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AI Powered System to Monitor - Analyze the Performance and Feedback of Student

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Abstract

The forecasting of this research work implements the use of networks and data integration presenting the solution to analyze the each and individual performance implementing the algorithms of machine learning. Study mainly outlines the profuse objectives to represent and review the performance plethora in identification of students' marks, co-curricular and extracurricular activities. It provides a casted layout in a definite display allowing the users to input the various data required as a part of academic curriculum. The dataset is comprehensive and more compact categorizing a real time features like marks and all other attributes taken by an institution. It is further processed in various models of classification including random forest, decision tree and other algorithms to obtain the score and its performance. The exploratory analysis of data along with evaluation of models in correspondence with feature engineering helps to cater with classification techniques to understand the performance of students in various levels. The live dashboard and an interactive system provide a definite outline to support practical usage and significant implementation in educational institutions. Statistical forecasting prevents the misleading of data keeping the clarity constant and supporting the efficacy of the system so that it supports as a tool of guidance in classification, generation and prediction of reports and results of students from the performance and gather the measures of feedback.

Keywords: Analysis, Classification, Dashboard, Feedback, Performance, Prediction.

Introduction

In proceeding day to day life activities in education, performance and other assignments continuous monitoring is a key to maintain stability and effectiveness in overall growth and development. In daily development and digital education, increasing demand in insight gathering and development planning is in demand. The potential extraction in terms of clarified angle is highly demanded for each student not only in terms of academic scores but also overall development. Personalized learning intervention is leading scope of business for ed tech product companies and it is increasing its demand for the sake of use of people. Traditional methods mostly deploy the scope of retrospection and it lacks the insights that are measurable and needs instant action. Quietly contradicting the prevailing system, ML offers a wide deployment scope to provide actionable feedback and totally outcome based. All types of students can be benefitted in terms of improvement and present performance. Comprehensive and presentable methods of ML system mostly analyses and predicts the student data in this work. Apart from classification, prediction is done in this work which is a scope of student improvement in future work. Subject specific feedback entails a classified performance management tool to fetch personalized recommendations and making more informed decisions to cater the learning and development outcomes. Thus, in its initial phase this study will pave a implemented live GUI system to make more automated system and analyze specified for student. Integrating ML in several environmental aspects of education has been instrumental to cater the research areas that are mostly in consideration and prevalence to emphasize the aspect of outcomes in student dealings and performance gathering. The following section provides a discussion of previous research conducted in this domain. Author demonstrated the classification algorithms and implemented its

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prevalence to identify the respective rate of results and demography (1). It was also discussed about the fundamental use of decision tree in the work. In similar approach only one study mostly emphasized on predicting the dropout of students using J48 decision tree and mostly achieving the accuracy around 80% (2). This work on literature review and laid a comprehensive layout of data mining techniques using the educational resources and highlighting the more personalized scope of analysis (3). Author worked on various comparisons of mathematical models (4) mostly focus on regression and svm models that characterized the nonlinear approach and sharpened the discipline of their prevalence. Innumerable researchers have worked and put their views on forward exploring various methods of classification. Author has compared the approaches in working with decision tree and neural network while performing the methods of prediction using variables like parental education and gender (5). Author worked on ML survey that involves the survey of ML algorithms to large datasets and employing KNN and SVM (6). This researcher worked on virtual analysis and behavioural analysis by click stream mechanism and environments that supports learning to flag at risk students (7). The application of neural networks and prediction of e learning dropouts in accuracy and significant single modeled systems (8). Collective analytics and learning propagations mostly derived the areas of intervention focusing on redesign of curriculum. Area identification and data mining has been a constant in a past work (9). Previous study mostly has their major contributions to interpretable models balancing the dropout identification and accuracy along with proper transparency (10). Researcher worked on similar traditional approach of classification suggesting the actions of remedy and feedback for weaker students only (11). Previous worked on student validation along with performance prediction of the students proving the significance of classification trees. ID3 and c4.5 is mostly required in predicting the educational tasks (12). Researcher developed a recommended framework based system to facilitate LMS including a tailored feedback system making significant resource suggestions along with intelligent settings in academics (13). Researcher applied various machine learning regression models to predict student academic performance using image and algorithm-based datasets. The study highlighted the effectiveness of linear and tree-based regression models in handling educational data for prediction accuracy (14). In past study developed a prediction model using educational data mining and machine learning techniques to forecast student outcomes (15). The authors emphasized the importance of data preprocessing and feature selection in improving model performance. In Previous research explored the use of multiple machine learning algorithms for predicting student performance, with a focus on classification accuracy (16). The study demonstrated that ensemble methods yielded higher prediction rates compared to standalone algorithms. Collective measures of these above studies recommend that one step feedback system is highly essential. Not only feedback system but also overall feedback will contribute to the development of students in all aspects like co-curricular extra-curricular etc.

Methodology

The system makes use of the Decision Tree, Random Forest, and XGBoost models. This, XGBoost demonstrated the highest accuracy and was used for final deployment. The dataset was gathered from real students with their consent and after appropriate anonymization. Academic performance, attendance, extracurricular activities, and behavioral characteristics are among the features that were extracted. RMSE, F1 Score, and Accuracy were used for evaluation. Cross-validation, pruning, and regularization approaches were used to address over fitting.

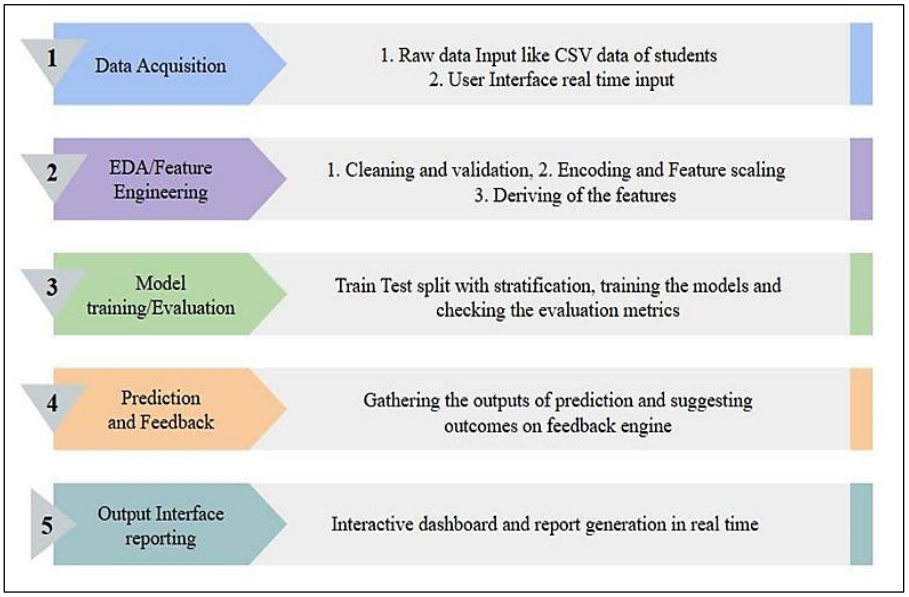

Figure 1: Process Flow Diagram of the Methodological Approach

Figure 1 illustrates the operational methodology, detailing the step-by-step process of the entire work. Adopted methodology in project mostly caters out casted and comprehensive machine learning approach to predict the academic record of students and gathering the respective feedback. Dataset featuring varieties of features mostly undergone exploratory data analysis and generating personalized feedback system. Labeling of data followed encoding as well as banalization of datasets to check the compatibility of ML models (one hot encoding is preferred). Descriptive statistical analysis has been conducted with various python libraries for checking if correlation existence is prevailing within the features. Each subject score based on individual thresholds has been depicted and derivation is made simpler based on comprehensive category.

In model training, the algorithms employing all supervised are mostly covered and the most accurate one has been taken into consideration to develop the model and GUI and post application. Interactive dashboard developed using GUI helps in real time prediction and engagement metrics in user accessibility format. Report generation in this methodology employed excels mostly to test in google colab.

Results and Discussion

Data analysis, visualization, and machine learning model evaluation produced a variety of enlightening results from the deployed system. The following components can be used to broadly classify the results.

Exploratory Data Analysis (EDA): To comprehend the distribution and structure of the dataset, EDA techniques were used. Important points to note are: Visualizations shown in Figures 2, 3 and 4, emphasize outliers and possible relationships while displaying the variation and distribution across academic and non-academic features. It was possible to identify trends in academic strengths and weaknesses for both individuals and groups by using subject-wise performance analysis, Figures 5 and 7.

Significant relationships between behavioral markers, extracurricular activities, and academic scores were shown by a heatmap in Figure 8. Statistical insights and feature correlation: To find connections between input features, correlation coefficients were calculated using statistical methods. Characteristics including attendance, extracurricular involvement, and past grades had a significant impact on total success, as seen in Figure 9. Evaluation of the Model: Several models for supervised learning were trained and evaluated. Among the main conclusions are: Model Accuracy: XGBoost regularly outperformed the other models tested (Decision Tree, Random Forest, Logistic Regression, KNN, SVM, and XGBoost), attaining up to 95% accuracy in Figure 11. Comparison of Training and Testing: Minimal over fitting is shown in Figure 10, indicating that the model performs well when applied to unknown

data. In terms of categorical performance: The correct classification of students into the three performance groups (Excellent, Average, and At-risk) is shown in Figure 6. The integration of a live, interactive dashboard in Figures 12 and 13 and system deployment allowed teachers to enter student data in real time and obtain performance insights and suggestions. Comprehensive student assessment is improved by the system's ability to save and export performance reports, which contain extra-curricular evaluation metrics in Figure 14. These findings support the viability and applicability of using a machine learning-driven system for academic tracking and feedback creation in learning environments.

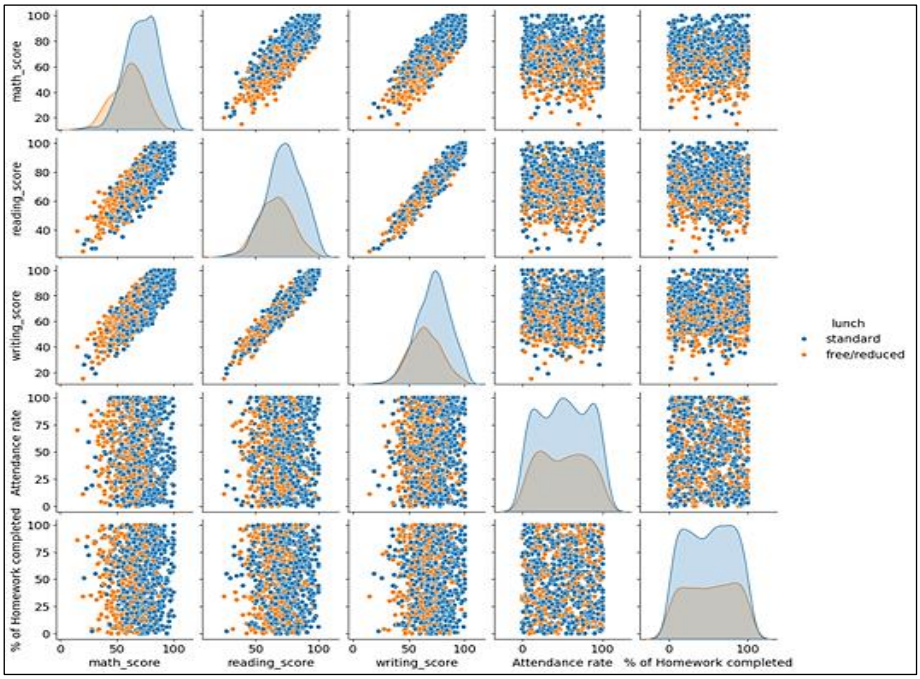

Figure 2: EDA and Visualization

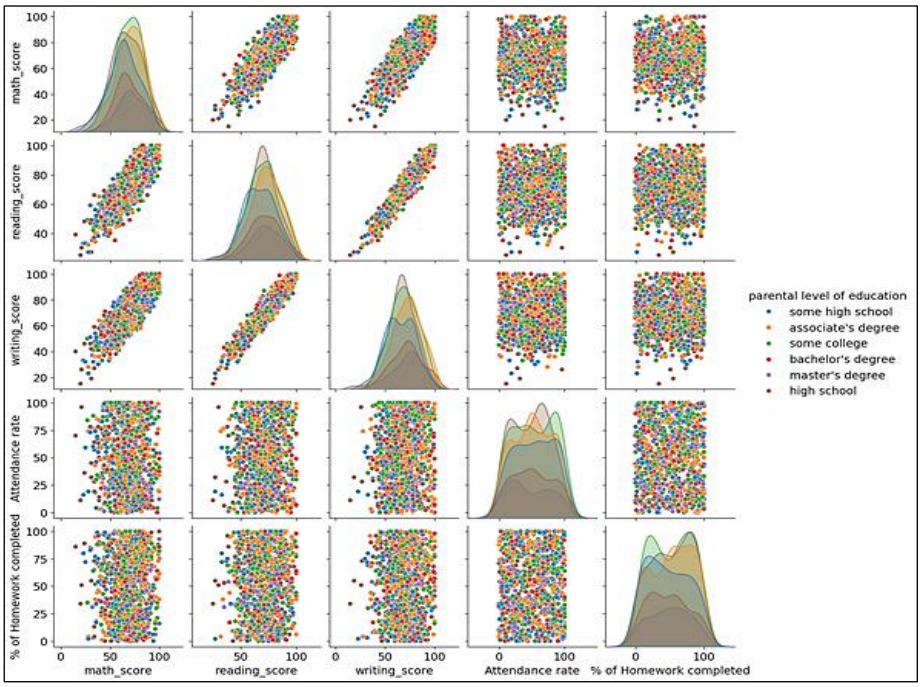

Figure 3: EDA and Visualization of Different Columns

	math_score	reading_score	writing_score	Attendance rate	% of Homework completed
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	67.810000	70.382000	69.140000	51.297000	51.110000
std	15.250196	14.107413	15.025917	29.843985	29.980573
min	15.000000	25.000000	15.000000	0.000000	0.000000
25%	58.000000	61.000000	59.000000	25.000000	25.000000
50%	68.000000	70.500000	70.000000	51.000000	53.000000
75%	79.250000	80.000000	80.000000	77.000000	77.000000
max	100.000000	100.000000	100.000000	100.000000	100.000000

Figure 4: Statistical Data Analysis

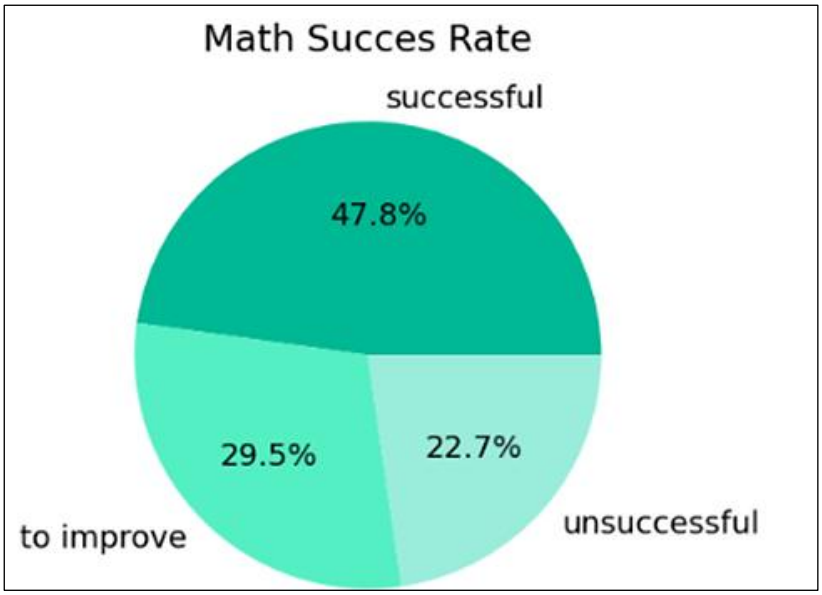

Figure 5: Subject Wise Analysis

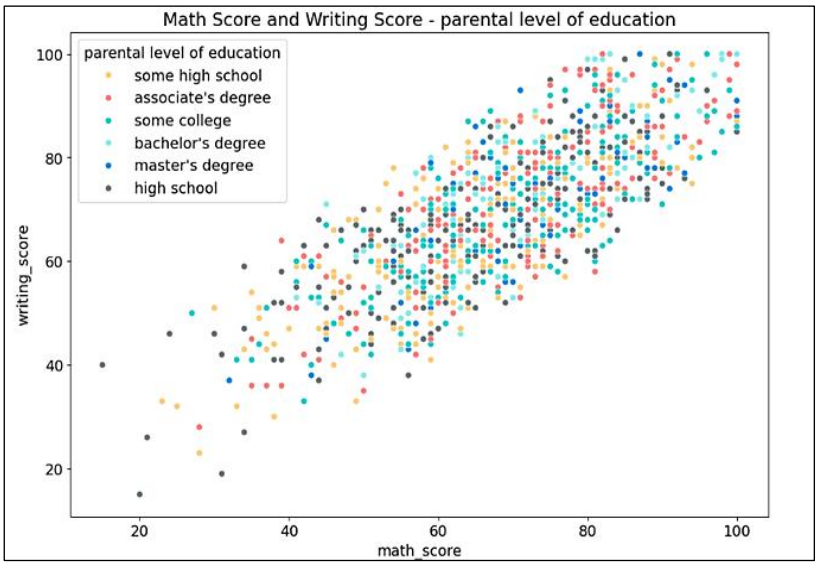

Figure 6: In Depth Categorical Analysis

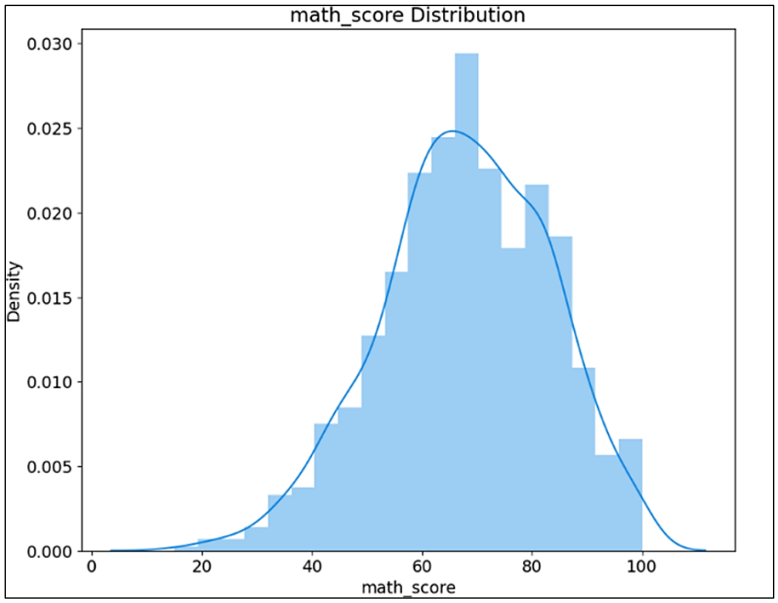

Figure 7: Subject Wise Distribution

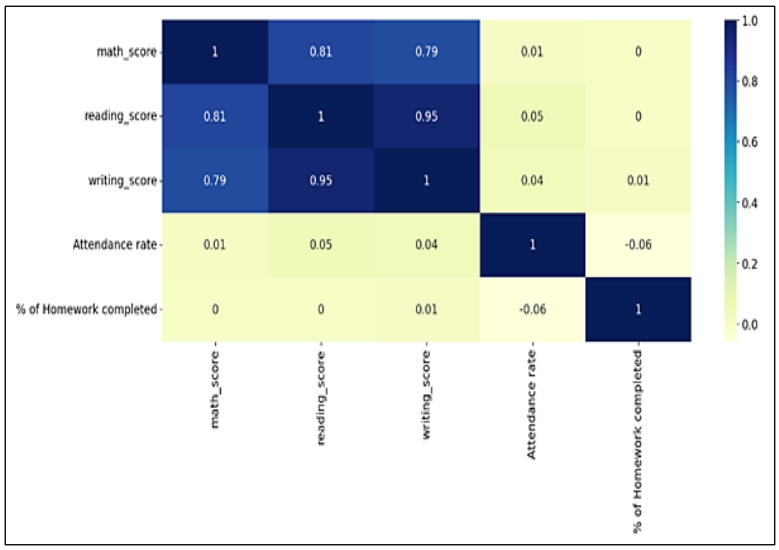

Figure 8: Heatmap and Correlation between Features

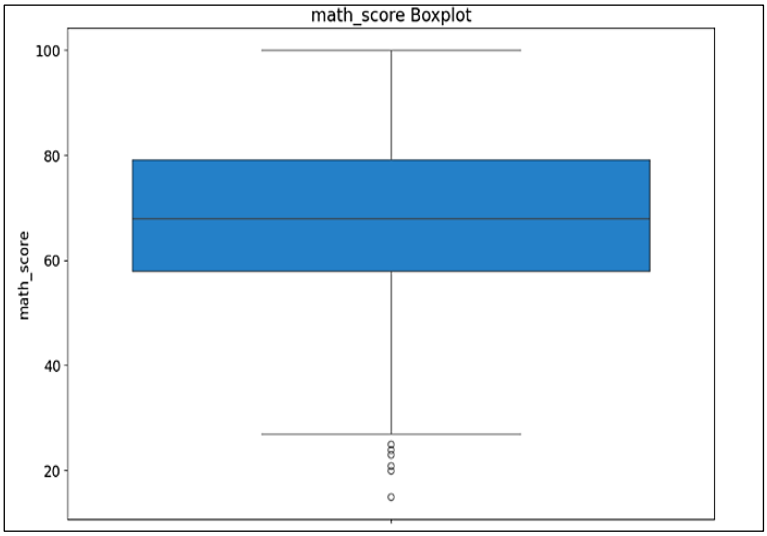

Figure 9: Statistical Distribution Display

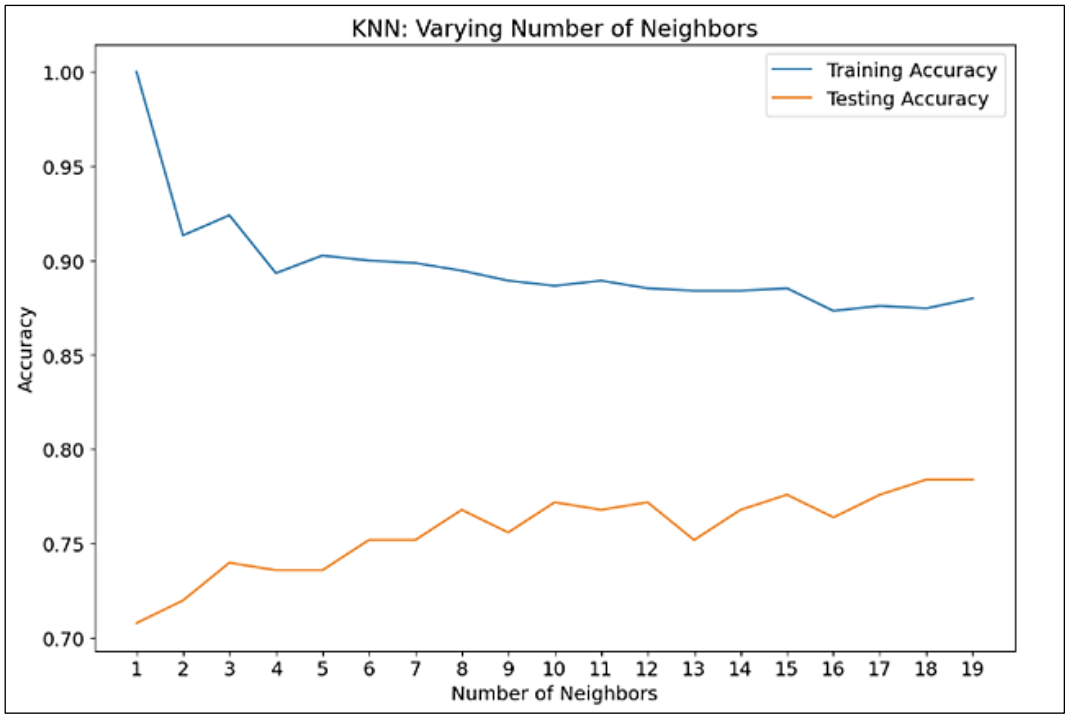

Figure 10: Sample Testing of Train vs Test Plot in Algorithm

Model: Logistic Regression

	precision	recall	f1-score	support
0	0.88	0.86	0.87	57
1	0.84	0.78	0.81	74
2	0.92	0.97	0.94	119
accuracy			0.89	250
macro avg	0.88	0.87	0.87	250
weighted avg	0.89	0.89	0.89	250

Model: Random Forest

	precision	recall	f1-score	support
0	0.98	1.00	0.99	57
1	0.97	1.00	0.99	74
2	1.00	0.97	0.99	119
accuracy			0.99	250
macro avg	0.99	0.99	0.99	250
weighted avg	0.99	0.99	0.99	250

Model: XGBoost

	precision	recall	f1-score	support
0	1.00	1.00	1.00	57
1	1.00	1.00	1.00	74
2	1.00	1.00	1.00	119
accuracy			1.00	250
macro avg	1.00	1.00	1.00	250
weighted avg	1.00	1.00	1.00	250

Figure 11: Accuracy Report of Algorithms

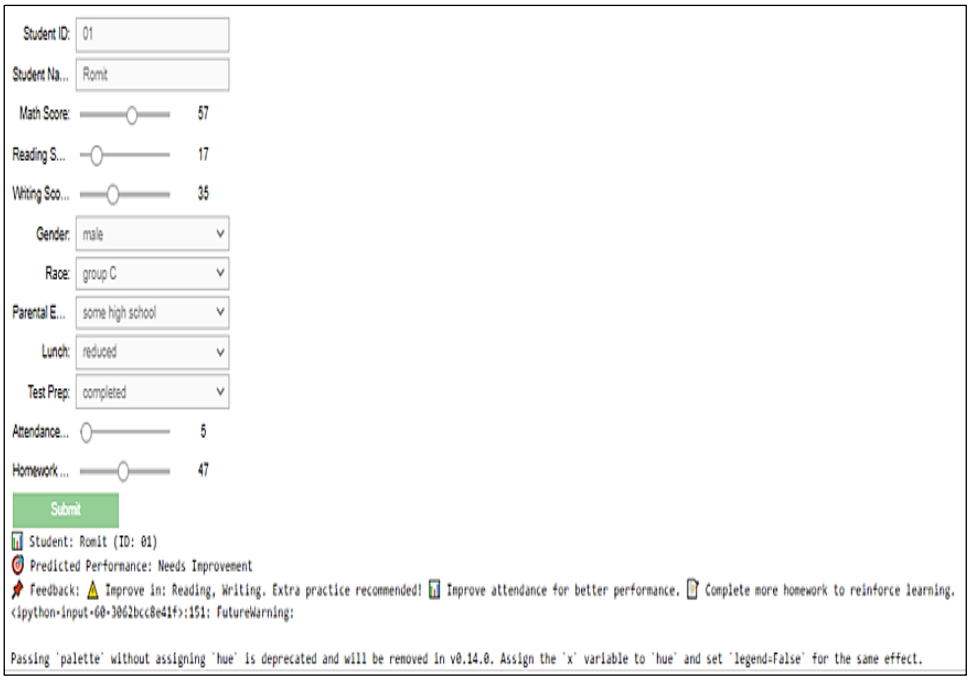

Figure 12: Interactive Dashboard

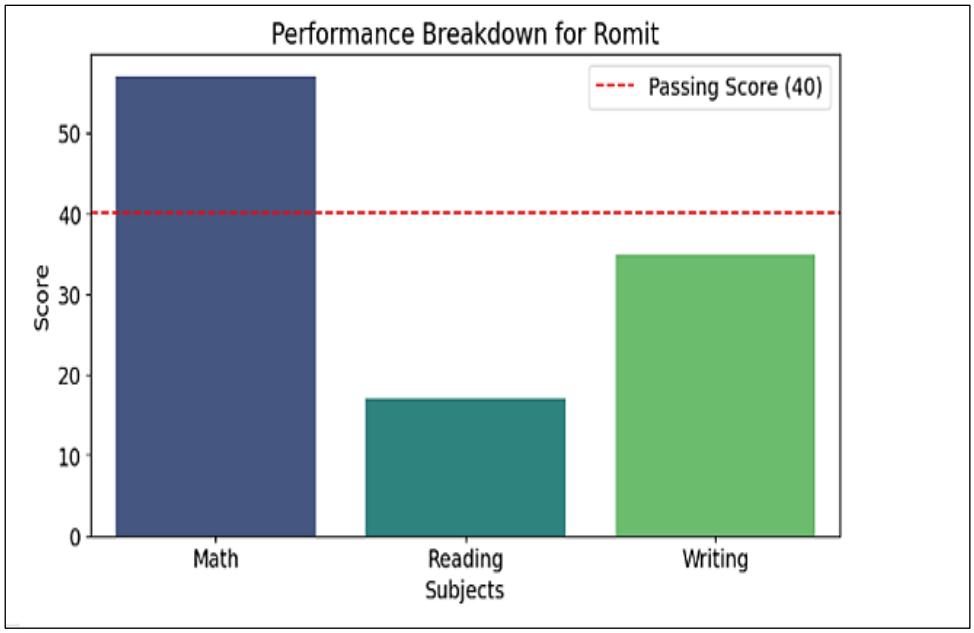

Figure 13: Real Time Visualization

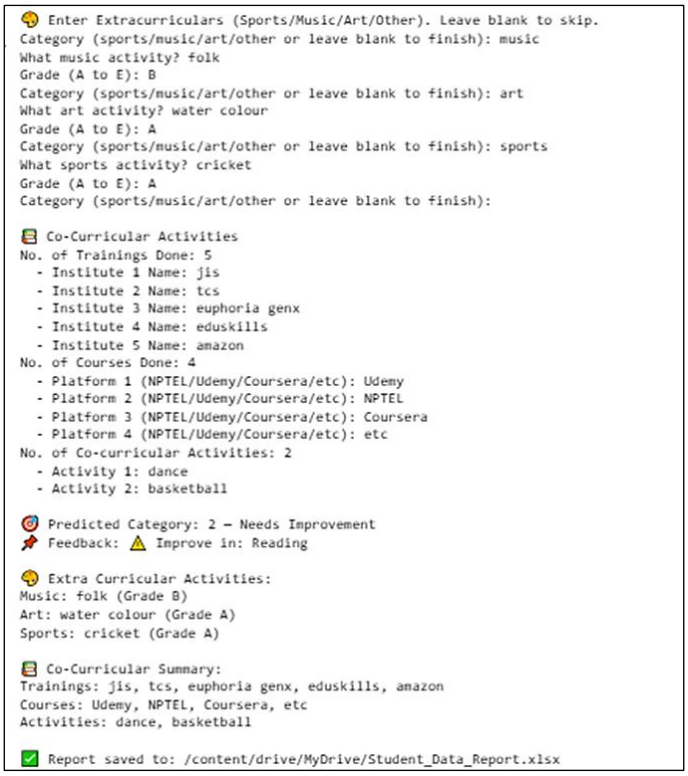

Figure 14: Extracurricular Activity Report Checking and Saving the Report in Excel Format to Drive

System developed effectively demonstrated the use of ML in educational purposes. Tested models mostly implement XGBoost with most reliability and accuracy for student classification. Ability of model to distinguish between various classifiers makes it ideal to work. Integration of academic and behavioral data makes it more versatile and robust to enable analysis more usable and feature oriented. Expansion of this system in academic predictors ratifies the volume of implementing unexplored areas of literature and aligns with definite findings with relevant cases. Thus, validation of the academic and entire architecture is done supporting the strategies of intervention. The dataset limited deployment validation, and reliance on institutional data availability are some of the limitations. Future plans call for field validation, improved personalization through adaptive learning models, and integration with larger LMS systems. Performance-driven academic planning, predictive intervention techniques, and customized learning plans are examples of real-world applications.

Conclusion

Based on student learning profiles and preferences as determined by dataset attributes, the feedback system adjusts. Although the original deployment was evaluated, more validation is suggested through field testing using engagement and learning objective metrics. Thus practical live feedback and student analyze system has been developed by leveraging feedback from the user. Combination of academic scores with other co-curricular and extracurricular factors creates better results in classification for poper detection and feedback gathering technique by XGBoost algorithm. 95% accuracy makes a suitable report generation technique and makes it more compact for real world use and also foundational application in real world tradition to monitor the performance in institution.

Abbreviation

None.

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Author Contributions

The work being executed under multiple authorship derived its conceptualization from the rigorous research carried out by Sharmistha Ghosh: Conceptualization, Methodology design, Manuscript preparation, Monali Sanyal: Data collection, Preprocessing, System validation, Suparna DasGupta: Algorithm development, Technical review, Soumyabrata Saha: Model training, Testing, Performance evaluation, Romit Ghosh: User interface design, Integration of AI modules, Soumya Bhattacharyya: Overall supervision, Technical guidance, Final manuscript review, Koushik Karmakar: Resources, Supported hardware setup, Assisted in interpreting results. All authors reviewed and approved the final version of the manuscript.

Conflict of Interest

The authors of this work state that they have no conflicts of interest about its publication.

Ethics Approval

Not applicable.

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