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Development of a Machine Learning Cumulative GPA Prediction Model using Explainable AI

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ABSTRACT Predicting student academic performance is an important component of academic early warning systems in higher education. Although previous studies have achieved high predictive accuracy using machine learning techniques, many models remain black-box systems, limiting their interpretability and practical use in academic decision-making. This study aims to develop an accurate and interpretable framework for predicting students' Cumulative Grade Point Average (CGPA) using Educational Data Mining and Explainable Artificial Intelligence (XAI). The study follows the Knowledge Discovery in Databases (KDD) framework, including data preprocessing, normalization, feature selection, modeling, and interpretation. Three machine learning algorithms, namely Random Forest, XGBoost, and Support Vector Machine (SVM), were evaluated using 10-fold cross-validation with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). SHAP and LIME were employed to provide global and local explanations of prediction outcomes. The results show that XGBoost achieved the best performance with a MAE of 0.097 and an RMSE of 0.117. Previous GPA, attendance percentage, and study hours per day were identified as the most influential predictors. The proposed framework supports transparent and evidence-based academic interventions in higher education.

KEYWORDS: educational data mining, machine learning, academic performance prediction, student academic performance, explainable artificial intelligence

I.INTRODUCTION

The high rate of student dropouts and the low rate of on-time graduation have become major challenges in higher education institutions in Indonesia. Data from Pangkalan Data Pendidikan Tinggi (PDDikti) indicate that the completion rate of undergraduate students within the expected study period remains relatively low, while dropout rates in the early years of study continue to increase [1]. These conditions affect institutional efficiency, accreditation performance, and the achievement of national higher education quality indicators. To address these issues, Law No. 12 of 2012 emphasizes the importance of information systems as instruments of transparency, accountability, and educational quality assurance. This policy is reinforced through the Regulation of the Minister of Research, Technology, and Higher Education No. 61 of 2016, which establishes PDDikti as the official national higher education database and the foundation for evidence-based policy development [2]. Consequently, universities are increasingly encouraged to implement data-driven Early Warning Systems (EWS) capable of identifying students at risk of academic failure and delayed graduation. However, the implementation of predictive systems must also comply with Law No. 27 of 2022 concerning Personal Data Protection, which highlights the principle of privacy by design. Therefore, higher education institutions require predictive models that are not only accurate but also transparent, interpretable, and institutionally accountable.

In recent years, Educational Data Mining (EDM) and machine learning approaches have been widely adopted to predict student academic performance and graduation outcomes [3]. Previous studies demonstrate that machine learning algorithms such as Decision Tree, Random Forest, Support Vector Machine (SVM), and ensemble-based methods are capable of identifying academic patterns and improving prediction accuracy compared to conventional statistical approaches [3],[4]. Systematic reviews further indicate that recent research trends have shifted toward ensemble learning and advanced predictive models because of their ability to capture non-linear relationships in educational datasets [3],[5]. Random Forest has been widely utilized due to its robustness against overfitting and its effectiveness in handling heterogeneous educational data [4],[6]. XGBoost has gained significant attention because of its high predictive performance, optimization efficiency, and capability to model complex feature interactions through gradient boosting mechanisms [7],[8]. Meanwhile, SVM remains relevant for educational prediction tasks because of its strong performance in high-dimensional data spaces and its ability to generalize effectively even with limited datasets [5]. Alongside these developments, Explainable Artificial Intelligence (XAI) techniques have increasingly been integrated into predictive systems to improve model transparency and trustworthiness [7],[9].

Despite the promising performance of machine learning approaches, previous studies still exhibit several important limitations that hinder practical implementation in higher education institutions, particularly in Indonesia. Most existing studies focus primarily on improving prediction accuracy while paying limited attention to model interpretability and institutional usability [10],[6]. As a result, many predictive models operate as black-box systems that are difficult for educators and academic advisors to understand conceptually [3],[5]. This limitation creates a significant gap between technical model performance and practical educational decision-making. In addition, existing research rarely incorporates legal and governance considerations related to personal data protection, even though predictive systems inherently process sensitive student information. Another major limitation is that prediction outputs are often restricted to risk scores without providing explanations regarding the academic factors contributing to those predictions. Consequently, institutions face difficulties in transforming predictive results into actionable academic interventions. Unlike previous studies, this research integrates predictive performance, interpretability, and regulatory considerations into a unified framework. The novelty of this study lies in the integration of Explainable AI techniques with comparative machine learning regression models to produce prediction outcomes that are not only accurate but also explainable and practically applicable within academic intervention systems.

Although previous studies have demonstrated the effectiveness of machine learning algorithms for predicting academic performance, most research focuses either on improving predictive accuracy or on applying explain ability techniques independently. Studies comparing multiple regression-based models for continuous GPA prediction while simultaneously integrating both global and local explain ability remain limited. Furthermore, existing research often presents prediction results without translating them into actionable recommendations for academic intervention. Therefore, this study contributes a unified framework that combines comparative machine learning regression analysis, SHAP-based global interpretation, and LIME-based local explanation to support transparent and evidence-based academic decision-making. This integrated approach represents the primary novelty of the study and addresses the gap between predictive performance and practical educational applicability.

To address these gaps, this study proposes a data-driven framework for predicting students' cumulative Grade Point Average (GPA) using historical academic and behavioral data, including attendance, previous GPA, study hours, sleep duration, social media usage time, and age. This study compares three machine learning regression algorithms, namely Random Forest, XGBoost, and Support Vector Machine, because these models represent different predictive characteristics and have demonstrated strong performance in educational prediction tasks [4],[6],[7]. To improve transparency and interpretability, this study integrates Explainable Artificial Intelligence techniques using SHAP and LIME. SHAP is employed because it provides consistent global and local interpretations by quantifying the contribution of each feature to prediction outcomes across the dataset [7],[8]. Meanwhile, LIME is utilized to explain individual predictions at the student level, enabling academic advisors to identify the specific factors influencing each prediction result [9],[11]. The combination of SHAP and LIME allows the predictive framework to provide both global feature importance analysis and instance-level explanations, thereby supporting more transparent and evidence-based academic decision-making. Accordingly, this study aims to develop a continuous GPA prediction model that fulfills the criteria of accuracy, interpretability, and regulatory compliance. Accordingly, this study aims to develop a continuous GPA prediction model that fulfills the criteria of accuracy, interpretability, and regulatory compliance. The contributions of this study are threefold: (1) comparing representative machine learning paradigms, namely Random Forest, XGBoost, and SVM, for continuous GPA prediction; (2) integrating SHAP and LIME to provide complementary global and local explanations of model predictions; and (3) transforming prediction outcomes into actionable recommendations that support academic early warning systems and evidence-based intervention strategies in higher education institutions.

II.METHOD

This study adopts the Knowledge Discovery in Databases (KDD) framework, as illustrated in

Figure 1. The framework consists of six systematic stages: data acquisition, pre-processing, feature selection, modelling, evaluation, and result interpretation. Figure 1 provides an overview of the research workflow and illustrates how Explainable Artificial Intelligence (XAI) is integrated into the final interpretation stage to enhance model transparency and support evidence-based academic decision-making.

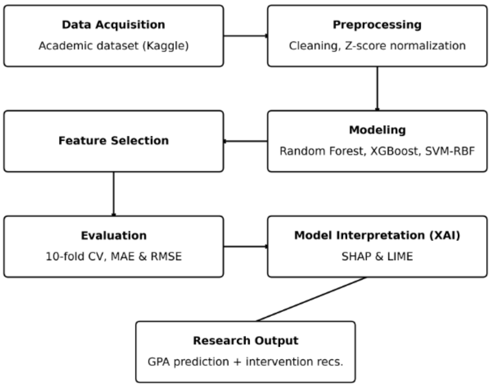

FIGURE 1. Research Workflow

This study was conducted in the context of Educational Data Mining (EDM) for higher education, focusing on the development of an interpretable predictive framework for students' academic performance. The dataset used in this study is a publicly available student academic dataset obtained from the Kaggle platform. To ensure compliance with research ethics and personal data protection principles, all records in the dataset were anonymized and contained no personally identifiable information. The dataset consists of 5,000 student records with historical academic and behavioral variables, including Previous GPA, Attendance Percentage, Study Hours per Day, Sleep Hours, Social Hours per Week, Age, Gender, and Major. The target variable in this study is Final Cumulative Grade Point Average (Final CGPA).

This study employed a quantitative predictive modeling design using machine learning regression approaches. The research framework consists of five main stages: data preprocessing, feature selection, model development, model evaluation, and model interpretation using Explainable Artificial Intelligence (XAI) [19].

The preprocessing stage was conducted to improve data quality and ensure the validity of the predictive model. Data cleaning procedures included the removal of missing values and duplicate records. Numerical features were normalized using the Z-score normalization method to reduce scale differences among variables. However, the target variable (Final CGPA) was not normalized in order to preserve prediction interpretability on the original GPA scale. Variables potentially causing data leakage, such as final graduation status, were excluded from the analysis to avoid biased predictions[20].

Feature selection was performed using Pearson correlation analysis to identify numerical variables significantly associated with students' GPA. Since Pearson correlation requires continuous numerical variables, only numerical academic variables were included in the correlation-based feature selection process. Based on this analysis, the final dataset consisted of six numerical features: Previous GPA, Attendance Percentage, Study Hours per Day, Sleep Hours, Social Hours per Week, and Age.

Data analysis was conducted using comparative machine learning regression techniques. This study compared three regression algorithms: Random Forest, Extreme Gradient Boosting (XGBoost), and Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel. These algorithms were selected because they represent three distinct machine learning paradigms that are widely applied in educational prediction research. Random Forest represents a bagging-based ensemble learning approach that is robust against overfitting and capable of handling heterogeneous educational datasets. XGBoost represents a boosting-based ensemble approach that has demonstrated superior predictive performance and effectiveness in capturing complex nonlinear relationships among academic variables. Meanwhile, SVM with an RBF kernel represents a kernel-based learning approach that performs effectively in high-dimensional feature spaces and nonlinear regression problems. The selection of these algorithms enables a comprehensive comparison of bagging, boosting, and kernel-based learning mechanisms, thereby providing a more rigorous evaluation of predictive performance and interpretability for student GPA prediction tasks [14], [4], [7], [15].

Model development was conducted using default hyperparameter configurations as baseline settings to ensure fair model comparison and reduce tuning bias. To improve model generalization and minimize overfitting, evaluation was performed using a 10-fold cross-validation scheme, where the dataset was repeatedly divided into training and validation subsets [12].

Model performance is evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). MAE measures the average absolute deviation between predicted and actual GPA values, while RMSE imposes a larger penalty on extreme prediction errors [13]. The model with the lowest combination of MAE and RMSE among the three algorithms is selected as the best model and subsequently used for interpretability analysis. The formulas for these metrics are given as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (2)$$

where:
n = number of observations
yi = actual GPA value
ŷi = predicted GPA value

To improve model transparency and support interpretable academic decision-making, this study implemented Explainable Artificial Intelligence (XAI) techniques using SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations). SHAP was selected because it provides theoretically consistent feature attribution based on Shapley values from cooperative game theory and enables both global and local interpretation of model behavior. This capability is particularly suitable for identifying the overall academic factors that influence GPA prediction across the dataset. In contrast, LIME was selected because it generates interpretable local approximations for individual predictions, making it useful for explaining student-specific outcomes and supporting personalized academic interventions. The combination of SHAP and LIME was chosen because they provide complementary perspectives: SHAP offers robust population-level explanations, while LIME provides detailed instance-level insights. Together, these methods align with the study’s objective of developing a predictive framework that is both accurate and actionable for academic decision-making.

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III.RESULT AND DISCUSSION

This section presents the research findings derived from the data and describes the results in accordance with the research objectives.

1. Data Quality and Preprocessing

Initial inspection of 5,000 student records from an anonymized public Kaggle dataset revealed no missing values or duplicate entries. Therefore, the imputation stage was not performed, as it was unnecessary for maintaining dataset quality.

Subsequently, outlier evaluation focused on the variables Study Hours Per Day and Social Hours Week. Observations with daily study hours exceeding 12 hours were further examined, as they may represent extreme values or anomalies in the data distribution. This approach was taken to ensure data reliability before proceeding to advanced preprocessing stages.

All numerical features were normalized using the Z-score to ensure consistent scaling across variables such as Attendance Pct (range 0–100) and GPA (range 0–4). This step prevents distance-based algorithms, such as SVM, from assigning disproportionate weight to features with larger scales.

The target variable, Final CGPA, was not normalized to preserve the interpretability of predictions in the standard GPA scale.

The dataset used in this study comprises several academic and behavioral features extracted from institutional records. A detailed description of the features, including their definitions and data scales, is presented in Table 1. These variables were specifically selected to capture both prior academic achievements and current learning habits.

Table 1. Feature Information of the Student Academic Dataset

Feature Name	Data Type	Unit	Description
Previous GPA	Numeric	Scale 0–4	Student's GPA from the previous semester
Attendance Pct	Numeric	Percent (%)	Percentage of class attendance
Study Hours Per Day	Numeric	Hours/ day	Average hours of self-study per day
Sleep Hours	Numeric	Hours/ day	Average hours of sleep per day
Social Hours Week	Numeric	Hours/ week	Total hours spent on social media per week
Age	Numeric	Years	Student's age at the time of data collection
Gender	Categorical	—	Student's gender (nominal)
Major	Categorical	—	Student's field of study or academic program (nominal)

Six numeric features (Previous GPA, Attendance Pct, Study Hours Per Day, Sleep Hours, Social Hours Week, and Age) were retained for modeling as they are continuous and compatible with Z-score normalization and Pearson correlation analysis. Previous GPA and Attendance Pct were identified as the strongest predictors based on their highest correlation values with the target variable. Study Hours Per Day was included as a reflection of self-study intensity, while Sleep Hours and Social Hours Week were retained as supporting factors that indirectly influence learning quality. Age was retained to capture potential differences in academic maturity across age groups. Two categorical variables, Gender and Major, were eliminated from the modeling process. Both are incompatible with Pearson correlation analysis, which requires continuous numeric data. Applying ordinal encoding to nominal variables risks inducing spurious relationships by implying a hierarchical ordering among categories that does not reflect substantive reality.

2. Comparison of Three Prediction Models

The three algorithms were evaluated using a 10-fold cross-validation scheme, with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) serving as the primary performance metrics. The comparative results are presented in Table 2. Based on these metrics, the model with the lowest error values was selected for further interpretability analysis.

Table 2. Comparison of Prediction Model Performance

Algorithm Model	MAE (Mean)	RMSE (Mean)	Generalization Capacity
XGBoost Regression	0.097	0.117	Very high; adaptive to nonlinear patterns.
Random Forest	0.102	0.127	High; stable and resistant to overfitting.
SVM (Kernel RBF)	0.112	0.138	Moderate; sensitive to hyperparameters.

The evaluation results indicate that XGBoost Regression achieved the best performance across both metrics, with an MAE of 0.097 and an RMSE of 0.117. This corresponds to an average prediction deviation of less than 2.5% of the 0–4 GPA scale, which is below the practical tolerance commonly used in academic early warning systems. Its performance may be attributed to the boosting mechanism, which iteratively minimizes residual errors and captures nonlinear relationships among academic features.

Random Forest ranked second (MAE = 0.102; RMSE = 0.127), showing only a small difference from XGBoost, suggesting that bagging-based ensembles remain competitive alternatives. SVM with the RBF kernel produced the highest error (MAE = 0.112; RMSE = 0.138), potentially due to sensitivity to hyperparameter settings. The RMSE-to-MAE ratio of approximately 1.2 across all models indicates relatively stable residual distributions without extreme outliers.

All three models were evaluated using default hyperparameter configurations as a fair and reproducible baseline. Although this likely limited the full potential of some algorithms particularly SVM the results demonstrate that XGBoost was able to achieve prediction accuracy within the practical tolerance threshold of academic early warning systems even without intensive tuning.

The validity of the evaluation results was further strengthened through 10-fold cross-validation, ensuring that all 5,000 observations served as validation data exactly once. The small variation in MAE across folds indicates stable generalization performance and reduces the likelihood that the results were influenced by a favorable train–test partition.

3. Global Model Interpretation Using SHAP

To enhance the transparency and clarity of model decisions, this study applies the SHapley Additive exPlanations (SHAP) method to the best-performing XGBoost model. The SHAP analysis is presented through two complementary visualizations: (1) a SHAP bar plot that illustrates the average magnitude of each feature's contribution globally (mean |SHAP value|), and (2) a SHAP beeswarm plot that shows the distribution of the direction and magnitude of feature contributions across individual observations. The global feature importance is summarized in Figure 2 and Figure 3, while the detailed interpretation and intervention implications are provided in Table 3.

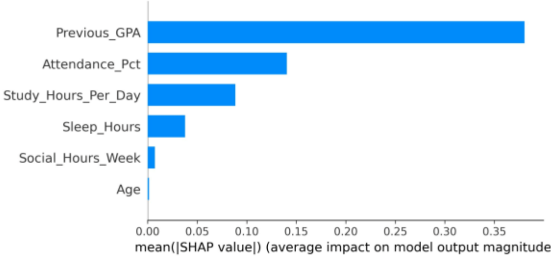

FIGURE 2. SHAP Bar Plot – Average Global Feature Contribution

Figure 2 presents the SHAP bar plot, which ranks features according to their average contribution to the model predictions.

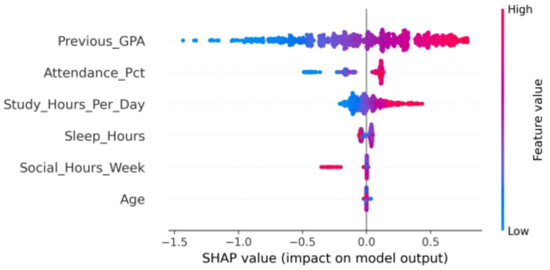

FIGURE 3. SHAP Beeswarm Plot – Distribution of Feature Contribution Direction and Magnitude

Meanwhile, Figure 3 presents the SHAP Beeswarm plot, illustrating both the magnitude and direction of feature contributions across individual observations. Together, these visualizations provide complementary insights into the global behavior of the XGBoost model.

Table 3. Feature Contributions Based on SHAP Analysis in the XGBoost Model

Feature	Mean |SHAP|	Direction of Influence	Intervention Implications
Previous GPA	≈ 0,38	Feature dominance is observed within	Prioritize early intervention

Feature	Mean |SHAP|	Direction of Influence	Intervention Implications
		the SHAP value range of −1.5 to +0.8, consistently influencing GPA predictions in both positive and negative directions.	starting from the first semester
AttendancePct	≈ 0,14	Low attendance consistently shifts predictions toward negative values	Actively monitor the 75% attendance threshold
Study Hours/Day	≈ 0,09	High study duration consistently contributes positively to SHAP values.	ncourage structured and independent learning programs
Sleep Hours	≈ 0,04	7–8 hours has a minor positive impact; < 6 hours has a slight negative effect	Promote sleep management as a supporting factor
Social Hours Week	≈ 0,02	10 hours/week begins to have a slight negative impact	Not critical; should be monitored if it exceeds the threshold
Age	≈ 0,01	Very minimal contribution; no predictive pattern based on age	No age-based intervention required

Table 3, together with Figures 2 and 3, summarizes the global feature contributions identified through SHAP analysis on the XGBoost model. The results indicate that Previous GPA is the most dominant predictor globally, with a mean |SHAP| ≈ 0.38 nearly three times higher than Attendance Pct (≈ 0.14), suggesting that historical academic performance strongly influences future GPA predictions. Meanwhile, Study Hours Per Day (≈ 0.09) consistently contributes positively to prediction outcomes, whereas Sleep Hours, Social Hours Week, and Age exhibit relatively minor contributions..

The beeswarm plot in Figure 3 further reveals a non-linear pattern in the influence of Previous GPA. Students with very low GPAs receive substantially larger negative SHAP corrections compared to the positive adjustments observed for high-performing students, indicating that academically vulnerable students exhibit more volatile academic trajectories than high achievers. These findings align with prior studies by Hong Sun et al [7], which emphasize that cognitive and learning behavior factors are more predictive than demographic variables in higher education contexts.

Furthermore, the beeswarm plot in Figure 3 reveals a pedagogically important pattern: the influence of Previous GPA is not linear, as students with very low GPAs (below 2.5) receive substantially larger negative SHAP corrections compared to the positive adjustments observed for high-performing students (above 3.5), indicating a “ceiling effect” in which high achievers tend to remain stable while at-risk students exhibit more volatile academic trajectories.

From the perspective of cross-validation with higher education literature, these findings demonstrate strong consistency. Academic momentum theory suggests that steady academic progress from the beginning of college contributes positively to student success and degree attainment [14], which aligns with the dominant contribution of Previous GPA in the SHAP analysis. The emergence of attendance as the second strongest predictor is also consistent with Tinto’s theory of academic engagement, emphasizing the importance of institutional integration and regular class participation for student retention. Therefore, the SHAP results are not only statistically meaningful but also theoretically supported within higher education research.

4. Local Model Interpretation Using LIME

Figures 4–6 present LIME explanations for three representative student profiles. Each figure illustrates how individual features contribute positively or negatively to the predicted GPA, enabling case-level interpretation of the model's decision-making process. These examples demonstrate how local explanations can support personalized academic intervention strategies.

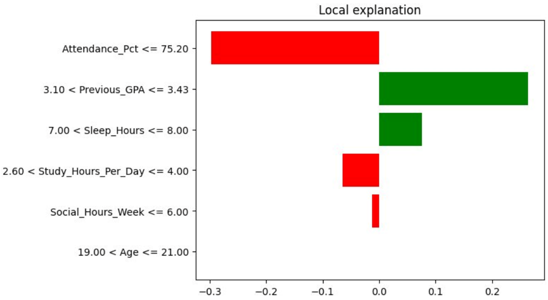

FIGURE 4. LIME Local Explanation – Student 1

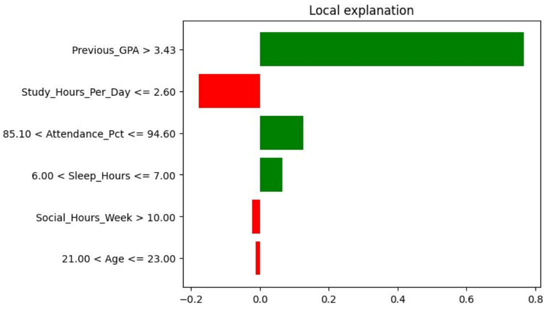

FIGURE 5. LIME Local Explanation – Student 2

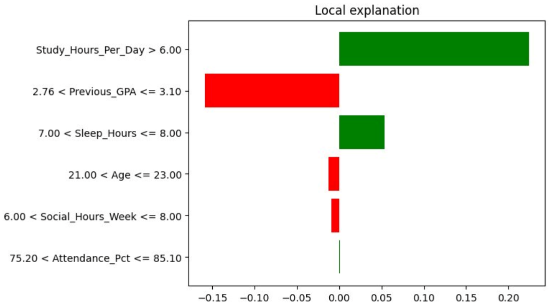

FIGURE 6. LIME Local Explanation – Student 3

Table 4. Summary of LIME Analysis on Three Sample Student Profiles

Sample	Driving Factors (+)	Hindering Factors (−)	Profile & Practical Implications
Student 1	Previous_GPA 3,10–3,43 (+0,27); Sleep_Hours 7–8 hour (minor)	Attendance Pct ≤75,20 (−0,29); Study Hours 2,60–4,00 (minor)	Low attendance becomes the main barrier for students with sufficient academic potential, thus requiring prioritized monitoring.
Student 2	Previous_GPA >3,43 (+0,76); Attendance Pct 85,10–94,60 (minor)	Study Hours ≤2,60 hour/day (−0,19); Social Hours >10 hour (minor)	High historical GPA dominates the prediction; however, improving daily study discipline remains a priority.
Student 3	Study Hours >6,00 hour/day (+0,22); Sleep_Hours 7–8 jam (+0,06)	Previous GPA 2,76–3,10 (−0,17)	High study intensity effectively compensates for low historical GPA, thereby increasing the potential for academic recovery.

The detailed characteristics and LIME explanation values for these representative cases are summarized in Table 4.

Student 1 in Figure 4 (Hidden Risk): Low attendance (Attendance Pct ≤ 75.20) reduces the predicted GPA by −0.29, even though the historical GPA is in the moderate range (3.10–3.43, SHAP +0.27). The negative impact of attendance outweighs the positive contribution of historical GPA, indicating that attendance below a critical threshold can negate existing academic potential.

Student 2 in Figure 5 (Gifted Underachiever): A high historical GPA (> 3.43) dominates the prediction with a SHAP value of +0.76, significantly higher than other features. However, Study Hours Per Day ≤ 2.60 contributes a negative correction of −0.19, suggesting that insufficient study time can hinder the achievement of an otherwise high GPA potential.

Student 3 in Figure 6 (Active Recovery): Although Previous GPA is lower (2.76–3.10) and contributes negatively (−0.17), intensive study duration (>6 hours/day) contributes positively (+0.22), partially offsetting the disadvantage and indicating potential academic improvement.

The three student sample profiles collectively form a risk typology with practical implications for academic advising. Student 1 represents a hidden-risk profile, where moderate historical GPA is weakened by low attendance. Student 2 reflects a gifted underachiever profile, characterized by strong prior academic performance that is not fully translated into current outcomes due to limited study time. Meanwhile, Student 3 represents an active recovery profile, in which intensive study behavior partially offsets a low historical GPA and indicates a positive academic trajectory.

Overall, the SHAP and LIME findings provide complementary yet non-interchangeable layers of information. SHAP operates at the population level, where Previous GPA emerges as the dominant global predictor, offering a foundation for designing broad intervention policies. In contrast, LIME functions at the individual level, revealing that feature importance may vary substantially across specific student profiles. For instance, in the case of Student 3, a low Previous GPA is offset by high study intensity, resulting in a net positive effect on the predicted outcome indicating an early recovery trajectory that may not yet be reflected in formal academic records. Without LIME, such individualized recovery patterns would remain obscured by the aggregated global patterns identified by SHAP, potentially leading to suboptimal allocation of academic support. The integration of SHAP for policy-level insights and LIME for personalized intervention thus positions the model not merely as a predictive tool, but as an evidence-based framework for academic decision-making.

5. Comparison with Previous Studies

The findings of this study are generally consistent with previous research in Educational Data Mining and academic performance prediction. Similar to the work of Aisyah et al. [4] and Sun et al. [7], ensemble-based algorithms demonstrated superior predictive performance compared with alternative machine learning approaches. In particular, XGBoost achieved the lowest prediction error, supporting previous evidence that boosting-based methods are effective in capturing complex nonlinear relationships within educational datasets.

The SHAP analysis further confirmed the importance of prior academic achievement and attendance as dominant predictors of future academic performance. These findings are aligned with studies by Sun et al. [7] and Pelima et al. [3], which reported that academic history and learning engagement factors consistently contribute more strongly to prediction outcomes than demographic characteristics. In contrast, Age exhibited minimal predictive influence in the present study, reinforcing previous observations that demographic variables often provide limited explanatory value in higher education performance prediction.

Unlike most previous studies that primarily focus on predictive accuracy, this research integrates both SHAP and LIME within a unified framework to provide complementary global and local explanations. This integration extends existing work by transforming model outputs into interpretable evidence that can support personalized academic interventions and institutional early warning systems. Therefore, the study contributes not only to prediction performance but also to the practical usability and transparency of machine learning models in higher education.

IV.CONCLUSION

This study successfully achieved its objective of developing an accurate and interpretable framework for predicting students' cumulative Grade Point Average (CGPA) using machine learning and Explainable Artificial Intelligence (XAI). Among the evaluated algorithms, XGBoost Regression demonstrated the best predictive performance with an MAE of 0.097 and an RMSE of 0.117, indicating its effectiveness in modelling complex academic data patterns. The integration of SHAP and LIME enhanced model transparency by providing complementary global and local explanations of prediction outcomes. The findings revealed that Previous GPA, Attendance Percentage, and Study Hours per Day were the most influential factors affecting academic performance, while demographic variables contributed minimally. By combining predictive accuracy with interpretability, the proposed framework transforms machine learning outputs into actionable evidence that can support academic advisors in implementing personalized interventions and strengthening academic early warning systems in higher education institutions. Future research may extend this framework by incorporating additional behavioural, psychological, and socioeconomic variables, exploring advanced optimization techniques, and validating the model using real-world institutional datasets from diverse educational contexts.

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