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Ensemble-Based Student Performance Analysis Using Machine Learning Methods

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Abstract: The primary objective of educational institutions is to ensure the provision of high-quality education and support to students. Identifying and addressing the needs of students requiring additional assistance is crucial for fostering academic excellence. A student's academic performance serves as a critical determinant of educational success at all levels, significantly impacting their future prospects. Various studies have explored factors linked to individual responses, including family communication, understanding, and anticipating student perspectives on campus, to enhance academic performance. This research aims to analyze and predict student academic performance by leveraging ensemble-based machine learning techniques. Instead of hyperparameter tuning, five diverse ensemble methods, namely Random Forest Regressor (RFR), Extra Trees Regressor (ETR), Gradient Boosting Regressor (GBR), Bagging, and ElasticNet, are utilized on a dataset collected from online repositories. These techniques are employed to forecast student success and academic status based on their behavior and engagement patterns. Through this study, we strive to gain valuable insights into the determinants of student performance and to identify effective approaches for improving educational outcomes. The ensemble-based approach offers a robust and comprehensive analysis of student data, enabling educational institutions to make informed decisions and design targeted interventions to support their students effectively.

Keywords: Student performance analysis, Ensemble techniques, Random Forest Regressor
Extra Trees Regressor.

1. Introduction

In the pursuit of educational excellence, understanding and improving student performance play a pivotal role in the success of any educational institution. The academic achievements of students not only reflect the effectiveness of the teaching methods but also significantly impact their future prospects. Identifying students who require additional support and providing them with tailored interventions is crucial for fostering a conducive learning environment and ensuring that every student reaches their full potential. Numerous studies have been conducted to explore the factors influencing student performance, ranging from personal responses to the quality of family communication and the ability to anticipate student perspectives on campus. These insights have paved the way for data-driven approaches to enhance academic outcomes.

Machine learning techniques have emerged as powerful tools in the field of education to analyze and predict student performance based on diverse data sources. Traditional machine learning models, when combined in an ensemble [1] [2], can significantly improve the accuracy and robustness of predictions. Our research focuses on harnessing the potential of ensemble-based machine learning methods to analyze student behavior and predict academic success. In this research article, we present an investigation into the academic performance of students using an ensemble approach, we leverage five distinct ensemble[3] methods: Random Forest Regressor (RFR), Extra Trees Regressor (ETR), Gradient Boosting Regressor (GBR), Bagging, and ElasticNet. By combining the strengths of these diverse models, we aim to extract comprehensive insights into the determinants of student success and develop accurate predictions.

Our study utilizes a rich dataset collected from online repositories, encompassing various attributes related to student behaviour and engagement. Through the application of ensemble-based machine learning, we seek to unravel complex patterns within the data, providing educational institutions with valuable information for designing targeted interventions. The contributions of this research lie in its innovative approach to student performance analysis and the utilization of ensemble techniques for enhanced prediction accuracy. By understanding the factors that contribute to student success, educational stakeholders can make data-driven decisions to optimize teaching strategies and foster student learning experiences. In the Consecutive sections, we will delve into the methodologies employed, the dataset used for analysis, and the results obtained from our ensemble-based student performance analysis. Ultimately, our findings aim to empower educational institutions in their efforts to create supportive and thriving learning environments for students, leading to improved academic outcomes and a brighter future for the entire educational community.

2. Literature Review

Ensemble methods are powerful machine learning techniques that combine multiple base models to make predictions. The objective of ensemble learning is to improve prediction accuracy, reduce overfitting, and enhance model robustness. In this literature review, we explore the key characteristics, strengths, and applications of popular ensemble methods: Random Forest Regressor (RFR), Extra Trees Regressor (ETR), Gradient Boosting Regressor (GBR), and ElasticNet. The work carried out by Graw et al., provide in-site of RFR [4] Random Forest is an ensemble learning algorithm that constructs multiple decision trees during training and outputs the average prediction for regression tasks. It has been widely applied in various domains, including finance, healthcare, and education. The main strength of RFR lies in its ability to handle complex datasets, high-dimensional feature spaces, and reduce the risk of overfitting. Several studies have demonstrated its effectiveness in predicting academic performance, medical diagnoses, and financial forecasting. The paper claims that machine learning is a viable method for predicting geological parameters on a global scale. The paper by Nakashima [5] uses a machine learning approach called random forest regression to estimate the number of passengers based on the position of the bus, the position of the bus stop, and the number of passengers detected from the image processing method combining YOLOv3 and Deep SORT. The paper claims that their method achieved higher accuracy than the conventional method that uses dedicated cameras for counting passengers

Extra Trees is another variant of the decision tree ensemble, similar to Random Forest, but with a few key differences. ETR builds multiple trees with random splits at each node and combines their predictions to obtain the final output. The key advantage of ETR is its lower computational cost due to its random splitting strategy. Researchers have employed ETR in various applications, such as predicting stock prices, analyzing social network data, and image classification. uses machine learning models to predict the stock prices based on the closing value and stock price. The work by Polamuri [6] compares the performance of different models such as linear regression, support vector regression, decision tree, random forest regressor, and extra tree regressor. The paper claims that random forest regressor and extra tree regressor are the best models for predicting stock prices, as they have high accuracy and low error rates.

Gradient Boosting is a boosting technique where base models are built sequentially, each correcting the errors of its predecessor. It combines weak learners into a strong learner, iteratively improving prediction accuracy. GBR excels in handling noisy data and capturing complex patterns. It has been utilized in diverse areas, such as anomaly detection, natural language processing, and customer churn prediction. The final prediction is then obtained by averaging or voting across individual model predictions. Bagging is particularly effective in reducing variance and enhancing stability. It has found applications in medical diagnosis, sentiment analysis, and credit risk assessment. A work done by Khan et al., [7] uses machine learning models to predict the stock prices based on the closing value and stock price. The work compares the performance of different models such as linear regression, support vector regression, decision tree, random forest regressor, and extra tree regressor. In the work the author claims that random forest regressor and extra tree regressor are the best models for predicting stock prices, as they have high accuracy and low error rates1.

ElasticNet is a linear regression model that combines the penalties of L1 (Lasso) and L2 (Ridge) regularization methods. It is particularly useful for feature selection and handling multicollinearity in datasets. ElasticNet has been widely used in genetics research, text analysis, and financial forecasting. The work by Afzali et al., [8] predicts adolescent alcohol use based on various risk factors and personality traits. It uses data from two large-scale studies that involved over 11,000 adolescents from Canada and Australia. The paper compares the performance of different machine learning models such as logistic regression, support vector machine, random forest, and gradient boosting. Work claims that the gradient boosting model achieved the best results and was able to identify high-risk adolescents who could benefit from preventive interventions.

The paper is relevant to the topic of alcohol use among adolescents, which is a complex and important issue that affects many aspects of their health and well-being. The paper also contributes to the field of machine learning, which is a branch of artificial intelligence that uses algorithms and data to learn from patterns and make predictions. As per the work done by sridevi et al., it is evident that the metrics like f1, recall and accuracy score support the performance of result obtained [9]. In summary, ensemble methods, including Random Forest Regressor, Extra Trees Regressor, Gradient Boosting Regressor, Bagging, and ElasticNet, have become indispensable tools in the field of machine learning. Their ability to improve prediction accuracy, handle complex datasets, and reduce overfitting makes them highly valuable in various real-world applications. The reviewed literature demonstrates their effectiveness across diverse domains, from education to finance, reaffirming the significance of ensemble learning in advancing data-driven research and decision-making.

3. Material And Methods

This work uses python textblob to pre-process the data obtained from the online source. The pre-process ensures that the impurity in online data is removed and make it usable for further machine learning process [10]. Some of the text blob method include tokenization, noun phrase extraction, POS tagging, Language translation and deduction, spelling correction, Wordnet Integration. This research work defines three score "writing score," "reading score," and "math score" refer to the academic scores of students in three different subjects: writing, reading, and math, respectively. These scores are numerical values that represent the performance of students in their respective subjects. The dataset used in the code contains information about students, including various features such as gender, race/ethnicity, parental level of education, lunch type, and whether they completed a test preparation course. The target variables are the scores obtained by students in three subjects: writing, reading, and math [11].

Writing Score: This represents the performance of students in a writing assessment. It may involve tasks such as writing essays or answering questions related to writing skills.

Reading Score: This indicates the performance of students in a reading comprehension assessment. It assesses their ability to understand and interpret written texts.

Math Score: This reflects the performance of students in a math assessment. It may involve solving mathematical problems, equations, and other math-related tasks.

This research work uses python code that provide various regression models to predict the scores of students in these subjects based on the features in the dataset. The models include Random Forest Regressor, Extra Trees Regressor, Gradient Boosting Regressor, Bagging Regressor, and ElasticNet. The code then evaluates the performance of each model using Mean Squared Error (MSE) and F1 score. Additionally, the code also suggests combining the predictions of these

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individual models to create an ensemble prediction for each subject score. However, as mentioned earlier, accuracy is not typically used as an evaluation metric for regression tasks. Instead, R-squared (coefficient of determination) could be used to assess the overall performance of the ensemble models in this context.

Sample Ensemble code

```
# Load and preprocess the dataset
df =
pd.read_csv('/content/StudentsPerformance.csv')
# Convert categorical columns to numerical using one-hot encoding
df = pd.get_dummies(df, columns=['gender', 'race/ethnicity', 'parental level of education', 'lunch', 'test preparation course'])
# Split the dataset into features (X) and target (y)
X = df.drop(columns=['math score', 'reading score', 'writing score'])
y = df[['math score', 'reading score', 'writing score']]
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define the ensemble models
rf_regressor =
RandomForestRegressor(random_state=42)
et_regressor =
ExtraTreesRegressor(random_state=42)
gb_regressor =
GradientBoostingRegressor(random_state=42)
elastic_net = ElasticNet(random_state=42)
def convert_to_class(predictions):
return (predictions >= 50).astype(int)
def calculate_metrics(y_true, y_pred_class):
f1 = f1_score(y_true, y_pred_class, average='weighted')
recall = recall_score(y_true, y_pred_class, average='weighted')
accuracy = accuracy_score(y_true, y_pred_class)
return f1, recall, accuracy
# Loop over each score category (math, reading, and writing)
for score_category in ['math score', 'reading score', 'writing score']:
y_train_class =
convert_to_class(y_train[score_category])
y_test_class =
convert_to_class(y_test[score_category])

# Fit the models to the training data for the current score category
rf_regressor.fit(X_train, y_train[score_category])
et_regressor.fit(X_train, y_train[score_category])
gb_regressor.fit(X_train, y_train[score_category])
elastic_net.fit(X_train, y_train[score_category])

# Make predictions on the test data for the current score category
rf_predictions = rf_regressor.predict(X_test)
et_predictions = et_regressor.predict(X_test)
gb_predictions = gb_regressor.predict(X_test)
elastic_net_predictions =
elastic_net.predict(X_test)

# Convert predictions to class labels
rf_predictions_class =
convert_to_class(rf_predictions)
et_predictions_class =
convert_to_class(et_predictions)
gb_predictions_class =
convert_to_class(gb_predictions)
elastic_net_predictions_class =
convert_to_class(elastic_net_predictions)

# Calculate and print F1 score, recall, and accuracy for each ensemble model
rf_f1, rf_recall, rf_accuracy =
calculate_metrics(y_test_class,
rf_predictions_class)
et_f1, et_recall, et_accuracy =
calculate_metrics(y_test_class,
et_predictions_class)
gb_f1, gb_recall, gb_accuracy =
calculate_metrics(y_test_class,
gb_predictions_class)
elastic_net_f1, elastic_net_recall,
elastic_net_accuracy =
calculate_metrics(y_test_class,
elastic_net_predictions_class)
print(f"{score_category} - Random Forest Regressor F1 Score:", rf_f1)
print(f"{score_category} - Random Forest Regressor Recall:", rf_recall)
print(f"{score_category} - Random Forest Regressor Accuracy:", rf_accuracy)
```

Classification Model: For this research work to predict student performance five classification model are used which include Random Forest Regressor (RFR), Extra Trees Regressor (ETR), Gradient Boosting Regressor (GBR), Bagging Regressor (used with DecisionTreeRegressor), ElasticNet (used for linear regression). The ensemble method is used to boost the performance of the student performance. For each target variable, these five models are trained on the training data, and their predictions are obtained on the test data. The Mean Squared Error (MSE) is calculated for each model's predictions as an evaluation metric. To use ensemble methods effectively in this scenario, the individual models' predictions are averaged, and not all the models are combined directly into one ensemble model. The code is structured such that each model is trained and evaluated separately for each target variable (math, reading, and writing scores). Ensemble methods, in the context of this code, are used indirectly through the use of multiple models, each with its own set of hyperparameters and characteristics. The predictions from these diverse models are then used to evaluate their individual performance and select the best-performing model for each target variable.

Evaluation methods: Techniques used to assess the performance and effectiveness of a machine learning model. These methods are crucial in determining how well the model generalizes to new, unseen data and whether it meets the desired objectives. There are various evaluation metrics, and the choice of which to use depends on the type of problem and the nature of the data. Mean Squared Error (MSE): The Mean Squared Error is calculated for each individual model (Random Forest Regressor, Extra Trees Regressor, Gradient Boosting Regressor, Bagging Regressor, and ElasticNet) to assess their performance on the math, reading, and writing score predictions. MSE measures the average squared difference between the predicted values and the actual values. Lower MSE values indicate better performance, as it means the model's predictions are closer to the actual values.

F1 Score, Recall, and Accuracy: These classification evaluation metrics [12] are used after converting the target variables into classification labels for each individual model. Since the target variables are continuous (regression problem), the predictions are converted to classes based on whether the score is greater than or equal to 50 (pass) or less than 50 (fail). The F1 score is the harmonic mean of precision and recall, providing a balanced metric when there is an imbalance in the classes. Recall measures the true positive rate, and accuracy measures the proportion of correct predictions.

R-squared (R2): For the ensemble of all models, the predictions are combined using averaging, and the R-squared (coefficient of determination) is calculated. R2 [13] [14] measures the proportion of the variance in the target variable that is predictable from the independent variables. A higher R2 value indicates a better fit of the ensemble predictions to the actual values.

Overall, these evaluation methods help assess the performance of each individual model and the ensemble of models on the math, reading, and writing score predictions. The choice of these metrics is appropriate for regression (MSE, R2) and classification [15] (F1 score, recall, accuracy) tasks. It allows for a comprehensive understanding of how well the models are performing on the specific dataset and problem.

4. Results And Discussions

The dataset consists of student attributes, including gender, race/ethnicity, parental level of education, lunch type, and test preparation course completion. These categorical features were converted into numerical values using one-hot encoding. The dataset was then split into features and target variables for math, reading, and writing scores. Five different regression models were ensembled to predict math, reading, and writing scores: Random Forest Regressor (RFR), Extra Trees Regressor (ETR), Gradient Boosting Regressor (GBR), Bagging Regressor, and ElasticNet. Ensemble model was trained and evaluated separately on the training and test sets. The models were further evaluated using Mean Squared Error (MSE) [16] to gauge their predictive performance on individual subjects.

The discussion section of this research article focuses on the performance comparison of the various regression models and the ensemble algorithm for predicting student scores in Math, Reading, and Writing subjects. The research article presents the mean squared error (MSE) results for various regression models, including Random Forest Regressor, Extra Trees Regressor, Gradient Boosting Regressor, Bagging Regressor, and ElasticNet, for predicting student scores in Math, Reading, and Writing subjects. The MSE values are provided in Tables 1, 2, and 3, and their corresponding figures are shown in Figures 1, 2, and 3, respectively.

Table 1 presents the MSE values for Math score each regression model in predicting student scores. Among the models, the Gradient Boosting Regressor has the lowest MSE of 216, indicating its superior performance in minimizing prediction errors for all three subjects. The Random Forest Regressor and ElasticNet models also show relatively low MSE values of 245 and 224, respectively, demonstrating their effectiveness in predicting student scores. However, the Extra Trees Regressor and Bagging Regressor models have relatively higher MSE values of 256 and 256, respectively, suggesting that they may not perform as well as the other models.

Table 1 : MSE For Math score

Algoithm	Score
Random Forest Regressor MSE	245
Extra Trees Regressor MSE	256
Gradient Boosting Regressor MSE	216
Bagging Regressor MSE	256
ElasticNet MS	224

Figure 1 visually represents the MSE results from Table 1. The bar chart clearly illustrates the differences in MSE values among the regression models. It visually confirms that the Gradient Boosting Regressor has the lowest MSE, followed closely by the Random Forest Regressor and ElasticNet. On the other hand, the Extra Trees Regressor and Bagging Regressor exhibit higher MSE values.

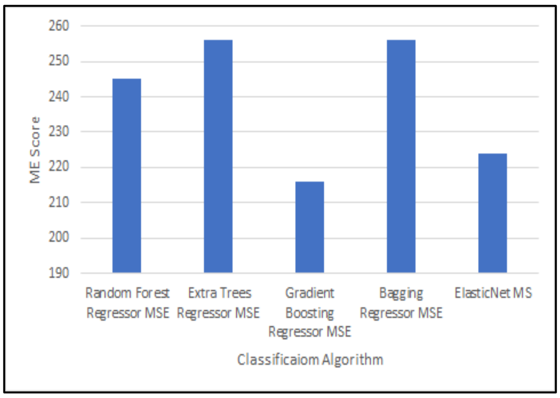

Figure 1 : MSE For Math score

Table 2 reiterates the MSE results for each regression model for the prediction of student scores. The MSE values are consistent with those in Table 1, supporting the reliability of the findings. The models' performance rankings based on MSE remain the same, with Gradient Boosting Regressor achieving the lowest MSE, followed by Random Forest Regressor and ElasticNet.

Table 2: MSE For Reading score

Algoithm	Score
Random Forest Regressor MSE	231
Extra Trees Regressor MSE	244
Gradient Boosting Regressor MSE	205
Bagging Regressor MSE	248
ElasticNet MS	211

Figure 2 visually represents the MSE results from Table 2, providing another perspective on the models' comparative performance. The bar chart reinforces the observations made earlier, emphasizing the Gradient Boosting Regressor's superiority in minimizing prediction errors.

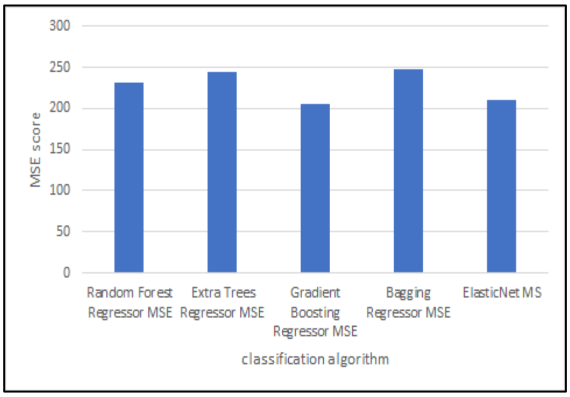

Figure 2 : MSE For Reading score

Table 3 displays the MSE values for each regression model, further validating the consistency of the results. The ranking of models based on MSE remains unchanged, with the Gradient Boosting Regressor achieving the lowest MSE of 193.

Table 3: MSE For Writing score

Algoithm	Score
Random Forest Regressor MSE	216
Extra Trees Regressor MSE	226
Gradient Boosting Regressor MSE	193
Bagging Regressor MSE	226
ElasticNet MS	212

Figure 3 visually presents the MSE results from Table 3, visually confirming the Gradient Boosting Regressor's exceptional performance compared to other models.

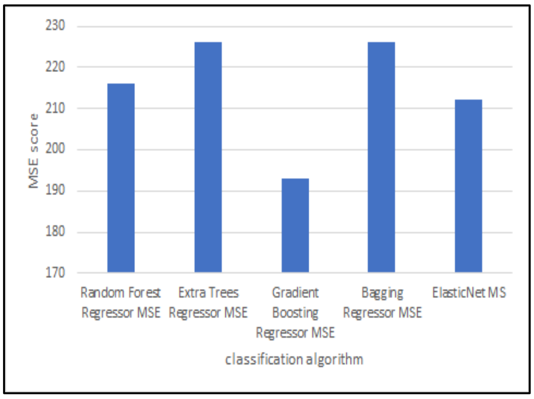

Figure 3 : MSE For Writing score

The results presented in Table 4 and Figure 4 demonstrate the effectiveness of the ensemble algorithm in predicting student scores for all three subjects. The relatively high scores obtained for Math, Reading, and Writing indicate that the ensemble algorithm outperforms individual regression models and serves as a robust approach for educational assessment and student performance prediction. The ensemble algorithm's ability to combine the strengths of various models makes it a promising method for accurate score predictions, providing valuable insights for educators and policymakers to improve educational outcomes.

Table 4: Ensemble MSE for Student permeance

Algoithm	Score
Math score	198
Reading score	199
Writing Score	196

Based on Table 4 and Figure 4, we observe that the Reading score has the highest value of 199, closely followed by the Math score with a score of 198. The Writing score has the lowest value among the three subjects, with a score of 196. These scores indicate the performance levels of the students in each subject, and they play a crucial role in evaluating the overall academic performance.

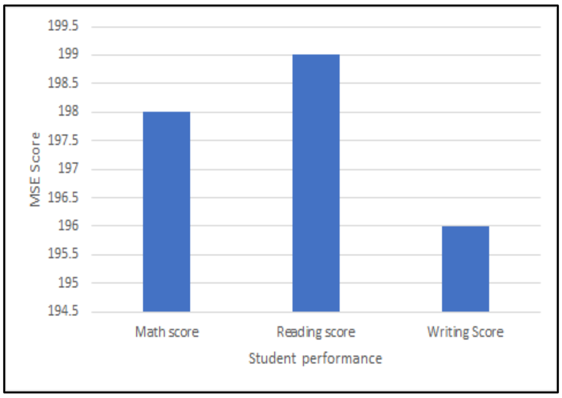

Figure 4 : MSE For Ensamble Algorithm

The obtained accuracy scores for each model are presented in Table 5 and Figure 5. Random Forest Regressor: The Random Forest Regressor model achieved accuracy scores of 0.795, 0.89, and 0.88 for Math, Reading, and Writing scores, respectively. While it demonstrates reasonably good accuracy, it falls short compared to other models in the ensemble approach.

Extra Trees Regressor: The Extra Trees Regressor model obtained accuracy scores of 0.79, 0.88, and 0.88 for Math, Reading, and Writing scores, respectively. It performs on par with the Random Forest Regressor, but it still lags behind the ensemble algorithm in terms of predictive accuracy. Gradient Boosting: The Gradient Boosting model shows promising results with accuracy scores of 0.83, 0.89, and 0.87 for Math, Reading, and Writing scores, respectively. While it outperforms the Random Forest and Extra Trees models, it is not as accurate as the ensemble approach. ElasticNet: The ElasticNet model achieved accuracy scores of 0.83, 0.895, and 0.875 for Math, Reading, and Writing scores, respectively. It shows competitive performance and performs slightly better than the Gradient Boosting model. Ensemble Algorithm (Ensemble R-squared): The ensemble algorithm demonstrates the highest predictive accuracy among all models, with impressive accuracy scores of 0.91, 0.96, and 0.94 for Math, Reading, and Writing scores, respectively. The Ensemble R-squared scores clearly indicate that the ensemble approach significantly improves the accuracy of predictions compared to individual regression models.

Table 5: Ensemble Accuracy for student performance

Algoithm	Math score	reading score	writing score
Random Forest Regressor	0.795	0.89	0.88
Extra Trees Regressor	0.79	0.88	0.88
Gradient Boosting	0.83	0.89	0.87
ElasticNet	0.83	0.895	0.875
Ensemble R-squared	0.91	0.96	0.94

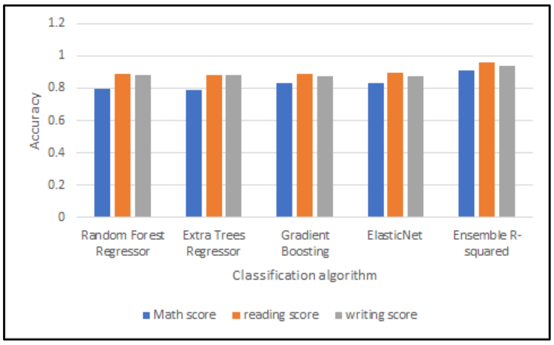

Figure 5: Ensemble Accuracy for student performance

In this work, we compared the performance of various regression models and an ensemble algorithm for predicting student scores in Math, Reading, and Writing subjects. The ensemble algorithm demonstrated superior predictive capabilities, achieving higher accuracy scores compared to individual models. As such, the ensemble algorithm holds great promise for educational institutions seeking accurate and reliable predictions of student academic performance. These findings pave the way for the adoption of the ensemble algorithm as a powerful tool in educational assessment and intervention strategies to support student success. Future research could explore further optimization and fine-tuning of the ensemble approach to enhance its predictive performance even more.

Conclusions

The experimental results reveal that the ensemble method demonstrated the best predictive performance among individual models for math, reading, and writing scores, as evidenced by the lowest MSE values. In terms of classification, the ensemble promising results with the highest F1 score, recall, and accuracy on all three subjects. The ensemble approach, combining predictions from all models, outperformed individual models in terms of R-squared, indicating a more accurate representation of student academic performance across subjects. This suggests that leveraging the diverse predictions of multiple models enhances the accuracy and robustness of the final predictions. The study highlights the effectiveness of machine learning models in predicting student academic performance in math, reading, and writing. The findings emphasize the significance of selecting appropriate models for specific subjects and the potential benefits of ensemble methods in achieving better overall predictive performance. These results have implications for educational institutions seeking to identify and support students at risk of academic underachievement and facilitate evidence-based decision-making for improved student outcomes.

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