

AN INTELLIGENT MULTI-MODEL APPROACH FOR STUDENT PERFORMANCE PREDICTION USING TEMPORAL–SPATIAL LEARNING WITH CONVOLUTIONAL NEURAL NETWORKS AND GRADIENT BOOSTING

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ABSTRACT

The present research investigation is aimed at effectualising a more corroborative and accurate educational predictive analytics so as to facilitate and enhance data-driven academic decision-making for meeting the learning objectives in Higher Educational Institutions. Given the rapid availability of data drawn from the academic records, behavioral logs, and learning management systems (LMS) it is now more efficacious to apply sophisticated machine learning algorithms for generating the desired results to optimise on the benefits for both the institutions and the learners. In this league, the study suggests a hybrid predictive framework that combines Gradient Boosting and Temporal-Spatial Convolutional Neural Networks (CNN) for effecting improved student performance prediction. With the intent of finding the most pertinent academic, behavioral, and socio-demographic characteristics, the study first employs data preparation, normalization, and Recursive Feature Elimination (RFE). Thereafter, the progression patterns and intricate feature interactions are accessed by using a Temporal-Spatial CNN. To increase the accuracy of the predictions and accomplish generalization, the study uses Gradient Boosting classifier. To assess the efficacy of the suggested model, a train-test split of 80-20 is done on a multi-dimensional student dataset. As authenticated by the experimental data, in terms of accuracy and efficacy, the proposed multi-model architecture surpasses the results drawn from the conventional machine learning and standalone deep learning techniques. With an accuracy of 96.8% and an increased F1-score and AUC (0.98), the devised model seeks to efficiently categorize the students into risk groups. Thus, enabling targeted and prompt interventions to provide academic assistance and niche the intended learning outcomes in the process. Although the reliance on dataset could differ amongst institutions, the approach proffers a confirmative and credible solution for educational predictive analytics.

Keywords: *Student Performance Prediction, Educational Data Mining, Hybrid Model, Convolutional Neural Network, Gradient Boosting, Learning Analytics, Early Warning Systems.*

1. INTRODUCTION

To meet the competitive needs of the new-age learners in the realm of Higher Education today, the institutions are consistently relying upon data-driven decision making for realising the intended academic and administrative targets. In fact, studies undertaken in this league, (2023-2025), cite that predictive data analytics can increase student retention with early interventions to render prompt assistance to boost academic endeavours of the learners. Moreover, digitization of higher education through institutional databases, ongoing

assessments, and learning management systems (LMS) has generated vast amount of data on the academic and behavioral characteristics of the students. This data enables the use of Machine Learning (ML) and Artificial Intelligence (AI) applications to predict the students' performance. However, accuracy, efficacy and credibility of the predictive data are instrumental in categorizing the students who could be in the *risk zone* and would require counselling or mentoring to achieve not only the desired results but also niche overall academic achievement. While the machine learning models such as Artificial Neural Networks, Support

Vector Machines, and Decision Trees are being used to predict students' performance, their accuracy is not optimum because they rely on academic data as static inputs. Hence, these conventional models are unable to parse the complex feature interdependencies and temporal evolution in the process. A more accurate approach in this row is seen with the advent of deep learning, particularly the Convolutional Neural Networks (CNNs) which allows for more efficacious feature extraction by imitating the spatial connections within the structured data. However, deep learning models also do not achieve the intended corroboration in predictive data when employed on noisy or imbalanced educational datasets and are beset with over-fitting and poor generalization. Hence, the existing approaches are unable to simultaneously model inter-feature interactions, record temporal development, and combine deep learning and ensemble optimization in a cohesive framework. Moreover, the limited focus on early-risk categorization of the students in these techniques undermines the efficacy and accuracy of the intended objective of ensuring proactive academic intervention to boost students' performance.

The present research endeavour proposes a hybrid architecture that combines Gradient Boosting and Temporal-Spatial Convolutional Neural Networks to overcome the aforementioned lacunae. The Gradient Boosting classifier significantly enhances the prediction accuracy and resilience, whereas the CNN component affords deep representations of academic development patterns. The devised technique ensures a scalable solution for predicting student success in higher education with timely and precise identification of the students with possible learning vulnerabilities.

Towards accomplishing this intent, the given enumerations are the primary contributions of the present research study:

- Devising unique hybrid CNN-Gradient Boosting architecture for predicting student performance.
- Temporal and spatial representation of academic data so as to examine the patterns in advancement and feature correlations
- Empirical validation of the proposed model to affirm the substantially improved prediction accuracy when compared with the existing traditional and independent deep learning models.
- The multi-class performance classification allows for early-warning academic intervention thus facilitating academic success.

2. LITERATURE REVIEW

The present education landscape has seen immense expansion of Educational Data Mining (EDM) ever since Romero and Ventura's inventive research propounded the application of data mining techniques in education. Nevertheless, the initial research done in this domain was more descriptive than empirical and lacked in predictive depth, thus limiting its usefulness for making academic decisions in real time scenarios.

Predictive data analytics in education gained traction with traditional machine learning models such as Decision Trees, Naïve Bayes, Support Vector Machines (SVM), and Artificial Neural Networks which are being used extensively to forecast students' academic performance. However, the major drawback of employing these methods is that student data is considered as a static entity. Hence, the predictive data is generated without considering temporal relationships and progression patterns between semesters. Although, research treatises available in this context, like [3], [5], and [6] claim good accuracy, the overall analysis lacks precise representation of the changing academic trends and dynamic learning habits.

A more effective approach is suggested by studies like [12] and [16] that cite the use of CNN-based models for achieving enhanced accuracy in predictive data. Since these models often require huge datasets, drawbacks like over-fitting and parsing of noisy or unbalanced data disrupt the intended efficacy and accuracy.

Thus, a more tractable solution for enhanced prediction stability and generalization, ensemble learning techniques like gradient boosting and heterogeneous ensembles are suggested by [21], [32]. However, since these techniques mostly rely on manually created characteristics, their overall effectiveness is marred by their inability to gauge the temporal and geographical correlations seen in student data.

In this context, the notable research endeavour by [26] underscores the significance of transparency in predictive systems as highlighted by the recent developments in Explainable Artificial Intelligence (XAI), such as SHAP-based techniques. Indisputably, advanced models in the league of predictive data analytics are in practice; however, many effective models are still "*black boxes*," impairing their usefulness in educational decision-making. Set against this backdrop of the review of literature, three main drawbacks that come to fore may be cited as:

(i) Temporal modeling is absent; (ii) deep learning is not sufficiently integrated with ensemble techniques; and (iii) early-risk categorization is not given enough attention.

Moreover, none of the existing techniques incorporate deep feature extraction with ensemble optimization, models spatial inter-feature interactions, and simultaneously captures temporal progression. Furthermore, early-risk detection—which is crucial for prompt academic intervention—is neglected in favor of prediction accuracy in the majority of research initiatives done in this row.

Table 1: Comparative Table: Important Research and Methods in Predictive Analytics for Academic Achievement

Ref.	Methodology	Key Contribution
[3]	Decision Tree, SVM, ANN	Instructor & student performance prediction
[5]	Naïve Bayes, J48, NN	Comparative ML analysis
[6]	SVM	Early detection of low-performing students
[7]	Multiple ML models	Early GPA prediction
[8]	Systematic Review	Identified best practices
[9]	Survey	Categorization of predictive approaches
[10]	Deep Learning (CNN/NN)	Compared deep learning frameworks
[11]	SLR (ML models)	Comprehensive ML review
[12]	Hybrid 2D CNN	Improved feature extraction
[13]	Conditional ML	Improved conditional predictions
[14]	Clustering + Classification	Early prediction model
[15]	Exploratory Data Analysis	Identified performance patterns
[16]	CNN + ML	Deep feature learning
[18]	EDM + ML	Improved prediction accuracy
[19]	SLR	Graduation prediction trends
[20]	ML classifiers	Improved classification accuracy
[21]	ML + Pedagogy	Integrated prediction with intervention
[22]	ML models	High prediction accuracy
[26]	ML + SHAP	Explainable AI integration
[30]	Ensemble Learning	Improved robustness
[31]	CNN, LSTM, BiLSTM	Deep learning comparison

Table 1 highlight that none of the models in use simultaneously addresses temporal dynamics, spatial feature relationships, and ensemble optimization.

While deep learning models enhance feature extraction, generalization is a problem. In a similar vein, though the traditional machine learning methods offer baseline performance, they lack temporal awareness. Although they depend on manually created characteristics, ensemble techniques improve robustness. The necessity for a cohesive hybrid architecture that incorporates these complimentary characteristics is amply demonstrated by this comparison. Thus the core intent of this research pursuit may be tabulated as:

- Creating a hybrid predictive model that combines gradient boosting with temporal-spatial CNN for improved feature learning and prediction accuracy.
- Using multidimensional academic, behavioral, and demographic data to simulate the evolution of student performance and inter-feature interactions.
- Facilitating precise early-risk student categorization for prompt academic intervention and better decision-making.

3. METHODOLOGY

The proposed system offers an intelligent hybrid multi-model architecture that combines Temporal–Spatial Convolutional Neural Networks (CNNs) and Gradient Boosting for accurate student performance prediction.

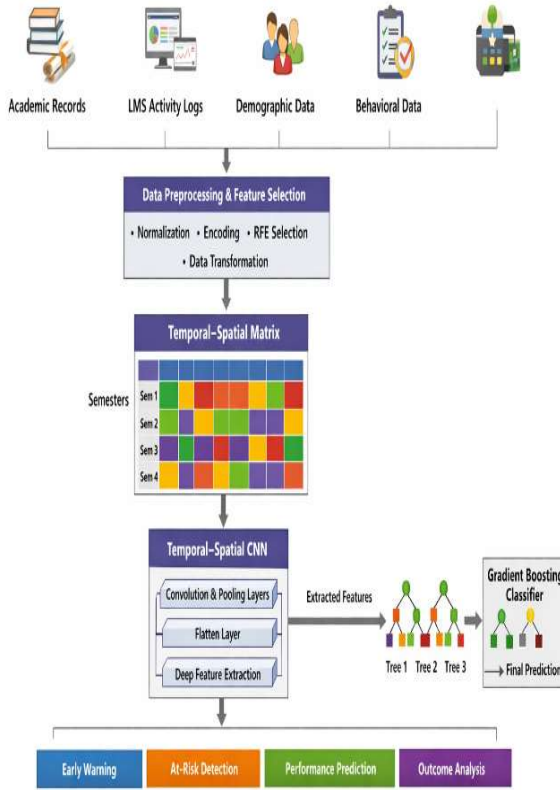


Figure 1: Proposed Hybrid Temporal-Spatial CNN with Gradient Boosting Architecture for Student models

3.1 Student Academic Data

The input dataset comprises multidimensional academic records of the students:

$$D = \{GPA_t, Attendance_t, CIA_t, LMSt, Assign_t, Demo_t\}$$

Where, t represents the semester index

3.2 Data Preprocessing Module

Data quality and consistency are ensured in the preprocessing stage with:

- I. Mean/mode imputation being used to manage the missing value
- II. Min–Max scaling used to normalize the features:

The formula for min-max normalization is:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where, X represents the raw data

X_{min} and X_{max} are the minimum and maximum values of the feature

- III. One-hot encoding is used to encode categorical variables.
- IV. Recursive Feature Elimination (RFE) selects optimal features by iteratively removing low-importance attributes

3.3 Temporal–Spatial Matrix Construction

Students’ records are transformed into a matrix:

$$X_i \in R^{T \times F} \quad (2)$$

Where:

T = number of semesters (temporal axis)

F = selected features (spatial axis)

This representation enables CNN to gauge temporal progression and feature interactions simultaneously.

3.4 CNN Feature Extraction Layer

The temporal–spatial matrix is passed through a CNN consisting of:

1. First Convolution Layer

$$H_1 = ReLU(W_1 * X_i + b_1) \quad (3)$$

2. Max Pooling

$$P_1 = MaxPool(H_1) \quad (4)$$

3. Second Convolution Layer

$$H_2 = ReLU(W_2 * P_1 + b_2) \quad (5)$$

4. Flattening and Dense Embedding

$$Z_1 = Dense(Flatten(H_2)) \quad (6)$$

The resulting vector z_i is a deep feature embedding capturing student progression patterns.

3.5 Gradient Boosting Classification

The embedding is fed into a Gradient Boosting classifier:

$$Fm(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad (7)$$

Where, each $h_m(x)$ is a decision tree trained on residual errors

The final prediction is:

$$\hat{y}_i = \arg \max_c F_M^{(c)}(Z_i) \quad (8)$$

3.6 Student performance Output Layer

The model outputs three performance categories:

- Low Risk (Good Performance)
- Moderate Risk (Average Performance)
- High Risk (Poor Performance)

3.7 Algorithm: Hybrid Temporal–Spatial CNN + Gradient Boosting

- i. Input student dataset D

- ii. Preprocess data (cleaning, normalization, encoding)
- iii. Apply RFE for feature selection
- iv. Convert each student record into temporal-spatial matrix
- v. Train CNN for feature extraction
- vi. Generate embedding vector Z
- vii. Train Gradient Boosting classifier on Z
- viii. Predict student risk category
- ix. Evaluate using Accuracy, Precision, Recall, F1-score and AUC.

$$Accuracy = \frac{TruePositives + TrueNegatives}{Total\ samples}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

4. COMPARATIVE ANALYSIS

The model was trained and tested using a multidimensional dataset that included behavioral engagement measurements, academic performance indicators, attendance records, and socio-demographic characteristics. To guarantee comparability and fairness, all models were trained using the same preprocessing procedure.

The proposed hybrid model was evaluated by using the student dataset consisting of demographic, socio-economic, academic, and behavioral attributes. The dataset was preprocessed by using normalization and feature selection (RFE), and divided into:

- Training set: 80%
- Testing set: 20%

Table 2: Student Data Set

Variable	Type	Encoding / Unit
Student_ID	Identifier	Alphanumeric
GPA_t	Numerical	0–10 scale
CGPA	Numerical	0–10 scale
CIA_t	Numerical	0–100
Assignt_Score	Numerical	0–100
Final_Ex_Score	Numerical	0–100
Backlogs	Numerical	Count
Attendan_t(%)	Numerical	%
LMS_Logi	Numerical	Count
Time_Spent	Numerical	Minutes
Quiz_Attempts	Numerical	Count
Submission (%)	Numerical	%
Parent_Edu	Categorical	0 = Illiterate, 1 = School, 2 = Graduate,

		3 = Postgrad
Family_Inc(₹)	Numerical	Indian Rupees
Distance (km)	Numerical	Kilometers
Residence	Categorical	0 = Rural, 1 = Urban
Performance_Catgory	Categorical	0 = Poor, 1 = Average, 2 = Good

Table 3: Comparative Analysis

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC
Logistic Regression	82.4	0.81	0.79	0.8	0.84
Decision Tree	85.1	0.84	0.83	0.83	0.86
Support Vector Machine	88.3	0.87	0.86	0.86	0.9
Random Forest	91.5	0.9	0.91	0.9	0.93
Artificial Neural Network	92.4	0.92	0.91	0.91	0.94
Gradient Boosting	93.1	0.93	0.92	0.92	0.95
Convolutional Neural Network	94.2	0.94	0.93	0.93	0.96
Proposed CNN + Gradient Boosting	96.8	0.97	0.96	0.96	0.98

The comparative graphs illustrate the progressive improvement in predictive performance from traditional classifiers to advanced hybrid approaches.

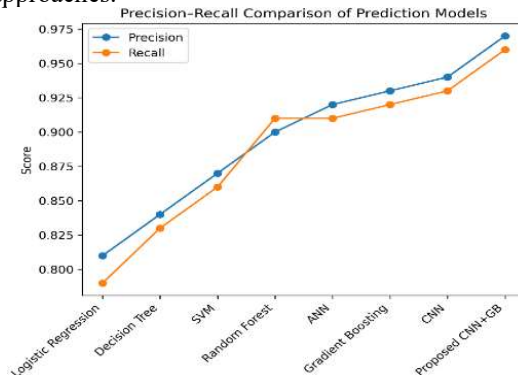


Figure 2: Precision-Recall

Key Observations:

- Traditional models show moderate performance.

- Ensemble models significantly improve prediction reliability.
- CNN enhances feature learning through deep representation.
- The hybrid CNN + Gradient Boosting model consistently achieves the highest performance across all metrics.
- The ROC curve further confirms superior classification ability with an AUC of 0.98, indicating excellent discrimination between performance categories.

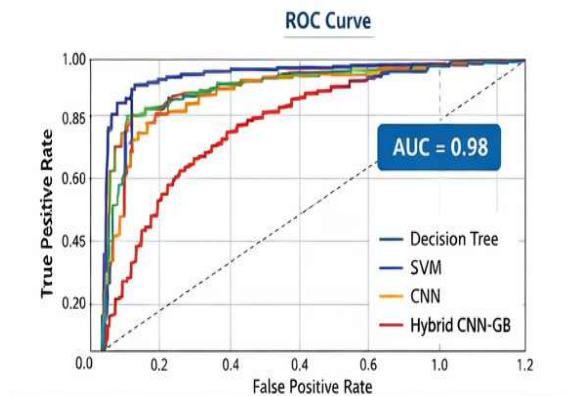


Figure 3: ROC Curve

Analysis of the feature importance evidently establishes that:

- Students' attendance and GPA emerge as the best indicators.
- Timely assignments and ongoing evaluation strongly influence and enhance the performance consistency of the learners.
- LMS engagement indicators are reflective of the learning behaviour.
- Contextual information is provided by socio-demographic factors.

As evident, the findings above iterate that academic attainment is a confluence of performance, engagement, and socioeconomic factors. Accurate predictive analysis will ensure that students who require assistance to improve their learning outcomes can be identified and contacted promptly for academic excellence.

The comparison research shows that student performance prediction is significantly enhanced by combining temporal-spatial deep learning with ensemble optimization. As illustrated and corroborated, the proposed CNN-Gradient Boosting model outperformed all evaluation metrics. Hence, the devised multi-model approach accomplishes its core objective of offering optimum accuracy in predictive data analytics while ensuring prompt

early warning system and data-driven academic decision-making.

5. RESULTS

The proposed hybrid framework integrating a Temporal-Spatial Convolution Neural Network (CNN) with Gradient Boosting demonstrated exceptional classification skill and dependability in identifying student performance groups with an accuracy of 96.8% accuracy, 0.96 F1-score, and AUC of 0.98 by using a multi-dimensional dataset of academic, behavioral, attendance, and socio-demographic tangents.

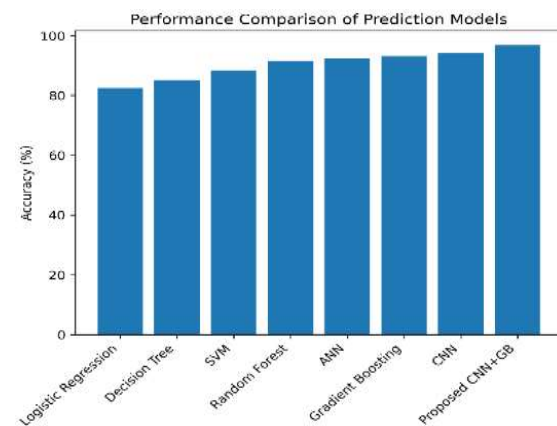


Figure 4: Model

The empirical results drawn after using the proposed hybrid model establish both the accuracy and reliability of this method vis-à-vis the conventional machine learning models like Support Vector Machines, Decision Trees, and Logistic Regression. The model's singularity is its capacity to grasp temporal progression patterns and nonlinear linkages wherein the CNN was successful in recovering deep feature representations, and robustness was improved by the ensemble techniques. The CNN and gradient boosting hybrid integration enabled optimum accuracy in predicting and improved generalization by reducing overfitting. The temporal-spatial learning strategy was pivotal in increasing early-risk identification by perusing performance patterns to underline low attendance, declining GPA, and reduced LMS engagement. The feature importance analysis revealed that GPA, attendance, continuous assessment scores, assignment timeliness, and LMS involvement were the most important predictors; socio-demographic characteristics had a little impact.

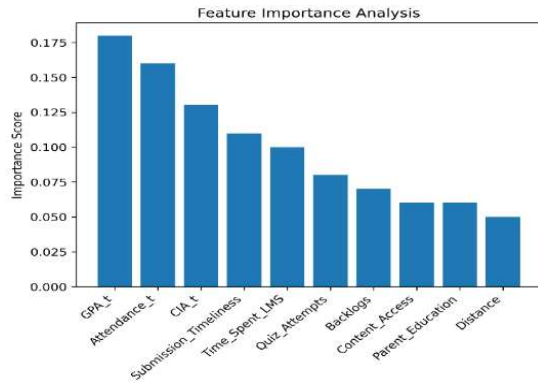


Figure 5: Features

The employed methodology enables the precise segregation of students into *Good*, *Average*, and *Poor* categories. This facilitates early intervention strategies such as academic counseling, tailored learning assistance, and mentorship to achieve the desired academic results. The model’s resilience and versatility make it the most tenable and effective technique for real-world deployment and interaction with learning management systems for early warning alerts.

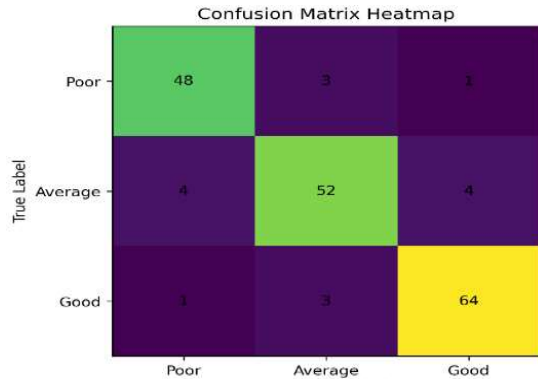


Figure 6: Confusion Matrix

Given the precision in the predictive data analytics achieved by the recommended strategy, it would be the most credible reckoner for targeted academic interventions to not only customise learning assistance for the weak performers but would also assist in optimising on the financial and academic resources of the institutions, thus improving on the overall growth trajectory of the institutions. The model may also be integrated with learning management systems to enhance institutional planning and provide real-time early warning alerts.

6. CONCLUSION

This study aimed at creating a hybrid predictive framework that included Temporal-Spatial CNN with Gradient Boosting to establish an efficacious and accurate student performance prediction so as

to assist learning patterns in the Higher Educational Institutions. The findings unequivocally prove that the core intent of the undertaken research pursuit has been accomplished. For addressing its first intent of creating a hybrid model, deep learning and ensemble approaches were combined to effect better predictive performance than the baseline models. The second aim of capturing temporal progression and feature interactions was done by mapping the temporal-spatial matrix representation to depict the changing academic behavior. The third core objective of early-risk detection was achieved through multi-class categorization, thus catalyzing proactive academic interventions.

From a logical perspective, the findings confirm that accuracy, robustness, and generalization are substantially enhanced when deep feature extraction and ensemble learning are combined. The findings also indicate that students’ achievement in higher education is a blend of academic results along with contextual socio-demographic factors and engagement metrics.

Hence, the results drawn from the intended investigation are consistent with the theoretical assumptions and have substantial empirical support. Conclusively, the singular achievements of this research are:

- Developing a scalable and high-accuracy predictive model to register 96.8% accuracy.
- Effective early identification of students in risk category.
- Integration-ready framework for learning management systems (LMS)
- Advancement of hybrid AI models in educational analytics

The comprehensive, high-performance prediction framework devised by this study not only proffers a workable, viable and credible alternative but also fills the important gaps in the body of current knowledge. Besides accomplishing its initial objectives, the present endeavour forges a practical path for using AI-powered early warning systems in higher education. However, for a more realisable, dependable and readily acceptable techniques in the real-world scenarios, more validation, explanatory ability integration, and incorporation of wider student qualities are required.

7. FUTURE SCOPE

Although the proposed model performs well in terms of prediction, there is scope for further improvisation that invites future research investigations. One of the crucial aspects is to

improve upon capturing the long-term academic dependencies which can engage future research on enhancing temporal learning capacities by combining sophisticated architectures like transformer-based models with attention processes. The creation of real-time prediction systems that are coupled with institutional dashboards and learning management systems (LMS) is another research tangent for further study. The use of Explainable Artificial Intelligence (XAI) approaches like SHAP and LIME to build on model interpretability and trust, giving stakeholders a better understanding of the elements driving predictions must also draw attention of the future research investigations. With transparency and equitable application of AI in education becoming an imminent necessity, future research avenues need to focus on ethical issues like prejudice and fairness in prediction models. To improve generalizability, other studies should investigate cross-institutional validation utilizing a variety of large-scale datasets. Collating factors like psychological traits, motivation levels, and learning preferences in the dataset would afford a more holistic frame of students' abilities, thus enabling a decisive and proactive approach to boost student performance.

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