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A Comprehensive Machine Learning and Explainable AI Approach for Modeling and Interpreting Student Academic Performance

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Abstract: Accurately estimating student academic performance is central to educational planning and early intervention strategies. Performance outcomes are influenced by multiple academic, behavioral, and lifestyle factors, making predictive modeling an important tool for educators and institutions. This study proposes a machine learning framework integrated with explainable artificial intelligence (XAI) to predict students' performance scores using features such as study duration, previous academic results, extracurricular participation, sleep patterns, and practice of sample question papers. The dataset was preprocessed through imputation of missing values and exploratory visualization techniques, including histograms, kernel density plots and correlation heatmaps, to assess distributions and identify anomalies. A diverse set of regression models, including Linear Regression, Bayesian Ridge, Ridge, Lasso, Elastic Net, Decision Tree Regressor, Random Forest, XGBoost, and LightGBM, was evaluated using MSE, MAE, RMSE, R^2, PSNR, and SNR. Linear Regression emerged as the best-performing method, achieving an MSE of 4.06, MAE of 1.60, RMSE of 2.01, R^2 of 0.98, and the highest PSNR and SNR values. To improve interpretability, SHAP and LIME techniques were applied to identify both global and local feature influences. The findings demonstrate that interpretable models supported by XAI can provide accurate predictions while enhancing transparency, thereby offering meaningful insights for educational research and policy formulation.

Keywords: Machine Learning, XAI, SHAP, LIME.

I. INTRODUCTION

Education is fundamental to personal, professional, and societal development. Academic performance serves as a key indicator of student learning, influencing educational decisions, scholarship opportunities, and long-term career trajectories. However, student performance is shaped by a combination of cognitive, behavioral, environmental, and lifestyle factors, such as study consistency, prior achievements, engagement in extracurricular activities, sleep quality, and exposure to practice materials. Understanding how these factors collectively contribute to academic outcomes is essential for designing effective strategies to support student success.

Recent advancements in machine learning (ML) have created opportunities to analyze complex educational data and uncover patterns that traditional statistical techniques may overlook. ML-based predictive models have been applied in diverse areas of educational analytics, including early identification of at-risk learners, performance forecasting, and learning behavior analysis. Prior studies, such as those by [1-3], highlight the effectiveness of ML methods, including decision trees, SVM, and ensemble models, in predicting academic outcomes.

Despite progress in predictive modeling, interpretability remains an essential requirement, particularly in educational contexts where transparency influences trust and adoption. Explainable Artificial Intelligence (XAI) offers tools that clarify how models derive their predictions, enabling educators and stakeholders to understand the contribution of individual factors. Building upon these motivations, this study introduces a complete ML–XAI pipeline for predicting student performance based on behavioral and academic attributes. Key contributions of this research include:

- A comprehensive analysis of student performance using multiple regression-based models.
- Evaluation of predictive accuracy using six performance metrics (MSE, MAE, RMSE, R^2, PSNR, SNR).
- Integration of SHAP and LIME to provide both global and instance-level interpretability.

The remainder of this paper is structured as follows: Section II explains the methodology, including data preprocessing and model development. Section III presents the results and performance comparison. Section IV discusses the findings and limitations. Section V concludes the study and suggests directions for future research.

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II. METHODOLOGY

The methodological framework adopted in this study consists of several interconnected stages that collectively enable accurate prediction and interpretation of student academic performance. Fig. 1 outlines the top-level workflow, while this section provides an expanded explanation of each procedural step, including dataset preparation, exploratory analysis, preprocessing, model development, evaluation, and interpretability components. The methodology is presented across six detailed subsections for clarity.

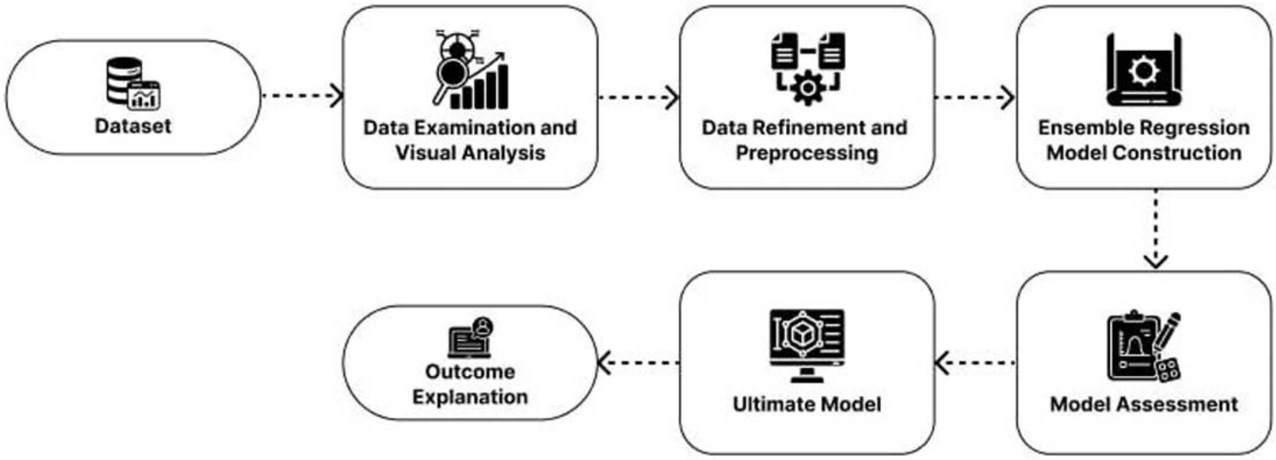

Fig. 1. Architecture of the research.

A. Dataset Description

The dataset used in this research contains a collection of academic, behavioral, and lifestyle-related attributes that influence student performance. Each record represents an individual student, characterized by features such as:

- **Hours Studied (continuous variable):** Indicates average daily or weekly study commitment.
- **Previous Academic Scores (continuous variable):** Represents the historical academic achievements of each student.
- **Extracurricular Activities (binary variable):** Coded as 1 for participation and 0 for non-participation.
- **Sleep Duration (continuous variable):** Average daily sleep hours.
- **Practice of Sample Question Papers (continuous variable):** Reflects the frequency or quantity of practice attempts.
- **Performance Index (continuous output variable):** Target variable representing the overall academic performance score.

Some observations contained missing values, making the preprocessing step essential for reliability. The dataset comprises more than a thousand samples, enabling meaningful training and validation of machine learning models [4].

B. Data Examination and Visual Analysis

Before model development, exploratory data analysis was conducted to understand feature behavior, detect inconsistencies, and examine statistical distributions. Visual tools, including histograms with density plots, and correlation heatmaps, were used to identify patterns, feature skewness, outliers, and multicollinearity. These visual insights supported informed preprocessing decisions and enhanced dataset interpretability, ensuring meaningful model learning [5-7].

A histogram combined with a density plot serves as an effective visualization for understanding the distribution of numerical features within a dataset. The histogram displays the frequency of data values across defined intervals, revealing patterns such as skewness, concentration, or spread. The overlaid density curve provides a smooth, continuous estimate of the underlying probability distribution, making it easier to observe trends that may not be immediately visible from the bars alone. Together, these visual components help identify central tendencies, variability, and the presence of possible outliers. Fig. 2 illustrates histogram–density plots for key variables in the dataset, offering an intuitive understanding of how feature values are distributed among students.

A heatmap is a visual tool that uses color gradients to represent the strength of relationships between different features. Darker red shades indicate a strong positive correlation, while darker blue shades represent a strong negative correlation. This type of visualization helps in quickly identifying which variables are closely connected. Fig. 3 presents a correlation matrix heatmap used to examine the relationships among the dataset's features.

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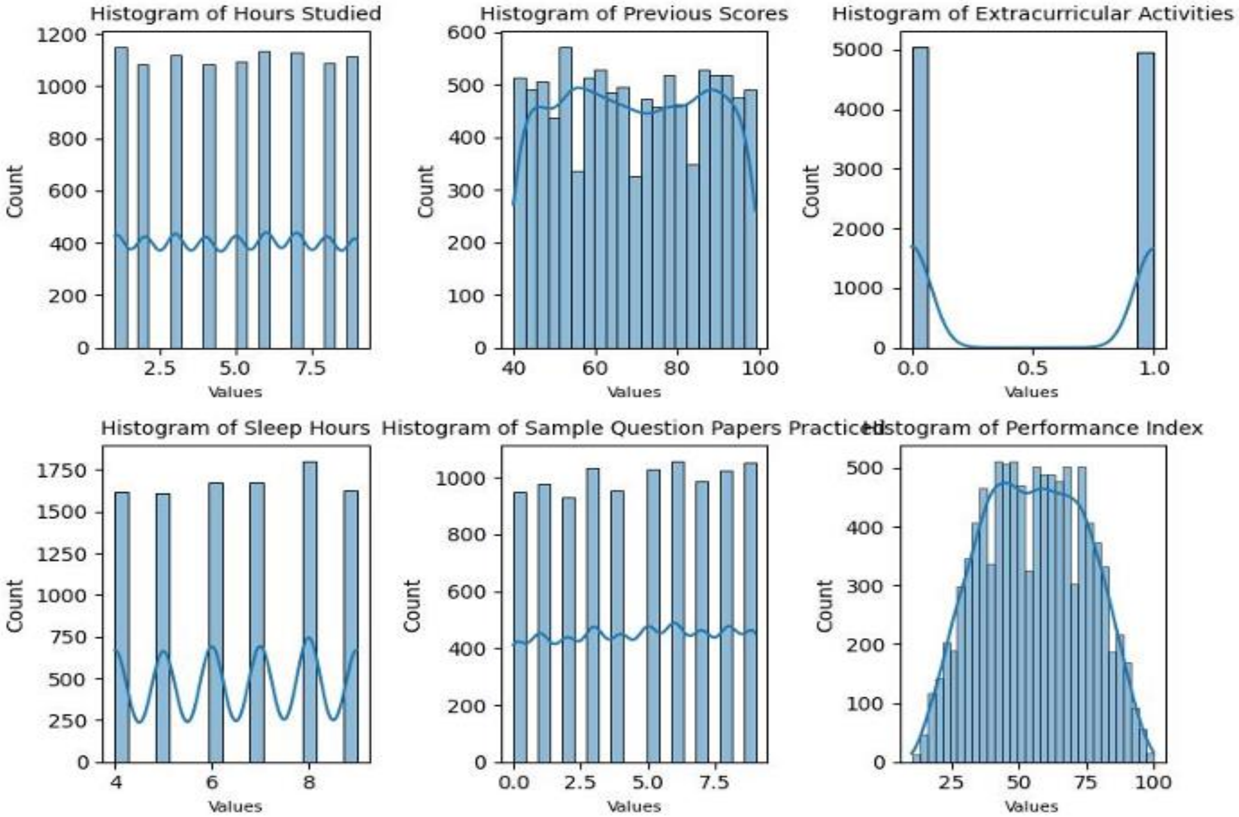

Fig. 2. Histogram illustrating the distribution of different features.

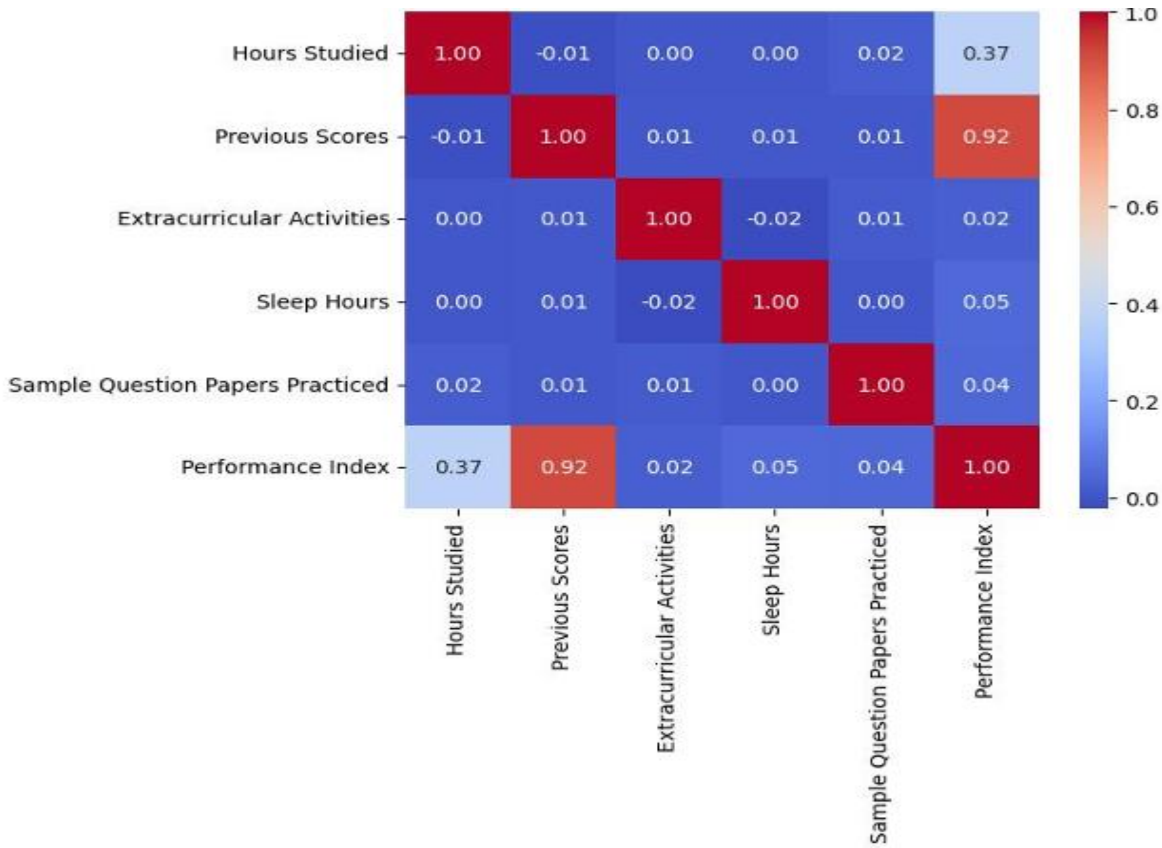

Fig. 3. Correlation matrix with a heat map.

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C. Data Cleaning and Preprocessing

Data preprocessing involved addressing missing values, removing irrelevant fields, and preparing the dataset for modeling. Missing numerical values were imputed using mean substitution, while categorical or binary variables were filled using mode values. Additionally, non-informative identifiers were excluded to avoid redundancy. These steps improved data completeness, minimized bias, and ensured consistency across features before model training [8-10].

D. Model Development

Multiple regression-based machine learning models were implemented to predict student performance. These included Linear Regression, Bayesian Ridge, Ridge, Lasso, Elastic Net, Decision Tree Regressor, Random Forest, XGBoost, and LightGBM. Each model was trained using the processed dataset, allowing comparative analysis between simple linear models and more complex ensemble-based approaches. The objective was to identify the most accurate, stable, and generalizable model [11-13].

E. Performance Evaluation

To assess model effectiveness, several evaluation metrics were utilized, including Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R-squared (R^2), Peak Signal-to-Noise Ratio (PSNR), and Signal-to-Noise Ratio (SNR). These metrics provided a multidimensional understanding of prediction accuracy, error magnitude, and model generalization capability. The ideal model is expected to achieve higher R^2, PSNR, and SNR values while minimizing MSE, MAE, and RMSE [14].

F. Model Selection

Based on the comparative performance evaluation across all regression models, Linear Regression demonstrated the strongest predictive capability, achieving the highest R^2 and the lowest error measurements. Its simplicity, computational efficiency, and interpretability made it the most suitable model for final deployment in student performance prediction.

G. Explainable Outcome

To enhance transparency and trust in predictions, Explainable Artificial Intelligence (XAI) techniques were applied to the best-performing model. SHAP (Shapley Additive Explanations) was used to determine global feature importance and quantify each attribute's contribution to prediction outcomes. Additionally, LIME (Local Interpretable Model-Agnostic Explanations) provided instance-level interpretability, enabling case-specific insights. These methods supported human-centric analysis and facilitated informed decision-making for educators and policymakers. [15-18].

III. RESULTS AND DISCUSSION

This study evaluated the performance of multiple regression models to determine the most effective predictor of student academic outcomes. The comparison was based on several metrics, including MAE, MSE, RMSE, R^2, PSNR, and SNR. Table I summarizes the results obtained from each model. Among all tested approaches, Linear Regression achieved the highest predictive accuracy, recording the lowest MAE (1.60), MSE (4.06), and RMSE (2.01), along with the highest R^2 value of 0.98. It also attained superior PSNR and SNR values, indicating strong signal quality and minimal prediction noise. Models such as Bayesian Ridge and Ridge demonstrated similar performance, whereas Elastic Net and Decision Tree Regressor exhibited comparatively weaker accuracy and higher error magnitudes.

TABLE I MODEL PERFORMANCE METRICS.

Models	MAE	MSE	RMSE	R^2	PSNR	SNR
Linear Regression	1.60	4.06	2.01	0.98	33.82	28.70
Bayesian Ridge	1.59	4.05	2.06	0.97	33.84	28.69
Ridge	1.58	4.03	2.04	0.98	33.81	28.68
Lasso	2.09	6.89	2.62	0.98	31.52	26.41
Elastic Net	5.90	50.64	7.11	0.86	22.86	17.75
Decision Tree Regressor	2.42	9.47	3.07	0.97	30.14	25.03

To further validate the robustness of the best-performing model, a 10-fold cross-validation procedure was conducted. As shown in Table II, Linear Regression consistently produced high R^2 values (0.98) across all folds, with only slight fluctuations in error values. Fold 10 achieved the best results, displaying the lowest MSE (5.09) and MAE (1.77), confirming model stability and generalization capability.

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TABLE II 10-FOLD CROSS-VALIDATION RESULTS

Fold	MAE	MSE	RMSE	R^2
Fold 1	1.83	5.22	2.28	0.98
Fold 2	1.85	5.25	2.29	0.99
Fold 3	1.79	5.25	2.29	0.98
Fold 4	1.79	5.18	2.27	0.98
Fold 5	1.86	5.41	2.32	0.97
Fold 6	1.83	5.28	2.29	0.99
Fold 7	1.79	5.16	2.27	0.98
Fold 8	1.77	4.97	2.22	0.96
Fold 9	1.83	5.37	2.31	0.99
Fold 10	1.77	5.09	2.25	0.98

Beyond numerical performance, explainability analyses were conducted to understand feature influence on predictions. SHAP visualizations (Fig. 4) revealed that variables such as previous academic scores and study hours contribute most significantly to predicted performance outcomes. LIME explanations (Fig. 5) further supported this by offering localized interpretations for individual predictions, strengthening trust and clarity in the model's decision process.

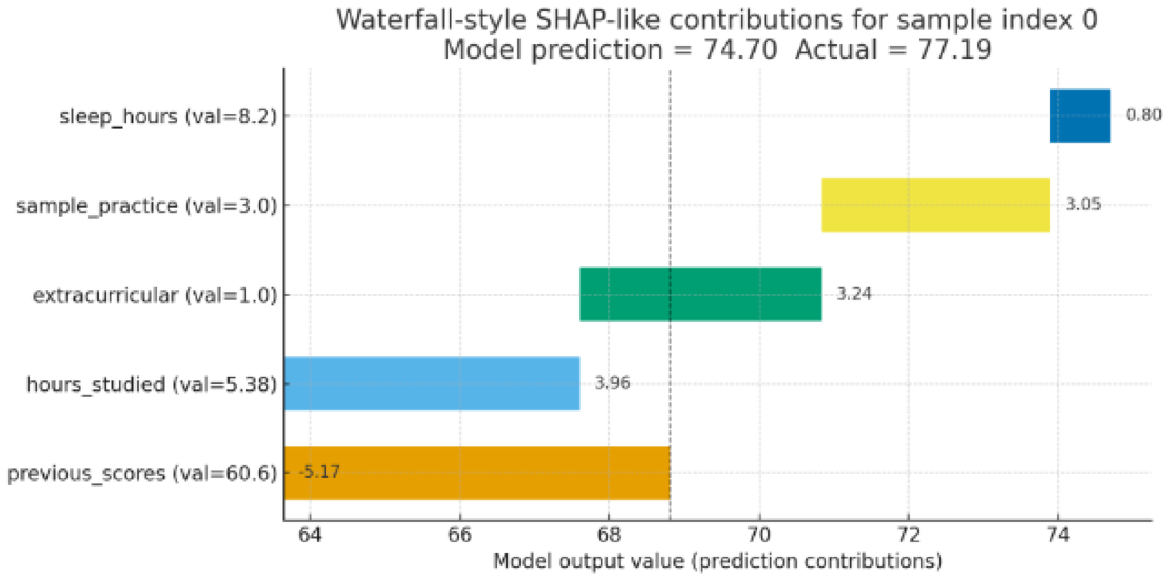

Fig. 4. The impact of various features on the model's output.

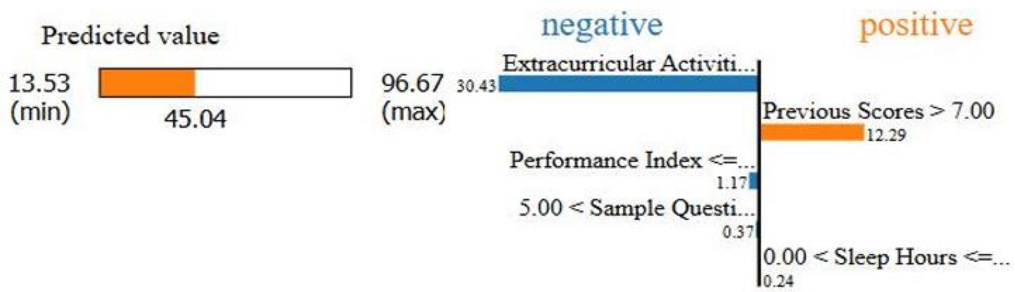

Fig. 5. LIME analysis with key features.

Overall, the results demonstrate that a simple, interpretable model such as Linear Regression can outperform more complex ensemble methods in predicting student performance, while also offering transparency through XAI-supported explanations. This makes it a strong candidate for practical deployment in educational analytics and intervention planning.

IV. CONCLUSION

This study shows that machine learning, supported by explainable AI techniques, can effectively predict student performance with high accuracy. Among all evaluated models, Linear Regression delivered the best results,

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demonstrating strong predictive capability while remaining transparent and easy to interpret. SHAP and LIME further clarified feature influence, helping identify key academic and behavioral factors affecting outcomes. Although the dataset and features were limited, the findings highlight the potential of interpretable predictive models to support early academic intervention and data-driven decision-making. Future work may expand feature diversity, dataset size, and modeling approaches to enhance generalizability and real-world applicability.

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