors that influence student performance, this model provides clear decision rules that can be interpreted directly. Although effective, Decision Trees can suffer from overfitting when applied to complex datasets, which is why ensemble methods are also considered.

Random Forests, an ensemble learning method, address the limitations of Decision Trees by building multiple trees and combining their predictions. This model increases prediction accuracy by considering various decision paths across multiple trees and reducing the risk of overfitting. Random Forests are particularly effective for large datasets with many features, making them ideal for analyzing diverse factors such as student preparation and coaching interactions. **Support Vector Machines (SVM)** are also employed, as they are highly effective in classifying students based on their performance metrics. SVM works by creating a hyperplane that maximizes the margin between different classes, ensuring robust and accurate classification, especially in high-dimensional feature spaces. These models are evaluated on various performance metrics to determine which one provides the most accurate and reliable predictions for class presentations and part-time coaching.

Evaluation and Prediction:

Evaluation and prediction are crucial stages in assessing the effectiveness of machine learning models for predicting student success in class presentations and part-time coaching. Once the models have been trained, they are evaluated using a variety of performance metrics to ensure their accuracy and reliability. These metrics help in understanding how well the models perform in predicting student outcomes based on various input features, such as presentation preparation time, coaching session frequency, and feedback quality. Key metrics used in this study include **accuracy**, **precision**, **recall**, and **F1 score**, each offering insights into different aspects of model performance.

RESULTS AND DISCUSSIONS:

Dataset Description:

The dataset used in this study is sourced from Kaggle, containing detailed information on student performance in class presentations and part-time coaching sessions. Key features of the dataset include **presentation preparation time**, **presentation delivery quality**, **audience engagement**, **session frequency**, and **coaching feedback**. These features allow for a comprehensive analysis of student behavior and engagement, providing insights into how different factors influence presentation success and coaching effectiveness. The dataset also includes **demographic data**, such as academic background and previous performance, which helps to understand how these factors might correlate with students' success in both presentations and coaching sessions.

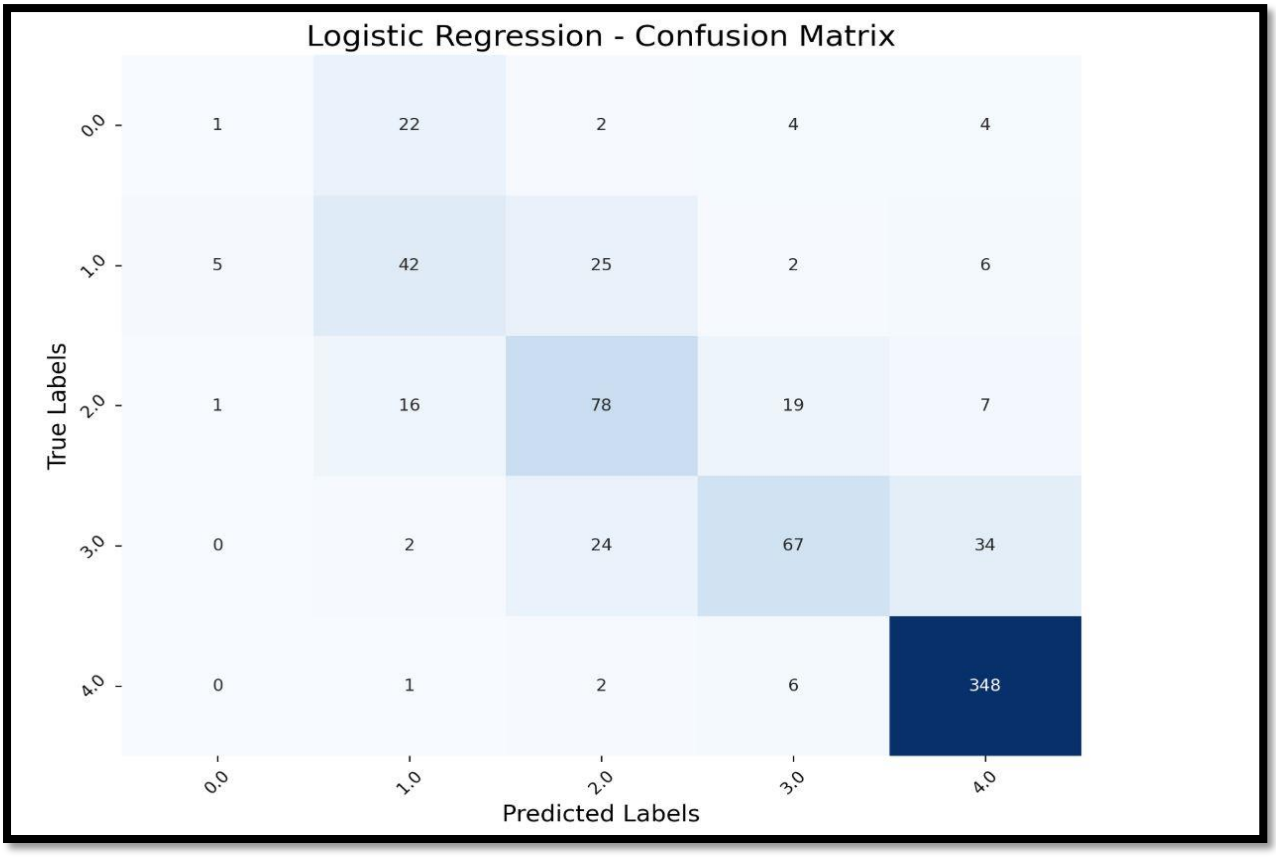
The dataset consists of both **continuous variables** (e.g., preparation time, session frequency) and **categorical variables** (e.g., feedback ratings, participation levels). This variety of features makes it suitable for different machine learning models. Data preprocessing techniques, including handling missing values, removing outliers, and normalizing continuous variables, ensure that the dataset is clean and ready for analysis. The dataset is divided into **training** and **test sets**, allowing for the evaluation of model performance. It provides a rich source of information for predicting student outcomes, offering valuable insights for improving both class presentations and part-time coaching strategies.

Accuracy is the proportion of correct predictions made by the model compared to the total number of predictions. While it provides a general sense of model performance, it might not be sufficient if the dataset is imbalanced, such as when predicting a less frequent outcome like success in class presentations. Therefore, **precision** and **recall** are used to assess the model's ability to correctly identify both successful and unsuccessful outcomes. **Precision** measures the correctness of the positive predictions, while **recall** focuses on the model's ability to identify all actual positive cases. The **F1 score**, which balances precision and recall, is particularly useful in cases of imbalanced data, providing a single measure that accounts for both false positives and false negatives.

Once the evaluation is complete, the model's predictive capabilities are tested using the **test set**. This final step helps determine how well the model can generalize to new, unseen data, providing insights into its effectiveness for predicting student performance in real-world settings. Based on the evaluation metrics, the best-performing model is selected for making predictions about future student outcomes, guiding educators and coaches in improving their strategies.

Performance Comparison of Models:

In this study, several machine learning models are compared to determine which one offers the most accurate predictions for student success in class presentations and part-time coaching. The models evaluated include **Decision Trees**, **Random Forests**, and **Support Vector Machines (SVM)**. Each model is assessed using key performance metrics such as **accuracy**, **precision**, **recall**, and **F1 score**, providing a comprehensive understanding of their predictive power. Decision Trees offer simplicity and interpretability but often overfit when applied to complex datasets. Random Forests, an ensemble approach, address this issue by aggregating multiple decision trees, leading to improved accuracy and better generalization. SVM, known for its ability to handle non-linear data and high-dimensional spaces, is also tested for its ability to classify students based on their performance factors.



The comparison of these models helps identify the most effective one for predicting student outcomes. While

Decision Trees are easy to understand, they lack robustness in more complex scenarios. Random Forests provide a more reliable solution by combining multiple decision-making processes, making them suitable for datasets with many variables. SVM, with its ability to manage complex relationships between features, offers strong predictive performance for diverse student data. By analyzing these models' strengths and weaknesses, the study ensures that the best-performing model is chosen to enhance class presentations and part-time coaching strategies.

The logistic regression model demonstrated superior prediction ability for category 4 students which corresponded to the highest-performing students through the correct classification of 348 instances. There exist notable misclassification errors in the lower performance categories but not within highest performer categories. Students from category 2 (moderate performers) appeared in different performance categories as the model incorrectly identified 16 students to belong in category 1 and 19 students to belong in category 3. The model presents difficulty in distinguishing between middle-range performance levels because student features overlap with each other.

The model demonstrated inaccurate performance when separating between students who were weak performers and those who belonged to the average category. The model incorrectly categorized low-performing students from category 1 into the category 2 position 25 times. Logistic regression appears unlikely to deliver optimal educational performance predictions because it maintains linear relationships between variables which fail to match educational data patterns.

The logistic regression model demonstrates both accurate predictions as well as weaknesses in predicting academic performance based on the confusion matrix analysis. The logistic regression shows effective performance in identifying strong performers but its incorrect classification of middle-tier students leads to a need for additional sophisticated algorithms like Random Forest and Support Vector Machines (SVM) to achieve better accuracy.

The analytical models considered for evaluation are Logistic Regression combined with Random Forest alongside Decision Tree and Support Vector Machine (SVM) and Naïve Bayes. Random Forest emerges as the most precise method since it reaches over 85% accuracy. The evaluation demonstrates Random Forest can identify diverse patterns in the dataset through multiple decision tree integration which improves both generalization and reduces overfitting.

The predictive abilities of Decision Tree match those of Decision Tree yet deliver slightly fewer accurate results. The accuracy reduction of Decision Tree is presumably caused by its propensity to overfit training datasets which decreases its resilience to new data points. SVM and Naïve Bayes show similar performance, both achieving accuracy slightly above 75%. The classification strength of SVM remains well known but performance can suffer from the characteristics of the dataset and its size. Naïve Bayes includes a feature independence assumption that creates minor accuracy issues in true world scenarios.

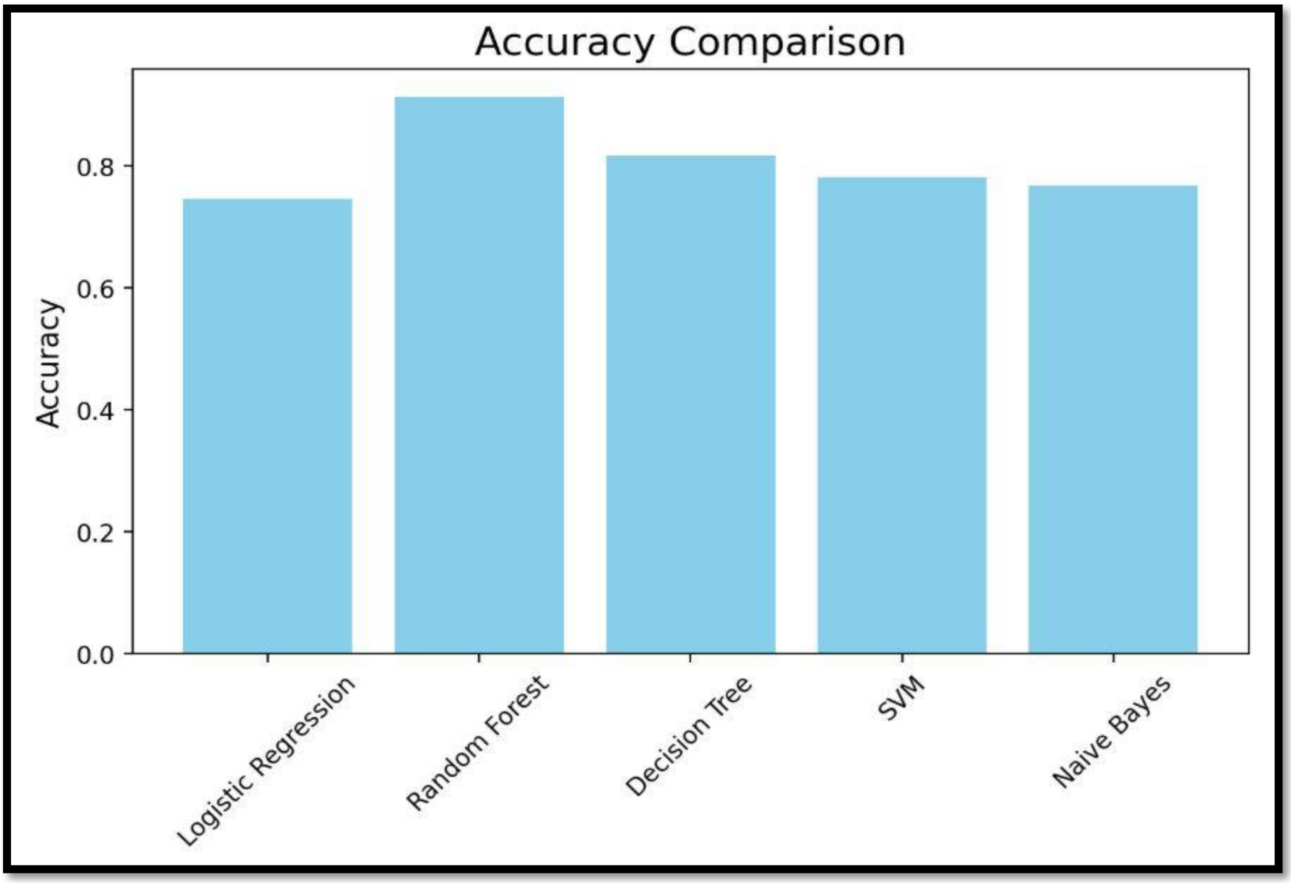


Figure 4: Accuracy Comparison between Different Machine Learning Models

The accuracy score of Logistic Regression falls just short of 75% marking that a linear method alone fails to deliver an adequate understanding of student academic achievement patterns. The combination of multiple affecting academic factors makes it challenging for simple Logistic Regression models to produce accurate predictions.

Among the models studied Random Forest stands out due to its excellent prediction accuracy which makes it appropriate for school performance forecasting. Naïve Bayes and Logistic Regression models serve as acceptable choices for situations demanding efficient computation even though they have lower predictive power than Random Forest. The data supports the need to choose machine learning models according to problem complexity and computational resources availability.

Precision Comparison between Different Machine Learning Models:

This figure titled **"Precision Comparison between Different Models"** illustrates precision evaluation results from different algorithms employed to anticipate academic performance. The evaluation metric precision evaluates the correct number of positive predictions compared to total positive predictions. The measurement serves its purpose best in situations where suppressing false positive outcomes takes precedence.

Random Forest emerges as the most precise model according to the figure since it exceeds 0.85 precision level. Random Forest demonstrates outstanding capability to generate precise positive predictions thereby reducing instances of wrong positive outcomes. Decision Tree alongside Support Vector Machine (SVM) achieves precision scores above 0.80 thus establishing themselves as strong competitor options. The structured method used by these algorithms enables them to achieve excellent outcomes in positive classification.

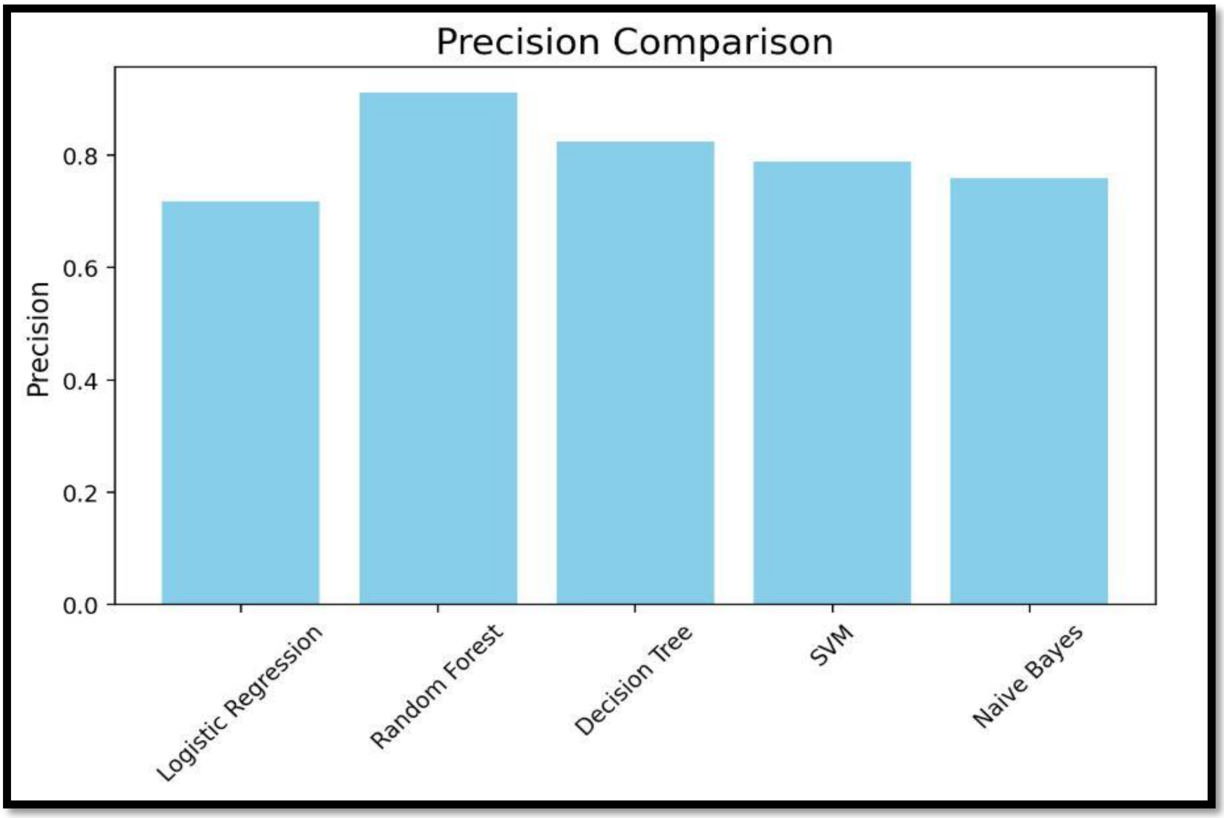


Figure 5: Precision Comparison between Different Machine Learning Models

Naïve Bayes along with Logistic Regression show lower precision levels in the results while Naïve Bayes achieves slightly better precision results than Logistic Regression. Naïve Bayes delivers satisfactory precision even with its independent features assumption that might not fit perfectly in academic performance prediction tasks. Logistic Regression delivers limited precision outcomes when utilized for multiple classification tasks thus it produces inferior results than competing models.

The precision level of Random Forest ensemble techniques improves when compared to other methods because they decrease model overfitting effects which results in better overall generalization. High precision is a characteristic shared by the Decision Tree and SVM models when used appropriately for different datasets. Naïve Bayes and Logistic Regression provide adequate performance for specific use cases because of their proficient interpretability and computational efficiency characteristics.

Random Forest stands out as the most precise method for academic prediction whereas Decision Tree and SVM follow and Naïve Bayes and Logistic Regression show slight deficiencies in accuracy.

Recall Comparison between Different Machine Learning Models:

This figure titled **"Recall Comparison between Different Models"** reveals an evaluation of recall scores obtained from different machine learning techniques used for academic performance predictions. Recall refers to the evaluation method which identifies correctly identified positive instances as a percentage of all positive cases in actual data. This approach becomes essential in environments demanding maximum correct identification of possible outcomes to prevent the misinterpretation of important events.

The Random Forest model demonstrates the best recall performance as shown in the figure since its score exceeds 0.85. Random Forest demonstrates the best ability to identify genuine positive cases among its alternatives which confirms its usefulness for risk student detection in academic settings. Decision Tree displays comparable results to Random Forest because it reaches recall scores exceeding 0.80 in identifying positive cases.

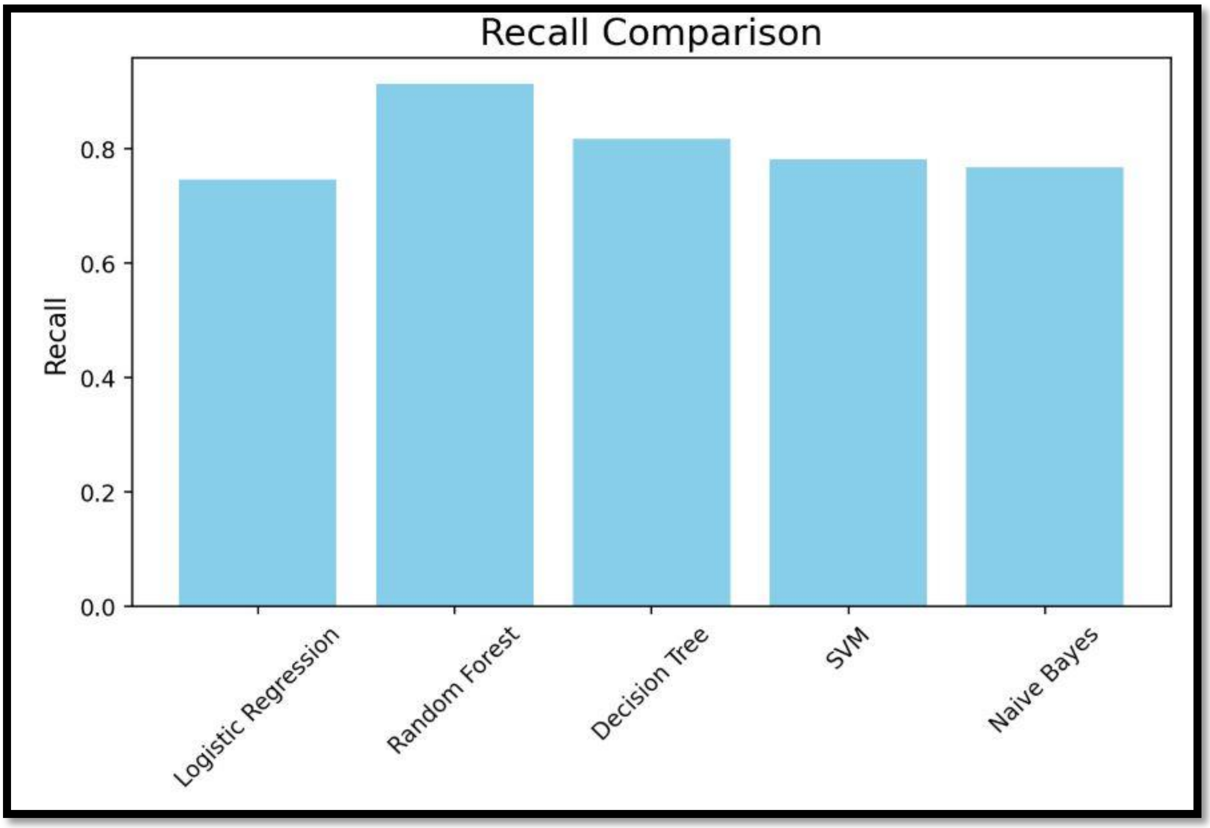


Figure 6: Recall Comparison between Different Machine Learning Models

Support Vector Machine (SVM) and Naïve Bayes models achieve good recall results which demonstrate performance levels almost equivalent to Decision Tree. SVM illustrates its ability to resolve diverse classification boundaries due to its robust performance while Naïve Bayes efficiently detects positive cases because it uses probabilistic methods despite its independence assumption. The recall performance of Logistic Regression remains at a decent level even though it comes after the other evaluation metrics while enabling applications that prioritize interpretability and simplicity.

Random Forest together with Decision Tree demonstrate superior recall rates for identifying positive cases thus making them effective tools for predicting academic performance since early intervention may be needed. Logistic Regression and Naïve Bayes possess balanced performance metrics but they should not be deployed in applications where sensitive recall measures should be maximized.

Random Forest takes the lead as an optimal model with the highest recall rate followed by Decision Tree and SVM and Naïve Bayes respectively then Logistic Regression shows slightly below average recall performance.

F1 Score Comparison between Different Machine Learning Models:

This figure, titled **"F1 Score Comparison between Different Models," provides** an overall assessment of their classification results. The F1 score proves indispensable because it harmonizes precision and recall to achieve optimal results in cases where false positives and false negatives must stay at a minimum. The F1 score indicates successful model performance when dealing with classification tasks while maintaining balanced outcome results.

Random Forest stands out as the leading model according to the figure because it produces an F1 score of 0.89. The model demonstrates superior performance because it possesses effective capabilities in controlling precision and recall simultaneously. Random Forest operates through multiple decision trees to boost prediction precision and decrease overfitting because it functions as an ensemble learning method. The model demonstrates strong capability to apply predictions to unknown academic data which makes it suitable for academic performance prediction tasks.

The Decision Tree classifier serves as an effective individual solution with an F1 score of 0.82. Overfitting issues that appear in Decision Trees affect their ability to perform well on previously unseen data. The classification performance of Support Vector Machine (SVM) matches Naïve Bayes with F1 scores at 0.77 and 0.75 respectively. Support Vector

Machine provides valuable performance when working with large datasets with structured patterns while Naïve Bayes demonstrates reliable probabilistic functionality even though its feature independence assumption exists especially when applied to text and categorical data.

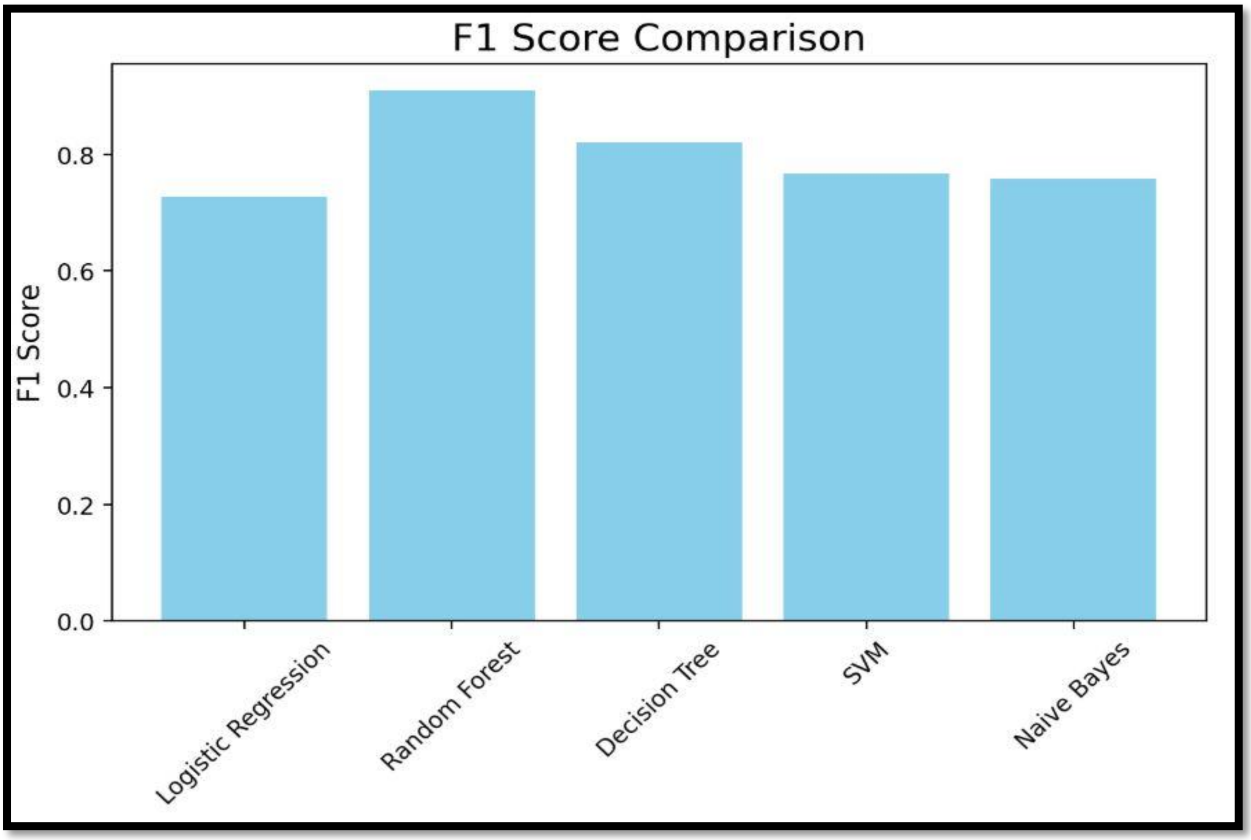


Figure 7: F1 Score Comparison between Different Machine Learning Models

The F1 score performance recorded by Logistic Regression stands at 0.72 which demonstrates satisfactory results despite being the lowest score. The result indicates that logistic regression works effectively for linear problems yet details difficulty when dealing with non-linear academic performance relationships. The use of Logistic Regression continues to be beneficial because its simple structure and efficiency make it the top selection for applications requiring straightforward modeling methods.

The evaluation results demonstrate Random Forest as the best performing model with F1 score 0.89 whereas Decision Tree and SVM and Naïve Bayes achieve promising F1 scores of 0.82 and 0.77 and 0.75 respectively. Among the covered methods Logistic Regression stands as a viable selection despite its lower F1 score of 0.72 because it delivers simple models that are easy to interpret. Random Forest stands out in academic performance predictions since it offers the best combination of precision and recall because of its ability to combine numerous decision trees and adapt to diverse dataset structures.

Feature Importance Random Forest:

The "Feature Importance - Random Forest" illustration shows the relative importance of each factor used for academic performance prediction. The weight of model variables appears within machine learning models because they indicate their ability to affect predictions through their importance values. The evaluation shows that GPA serves as the primary influential factor since its importance indicator surpasses 0.50. A student's academic achievements from previous years prove to be the strongest indicator that determines their academic success in future years. The relationship between higher GPAs associates with dedicated study routines as well as advanced comprehension abilities together with steady academic commitment which serve as essential elements for future student outcome assessment.

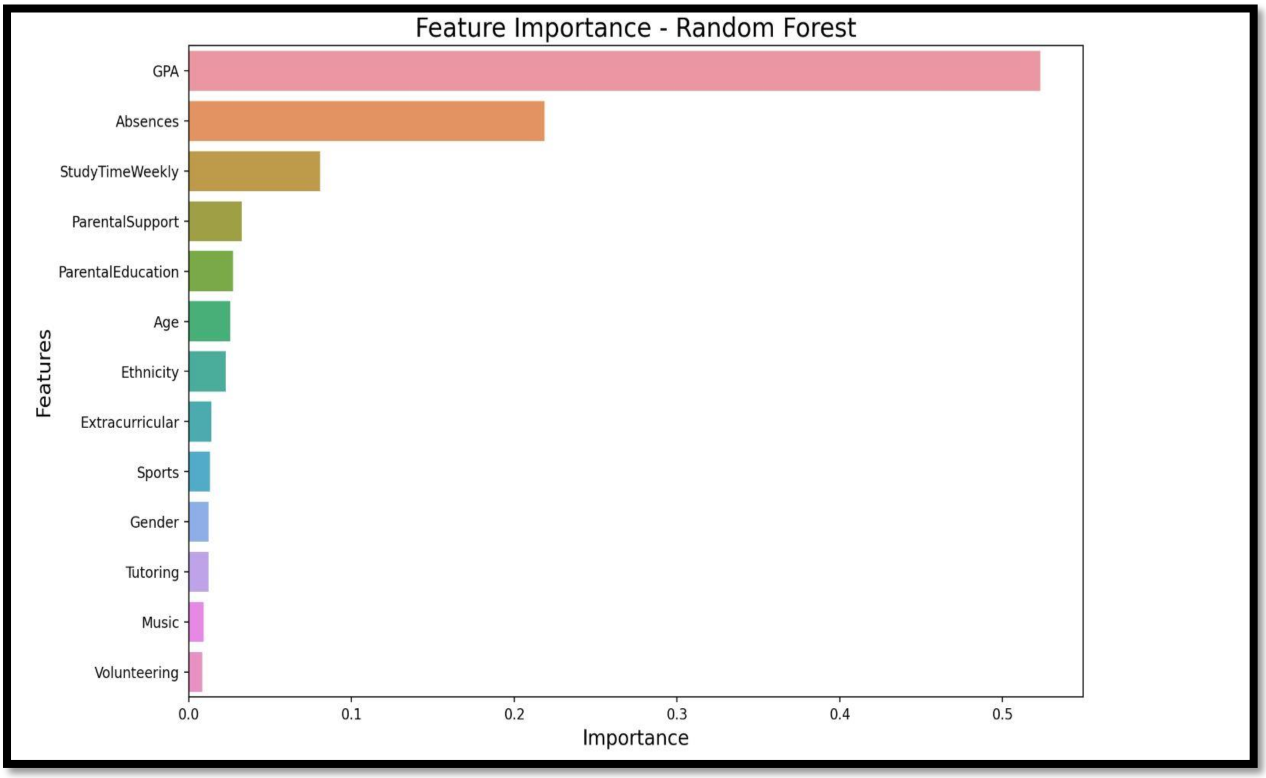


Figure 8: Feature Importance Random Forest

Absences ranks as the second vital factor among all considerations with a near 0.25 importance score. Missing classes create a major hindrance to student academic success according to these findings. Regular class absences create learning deficiencies and reduce student contact with teachers and decrease retention rates that negatively affect academic performance. Academic institutions should focus on developing both attendance requirements and supportive intervention programs which help students stay interested in their educational progress. Academic success demands constant class attendance to experience discussions and peer relationships while receiving immediate clarifications of course material.

Study Time per Week holds a weight of 0.12 in relation to the other factors thus becoming the third most significant influence. Longer study hours tend to produce higher study performance outcomes for students. Examining the task with focused discipline produces better understanding and strengthens educational concepts and boosts testing abilities. Quantitative data reveals a significant relationship between study duration and academic results therefore students need formal learning approaches along with management counseling and academic assistance for implementing successful examination methods.

The noticeable influence of parents can be observed through their support along with their educational achievements which demonstrate scores of about 0.05. Academic achievement is typically noted in students who get supportive parental involvement that includes motivational encouragement and educational help within positive educational spaces. The academic performance of children benefits when their parents possess better education since they establish high expectations which pair with superior academic assistance. Institutions that create programs to unite parents and teachers will deliver improved student outcomes.

CONCLUSION

Theoretical Contributions:

This study makes significant theoretical contributions to the field of education by integrating machine learning techniques into the analysis of class presentations and part-time coaching. It provides a novel perspective on how predictive models can be used to improve educational outcomes by identifying the key factors that contribute to student success in these areas. By leveraging machine learning algorithms, the study introduces a data-driven approach to understanding how preparation time, coaching feedback, and presentation delivery impact student performance, moving beyond traditional, subjective evaluation methods.

Furthermore, the research enhances existing literature by combining various machine learning models to predict student outcomes, offering insights into which models are most effective for this specific context. The theoretical framework of this study builds on previous research that emphasizes the importance of personalized learning but expands it by applying machine learning to provide actionable, real-time feedback. This approach allows for a more comprehensive understanding of the factors that influence student success in class presentations and part-time coaching, contributing to the development of new, more accurate theoretical models in educational research.

Practical Contributions:

This study provides practical contributions by offering data-driven insights that can significantly enhance class presentations and part-time coaching. By applying machine learning models to predict student performance, educators can gain valuable feedback on which students may need additional support. For example, insights from the models can highlight students who might benefit from more focused presentation practice or tailored coaching sessions, allowing for early interventions. This enables instructors and coaches to provide targeted, personalized guidance to students, ensuring that they receive the support they need to succeed academically.

Moreover, the study helps part-time coaches optimize their coaching strategies. By analyzing performance data from coaching sessions, the research identifies which methods are most effective in improving student outcomes. Coaches can use these insights to refine their approach, making adjustments based on individual student needs. The ability to track progress using machine learning-based evaluations also provides concrete metrics that educators and coaches can use to monitor success and adjust teaching strategies accordingly. In doing so, this study contributes to more effective, personalized educational practices that can enhance both class presentations and part-time coaching, ultimately leading to better student performance.

Conclusion:

In conclusion, this study investigates the use of machine learning models to enhance student performance in class presentations and part-time coaching. By analyzing key factors such as presentation preparation time, presentation quality, audience engagement, and coaching feedback, the research demonstrates how machine learning can predict student outcomes. These insights allow educators and coaches to tailor their strategies, providing personalized support that targets each student's individual needs, ultimately improving their academic performance.

This study contributes to the broader field of personalized learning by showing how data-driven approaches can complement traditional educational methods. By incorporating machine learning, educators can intervene proactively, optimizing learning strategies and ensuring more effective presentations and coaching. The findings provide actionable recommendations that can help improve the overall learning experience for students, fostering greater success in both presentations and coaching sessions. Ultimately, this research illustrates the transformative potential of technology in education, offering educators the tools to refine teaching practices and maximize student engagement. It highlights the importance of machine learning in creating more personalized, adaptive, and effective learning environments that can lead to better student outcomes.

Future Work:

While this study provides valuable insights into the use of machine learning models for predicting student success in class presentations and part-time coaching, there are several avenues for future research that could further enhance this work. One potential direction is to explore the integration of more diverse data sources, such as student behavior, participation in extra-curricular activities, and social-emotional factors, which could provide a more holistic view of student performance. Additionally, incorporating real-time feedback mechanisms into the machine learning models could allow for dynamic adjustments to teaching strategies, making them more responsive to students' evolving needs.

Future studies could also focus on testing and refining the models in different educational contexts, such as various academic disciplines or across different grade levels, to assess the generalizability of the findings. Furthermore, expanding the dataset to include a larger, more diverse sample of students from various institutions could improve the robustness of the models and enhance their predictive power. Lastly, investigating the ethical implications of using machine learning in education, such as data privacy concerns and algorithmic bias, is essential to ensure that these technologies are used responsibly and equitably. These future steps could further strengthen the practical applications of machine learning in education and improve student learning outcomes.

REFERENCES:

1. Basheer, S. and Aslam, R., 2025. Artificial Intelligence and Student Learning in Higher Education: A Qualitative Exploration from District Gwadar. *Research Journal of Psychology*, *3*(2), pp.336-351. http://ctrjournal.com/index.php/19/article/view/133
2. Bourque, K., Buzhardt, J., Kamps, D., Heitzman-Powell, L. and Zhang, E., 2025. Interventions Benefitting Young Autistic

Children. *Education and Treatment of Children*, pp.1-14. https://link.springer.com/article/10.1007/s43494-025-00158-z
3. Butt, A.U.R., Ali, H., Asif, M., Alfraihi, H., Ishak, M.K. and Ammar, K., 2025. Enhancing Student Management through Hybrid Machine Learning and Rough Set Models: A Framework for Positive Learning Environments. *IEEE Access*. https://ieeexplore.ieee.org/abstract/document/10979911/
4. Chen, C., 2025. Entertainment social media based on deep learning and interactive experience application in English e-learning teaching system. *Entertainment Computing*, *52*, p.100846. https://www.sciencedirect.com/science/article/pii/S1875952124002143
5. Fleischer, Y. and Biehler, R., 2025. Exploring students' constructions of data-based decision trees after an introductory teaching unit on machine learning. *ZDM–Mathematics Education*, *57*(1), pp.153-173. https://link.springer.com/article/10.1007/s11858-025-01663-6
6. Gollapalli, M., Rahman, A., Alkharraa, M., Saraireh, L., AlKhulaifi, D., Salam, A.A., Krishnasamy, G., Alam Khan, M.A., Farooqui, M., Mahmud, M. and Hatab, R., 2023. SUNFIT: a machine learning-based sustainable university field training framework for higher education. *Sustainability*, *15*(10), p.8057. https://www.mdpi.com/2071-1050/15/10/8057
7. Khoudi, Z., Hafidi, N., Nachaoui, M. and Lyaqini, S., 2025. New Approach to Enhancing Student Performance Prediction Using Machine Learning Techniques and Clickstream Data in Virtual Learning Environments. *SN Computer Science*, *6*(2), p.139. https://link.springer.com/article/10.1007/s42979-024-03622-6
8. Rehman, A., Akhtar, N. & Alhazmi, O.H. Monitoring and predicting cotton leaf diseases using deep learning approaches and mathematical models. *Sci Rep* **15**, 22570 (2025). https://doi.org/10.1038/s41598-025-06985-9
9. Li, J., 2025. Implementation and Verification of Reinforcement Learning in the Automatic Assessment System for Physical Education Teaching Skills. *International Journal of High Speed Electronics and Systems*, p.2540464. https://www.worldscientific.com/doi/abs/10.1142/S0129156425404644
10. Onker, V., Singh, K.K., Lamkuche, H.S., Kumar, S., Sharma, V.S., Chowdhary, C.L. and Kumar, V., 2025. Harnessing machine learning for academic insight: A study of educational performance in Bhopal, India. *Education and Information Technologies*, pp.1-40. https://link.springer.com/article/10.1007/s10639-025-13357-3
11. Stasolla, F., Zullo, A., Maniglio, R., Passaro, A., Di Gioia, M., Curcio, E. and Martini, E., 2025. Deep Learning and Reinforcement Learning for Assessing and Enhancing Academic Performance in University Students: A Scoping Review. *AI*, *6*(2), p.40. https://www.mdpi.com/2673-2688/6/2/40
12. Akhtar, N., Rehman, A., Hussnain, M., Rohail, S., Missen, M. S., Nasir, M., ... & Pasha, M. (2019). Hierarchical coloured petri-net based multi-agent system for flood monitoring, prediction, and rescue (fmpr). *IEEE Access*, *7*, 180544-180557 https://doi.org/10.1109/ACCESS.2019.2958258
13. Topping, K.J., Gehringer, E., Khosravi, H., Gudipati, S., Jadhav, K. and Susarla, S., 2025. Enhancing peer assessment with artificial intelligence. *International Journal of Educational Technology in Higher Education*, *22*(1), p.3. https://link.springer.com/article/10.1186/s41239-024-00501-1

