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Research Article

Explainable AI Methods for Predicting Student Grades and Improving Academic Success

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ABSTRACT

Introduction: This study explores applying Explainable Artificial Intelligence (XAI) techniques to predict student performance in educational settings. Predicting student outcomes in advance has become more accurate with the help of AI and machine learning. However, there is a lack of clarity in many AI models and their predictions, which are termed black box models. This is a significant problem in the education industry because it can erode administrators' and educators' faith in the explainability or openness of predicted outcomes.

Objectives: This research aims to reduce the shortcomings of traditional AI models by making them more understandable using XAI. XAI provides stakeholders with a better understanding of the underlying logic of the predictions to make better decisions. By utilizing XAI techniques, this paper provided valuable and reasonable intelligence-driven student grade predictions to increase confidence in AI systems. These interpretable predictions will guide students who may perform poorly at the very early stage.

Methods: This research employs XAI techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to explain the predictions. Students' performance scores, such as quizzes, midterm examinations, practical tests, assignments, and activities were used as features to predict the final grades using the Random Forest Classifier (RFC). The investigation uses Partial Dependence Plots (PDPs), SHAP, and LIME to improve the comprehension of the model's predictions.

Results: Applying these XAI techniques will enhance comprehension of the critical features impacting student performance. The results provide clear insights into the areas students can improve to achieve higher grades. They also provide a broader view of the factors that influence academic accomplishment or failure, aiding educators and stakeholders in making proper decisions.

Conclusions: The findings demonstrate that using XAI in student performance data will provide transparency in predicting results. The outcome of this research will help create more effective instructional techniques, and students can improve their weaknesses.

Keywords: explainable artificial intelligence, student performance prediction, shapley additive explanations, local interpretable model-agnostic explanations

INTRODUCTION

Educational research predicting student performance has been developed to the extent of being used to discover students who perform well. The development of AI is aimed at more accurate prediction of academic performance and is a specific positive trend with the implementation of data-driven systems. However, a machine learning model can obtain a big picture by relating various factors and statistics. This approach allows more individualized learning instruction and better student performance in general [1][2]. Conversely, an important issue in educational contexts is the transparent nature of many AI models, also known as "black box" models. It is challenging for educators and administrators to trust and successfully implement these models because of this lack of openness [3]. The solution to this issue is Explainable AI (XAI). The stakeholders, especially educators, students, and administrators can comprehend the reasoning behind AI predictions using XAI to make machine learning models more transparent and interpretable. In education, where choices significantly influence students' academic careers, the interpretability of AI models is critical. Improved educational results and increased trust in AI-driven judgments are made possible by techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), which offer insights into the underlying causes driving predictions [4][5].

There is a shortage of research on the specific applications of XAI approaches to enhance academic predictions, especially in determining the elements that impact student performance most [6][17][20]. This study aims to bridge the knowledge gap and enhance AI predictions in education using XAI methods. By emphasizing explainability, this study attempts to increase confidence in AI-driven predictions by ensuring that predictions are practical and understandable. The findings will provide educators, administrators, and legislators with a greater understanding of how AI can be used to predict academic progress and guide decision-making. This study also has the practical ramifications for enhancing educational practices, specifically in terms of customizing interventions for students at risk of underperforming, which will result in a more effective and balanced learning environment [7][21]. The primary objective of this study was to determine how well explainable AI methods can predict student grades and enhance academic performance. This study aims to create a predictive model that analyzes the main variables affecting student performance by employing machine learning algorithms and explainability tools such as SHAP and LIME. This demonstrates how these features such as the assessments might help students' academic development. Data from various fields of study are included in the study's scope to guarantee an extensive understanding of the features influencing student achievement in diverse subject areas [8] [9].

The remainder of this paper is organized as follows: Section II reviews the relevant research in the areas of XAI and AI-based student performance prediction. Section III outlines the process of creating the prediction model, including the methods for gathering and analysing data. Section IV presents the study's findings, with knowledge from explainable AI as the primary focus. Section V concludes by discussing the significance of the findings and suggestions for further study and application in the field of educational AI.

LITERATURE REVIEW

The integration of (XAI) into education has significantly transformed the landscape of student performance prediction. This review focuses on the intersection of machine learning models and XAI techniques when predicting student performance, it examines the datasets, methodologies, and role of XAI in providing interpretability and actionable insights. The review is structured as follows: First, it examines predictive models for student performance and discusses prevalent methodologies and datasets. Next, it highlights the applications of XAI in education, presenting notable studies and their contributions to interpretability. The challenges involved in implementing XAI techniques in educational settings are explored. The review concludes with a synthesis of the findings, identification of research gaps, and recommendations for future work.

Decision Trees, Random Forests, Support Vector Machines (SVM), Neural Networks, and ensemble methods are widely used models for predicting student performance. Recently, deep learning models and hybrid approaches have also gained attention owing to their ability to handle complex patterns and relationships in data. Datasets sourced from Learning Management Systems (LMS), online courses, or academic records presents challenges include data sparsity, missing values, and the lack of standardization across datasets. The robustness and comprehension of Decision Trees and Random Forests make them important options. Chen et al.'s study [10] improved the accuracy of forecasts, but it was only usable in online situations and required more evaluation in conventional classrooms. By analyzing features from version control logs, Canale et al. [11] focused on how well students score on exams and found a high correlation between academic success and coding habits. However, this method's broader usefulness was limited because it was only available to students who used version control systems. Other studies aimed at AI's application in specific educational fields. Galvez et al. [12] applied process-oriented taxonomy in medical training to improve learning outcomes in surgical procedures. However, our results cannot be applied to other medical training areas because they are limited to a particular medical intervention. Similarly, Guo et al. [13] used functional near-infrared spectroscopy data to predict programming ability using an attention-based convolutional neural network (CNN). Although this method effectively connected programming ability to brain activity, its high cost necessitated neuroscience equipment, which prevented its widespread adoption.

To predict student performance, researchers have explored graph-based models and attention mechanisms. Wang et al. [14] introduced a heterogeneous learning interactive graph knowledge tracing model that integrates psychological factors into learning predictions. While the model effectively captured complex student behaviors, it also struggled with interpretability. Similarly, Li et al. [15] proposed a two-way attention approach to enhance predictions of academic success by incorporating student interaction data. Although this method improved accuracy, it largely depended on high-quality interaction datasets, which are often challenging to obtain. Numerous studies have identified the advantages of deep learning in educational AI applications. Islam and Khan [16] used structural equation modelling to evaluate the effectiveness of deep learning across various academic fields, highlighting its role in recognizing complex patterns. Nonetheless, the intricate nature of deep learning models often poses challenges relative to interpretability. Lakshmi and Maheswaran [22] tackled this problem by implementing a Gated Recurrent Unit (GRU) model optimized with Analysis of Variance (ANOVA), which enhanced the accuracy of grade predictions. Despite these improvements, deep learning models are computationally demanding and require significant data preprocessing.

Researchers have begun incorporating Explainable AI (XAI) methods into scholarly prediction frameworks to enhance model interpretability. Using XAI, Ujkani et al. [19] identified students who were at risk in course-level performance evaluations. Although this approach provided insightful information, it was limited to specific courses, suggesting that more extensive validation is required. The potential of AI-driven academic interventions was demonstrated by Afzaal et al. [23] and Afzaal et al. [24], who developed XAI-based feedback and suggestion systems to promote student self-regulation. However, the applicability of these models to other courses is limited because they were primarily assessed using datasets related to programming instruction. Fuzzy categorization, ensemble learning, and belief rule-based systems are other AI techniques that have been studied. A fuzzy ordinal classification system for academic performance prediction was proposed by Gámez-Granados et al. [25]. It successfully controlled the uncertainty but required complex parameter adjustment. Yan and Liu reported an ensemble model for student recommendations [26]. It had high prediction accuracy but had interpretability problems. Although these techniques were still computationally demanding, Zhang et al. [27] and Liu et al. [28] enhanced belief rule-based models to balance interpretability and accuracy in forecasting student achievement. Ben George et al. [29] evaluated incremental learning classifiers for predicting student performance across semesters and identified Aggregated Mondrian Forest (94%) and KNN (93%) classifiers as the most accurate but computationally expensive models.

The most significant challenge in applying XAI in the educational domain is that the datasets often contain diverse and multi-dimensional features, making interpretation challenging. Additionally, scalability issues in XAI techniques, such as LIME, struggle to handle large-scale data in real-time scenarios. Also, one of the main challenges are the bias and fairness in machine learning models and ensuring equitable interpretations across diverse student groups. Additionally, the majority of XAI's current educational applications are found in higher education, with little study being done in undergraduate levels. One of the gaps is the limited integration of XAI in real-time adaptive education environment, restricting its potential to enhance personalized education [18]. Additionally, the lack of standardized metrics for evaluating the interpretability of AI models in education. Also, Diverse student demographics are underrepresented in current research. To ensure that explainable AI (XAI) is utilized more broadly and equitably in education, these gaps need to be addressed. The XAI ensures that the explanations provided are meaningful and actionable for educators and students. Recent studies show how well XAI methods like SHAP and LIME work to provide clear predictions and build confidence in AI-driven judgment.

METHODS

Figure 1 indicates that the investigation collected information on a range of pupil performance metrics, including assignments, activities, quizzes, midterm exams, and practical tests. The pedictive models are constructed using these data sources as attributes. The dataset, which focuses on performance outcomes as the dependent variable, was gathered from one of Oman's most reputable higher education institutions, guaranteeing a varied depiction of learning contexts.

The Random Forest (RF) classifier is the main machine learning framework for forecasting student outcomes. The RF classifier was selected owing to its resilience and capacity to manage several parameters with comparatively high accuracy. The model undergoes training using previous student data to forecast future educational achievement based on previously described attributes. Techniques for Explainable AI: Two XAI approaches were employed to solve the problem of model interpretability and raise stakeholders' confidence in forecasting.

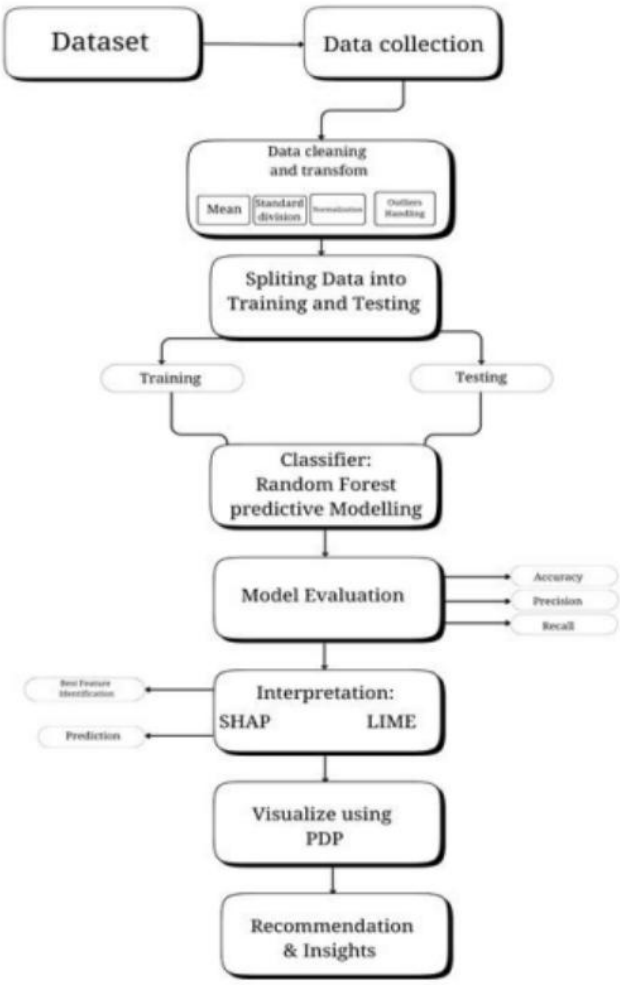

Figure 1: Proposed Methodology

The SHAP values consistently indicate each feature's influence on the prediction. This method describes how each unique feature (such as quiz results, midterm results, etc.) influences the model's output for a particular student. SHAP Summary Plots can illustrate the significance of various features throughout the dataset, and the SHAP values are used to determine the primary elements that influence projections. LIME was used to understand how the algorithm's estimates differ for different circumstances (students). By altering the input data and tracking any modifications in expectations, LIME produces interpretable insights that highlight the characteristics responsible for a particular student's expected success. This approach provides insights into areas for development by illuminating local causes for why particular students are expected to perform satisfactorily or not.

With other features held constant, PDPs illustrate the connection between a feature and the anticipated result. Charting these associations, PDP demonstrates how modifications to a particular aspect (such as quiz performance) affect student performance. The use of PDPs can highlight nonlinear correlations and interactions among characteristics that might not be immediately obvious from the raw results. To ensure that the framework produces accurate projections, the Random Forest classifier's efficiency is assessed using conventional measures, including accuracy, precision, and recall. In the model evaluation phase, educators' and administrators' user feedback is used to gauge how well the XAI techniques improve interpretability by gauging their comprehension of the model's logic and their comfort level with AI-driven forecasts for decision-making processes. Our proposed model outperformed the others.

RESULTS

This section provides a comprehensive analysis of the performance of the Random Forest classifier in predicting student academic performance, as well as the interpretability gained from the XAI methods. The performance outcome is obtained from a student performance dataset, such as a quiz, midterm exam, practical test, assignment, and activity marks. Explainability techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are applied to interpret the model predictions and understand key factors driving student success.

The confusion matrix provides a detailed breakdown of the model's performance in terms of grades. As shown in Figure 2, the model achieved high performance for grades A, A-, C, C-, D, and F but minor misclassifications were found for B and B+ grades and C+ and B- grades, suggesting similar feature distributions. The classification report indicates that the model can predict with 92 % accuracy and a weighted F1-score of 0.90. This shows that the model is highly reliable in predicting grades. The model also derives perfect precision and recall for grades A, C-, D, and F, but there is relatively less recall and F1-scores for grades B and B+. These results confirm the robustness of the model and highlight areas for further tuning. The feature engineering and interpretability methods (SHAP, LIME) yielded more interpretable results

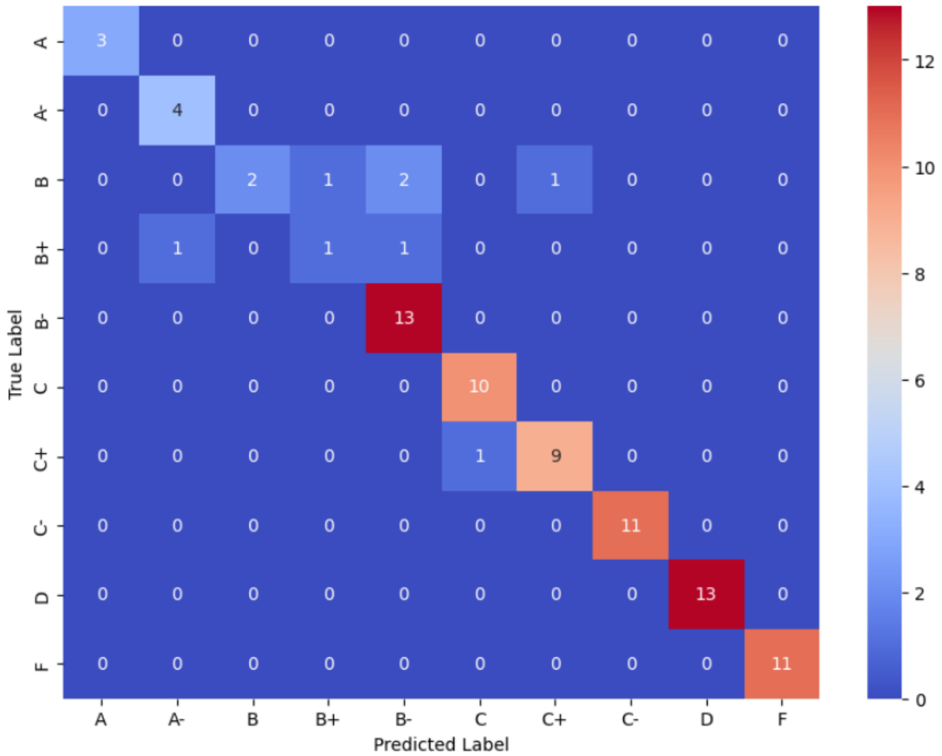

Figure 2: Confusion Matrix for Random Forest Predictions

A more comprehensive study of feature contributions across predictions was conducted using global interpretability analysis with SHAP. Figure 3 SHAP summary plot showing how different student performance indicators affect the model's predictions. The SHAP value, which indicates the extent to which a feature influences the projected grade, is indicated by the position of each dot on the x-axis, representing a data point. The distribution of feature values was represented by a color gradient ranging from blue (low values) to red (high values). Assignment and midterm scores have a significant favorable influence, with greater values typically pushing the model toward higher grades.

The distributions of quiz marks and practical exam scores are more diverse, suggesting that their impact may vary depending on the circumstances. These two assessments have neutral effects in some situations but continue to impact particular student predictions, as seen by the concentration of points around zero. One important finding is that activity marks have a smaller impact on final grades, despite their influence on student outcomes. This suggests that structured assessments, such as midterms and assignments, have a more influence on predicting strong or poor performance than in-class participation alone. According to the summary plot, students who want to improve their marks should prioritize doing well on midterm examinations and assignments. This analysis aids in understanding the transparency of the model and identifies the academic components that contribute most significantly to classification decisions.

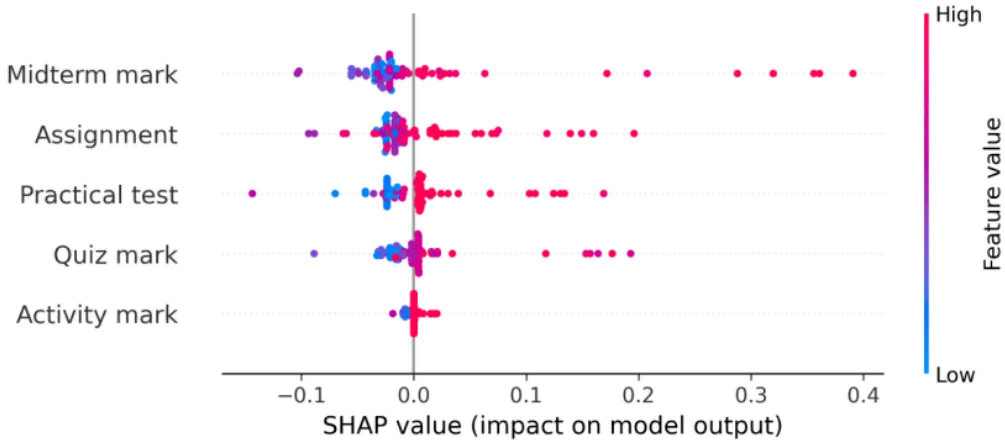

Figure 3: SHAP Summary Plot for Global Interpretability

A random student who received a B- grade was selected to understand the factors contributing to a specific student's performance. The SHAP force plot in Figure 4 reveals that the students' midterm marks (14.5) and Assignment marks (13.75) were the primary contributors to their final grade. These two scores were above the failing threshold, but the student did not achieve a higher grade. The Quiz mark (5.0), Practical test mark (9.75), and Activity mark (5.0) were almost close to the maximum marks but had minimal impact on the final grades.

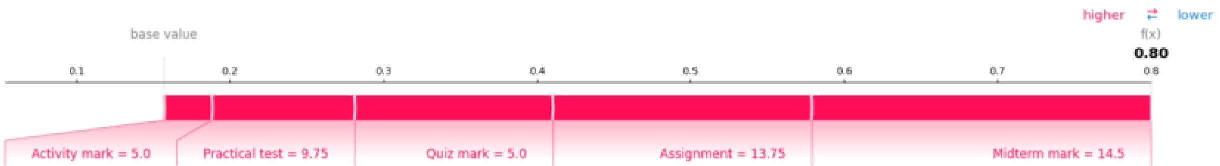

Figure 4: SHAP Force Plot for Individual Prediction

The LIME explanation given in Figure 5 highlights the thresholds for each feature that contributed to the B- grade. The LIME local explanation plot illustrates the key features influencing the model's prediction for a student classified as B-. The horizontal bars represent the impact of each feature on the final classification, where red indicates a negative influence and green indicates a positive influence. In this figure, the Quiz mark between 4.75 and 6.00 has the most significant effect, strongly contributing to the prediction of B- grade. Similarly, Practical tests with marks ranging between 7.5 and 9.75, assignment marks between 12 and 14 and midterm marks between 11 and 14.5 also play a crucial role in this classification of the B- grade. The Activity mark had a negative score, suggesting that it had a relatively weaker influence on the final grade. This analysis helps explain how different academic components affect student performance predictions and provides transparency into the model's decision-making process.

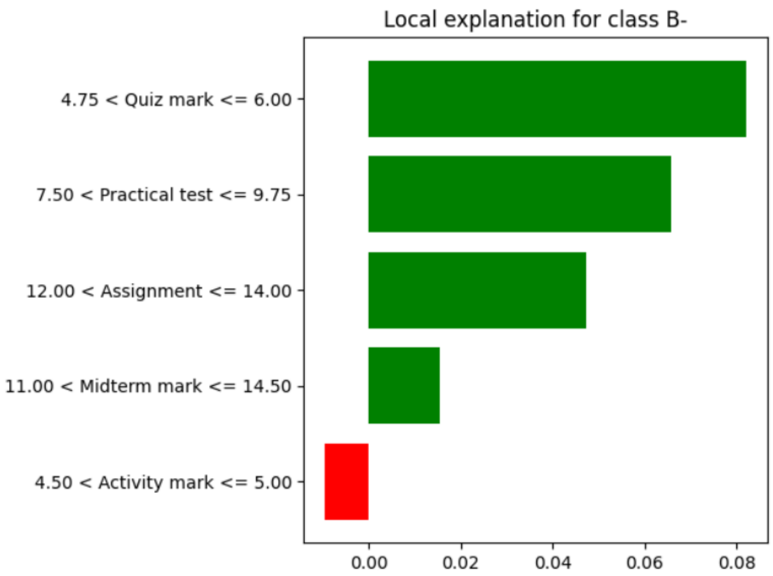

Figure 5: LIME Feature Importance Plot for Grade B-

The SHAP interaction value plot in Figure 6, explores the interactions between features and their combined impact on student performance. The x-axis displays the SHAP interaction value, which demonstrates how the combination of two variables affects the model's output. Each dot represents an interaction effect between two features. The plot shows a significant positive correlation between midterm, quiz, and assignment scores, indicating that students who do well on these measures have a high chance of passing. The sparse distribution of specific characteristics, such as the Practical test and the activity mark, suggests that their interactions less strongly impact the model's decision-making.

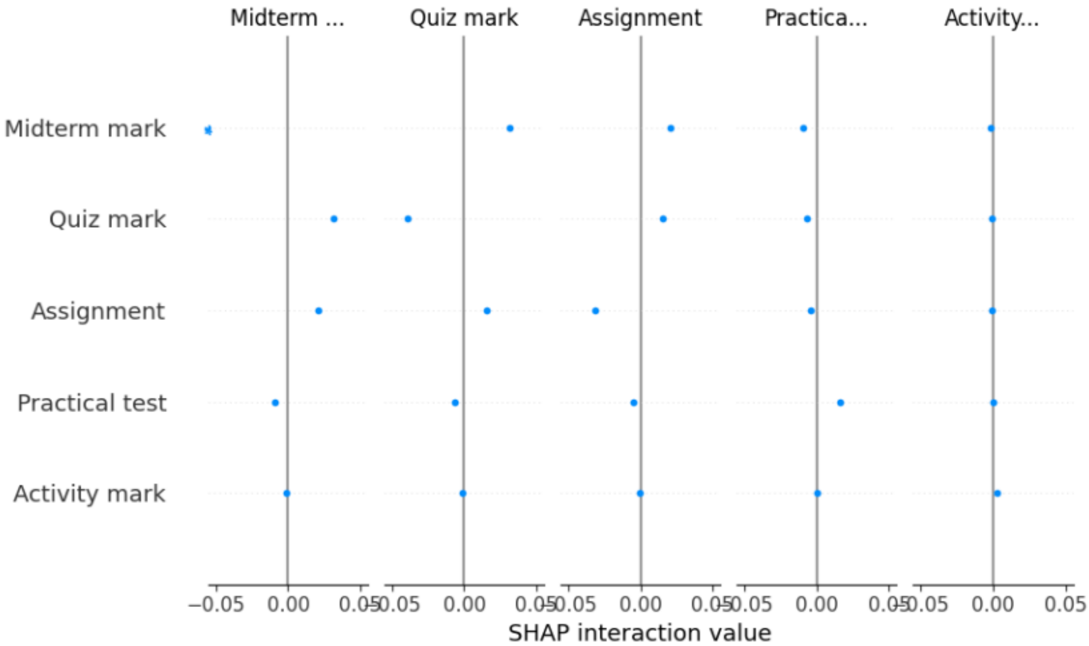

Figure 6: SHAP interaction plot

The Partial Dependence Plot in Figure 7 highlights the primary factors influencing the students' grade predictions. The features that exhibit the most substantial positive relationships with final grades are the quiz and midterm scores. The model's output rose considerably when the quiz scores exceeded five and midterm scores exceeded 14. Assignment scores show a notable increase in significance for scores greater than 10 points. In addition, the practical test scores influenced the predictions if they rose above 7, suggesting a moderate contribution. Activity marks consistently increase despite having a relatively lesser impact, indicating that participation and engagement affect final performance.

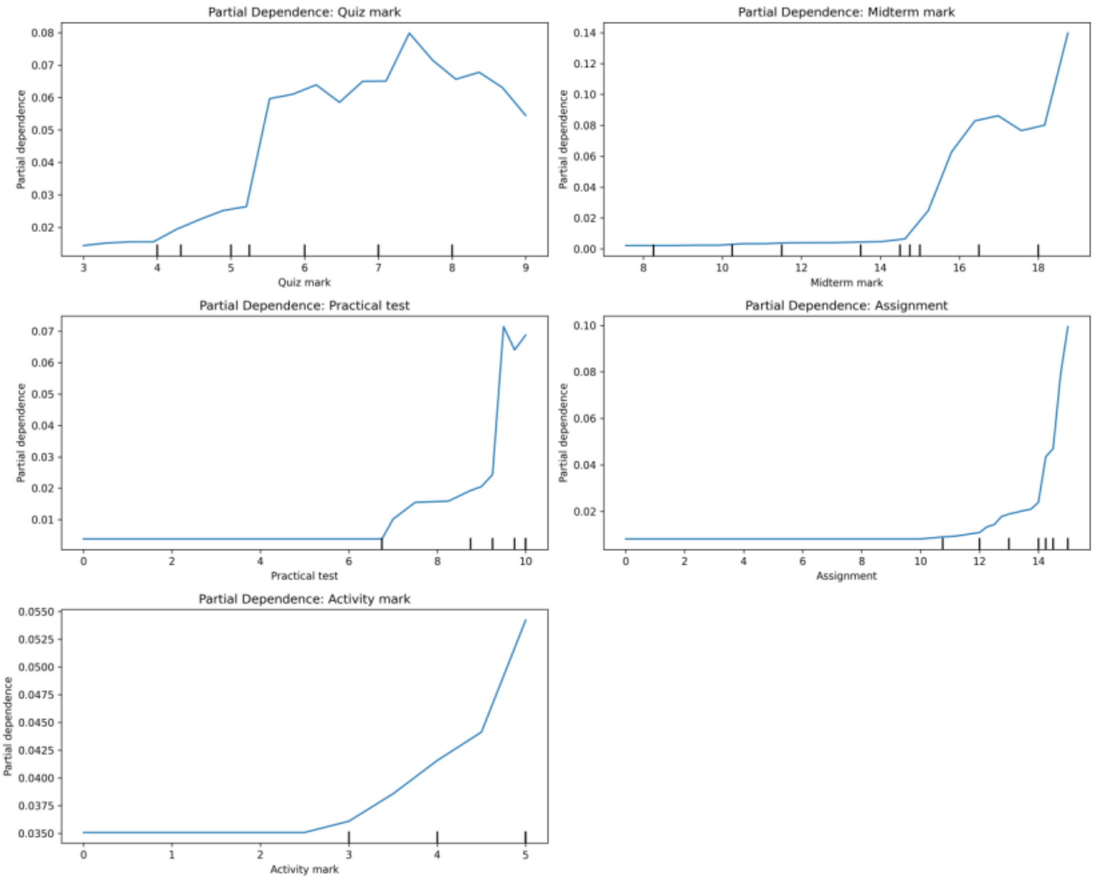

Figure 7: Partial Dependence Plot

DISCUSSION

Based on the XAI analysis of student performance prediction, the following strategies were recommended for improving students' grades. All assessments are important for students to achieve good grades. Based on the data analyzed, midterm examinations and assignments were the most influential factors in determining student success. Students should allocate more time and resources to prepare for midterm exams and complete assignments. It is also recommended that Quiz and Practical Test Performance be improved because these features have a moderate impact but still contribute to overall performance. Regular practice and targeted study can help students improve in these areas. Activity marks have the slightest impact but must boost overall grades. These indicate the assessments that students must focus on to achieve better grades.

The results show the power of XAI techniques in delivering insightful information into student performance. By defining the key features that affect grades and understanding their interactions, educators and students can come up with targeted strategies to improve academic results. The findings demonstrate the critical role of midterm exams and assignments, while also emphasizing the importance of a balanced approach to academic preparation. These insights can inform interventions and support systems to enhance student success.

CONCLUSION AND FUTURE WORK

The research paper explored ways to predict student academic performance and explore the results using XAI. The students' grades were predicted using a Random Forest Classifier, which achieved an impressive accuracy rate of 90%. The key factors influencing the prediction of the student grade were identified through explainability techniques such as SHAP and LIME. The findings revealed that midterm marks, Quiz scores, and Assignment were the most critical features determining students' grades. The individual student case studies provided clear insight into the model's decision-making process and demonstrated the role of features in predicting the final grades. These revelations highlight teachers' and students' use of predictive models when making academic decisions and interventions. Future research should explore the integration of behavioral and engagement data such as attendance, participation in learning platforms, and study habits to develop a more comprehensive predictive model. In addition, using deep learning models against traditional classifiers can further optimize prediction accuracy.

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