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RESEARCH ARTICLE

A Stacking-Based RF-CatBoost Model for Student Performance Prediction

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Abstract

To address the student performance problem in educational data mining, this study proposes a stacking-based RF-CatBoost model that integrates the complementary strengths of ensemble learning methods to enhance prediction accuracy and robustness. In the proposed framework, Random Forest (RF) and CatBoost are employed as the base learners to capture both global feature interactions and complex non-linear relationships within multi-source educational data. Their outputs are then stacked and fused using a combination strategy to generate the final prediction. Experimental results based on two educational datasets demonstrate that the stacking-based RF-CatBoost model consistently achieves superior predictive performance, reflected in prediction accuracy and robustness. The results confirm that the proposed hybrid stacking RF-CatBoost can effectively leverage the diversity of ensemble learners, offering a robust solution for early student performance prediction, enabling timely interventions and personalized learning support in educational setting.

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1 Introduction

The rapid development of online learning systems and educational information systems has generated massive amounts of data [1], including students' learning behaviors [2], engagement patterns [3], and assessment outcomes [4]. Data mining for these educational data is to uncover meaningful patterns, and the prediction of student performance has become a central focus in educational data mining (EDM) and learning analytics [5]. Accurate prediction of student achievement not only supports early identification of at-risk learners, but also facilitates personalized interventions and data-driven educational decision-making [6, 7].

Students' academic performance prediction has become a key research topic in EDM. Recent studies have utilized various machine learning algorithms to predict student achievements based on academic, demographic, and behavioral features gathered via online learning platforms. For example, traditional machine learning methods have been widely applied to student performance prediction and shown high performance [8, 9]. For example, Fan et al. [10] applied the machine learning models for student performance prediction. Their results showed that the Categorical Boosting (CatBoost) outperformed the Multi-Layer Perceptron (MLP) [11], Support Vector Machine (SVM) [12], Random Forest (RF) [13], and

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eXtreme Gradient Boosting (XGBoost) [14]. Nayak et al. [15] utilized multiple classifiers such as Decision Tree, Naïve Bayes, RF, and MLP to analyze student datasets. Experimental results revealed that the optimized MLP achieved superior accuracy across datasets, reaching up to 90.74% accuracy.

Despite their effectiveness, standalone models still exhibit certain limitations. For instance, the RRF model emphasizes feature randomness and ensemble diversity, but may underfit when modeling complex nonlinear interactions. Conversely, CatBoost excels at handling categorical variables and capturing intricate data patterns through gradient boosting, yet it can be prone to overfitting when trained on small datasets. To exploit their complementary strengths, this study proposes a stacking-based RF-CatBoost model for student performance prediction. In the proposed framework, RF and CatBoost act as base learners that generate predictive outputs representing diverse perspectives of the data distribution. These outputs are then stacked and combined to produce the final prediction, thereby enhancing both accuracy and robustness.

The main contributions are:

- A novel stacking-based hybrid ensemble model is proposed, integrating RF and CatBoost to leverage their complementary learning characteristics for student performance prediction.
- A ensemble fusion strategy is designed to combine the outputs of multiple base learners, enabling adaptive weighting and improved generalization performance.
- Comprehensive experiments are conducted across multiple educational datasets. The results show the proposed model outperforms the established baselines (SVM, XGBoost, RF, CatBoost).

2 Methods

In this section, we first introduce the baseline models, followed by the proposed stacking model for student performance prediction.

2.1 Baseline models

To provide a comprehensive performance comparison, four widely used machine learning models, including the SVM, XGBoost, RF, and CatBoost. These models have demonstrated strong predictive capabilities in educational data mining tasks and represent diverse families of algorithms, including kernel-based methods, decision-tree ensembles, and gradient boosting frameworks.

(1) Support Vector Machine (SVM) is a widely used supervised learning algorithm based on statistical learning theory [16]. It seeks to find the optimal hyperplane that maximizes the margin between different classes in the feature space. By employing kernel functions [17], SVM can efficiently handle non-linear classification and regression tasks. In the context of student performance prediction, the SVM can be serveed as a robust baseline for modeling complex feature relationships, though its performance can be sensitive to kernel selection and parameter tuning.

(2) The eXtreme Gradient Boosting (XGBoost) is an efficient and scalable implementation of gradient boosting, and its target is to construct an ensemble of decision trees in a sequential manner [18]. Each tree is trained to minimize the residual errors of the previous trees, enabling strong bias-variance trade-off optimization. The XGBoost introduces regularization terms in its objective function to prevent overfitting and supports parallel computation, making it suitable for large-scale educational datasets. Its ability to capture complex non-linear dependencies among features makes it a competitive baseline for predicting student academic outcomes.

(3) Random Forest (RF) is an ensemble learning method that aggregates the predictions of multiple decision trees trained on random subsets of features and samples [19]. Such randomization is able to reduce overfitting and enhances model robustness. The RF performs well in scenarios where data contain noise or irrelevant features, as it inherently evaluates variable importance during the training process. In student performance prediction, the RF is particularly effective for capturing diverse feature interactions and providing interpretable importance measures that aid in understanding key learning factors.

(4) The CatBoost is a gradient boosting algorithm that introduces several innovations for handling categorical features and mitigating prediction shift problems [20]. It employs ordered boosting and target statistics encoding to reduce overfitting and improve generalization, particularly in datasets with mixed data types. The CatBoost's ability to model complex feature hierarchies and automatically process categorical variables makes it well-suited for educational datasets, which often include heterogeneous variables such as demographic information, engagement metrics, and assessment scores.

2.2 The proposed stacking model

To enhance predictive performance and generalization capability, a stacking ensemble model is proposed by integrating the RF and CatBoost within a hierarchical framework. The proposed model leverages the complementary strengths of both RF's capability for robust feature selection and CatBoost's proficiency in handling categorical data and complex nonlinear relationships.

As we can see from Algorithm 1, The proposed stacking-based RF-CatBoost model is designed to combine the complementary strengths of RF and CatBoost for robust student performance prediction. The model operates in a two-layer framework. In the first layer, the RF and CatBoost models are trained as base learners using k-fold cross-validation [21]. During this process, each dataset fold is used once as the testing set, with the remaining folds serving as the training set. The base learners generate out-of-fold predictions for each validation subset. This procedure ensures that the multi-source results obtained are unbiased and prevents overfitting. In the second layer, a the simple fusion strategy is used to ensemble the base learners using the average weighted operation. This step combines the predictions from RF and CatBoost base models, effectively capturing complementary information and correcting errors made by individual models, and then obtain the final output. This two-layer stacking procedure provides several advantages. First, it leverages the diversity of base learners to improve overall predictive accuracy. Second, cross-validation in the base layer enhances robustness and generalization by reducing overfitting. Finally, by combining RF and CatBoost, the model balances variance and bias, making it particularly suitable for educational datasets with heterogeneous and nonlinear features.

Algorithm 1 Stacking-Based RF–CatBoost Model for Student Performance Prediction

Require: Training dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$, number of folds K, weights ω_{RF} and ω_{CB} for fusion

Ensure: Final trained stacking model $\mathcal{M}_{\text{stack}}$

Split $\mathcal{D}$ into K folds: $\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_K$

Initialize prediction vectors $\hat{y}^{(\text{RF})}$ and $\hat{y}^{(\text{CB})}$ of length N

▷ — Base-Layer Training via K-Fold Cross-Validation —

for $k = 1$ to K **do**

  $\mathcal{D}_{\text{train}} \leftarrow \mathcal{D} \setminus \mathcal{D}_k, \quad \mathcal{D}_{\text{valid}} \leftarrow \mathcal{D}_k$

  Train RF model $\mathcal{M}_{\text{RF}}^{(k)}$ on $\mathcal{D}_{\text{train}}$

  Train CatBoost model $\mathcal{M}_{\text{CB}}^{(k)}$ on $\mathcal{D}_{\text{train}}$

  Obtain out-of-fold predictions:

$$\hat{y}_{\mathcal{D}_k}^{(\text{RF})} \leftarrow \mathcal{M}_{\text{RF}}^{(k)}(x_{\mathcal{D}_k}), \quad \hat{y}_{\mathcal{D}_k}^{(\text{CB})} \leftarrow \mathcal{M}_{\text{CB}}^{(k)}(x_{\mathcal{D}_k})$$

end for

▷ — Fusion Layer (Stacking Integration) —

Combine base-level predictions using a weighted average:

$$\hat{y}_{\text{final}} = \omega_{\text{RF}} \cdot \hat{y}^{(\text{RF})} + \omega_{\text{CB}} \cdot \hat{y}^{(\text{CB})}$$

Normalize weights such that $\omega_{\text{RF}} + \omega_{\text{CB}} = 1$

▷ — Model Deployment —

Train final RF and CatBoost on the full dataset $\mathcal{D}$

The final stacking model is

$$\mathcal{M}_{\text{stack}} = \{\mathcal{M}_{\text{RF}}, \mathcal{M}_{\text{CB}}, \omega_{\text{RF}}, \omega_{\text{CB}}\}$$

▷ — Inference for a New Sample x —

Obtain base predictions:

$$\hat{y}_{\text{RF}} = \mathcal{M}_{\text{RF}}(x), \quad \hat{y}_{\text{CB}} = \mathcal{M}_{\text{CB}}(x)$$

Compute final output:

$$\hat{y} = \omega_{\text{RF}} \cdot \hat{y}_{\text{RF}} + \omega_{\text{CB}} \cdot \hat{y}_{\text{CB}}$$

return $\hat{y}$ and $\mathcal{M}_{\text{stack}}$

3 Experimental results and discussions

This section presents the evaluation of the proposed model for student performance prediction, including data description, evaluation metrics, and detailed analysis of the results.

3.1 Data description

To assess the effectiveness of the proposed model, two benchmark educational datasets were obtained from the UCI Machine Learning Repository [22]. These datasets capture student academic performance in two distinct courses: Mathematics and Portuguese Language. The Mathematics dataset contains 395 student samples, while the Portuguese Language dataset comprises 649 samples. Each dataset

Table 1. Statistical properties of the student performance dataset.

Feature	Symbol	Type	Values
School	School	Binary	Gabriel Pereira; Mousinho da Silveira
Sex	Sex	Binary	Female; Male
Age	Age	Numeric	15-22 (in years)
Address	Address	Binary	Urban; Rural
Family Size	Famsize	Binary	≤ 3 (small); > 3 (large)
Parent Status	Pstatus	Binary	Living together; Living apart
Mother's Education	Medu	Numeric	0 (none) - 4 (higher education)
Father's Education	Fedu	Numeric	0 (none) - 4 (higher education)
Father's Job	Fjob	Nominal	Teacher; Health care; Civil services (e.g., administrative, police); At home; Other
Mother's Job	Mjob	Nominal	Teacher; Health care; Civil services (e.g., administrative, police); At home; Other
School Choice Reason	Reason	Nominal	Close to home; School reputation; Course preference; Other
Guardian	Guardian	Nominal	Mother; Father; Other
Travel Time	Traveltime	Numeric	1 ($<$ 15 min); 2 (15-30 min); 3 (30 min-1 hour); 4 ($>$ 1 hour)
Study Time	Studytime	Numeric	1 ($<$ 2 hours); 2 (2-5 hours); 3 (5-10 hours); 4 ($>$ 10 hours)
Past Failures	Failures	Numeric	1 (1 failure); 2 (2 failures); 4 ($\geq$ 3 failures)
School Support	Schoolsup	Binary	Yes; No
Family Support	Famsup	Binary	Yes; No
Paid Extra Classes	Paid	Binary	Yes; No
Extracurricular Activities	Activities	Binary	Yes; No
Nursery Attendance	Nursery	Binary	Yes; No
Pursue Higher Education	Higher	Binary	Yes; No
Home Internet Access	Internet	Binary	Yes; No
Romantic Relationship	Romantic	Binary	Yes; No
Family Relationship Quality	Famrel	Numeric	1 (very bad) - 5 (excellent)
Post-School Free Time	Freetime	Numeric	1 (very low) - 5 (very high)
Socializing with Friends	Goout	Numeric	1 (very low) - 5 (very high)
Weekday Alcohol Consumption	Dalc	Numeric	1 (very low) - 5 (very high)
Weekend Alcohol Consumption	Walc	Numeric	1 (very low) - 5 (very high)
Current Health Status	Health	Numeric	1 (very bad) - 5 (very good)
School Absences	Absences	Numeric	0-93 (number of days)
First-Period Grade	G1	Numeric	0-20 (grading scale: 0 = lowest, 20 = highest)

includes 30 input attributes representing diverse student-related factors, along with a single output variable corresponding to the first-period grade.

A comprehensive statistical summary of all attributes is provided in Table 1. For clarity, numeric features represented by codes (e.g., `Medu` and `Failures`) are explicitly defined. For binary and nominal features, discrete categories are separated by semicolons to ensure consistent formatting and facilitate interpretation.

3.2 Evaluation metrics

The performance of student prediction models is evaluated using four widely adopted metrics: Mean Absolute Error (MAE), Standard Deviation of prediction errors (SD), Root Mean Squared Error (RMSE), and Robustness (MAC). The objective is to minimize MAE, SD, and $RMSE$, while maximizing MAC, which quantifies the alignment between the true and predicted values. The mathematical formulations of these metrics are as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \,, \tag{1}$$

$$SD = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (e_i - \bar{e})^2}, \tag{2}$$

Table 2. Experimental results for the prediction of Mathematics course in the first-period grade using the SVM, RF, XGBoost, CatBoost, and RF-CatBoost.

Model	MAE	SD	$RMSE$	MAC
SVM	2.6259	3.1487	3.1956	0.9227
XGBoost	2.6257	3.2020	3.2591	0.9205
RF	2.5228	2.9784	3.0249	0.9312
CatBoost	2.5032	3.0411	3.0791	0.9284
RF-CatBoost	**2.4717**	**2.9771**	**2.9999**	**0.9316**

Table 3. Experimental results for the prediction of Portuguese Language course in the first-period grade using the SVM, RF, XGBoost, CatBoost, and RF-CatBoost.

Model	MAE	SD	$RMSE$	MAC
SVM	1.9861	2.5102	2.5263	0.9536
XGBoost	1.9233	2.4130	2.4319	0.9573
RF	1.8131	2.2859	2.3027	0.9616
CatBoost	1.8193	2.3034	2.3253	0.9607
RF-CatBoost	**1.7861**	**2.2822**	**2.2943**	**0.9619**

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}, \tag{3}$$

$$MAC = \frac{(\boldsymbol{y}^T\hat{\boldsymbol{y}})^2}{(\boldsymbol{y}^T\boldsymbol{y})(\hat{\boldsymbol{y}}^T\hat{\boldsymbol{y}})}, \tag{4}$$

where n is the number of test samples, y_i denotes the true value of the i-th sample, $\hat{y}_i$ is its corresponding predicted value, $e_i = \hat{y}_i - y_i$ is the prediction error, and $\bar{e} = \frac{1}{n}\sum_{i=1}^{n} e_i$ represents the mean prediction error. Lower MAE, SD, and $RMSE$ values indicate higher prediction accuracy and stability, while higher MAC values reflect greater model robustness.

3.3 Experimental results

Table 2 summarizes the experimental results for predicting the first-period grade performance in the Mathematics course for the SVM, XGBoost, RF, CatBoost, and the proposed stacking-based RF-CatBoost model. From the results, it is evident that the proposed RF-CatBoost model outperforms all baseline models across the majority of evaluation metrics. Specifically, the RF-CatBoost achieves the lowest MAE (2.4717) and $RMSE$ (2.9999), indicating higher accuracy in predicting students' final grades. Its SD (2.9771) is marginally lower than RF and CatBoost, suggesting consistent prediction performance across different samples. Furthermore, the RF-CatBoost attains the highest MAC value (0.9316), demonstrating superior alignment between predicted and actual outcomes, and confirming its robustness.

Comparatively, among the baseline models, the RF and CatBoost perform better than the SVM and XGBoost, likely due to their ensemble nature and ability to capture non-linear feature interactions. The stacking-based RF-CatBoost model effectively combines the complementary strengths of RF and CatBoost, resulting in consistent improvements in both accuracy and robustness. These findings highlight the effectiveness of the proposed stacking approach for student performance prediction, particularly in complex educational datasets with heterogeneous features.

In addition, to further evaluate the performance of our proposed model for student performance prediction, Table 3 presents the experimental results for predicting the first-period grade performance in the Portuguese Language course using the SVM, XGBoost, RF, CatBoost, and the proposed stacking-based RF-CatBoost model. As shown in the table, the proposed RF-CatBoost model achieves the best overall performance. It obtains the lowest MAE (1.7861) and $RMSE$ (2.2943), indicating improved accuracy in estimating students' final grades. Its SD (2.2822) is marginally lower than that of RF and CatBoost, suggesting consistent performance across different data samples. Additionally, the RF-CatBoost achieves the highest MAC value (0.9619), confirming robust alignment between predictions and actual outcomes. Among the baseline models, the RF and CatBoost outperform the SVM and XGBoost, likely due to their ensemble strategies and ability to capture non-linear relationships in the features. The stacking-based RF-CatBoost model further enhances prediction

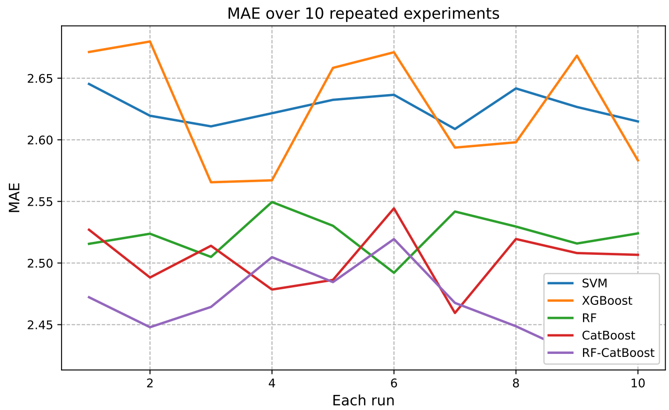

Figure 1. Comparison results from the 10 experimental runs in terms of MAE reported in Table 2.

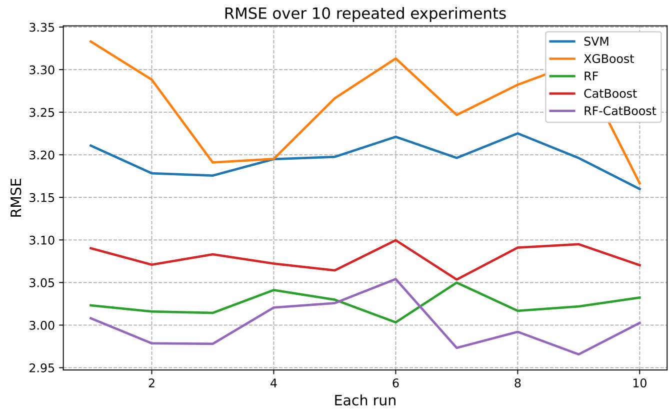

Figure 3. Comparison results from the 10 experimental runs in terms of $RMSE$ reported in Table 2.

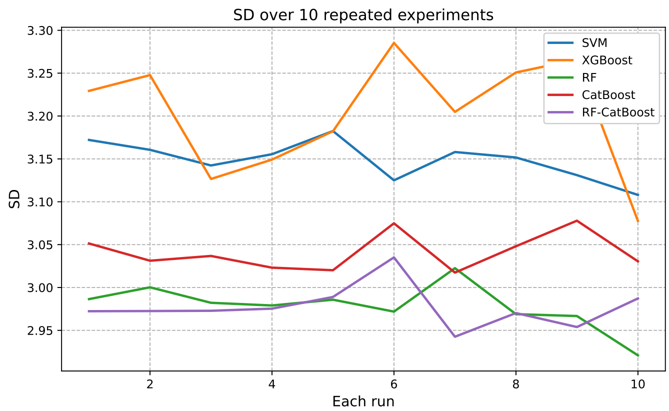

Figure 2. Comparison results from the 10 experimental runs in terms of SD reported in Table 2.

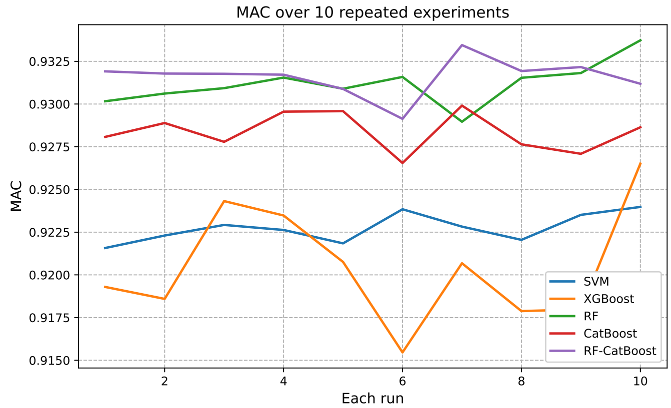

Figure 4. Comparison results from the 10 experimental runs in terms of MAC reported in Table 2.

accuracy and robustness by effectively combining the complementary strengths of RF and CatBoost. These results demonstrate that the proposed stacking framework consistently improves performance across different courses, highlighting its applicability to diverse educational datasets.

Furthermore, Figures 1 to 8 provide a visual representation of the experimental results reported in Tables 2 and 3, respectively, based on 10 repeated experiments. Each figure compares the performance of the baseline models (SVM, RF, XGBoost, and CatBoost) with the proposed stacking-based RF-CatBoost model across the four evaluation metrics (MAE, SD, $RMSE$, and MAC). The visualizations clearly demonstrate that the proposed RF-CatBoost consistently outperforms all baseline models across both datasets. In particular, it achieves lower MAE, SD, and $RMSE$ values, indicating more accurate and stable predictions of student performance. Simultaneously, it attains the highest MAC values, reflecting stronger robustness and better alignment between predicted and actual outcomes.

These results confirm that the stacking strategy effectively leverages the complementary strengths of RF and CatBoost. While the RF captures diverse feature interactions through bagging and reduces variance, the CatBoost complex non-linear relationships and handles categorical features efficiently. By combining these base learners, the proposed model achieves improved predictive performance, demonstrating its generalizability across different courses and its suitability for complex educational datasets. Moreover, the low variation across repeated experiments highlights the stability of the proposed approach, making it a reliable tool for early student performance prediction and personalized educational interventions.

4 Conclusion

In this study, we proposed a stacking-based RF-CatBoost model for predicting student performance in educational settings. The model

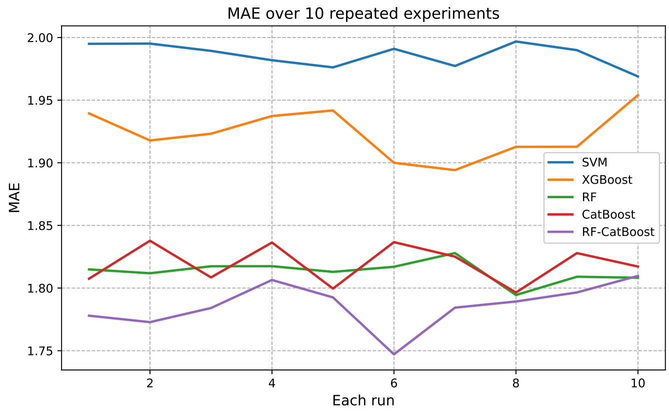

Figure 5. Comparison results from the 10 experimental runs in terms of MAE reported in Table 3.

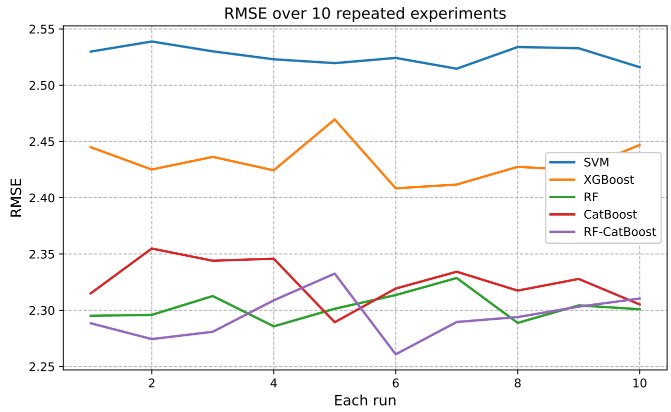

Figure 7. Comparison results from the 10 experimental runs in terms of $RMSE$ reported in Table 3.

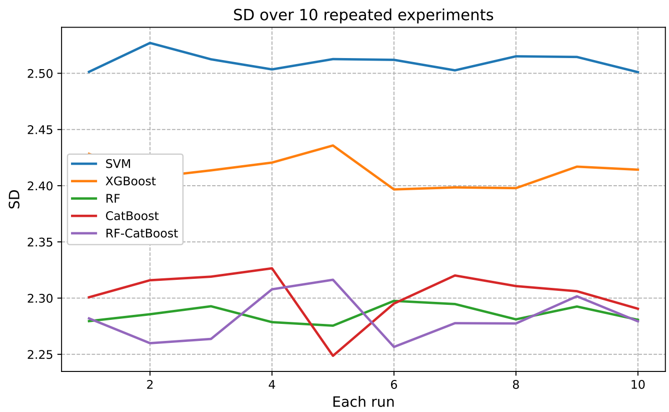

Figure 6. Comparison results from the 10 experimental runs in terms of SD reported in Table 3.

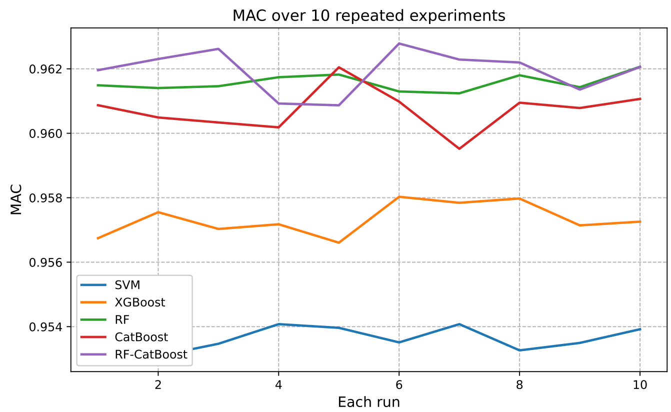

Figure 8. Comparison results from the 10 experimental runs in terms of MAC reported in Table 3.

combines the complementary strengths of RF and CatBoost, leveraging RF's ability to capture diverse feature interactions through bagging and CatBoost's capacity to model complex non-linear relationships and handle categorical variables efficiently. By employing a fusion strategy, the stacking result effectively integrates the predictions from multiple base learners, enhancing both accuracy and robustness. Extensive experiments conducted on two benchmark educational datasets confirmed the high performance of the proposed model, which was rigorously evaluated using 10-fold cross-validation repeated 10 times. The results consistently demonstrated that the RF-CatBoost stacking model outperformed all baseline models across multiple evaluation metrics (MAE, SD, $RMSE$, and MAC), achieving higher predictive accuracy, stability, and robustness.

Despite these promising results, this study has several limitations. First, the proposed model was tested on only two datasets, which may limit the generalizability of the findings to other educational contexts or courses. Second, while the stacking approach improves predictive performance, it increases model complexity and computational cost compared to individual base learners. Third, the current framework does not explicitly address model interpretability, which is important for educators to understand and act upon predictions.

Future work will aim to address these limitations by evaluating the stacking model on larger and more diverse educational datasets, integrating additional base learners, and incorporating multi-modal data sources [23] such as online learning behaviors and temporal features. Moreover, enhancing the interpretability of the model through explainable techniques [24, 25] will be an important direction to provide actionable insights for personalized learning interventions and early identification of at-risk students.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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