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E-Learning Outcomes of Engineering College Students Prediction Model Based on Machine Learning Technique

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Abstract: This study employs examined machine learning techniques to predict e-learning outcomes for engineering college students. Specifically, it focuses on the application of Decision Tree and Random Forest models to predict student performance metrics such as dropout rates and final grades. Utilizing a comprehensive dataset compiled from various sources, including student demographics, academic histories, course interactions, and assessment scores, the study aims to identify patterns and key predictors of academic success in an online learning environment. The models are trained and evaluated using a robust dataset, with performance metrics such as accuracy, precision, recall, and F1-score serving as benchmarks for model effectiveness. The Decision Tree model provides an intuitive understanding of the data by illustrating the decision paths based on feature importance, while the Random Forest model enhances prediction accuracy through ensemble learning, effectively managing class imbalances and complex data structures. Findings from this study reveal significant insights into factors influencing student performance, offering potential strategies for educational interventions. The research highlights the capability of machine learning models to not only forecast educational outcomes with considerable accuracy but also to empower educational institutions with data-driven tools for enhancing student engagement and educational planning. The predictive models developed and tested in this study demonstrate a promising approach to addressing challenges in e-learning systems, ultimately aiming to improve the educational achievements of engineering students in an online setting.

Keywords: e-learning, prediction model, decision tree and random forest, machine learning

1. Introduction

The integration of digital technologies into higher education has revolutionized the delivery of educational content, particularly in engineering disciplines where the combination of theoretical and practical knowledge is crucial. The shift towards e-learning platforms has transformed traditional engineering education, which was primarily based on hands-on activities and in-person interactions, to a more flexible and accessible format. This transition is vital in the contemporary global and digital landscape, enabling educational institutions to broaden their reach and foster more inclusive learning environments (Amhag et al., 2019; Jurayev, 2020; Alazemi, 2022; Quraishi et al., 2023).

Engineering education demands a comprehensive approach due to the complex nature of its subject matter, which requires high levels of problem-solving and critical thinking Dheeraj, 2022; Chen, 2023). E-learning platforms facilitate the delivery of such content in versatile ways that traditional classrooms cannot, offering tools like digital simulations and virtual labs. These technologies allow students to experience practical applications of theoretical knowledge without the constraints of physical labs, thus extending learning beyond conventional boundaries (Dhakal, 2022; Belessova et al., 2023; Yadav, 2024).

At the forefront of advancing these digital educational tools is Machine Learning (ML). By integrating ML algorithms into e-learning platforms, educational experiences can be customized to meet individual student needs (Fedeli and Tomezyk, 2022; Afzal et al., 2023). These algorithms process extensive data sets, including metrics on student engagement, progress rates, and feedback, to detect patterns that help predict student performance and outcomes (Seo et al., 2021; Alazemi, 2022; Viberg et al., 2024). This predictive capability is crucial for implementing proactive interventions that support at-risk students or adapt the curriculum to better meet the needs of all students (Gill, 2022; Yadav, 2024).

ML has revolutionized engineering education through its application in e-learning platforms. By leveraging ML techniques, educators gain a nuanced understanding of student interactions with course materials, identify challenging sections, and devise effective teaching strategies (Zawacki-Richter et al., 2019; Anja et al., 2023; Gligorea et al., 2023). For example, Decision Trees, Random Forest and neural networks analyze complex student data, enabling the prediction of future performance. This predictive capability guides both immediate and strategic educational institutions planning Gotardo, 2019; Li et al., 2019; Abba et al., 2021; Arifuzzaman et al., 2023).

However, integrating ML into e-learning platforms presents challenges. Ensuring data privacy, addressing biases in training data, and bridging the digital divide that limits access to advanced learning tools are significant issues. Moreover, the effectiveness of ML-driven interventions hinges on data quality and volume, which can vary across education institutions (Jurayev, 2020; Atkin and Carver, 2021; Alnagrat et al., 2022). To enhance educational outcomes for engineering students, future research should refine ML technologies and seamlessly integrate them into curricula.

Not to mention, investigating adaptive learning systems that dynamically adjust content based on student performance could further personalize education, improving engagement and retention (Fawu, 2019; Holger Gunzel et al., 2020; Belessova et al., 2023; Karabin et al., 2024). Ultimately, ML-enhanced e-learning platforms are reshaping engineering education. By continuously adapting to student needs, these platforms not only enhance educational outcomes but also revolutionize the pedagogical model within engineering education.

2. Problem Statement

E-learning, or online education, has become increasingly prevalent in higher education institutions, particularly in engineering schools, due to the widespread availability of digital technologies and platforms. E-learning offers convenience and flexibility by allowing remote students to access course materials, interact with peers, and submit assignments (Buchholz et al., 2020; Kurdi et al., 2020; Cabero-Almenara et al., 2023).

However, as this mode of instruction gains popularity, it presents challenges in accurately predicting the outcomes for engineering students. Typically, “at-risk” students exhibit early warning signs such as missing classes, high engagement in extracurricular activities, incomplete assignments, and noticeable shifts in behavior and academic performance, which are predictors of potential dropout and low retention (Chatti and Hadoussa, 2021; Alsousi and Zulkifli, 2022; Afzal et al., 2023; Olusegun et al., 2023). Institutions need to forecast student performance in online courses to provide timely interventions, personal support, and engaging learning opportunities.

Further, engineering students face a variety of challenges that can impact the effectiveness of online education, corresponding peers in traditional classrooms. These challenges include failing to graduate, low employability, low retention, high dropout rates, poor academic performance, self-discipline, learning styles, time management, technical skills, demanding work schedules, logistical challenges, financial strain, health issues and individual differences (Audrin and Audrin, 2022; Camilleri and Camilleri, 2022; Chu et al., 2022; Chen, 2023; Bashar and Naaz, 2024). The impersonal nature of E-learning and the lack of face-to-face interaction with instructors can exacerbate these difficulties. Therefore, there is a pressing need to develop reliable prediction models that consider numerous factors influencing the success of E-learning for engineering students.

While research on e-learning prediction models has increased in online education for digitalization, its application to engineering students in higher education institutions has been limited and overwhelmingly (Li and Li, 2019; Liu et al., 2020; Khan et al., 2022; Ministry of Education of China, 2022). Most previous studies have focused on non-engineering contexts, overlooking the specific academic demands and technical complexities of engineering courses (Milakovich and Wise, 2019; Knox, 2020; Haleem et al., 2022; Luo, 2023). Consequently, there is a significant gap to be filled in the ocean of literature in academic research traditions in relation to the development and empowerment of prediction models tailored to the unique challenges and needs of engineering students in online education.

Indeed, previous studies portrays the alarming of unsuccessful to address the issues about how factors corresponding to the students’ prior academic performance, learning styles, and technical ability interact to affect e-learning outcomes (Guo et al., 2019; Campbell and Kapp, 2020; Augutis et al., 2022; Chen, 2023; Fatima and

Munna, 2024). Furthermore, accurate and comprehensive prediction models require an understanding of the interplay between and contributions of these elements to student success in 21st century on the segment of blended learning or online learning such online engineering in any education institutions around the globe (Fessl et al., 2022; Yu et al., 2023; Yadav, 2024).

Indeed, digitalization of education institutions, particularly online education, plays a pivotal role due to its long-term impact on individuals' lives. However, students often encounter situations that could jeopardize or endanger their educational pursuits (Fawu, 2019; Dheeraj, 2022; Fedeli and Tomezyk, 2022; Deacon et al., 2023). In fact, most of the education institutions tend to focus more on dropout and delay issues than student performance in academic programs (Guo et al., 2019; Campbell and Kapp, 2020; Augutis et al., 2022; Chen, 2023; Fatima and Munna, 2024), yet the challenges that lead graduate students to leave or postpone their studies are less studied.

Despite documented dropout rates at many universities, there remains a lack of effective predictive models for these outcomes. Moreover, although enrolments in undergraduate programs in any academic institutions around the globe have increased, there is limited understanding of the factors influencing students' decisions in relation to learning outcome concerning discontinuing their studies. Given these challenges, educational institutions face significant hurdles in accurately predicting student completion and dropout rates. Predicting these rates is crucial as it enhances the decision-making processes and resource allocation within educational settings. Traditional methods fall short in accurately forecasting such outcomes, and manual data analysis proves too labor-intensive and costly (Gill, 2022; Fatima and Munna, 2024).

To address these issues, this study introduces a supervised machine learning algorithm aimed at predicting college dropout and learning performances. This model comprises by the employments a mix of between Decision Trees and Random Forests classification models investigate the strengths and limitations of existing ML algorithms used to support e-learning platform; to develop an e-learning platform incorporates ML algorithm to improve learning outcomes; besides to evaluate the effectiveness of ML supported e-learning platform to improve student learning outcomes in any academic institution particularly focusing on the segment of engineering program.

The exponential growth in online learning, especially in the era of post COVID-19 pandemic, has necessitated efficient methods to predict student performance and learning outcomes to avoid the dropouts as well left behind the future job market (Liu et al., 2020; Seo et al., 2021; Chu et al., 2022; Ahmad et al., 2023; Chen, 2023). Thus, this study assumes hypothetically that most of the engineering college students face unique challenges in an online learning environment due to the technical nature of their coursework and the need for practical engagement although engineering courses often involve complex concepts that require practical, hands-on learning experiences.

Not to mention, online platforms for e-learning may struggle to effectively deliver these experiences compared to traditional classroom settings for engineering courses (Bir, 2019; Gherhes et al., 2021; Oyewola et al., 2022; Abdullah et al., 2023). The absence of laboratory sessions and hands-on workshops can significantly affect learning outcomes. This technical complexity makes it difficult for students to grasp intricate engineering principles through online mediums alone. Additionally, courses in engineering frequently involve laboratory work, projects, and teamwork, which are challenging to replicate in an online environment. The lack of direct supervision and immediate feedback can hinder students' learning experiences, leading to decreased engagement and understanding (Abumandour, 2021; Balta-Salvador et al., 2021; Darkwa and Antwi, 2021; Spencer and Temple, 2021).

3. Research Objectives

a. To investigate the strengths and limitations of existing ML algorithms used to support e-learning platform.
b. To develop an e-learning platform incorporates ML algorithm to improve learning outcomes.
c. To evaluate the effectiveness of ML supported e-learning platform to improve learning outcomes.

4. Literature Review

Several studies have utilized machine learning models to predict academic outcomes, but there remains a critical gap in accurately identifying key predictors and optimizing model performance specifically for engineering disciplines. Commonly used models include decision trees and random forests, which are valued for their interpretability and ability to handle complex datasets.

Random forests enhance prediction accuracy through ensemble learning, which helps manage class imbalances and complex data structures (Hornstein et al., 2021). Neural networks are also effective for their high accuracy in classification tasks, though they may require significant computational resources and are less interpretable than tree-based models (Musso et al., 2020). Additionally, the Naive Bayes classifier has been shown to perform well in some educational datasets due to its simplicity and effectiveness in handling small datasets (Chandra et al., 2021).

Despite the advancements in machine learning applications, there is a need for more targeted research on identifying the specific predictors that influence the academic success of engineering students in online learning environments (Selvakumar and Sivakumar, 2019; Kanetaki et al., 2021; Freitas Rocha et al., 2022). Without doubt, the objectives of today's current research include developing robust predictive models tailored to the unique needs of engineering students, evaluating these models to identify the most effective predictors of student performance and dropout rates, and offering actionable insights for educational interventions to improve student outcomes (Garcia-Alberti et al., 2021; Supernak et al., 2021; Nazempour et al., 2022).

Setiyawan et al. (2019) explored the effect of blended learning on the student's learning achievements in the Department of Mechanical Engineering. The study also focused on engineering students' perceptions of problems and project-based learning (PBL) in an online learning environment beside classifying engineering students' performance in online education with machine learning by investigating effective, cognitive, and behavioral aspects (O'Connor et al., 2024). Further, Indira (2022) examines the blended learning approach to engineering education to understand the students' perceptions on learning experience and effectiveness. The study founds influence of in-person and on-line modes of instruction on academic performance in engineering capstone design courses using a comparative study based on non-parametric statistics (Khel et al., 2021; Oyewola et al., 2022; Ahmad Mahdzir et al., 2024).

Further, Watson et al. (2020) highlights the impact of online learning on engineering students' learning motivation in design classes besides blended learning in an upper year engineering course focusing on the relationship between students' program year, interactions with online material, and academic performance along with effect of e-learning on engineering student satisfaction and loyalty (Darius et al., 2021; Grodotzki et al., 2021; Aladib et al., 2024). While Wang et al., (2019) investigates the persistence of dropout patterns among engineering students in their initial semesters with lower income, academic performance, and levels of interaction. The study also undertakes a survey on the effectiveness of online teaching–learning methods for university and college students (Thurab-Nkhosi et al., 2021; Asiksoy and Islek, 2024).

Nuanmeesri et al. (2022) investigated feature selection with a multilayer perceptron neural network to improve dropout prediction accuracy, achieving 96.98 percent accuracy. The study's findings indicate that the feature selection technique can be used to improve the neural network model's efficiency in predicting student dropout during a COVID-19 pandemic. Furthermore, the simulation can improve student dropout forecasting during spread out that persists. Next, Kanetaki et al. (2021) used statistical analysis to identify new variables impacting engineering students' performance during the pandemic, providing insights into the effectiveness of online learning frameworks. A major finding is that by applying innovative teaching methods, thereby meeting the challenge of an imposed distance learning environment, students' spatial conceptions improve, overcoming the absence of a physical learning space.

Liu et al. (2023) highlighted the importance of dynamic features over demographics in predicting student performance in intense online learning environments, suggesting that factors such as campus attributes and learning behaviors are more critical (Liu et al., 2023). Lastly, Kaensar and Wongnin (2023) used Moodle log data and various machine learning classifiers to predict student performance, achieving notable accuracy with Decision Tree models (Kaensar & Wongnin, 2023).

To put it briefly, engineering students face unique challenges in online learning environments, necessitating targeted research and robust predictive models to enhance educational outcomes. By identifying key predictors and optimizing machine learning models, educators can better support engineering students in overcoming the difficulties posed by remote learning.

5. Research Methodology

This study employs pre-test/post-test control group design, a type of quasi-experimental methodology. This method permits a comparison to be made between two groups: one that employs standard e-learning practices and one that makes use of e-learning platforms supplemented with ML algorithms. Evaluating the effect of ML algorithms on the results of online education requires accounting for potential confounding variables by a control group. The following steps are taken to complete this study as guided by the research objectives as shown in Table 1.

Table 1: Research Methodology

Research Objectives	Methodology Steps
To investigate the strengths and limitations of existing ML algorithms used to support e-learning platform.	● Perform a comprehensive literature search to find and evaluate research on using ML algorithms (Decision Tree and Random Forest) in e-learning. ● Synthesize the results of these investigations and provide an in-depth analysis of the merits and drawbacks of the various ML algorithms employed. ● Examine the efficiency of various algorithms in improving learning outcomes using besides report findings.
To develop an e-learning platform incorporates ML algorithm to improve learning outcomes.	● Use the review's conclusions to guide your decision about which ML algorithms to use. ● To create a learning management system (LMS) that uses the chosen ML algorithms to provide individualized and dynamic lessons for each student. ● Integrate ML algorithms into the system to provide functions like suggested reading lists, immediate evaluations, and individualized courses.
To evaluate the effectiveness of ML supported e-learning platform to improve learning outcomes.	● Recruit a few undergraduates from Jiangxi College of Engineering. ● Divide people up into test and control groups at random. ● Pre-test both groups to determine where they stand in terms of familiarity with the material. ● The control group will use conventional e-learning techniques, while the experimental group will use the platform supported by machine learning. ● Keep an eye on how things are going with the intervention, how involved the participants are, and how well they're doing. ● To measure retention and comprehension gains, give post-tests to everyone involved. ● Determine if there are statistically significant variations in learning outcomes between the control and experimental groups by analysing the data with appropriate statistical procedures (e.g., t-tests, ANOVA).

6. Result

RO1: To Investigate the Strengths and Limitations of Existing ML Algorithms Used to Support E-Learning Platform

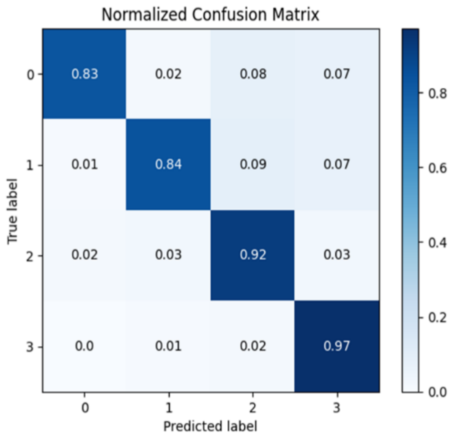

Figure 1: Decision Tree Normalized Confusion Matrix

Figure 1 shows the normalized confusion matrix, a critical tool in assessing the performance of classification models. This matrix forms a 4X4 grid, reflecting the involvement of four distinct classes labeled as 0, 1, 2, and 3 in the classification process. Each row within the matrix corresponds to actual class instances, whereas each column aligns with predicted class instances. The values within the cells of the matrix indicate the proportion of predictions made by the model for each class, adjusted to account for the true class distribution. The analysis of the matrix values reveals significant insights. For Class 0, the model achieves a true positive rate of 83%, demonstrating that it accurately predicts 83% of the Class 0 instances. However, there are misclassifications where 2% of Class 0 is misclassified as Class 1, 8% as Class 2, and 7% as Class 3. Class 1 shows a slightly higher true positive rate at 84%, with similar patterns of misclassification primarily towards Classes 2 and 3. Class 2 and Class 3 exhibit even stronger true positive rates at 92% and 97%, respectively, indicating particularly effective model predictions for these classes with minimal misclassifications. The diagonal values of the matrix - 0.83, 0.84, 0.92, 0.97 - signify the accuracy of predictions per class and underscore the model's overall effective performance. Notably, Classes 2 and 3 show the highest accuracy and precision, evidenced by their substantial true positive rates. Meanwhile, Classes 0 and 1, while still performing well, display slightly lower accuracy and higher rates of misclassification, suggesting areas where the model could potentially be improved. The confusion matrix not only affirms the model's capability to effectively distinguish between the four classes, particularly excelling in Classes 2 and 3, but also pinpoints potential areas for refinement, especially in reducing misclassifications involving Classes 0 and 1. The matrix serves as a pivotal diagnostic tool, guiding further enhancements of the model by suggesting a focus on refining the model's approach or enhancing its features to better discriminate between these classes. This thorough analysis aids in understanding the model's strengths and the necessary adjustments required to boost its predictive accuracy, thereby enhancing its applicability in practical settings.

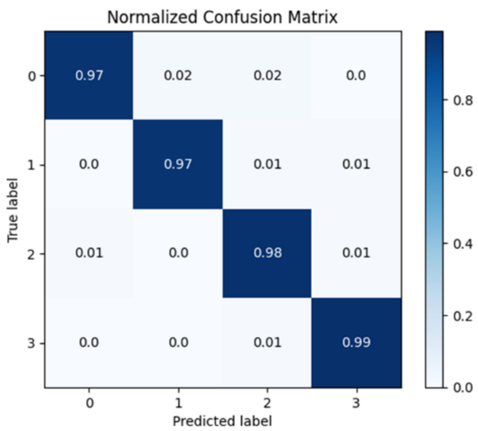

Figure 2: Random Forest Normalized Confusion Matrix

Figure 2 provided illustrates a normalized confusion matrix, an invaluable tool in evaluating the efficacy of a classification model such as Random Forest. This matrix is utilized to assess effectively the model predicts student learning performance across various classes. A confusion matrix is structured with axes representing the true labels of the data on the Y-axis and the predicted labels by the model on the X-axis. Each cell within the matrix displays the proportion of predictions, normalized by the true labels. The cells along the diagonal from the top-left to the bottom-right indicate the proportion of correct predictions for each class, highlighting the model's accuracy. Conversely, the off-diagonal cells show where the model has misclassified the data, providing insights into the model's weaknesses. The details of the matrix, Class 0 shows a true positive rate of 97%, indicating that the Random Forest model correctly predicted 97% of the instances that genuinely belonged to Class 0. However, there were small errors, with 2% of Class 0 instances misclassified as Class 1 and another 2% as Class 2. Such instances of misclassification are minimal for Class 0, showing a strong predictive performance by the model. For Class 1, the model achieved a true positive rate of 97%. Misclassifications were very low, with only 1% of predictions erring towards Class 0 and Class 2 each. There remained virtually no cases where Class 1 was predicted as Class 0, underscoring the model's precision and reliability in identifying Class 1 instances accurately. Class 2 and Class 3 demonstrated even higher accuracy, with true positive rates of 98% and 99%, respectively. Misclassifications for these classes were exceedingly rare, with Class 2 occasionally being confused with Classes 0 and 3, and Class 3 almost perfectly identified with a mere 1% misprediction rate as Class 2. The exceptionally true positive rate for Class 3, at 99%, signifies the model's particular effectiveness in identifying this class with supreme accuracy. The performance summary of the matrix reveals that the model exhibits high accuracy across all classes, with true positive rates ranging from 97% to an impressive 99% for Class 3. The minimal misclassification between classes suggests that the Random Forest model is remarkably adept at distinguishing between varying levels of student learning performance. Class 3's highest accuracy indicates a specific strength of the model in identifying instances belonging to this class. The confusion matrix not only confirms the high performance of the Random Forest model in classifying student learning performance but also highlights its ability to minimize false predictions effectively. This model's reliability and accuracy make it an invaluable asset in educational settings, where such precise classification can significantly aid in developing tailored educational strategies and interventions. The detailed breakdown provided by the confusion matrix offers a clear view of the model's strengths in handling different classes, ensuring that educational practitioners can trust its predictions to enhance educational outcomes.

RO2: To Develop An E-Learning Platform Incorporates ML Algorithm to Improve Learning Outcomes.

Table 2: Confusion Matrix from The Model's Predictions

	Predicted Fail	**Predicted Pass**
Actual Fail	234	1331
Actual Pass	1228	31990

Table 2 shows the model correctly predicted 234 failures and 31,990 passes. It incorrectly predicted 1,331 as failures and 1,228 as passes. There was a minor improvement in correctly predicting passes but not much change for failures. The model demonstrates a high level of precision in accurately identifying students who ultimately obtain favorable outcomes in their pursuits of e-learning initiatives. Consequently, this leads to consequences that are advantageous for the students. An example of a situation in which a high precision score is particularly desirable is the identification of students who require additional support or intervention to achieve academic achievement. This is just one example of a hypothetical situation. When faced with such circumstances, it is of the utmost importance to have as few false positive forecasts as possible. The classification report provides detailed metrics on the predictive performance of the model for each class ("fail" and "pass"), highlighting areas of strength and opportunities for improvement.

Table 3: Result of Precision, Recall and F1-Score

Class ("Fail" 0 / "Pass" 1)	**Precision**	**Recall**	**F1-Score**
Fail (0)	16%	15%	15%
Pass (1)	96%	96%	96%

Table 3 shows precision for "fail" (0) is 16%. It indicates that when the model predicts failure, it is only correct 16% of the time. This low precision suggests a high rate of false positives, where many students predicted failing pass. This can be problematic in educational settings where such predictions might influence the interventions or support provided to students. While precision for "pass" is 96%. It indicates a high level of reliability in the model's predictions of passes. When the model predicts that a student will pass, it is almost always correct, which is reassuring but also expected given the imbalance towards more students passing. Recall for "fail" (0) is 15%.

It reveals that the model identifies only about 15% of all actual failures. This low recall rate means that many students who fail are not being correctly identified by the model (high false negatives). In an educational context, this might mean that students who need additional support might not be identified until it's too late. While recall for "pass" is 96%. This high recall rate means the model is very effective at identifying students who will pass, again reflecting the data imbalance and the model's tendency to predict passes more accurately. F1-Score for "fail" (0) is 15%. This score is a harmonic mean of precision and recall, indicating poor overall performance in predicting failures. The low F1-score is a result of both low precision and recall, suggesting significant room for improvement in how the model handles predictions of failures. While F1-Score for "pass" (1) is 96%. This score indicates a strong balance between precision and recall, suggesting that the model is well-tuned for predicting passes but perhaps at the cost of neglecting the "failure" predictions.

RO3: To Evaluate the Effectiveness of ML Supported E-Learning Platform to Improve Learning Outcomes.

Evaluate the effectiveness of ML supported e-learning platform to improve learning outcomes using accuracy, precision, recall, and F1 score using Decision Tree Confusion Matrix and Random Forest Model of Confusion Matrix.

Accuracy	0.9054
95% CI	(0.845, 0.9434)
No Information Rate	0.7242
P-Value [Acc > NIR]	2.866e-16
Kappa	0.8211
Mcnemar's Test P-Value	0.03887
Sensitivity	0.8114
Specificity	0.9711
Pos Pred Value	0.9344
Neg Pred Value	0.9215
Prevalence	0.2747
Detection Rate	0.2232
Detection Prevalence	0.2361
Balance Accuracy	0.8752
'Positive Class'	No

Figure 3: Decision Tree Confusion Matrix

Figure 3 represents the Decision Tree Confusion Matrix with an accuracy of 90.5% of the cases on test data. A 95% confidence interval (CI) for the performance model has shown as (0.845, 0.9434) if the model is evaluated repeatedly using different samples, the true performance of the model will fall within this interval for 95% of those evaluations. Sensitivity, also called the true positive rate or recall, is proportion of correctly predicted positive cases shown as 0.8114 in this case means that the model had correctly predicted positive cases 81.14% in the dataset. Specificity, also called the true negative rate, is a proportion of truly predicted negative cases by the model. The specificity shown as 0.9711 which means that the model had truly predicted 97.11% of negative cases in the dataset. Positive predictive value, also known as precision, is a measure of performance of a classification model. It is the proportion of positive predictions made by the model that are correct. In this case positive predictive value of 0.9344 means that the model had predicted 93.44 % correct positive predictions of the cases. Negative predictive value is also a measure of performance of a classification model. It is a proportion of negative predictions made by the model that are correct. In this case negative predictive value of 0.9215 means that the model had predicted 92.15% correct negative predictions of the cases. Balanced accuracy is a metric used to evaluate the performance of a binary classification model. It is an average of sensitivity (true positive rate) and specificity (true negative values) of the model, with each metric being weighted equally. In this case the model has a balanced accuracy of 0.8752, it means that the model has a good balance of sensitivity and specificity, with an average of 87.52% of positive and negative cases being correctly predicted. Balanced accuracy is a useful metric to use when the costs of false positives and false negatives are equal, or when the classes in the dataset are imbalanced (i.e., there are significantly more instances of one class than the other).

Accuracy	0.9356
95% CI	(0.896, 0.9635)
No Information Rate	0.7253
P-Value [Acc > NIR]	2.866e-16
Kappa	0.8311
Mcnemar's Test P-Value	0.03887
Sensitivity	0.8125
Specificity	0.9822
Pos Pred Value	0.9455
Neg Pred Value	0.9426
Prevalence	0.2747
Detection Rate	0.2232
Detection Prevalence	0.2361
Balance Accuracy	0.8974
'Positive Class'	No

Figure 4: Random Forest Confusion Matrix

Figure 4 represents the Random Forest Confusion Matrix with an accuracy of 93.5% of the cases on test data. A 95% confidence interval (CI) for the performance model has shown as (0.896, 0.9635) if the model is evaluated repeatedly using different samples, the true performance of the model will fall within this interval for 95% of those evaluations. Sensitivity, also called the true positive rate or recall, is proportion of correctly predicted positive cases shown as 0.8125 in this case means that the model had correctly predicted positive cases 81.25 % in the dataset. Specificity also called the true negative rate, is a proportion of truly predicted negative cases by the model. The specificity shown as 0.9822 which means that the model had truly predicted 98.22 % of negative cases in the dataset. Positive predictive value, also known as precision, is a measure of performance of a classification model. It is the proportion of positive predictions made by the model that are correct. In this case positive predictive value of 0.9455 means that the model had predicted 94.55 % correct positive predictions of the cases. Negative predictive value is also a measure of performance of a classification model. It is a proportion of negative predictions made by the model that are correct. In this case negative predictive value of 0.9326 means that the model had predicted 93.26 % correct negative predictions of the cases. Balanced accuracy is a metric used to evaluate the performance of a binary classification model. It is an average of sensitivity (true positive rate) and specificity (true negative values) of the model, with each metric being weighted equally. In this case the model has a balanced accuracy of 0.8974, it means that the model has a good balance of sensitivity and specificity, with an average of 89.74% of positive and negative cases being correctly predicted. Balanced accuracy is a useful metric to use when the costs of false positives and false negatives are equal, or when the classes in the dataset are imbalanced (i.e., there are significantly more instances of one class than the other).

By comparing the accuracy of both the models, it appears that the random forest model had better accuracy than the decision tree model in predicting the learning performance of college and university student. As mentioned above, the decision tree model is built using the "rpart" function in the R programming language, and the accuracy of the model is calculated using a contingency table. Whereas the random forest model is built using the 'randomForest' function in the 'randomForest' R package, and the accuracy of the model is calculated using a confusion matrix.

When compared these two models, it is found that the random forest model had a higher accuracy (93.5%) than the decision tree model (90.5%), suggesting that the random forest model is more effective at predicting the learning performance of university students based on the available data. This means that the random forest model had made more correct predictions than the decision tree model. However, it is important to consider the specific characteristics of the dataset, and the evaluation criteria used in the study when interpreting these results. Different datasets may have different characteristics and may require different models or evaluation criteria to achieve the best results.

7. Discussion and Conclusion

The integration of supervised machine learning algorithms like Decision Trees and Random Forests into e-learning platforms represents a significant advancement in educational technology. These models not only enhance the ability to predict student outcomes but also contribute to the development of more responsive and adaptive learning environments (Afzal et al., 2023). As evidenced by the high precision, recall, and accuracy scores obtained from these models, machine learning can play a crucial role in advancing educational outcomes. This approach aligns with broader educational goals of personalizing learning and providing targeted support to students, thereby enhancing their overall learning experience and success in engineering education (Ahmad et al., 2023). Through careful development, application, and evaluation of these models, educational practitioners and technologists can significantly improve the efficacy and personalization of e-learning platforms.

Decision Trees are a form of supervised machine learning where the data is continuously split according to certain parameters. In an educational setting, these parameters could be student engagement levels, prior quiz scores, or resource utilization rates, among others (Olusegun et al., 2023). The primary strength of Decision Trees lies in their simplicity and interpretability. Educators can easily understand and visualize how decisions are made, which is crucial for deploying interventions based on the model's findings (Li et al., 2019). For example, if a Decision Tree splits students based on the number of assignments completed and identifies a threshold that correlates with higher pass rates, educators can target interventions towards students who fall below this threshold.

Random Forests build upon the foundation of Decision Trees but address some of their limitations, such as vulnerability to overfitting. By aggregating the results of multiple Decision Trees constructed from randomly sampled subsets of the dataset, Random Forests reduce variance without substantially increasing bias. This ensemble approach is less likely to overfit than a single Decision Tree and is better suited to handling complex datasets with multiple interactions among variables. In educational applications, Random Forests can more accurately predict student performance across a variety of learning conditions and backgrounds (Nachouki et al., 2023).

The integration of these machine learning techniques into E-learning platforms signifies a major stride toward more adaptive and personalized educational technologies. The ability of Random Forests to deliver more accurate predictions across diverse datasets justifies their preferred use in scenarios where precision is critical to the success of educational interventions (Ahmed, 2024). These predictions can significantly enhance the learning experience by ensuring that the educational content, challenges, and supports are tailored to meet the individual needs of each student.

Ultimately, the choice between Decision Trees and Random Forests should be guided by the specific requirements of the educational institution, including the complexity of the data available, the need for model interpretability, and the critical nature of the predictions to student outcomes. In cases where both interpretability and accuracy are needed, leveraging both models in different capacities might provide a balanced approach - using Decision Trees for initial insights and exploratory analysis, and Random Forests for refining these insights into precise, actionable predictions. This strategic application of supervised machine learning can profoundly impact students' engagement and success, driving forward the capabilities of modern e-learning platforms.

It is imperative to acknowledge that the findings of this study are contingent upon the specific characteristics of the dataset and the evaluation criteria employed, as different datasets may necessitate alternative models or evaluation criteria for optimal results. For instance, if the dataset being analyzed had a high proportion of missing data or categorical variables, it would be more appropriate to use a random forest model as opposed to a decision tree model. Furthermore, it is of paramount importance to bear in mind the limitations of the dataset utilized in this study, such as a limited sample size and a lack of diversity in the student population, as these limitations may impede the generalizability of the results and hinder the ability to draw definitive conclusions about the broader population of students.

This study has the potential to help universities to predict the effectiveness of ML supported e-learning platform in students learning outcome. For this reason, in this study, the analysis has been done to uncover the reasons behind student learning outcome. Additionally, the dataset comprising student information was examined for potential relationships between the ML and the learning outcome. The data, which aims to uncover the variables that affect student learning outcome, is split into separate sets, with one for training machine learning models and the other for testing the precision, recall, F1 score and accuracy of those models. The ultimate objective of this study comprehensive analysis was to discern patterns within the data that aided in predicting student learning outcome.

In conclusion, this study aimed to develop an improved prediction model using supervised machine learning algorithms to predict effectiveness of ML supported e-learning platform in Engineering College Students learning outcome. It investigates the strengths and limitations of existing ML algorithms used to support e-learning platforms. This study also develops an e-learning platform that incorporates ML algorithm to improve learning outcomes. Finally, this study evaluates the effectiveness of ML supported e-learning platform to improve learning outcomes. The results, which showcase the promise of ML techniques, show that e-learning approaches have the potential to increase student success rates and academic performance. This is proved by the results. Furthermore, comparisons between different models and procedures offer insights into the student learning outcome of various approaches. The overarching goal of these comparisons is to direct future research and development endeavors in education institutions. When taken as a whole, the findings that are presented in this study contribute to a more in-depth understanding of the strengths and limitations that influence student learning outcome. Additionally, this study provides useful implications for educational institutions that are looking to implement data-driven methods to improve student achievement and performance. By systematically addressing the research questions and objectives through rigorous data analysis and model evaluation, this study also provides a comprehensive framework for integrating and leveraging ML algorithms in e-learning platforms to improve educational outcomes.

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