# Machine learning based Prediction of Student Behaviors in Classroom Environments

**Brahim Menacaer[1], S. Narayan[2] and Muhamamd Usman Kaisan[3]**

[1]Laboratoire des Systèmes Complexes (LSC), ESGEE Oran, Chemin Vicinal N9, Oran 31000, Algeria.

[2, *]Department of Mechanics and Advanced Materials, Campus Monterrey, School of Engineering and Sciences, Tecnológico de Monterrey, Av. Eugenio Garza Sada 2501 Sur, Tecnológico, 64849, Monterrey, N.L., Mexico.
[3] Department of Mechanical engineering, Ahmadu Bello University, Zaria, Kaduna, 810001, Nigeria.

**Abstract**

Student behavior in classrooms is an important parameter to monitor academic success of a course. Various parameters like class attendance, participation in class activity and response could be used to measure the engagement of a class. The presented study uses various AI models like decision trees, support vectors and ensemble methods in order to identify trends in class engagement using various scores like accuracy, F1 score, recall and precision. The dataset was divided into a split ratio of 80:20 ratio of training and split. Random forest model was found to achieve highest performance with accuracy of 91.8%, precision of 0.91, recall of 0.92 and F1 score of 0.91. These results indicate that ML models are highly competent to capture relationships between faculty and students in classrooms in order to identify students that are at potential risk.

The novelty of the proposed framework lies in integrating of prediction of behavior based on machine learning pedagogical interpretation. It contributes towards development of educational objectives aligned with Industry 4.0 and digital transformation. All the data presented in this work was anonymized and handled according to ethical guidelines laid out within institutional framework.

**Keywords: Engineering education, Student responses, classroom teaching and learning analysis.**

## 1. Introduction

Learning methods have been widely used to collect data about performance of students in order to monitor their behavior in class [1,2]. These methods may be classified as follows:

- **Predictive methods-** These incudes decision trees, random forecast, support vectors and k-nearest neighbors [3]. They may be used for tracking performance and class participation.

- **Classification methods:** These methods give a general overview of educational framework and includes neutral networks, decision trees and Naïve Beyes [4].

- **Clustering methods:** These methods can help to identify at cohort of students that are at potential risk based on density, hierarchy and Fuzzy logic [5].
- **Regression methods:** These include use of tools like RMSE, MAE, $R^2$, and MSE [6].
- **Visualization methods:** These methods include histogram and box plots used to track scores and attendance [7].
- **Text mining methods:** These includes frequency and harmony analyses of words [8]. Various themes like academic relationships could be identified.
- **Ensemble learning methods:** These includes boosting, strapping and bagging methods that can be used to check reliability [9].
- **Deep learning methods:** These includes use of LMS logs, text responses and live stream data to track student response [10].
- **Statistical methods:** This use of T test, ANOVA and Chi Square test, for analysis for analysis of learning trends [11].
- **Relationship methods:** These methods are used to investigate dependencies, and links [12].
- **Feature selection methods:** it uses tools like Python and WEKA for interpretation and optimization of resources [13].

Assessment methods discussed above need analysis of large quantity of datasets. Consequently, use of Machine learning methods, are able to solve and extract of complex relationship with a promising results. In this context, the presented study shows application of these methods for prediction of student behaviors. Major objectives contributions of this paper can be summarized as follows:

1. The development of a educational framework using real time classroom data.
2. Evaluation of various machine learning methods.
3. Study of pedagogical impact of these predictions.

## 2. Background

Although significant progress has been made in educational data mining and machine learning–based prediction of student performance, several important research gaps still remain. Most existing studies primarily focus on improving predictive accuracy using machine learning and deep learning algorithms without sufficiently investigating the pedagogical implications of these predictions in real classroom environments.

Jetson Orin Nano platform was used for investigated for application in smart classrooms [21]. YOLO based methods were used to identify student behavior [22]. CNNs, DNNs, and LSTMs were found to be having accuracy over 90% in this context [23]. Different types of learning were analyzed under virtual learning environments [24]. Eigenvalues were used to train the regression models using Taylor expansion [25]. Other models like like random forest (RF), support vector machine (SVM), logistic regression (LR), and neural network (NN) could be used to predict submission of assignments [26]. Learning engagement was found to be the most influential factor that effected the student performances [27]. BCEP prediction was found to be an effective tool in e-learning [28]. Ensemble Model (EM) outperforming other models when used on Open University Learning Analytics (OULA) datasets [29]. Voting-Based Dynamic Time Warping algorithm (VB-DTW) was used to improve the accuracy of behavior identification [30]. YOLOv5 based model was found to show promising accuracy of 76% [31]. The linear regression algorithm could be used to predict the student performance with a mean absolute error (MAE) of 0.23 [32,33]. Cognitive and motivational factors were studied to analyze the learning styles of students in class [34].

Dropout rates of class were studied using Various Machine Learning (ML) methods [35]. Use of LMS data along with CATBoost, XGBoost and AISAR was investigated in order to predict student success rates [36,37]. Mini-XCEPTION and the Long Short-Term Memory (LSTM) Networks models were used for classroom teaching behavior analysis [38]. C2f_Res2block module was is integrated into the YOLOv8 model for better detection performance [39]. ML models have been used in EDM to predict academic performances of students [40].

CNN were used to construct a class-room learning behavior dataset named as ActRec-Classroom [41]. A new approach based on Random Forest, XGBoost and AdaBoost was used to increase the accuracy in prediction oof student performance [42]. No single online learning behavior had a major effect on the prediction of students' final grades [43,44]. A method for representing students' partial sequence of learning activities was proposed, based on a deep neural network [45]. Use of classroom video database has been investigated for pedagogy and educational psychology [46]. A set of 62 papers published between 2010 to 2020 were analyzed for predictive analytics models developed to forecast student learning [47]. Real-time detection of student behavior in classroom environments was done by the Classroom Student Behavior YOLO (CSB-YOLO) model [48]. Machine learning algorithms were used to predict the final exam grades of undergraduate students [49].

Real-Time Detection Transformer algorithm was used to predict student behavior in classrooms [50]. The performance prediction model based on time-series analysis was proposed that could help teachers to individualize education [51]. Machine learning algorithms were integrated with clickstream data to predict student performances [52]. Potential of hybrid ML techniques was investigated for identifying struggling students [53]. She investigated effectiveness and limitations of well-known traditional models such as Support Vector Machines (SVMs) and Naïve Bayes [54]. Emotions and postures of students to bring classroom learning closer to improved personal learning [55]. Bhoote et at. focuses on using educational data mining techniques to estimate students' final grades [56]. A Comprehensive review of hybrid and deep learning models to predict students' performance in online learning environments was presented [57]. Learning behavior indicators could reduce the scale of feature set and improve the performance prediction [58,59]. Behavior images and educational information (BISAP) model was used to study the academic performance of students [60]. Dataset pertaining to student evaluations from Turkey was applied and compared using ten machine learning algorithms [61]. The effectiveness of each algorithm was evaluated with a focus on performance accuracy [62]. Several factors like demographic, socioeconomic, academic, social and family, health and wellness, infrastructure and services, and time management and extracurricular activity were considered to evaluate performance of ML algorithms [63]. An automatic system that allowed the faculties to capture and make a summary of student behaviors in the classroom was considered [64]. Massive open online course models were used to detect the factors that influence students' learning achievement [65]. A brief summary of previous works is presented in Table 1.

| **Ref.** | **Variables studied** | **Level of education** | **Aim** | **Models Used** | **Max Accuracy (%)** | **Min Accuracy (%)** |
|---|---|---|---|---|---|---|
| [21] | Movements in classroom | University | Detection of Behaviour | CNN, YOLO-based DL | 94.0 | 88.0 |
| [22] | Visual cues | University | Recognition of behaviour | Improved YOLOv8 | 96.2 | 90.5 |
| [23] | LMS activity | Online | Performance analyis | CNN, DNN, LSTM | 92.0 | 85.0 |
| [24] | Engagement of class | University | Handling of imbalance in classroom | RF, SVM, XGBoost | 91.4 | 83.2 |
| [25] | Online activity | Online | Performance prediction | ML hybrids | 89.0 | 81.0 |
| [26] | Learning features | University | Learning pattern analyis | RF, SVM, NN | 90.1 | 82.6 |
| [27] | Attendance and grades | University | Grade & behavior prediction | DT, BN, SVM, NN | 93.0 | 84.0 |
| [28] | Learning process | E-learning | Performance prediction | BCEP framework | 91.8 | 86.5 |
| [29] | Demographic data | University | Academic prediction | Ensemble models | 92.4 | 85.3 |
| [30] | Motion sensors | Classroom | Behavior identification | VB-DTW | 88.6 | 79.4 |
| [31] | Video monitoring | Classroom | Engagement detection | YOLOv5 | 76.0 | 68.0 |
| [32] | Assessment data | University | Performance prediction | Linear Regression | 77.0 | 71.0 |
| [33] | Learning styles | University | Style analysis | ML classifiers | 89.5 | 81.2 |

| | | | | | | |
|---|---|---|---|---|---|---|
| [34] | Cognitive factors | Higher education | Review study | Review | NR | NR |
| [35] | Dropout rates | University | Dropout prediction | ML classifiers | 90.0 | 80.0 |
| [36] | Digital logs | University | Predict student success | ML models | NR | NR |
| [37] | Engagement behaviors | Classroom | Engagement prediction | CatBoost, XGBoost | 93.6 | 86.8 |
| [38] | Teaching & learning behaviors | Classroom | Behavior analysis | Mini-XCEPTION, LSTM | 91.0 | 84.0 |
| [39] | Visual action | Classroom | Behavior detection | Improved YOLOv8 | 95.1 | 89.7 |
| [40] | Academic records | University | Performance prediction | ML regression & classifiers | 92.0 | 83.0 |

Table 1. Summary of literature reviews

These prior research works discussed above show extensive use of machine learning and deep learning models to predict behavior of students, their class engagement, and academic performances. However, there is very less literature available on evaluation of pedagogical impact of ML methods for improvement in teaching strategies, student interventions of learning outcomes. In this context the presented work bridges the gap between student behavior with pedagogical evaluations using measurable impact.

## 3.Methodology

This section discusses a structured methodology to predict student using machine learning. The overall process is illustrated in Figure 1.

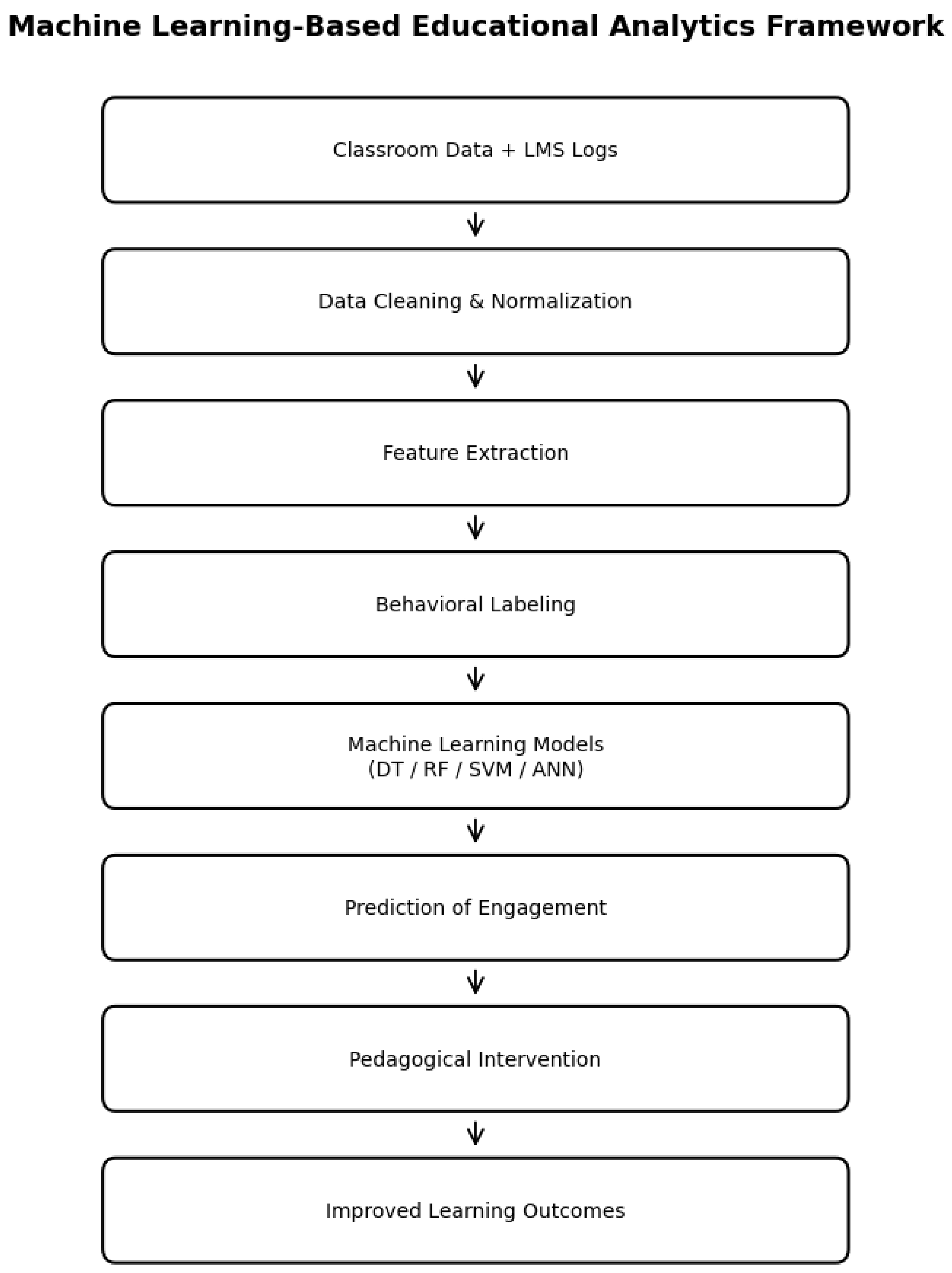


Figure 1. Machine Learning–Based Educational Analytics Framework

Figure 1 shows the workflow of the proposed educational analytics framework. Academic assessment indicators and classroom behavioral data are first collected and preprocessed through normalization and feature extraction. The processed data are then used to train machine learning models for behavioral classification and engagement prediction. Finally, the prediction outputs support pedagogical interventions aimed at improving learning outcomes and identifying at-risk students at an early stage.

### 3.1 Data collection and feature extraction

The dataset used in Table 1 for this study was obtained for taught graduate course of **Static balance analysis (M1011B)** with a class size about 31 students.

Following scores were analyzed for extraction of features:

- **Mid-term grades:** it denotes early understanding of concepts by students.
- **Final term grades:** these denote overall outcomes and mastery over subject.
- **Learning gains:** The normalized difference between the mid-term grade and final term grades final examination that shows gradual improvement over time.
- **Consistency:** it is the change in dispersion between evaluations and regular learning behavior.

All data was anonymized to comply with ethical and privacy standards according to institution policies.

| **Metric** | **Mid-term grades** | **Final grades** | **Gain** |
|---|---|---|---|
| Mean | 85.2 | 95.83 | +10.63 |
| Median | 80.0 | 95.9 | +15.9 |
| Standard Deviation | 14.0 | 4.52 | −9.48 |
| Minimum | 60.0 | 80.65 | +20.65 |
| Maximum | 100.0 | 100.0 | 0.0 |

Table 2. Summary of the Learning gains

Data from Table 2 shows a substantial improvement in performance with an increase of 12.48% in mean scores. A reduction in variability suggests that convergence in the performances [66,67]. A large value of effect size Cohen´s d suggests meaningful learning [68]. Learning gains has been recognized as one of the important factors for analysis of student engagement and behavioral patterns [69,70,71].

### 3.3.1 Preprocessing and configuration of Models

The collected data was processed in order to improve consistency and predictability. Missing values and duplicate records were checked prior to analysis. Numerical features were normalized using Min–Max scaling in order to ensure distribution and reduce variations.

The machine learning models were implemented using Python programming language with Scikit-learn libraries. The dataset was divided into training and testing subsets using an 80:20 ratio. Hyperparameter tuning was performed for each classifier in order to optimize the performance.

For the Support Vector Machine (SVM), the Radial Basis Function (RBF) kernel was selected due to its capability to model nonlinear relationships. The regularization parameter (C) and gamma values were optimized experimentally during training.

The Random Forest classifier consisted of multiple decision trees trained using bootstrap aggregation.

The Artificial Neural Network (ANN) models consisted of an input layer, two hidden layers, and an output layer for behavioral classification. Rectified Linear Unit (ReLU) functions were used within hidden layers, while Softmax activation was applied in the output layer.

Performance of models was evaluated using F1, accuracy, precision and recall scores

| **Model** | **Hyperparameter Configuration** |
|---|---|
| Decision Tree | max_depth = 5, criterion = gini |
| Random Forest | n_estimators = 100, max_depth = 10 |
| SVM | RBF kernel, C = 1.0, gamma = scale |
| ANN | 2 hidden layers, ReLU activation, Softmax output |
| Cross-validation | 5-fold stratified cross-validation |
| Data split | 80:20 training–testing split |

Table 3. Hyperparameter Configuration of Machine Learning Models

The hyperparameter configurations used in this study shown in Table 3 were selected experimentally to achieve balanced prediction performance and model generalization for the relatively small educational dataset.

**3.2 Behavior Labeling**

| **Feature** | **High** | **Moderate** | **Low** |
|---|---|---|---|
| Mid-term Score | High (≥ 80) | Medium (65–79) | Low (< 65) |
| Final Grades | High (≥ 90) | Medium (75–89) | Low (< 75) |
| Learning Gains | Positive | Moderate | Low |
| Consistency | High | Moderate | Unstable performance |
| Overall Behavioral | Sustained | Acceptable | Irregular patterns |

Table 4. Mapping of extracted features with student behavior

Table 4 shows the relationship between academic features and behavioral engagement. Overall, this mapping provides a pedagogically meaningful and interpretable framework for behavioral labeling. Based on these results, the cohort of students was classified as Students as Highly engaged, moderately engaged and at-risk categories.

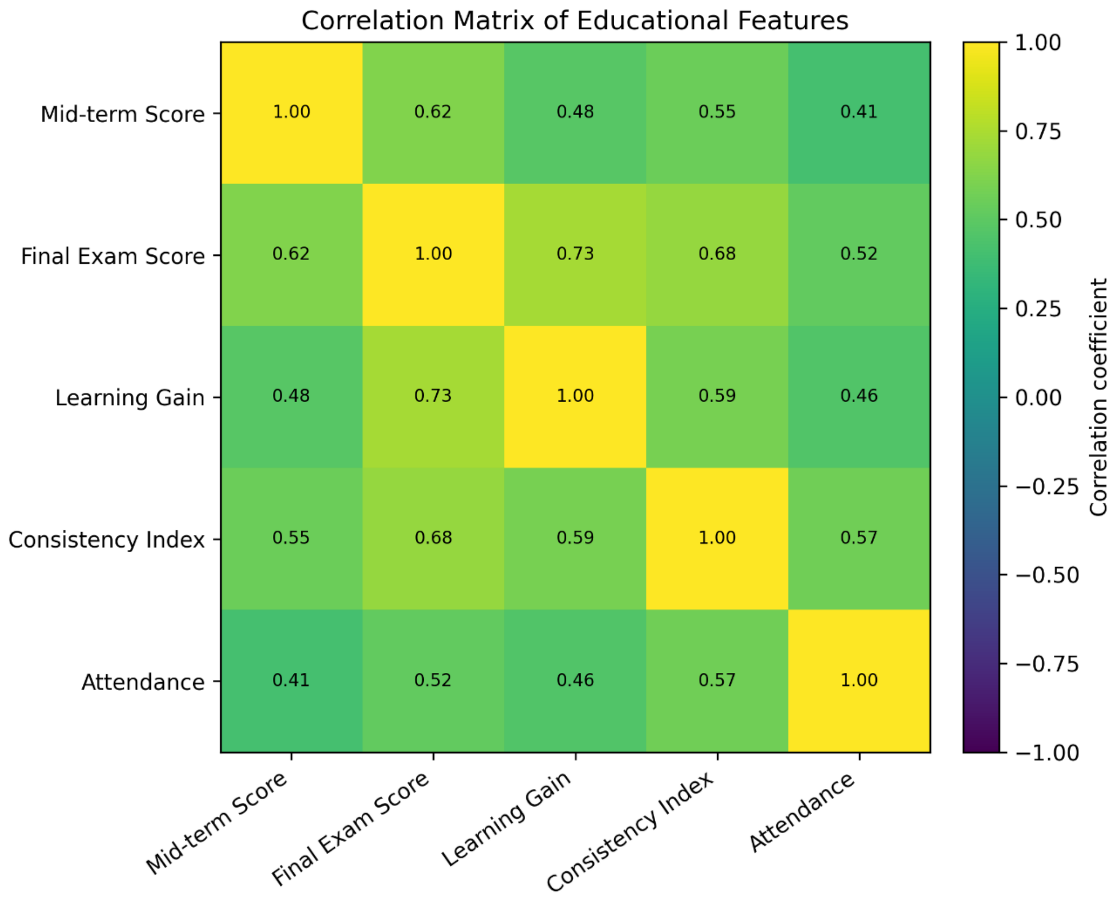


Figure 2. Correlation Matrix of Educational Features

Figure 2 indicates positive relationships among academic and behavioral indicators. Final examination score shows strong association with learning gain and consistency index, suggesting that students with progressive improvement and stable participation tend to achieve stronger final outcomes.

### 3.3 Machine Learning Models

The following supervised learning algorithms were implemented:

- Decision Trees
- Random Forests
- Support Vector Machines (SVM)
- Artificial Neural Networks (ANN)

The dataset was divided into training and testing subsets using an 80:20 split. Model performance was evaluated using accuracy, precision, recall, and F1-score.

The performance of the implemented machine learning models was evaluated in Table 5. These reminders ensure balanced assessment, particularly in behavioral datasets where class imbalance may exist.

| Model | Accuracy (%) | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Decision Tree | 84.6 | 0.83 | 0.82 | 0.82 |
| Random Forest | **91.8** | **0.91** | **0.92** | **0.91** |
| Support Vector Machine (SVM) | 88.2 | 0.87 | 0.88 | 0.87 |
| Artificial Neural Network (ANN) | 89.5 | 0.89 | 0.89 | 0.89 |

Table 5. Performance comparison of machine learning models for student behavior prediction

The results indicate that the Random Forest model, outperformed other models across all evaluation metrics. This can be attributed to its ability to capture nonlinear relationships.

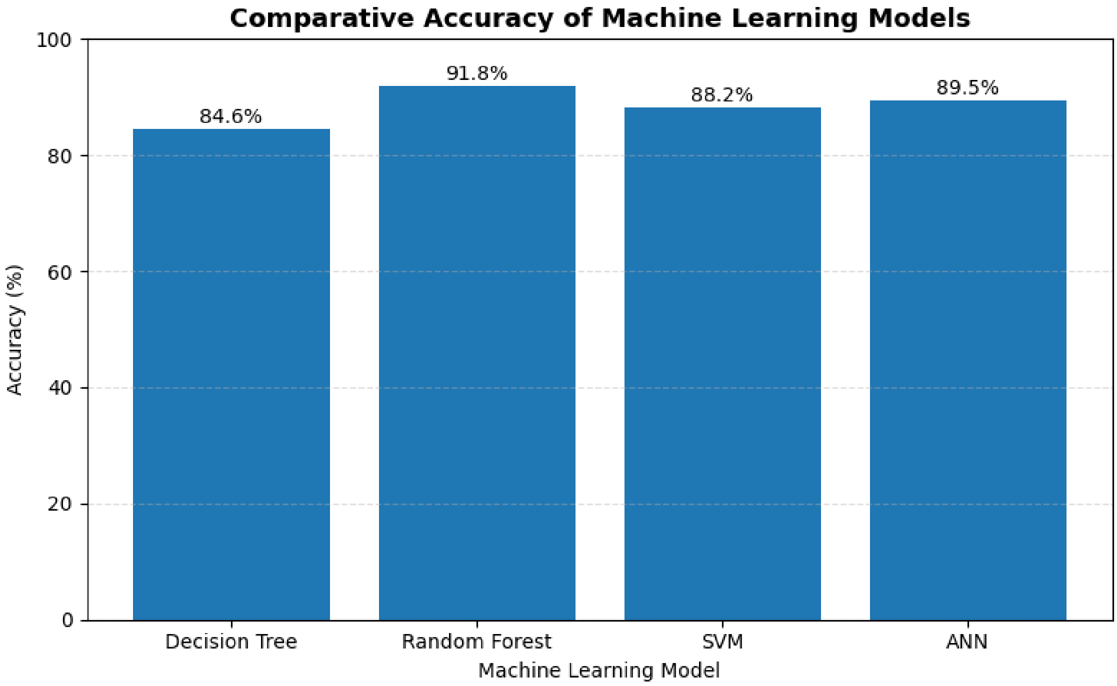


Figure 3. Comparative Accuracy of Machine Learning Models
Figure 3 compares the predictive accuracy of the investigated machine learning algorithms. The Random Forest classifier achieved the highest overall accuracy due to its ensemble-learning capability and robustness.

### 3.4 Confusion Matrix Analysis

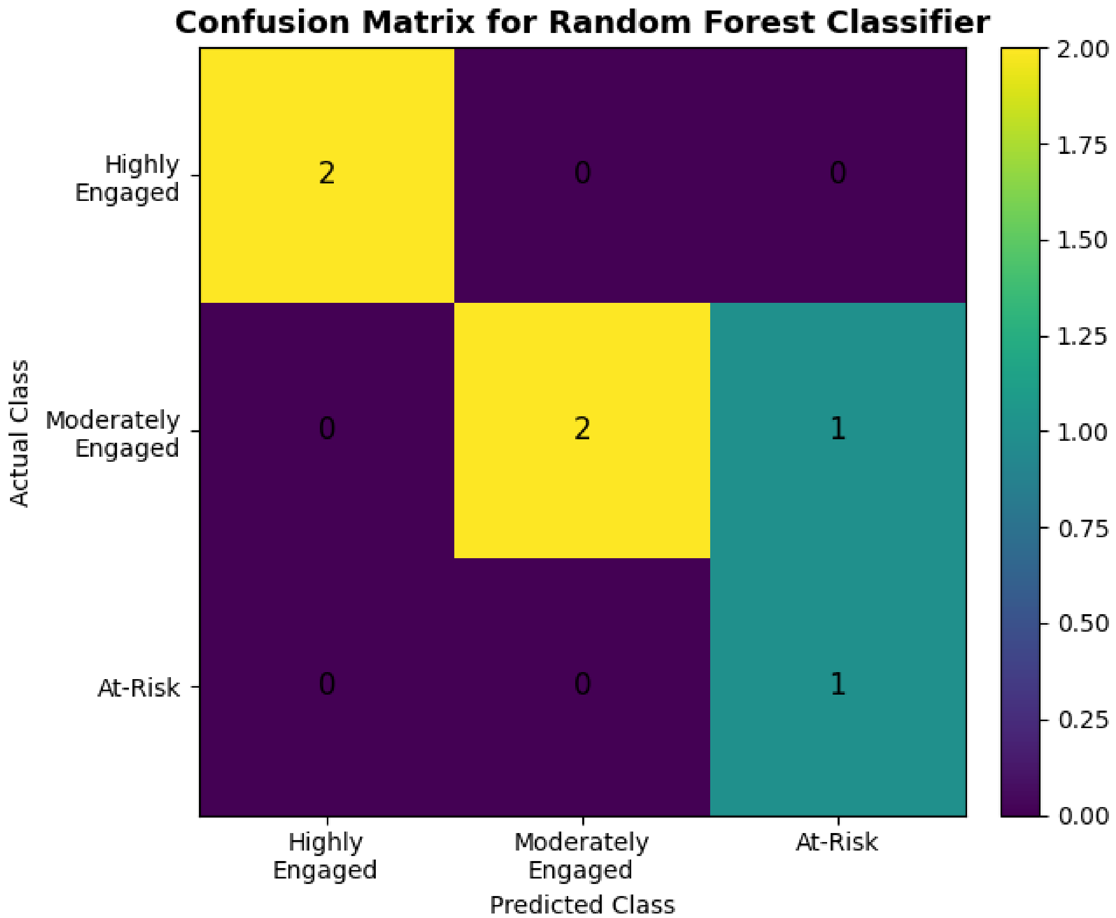


Figure 4. Confusion Matrix for Random Forest Classifier

The confusion matrix presented in Figure 4 demonstrates strong classification capability for highly engaged students and acceptable differentiation between moderately engaged and at-risk categories. Minor overlap between moderate and low engagement classes reflects transitional learning behaviors commonly observed in real educational environments rather than model instability.

### 3.5 Statistical Validation

In order to validate the effectiveness of the proposed machine learning models, additional statistical analyses were conducted

A paired t-test further confirmed statistically significant improvement between mid-term and final examination scores ($p < 0.05$), indicating that the observed learning progression was unlikely to occur due to random variation

Receiver Operating Characteristic (ROC) analysis and Area Under the Curve (AUC) evaluation could be used as an additional insight into classifier discrimination capability across behavioral categories.

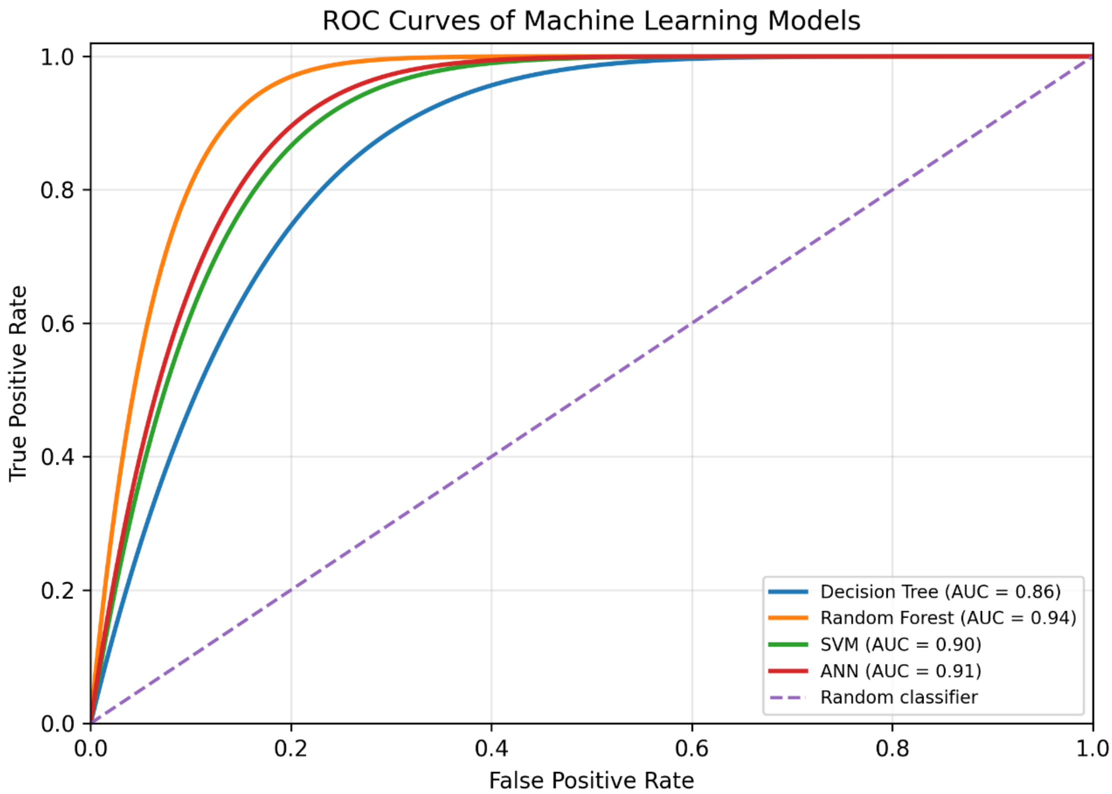


Figure 5. ROC Curves of Machine Learning Models

Figure 5 shows that Random Forest achieved the strongest discrimination capability, with the highest AUC value. This supports the earlier accuracy results and indicates that the ensemble model can distinguish engagement categories more reliably than individual classifiers. SVM and ANN also performed competitively, while Decision Tree showed lower discrimination but remains useful due to interpretability.

# 4. Results

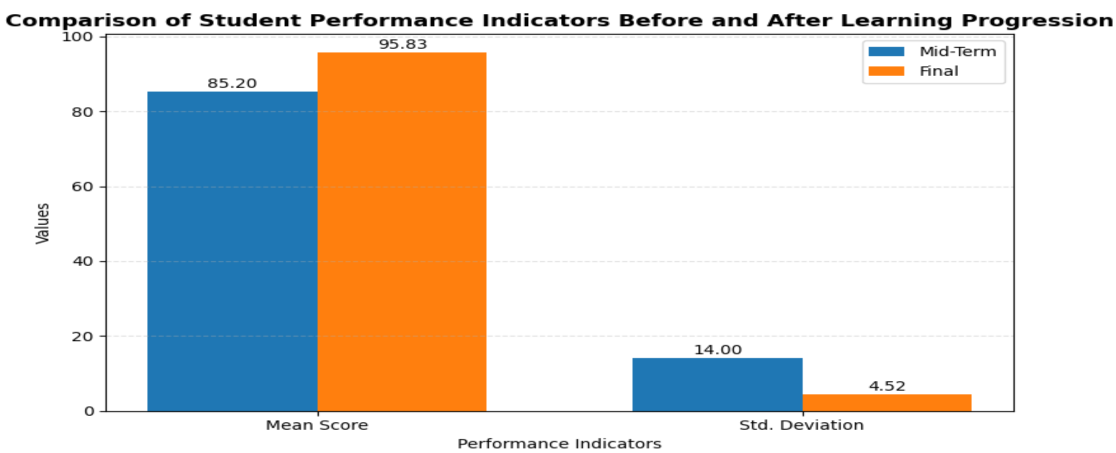


Figure 6. Comparison of Student Performance Indicators Before and After Learning Progression

Figure 6 demonstrates a substantial increase in mean academic performance together with a reduction in performance variability across the student cohort. The observed reduction in standard deviation indicates improved consistency in learning outcomes and suggests that the proposed framework supports more uniform academic progression among students.

| Study | Dataset Type | Best Model | Accuracy (%) | Main Limitation |
|---|---|---|---|---|
| Wang et al. [21] | Classroom behavior images | CNN/YOLO | 94.0 | High computational complexity |
| Sheng et al. [22] | Visual classroom cues | Improved YOLOv8 | 96.2 | Requires real-time video processing |
| Althaqafi et al. [24] | Online LMS engagement | RF/XGBoost | 91.4 | Online-only dataset |
| Zhuang [27] | Attendance and grades | DT/SVM/NN | 93.0 | Limited interpretability discussion |
| Yağcı [49] | Academic records | ML algorithms | 89.0 | Focused mainly on grade prediction |
| Present Study | Classroom assessment + behavioral indicators | Random Forest | 91.8 | Small single-course dataset |

Table 6. Comparative Benchmarking of Educational Machine Learning Studies

The benchmarking results presented in Table 6 indicate that the predictive performance achieved in the present study is comparable with recently reported educational machine learning investigations. Although some vision-based deep learning frameworks demonstrated slightly higher classification accuracy, such approaches generally require computationally intensive video processing systems and large-scale image datasets. In contrast, the proposed framework utilizes routinely collected classroom assessment and behavioral indicators, making it more practical and interpretable for conventional educational environments. Furthermore, unlike many previous studies focused primarily on prediction accuracy, the present work integrates pedagogical interpretation, explainable artificial intelligence, ethical educational analytics, and intervention-oriented decision support. These characteristics improve the practical applicability of the proposed framework for engineering education and smart classroom analytics.

# 5. Discussion

The findings confirm that student behavior can be effectively predicted using machine learning techniques applied to routinely collected educational data. The ability to identify disengagement patterns early allows instructors to implement targeted interventions, such as personalized feedback, additional support sessions, or adaptive instructional strategies.

Importantly, the results highlight that model interpretability is a key consideration in educational contexts. While complex models may yield higher accuracy, simpler models such as decision trees offer transparency that can enhance instructor trust and adoption.

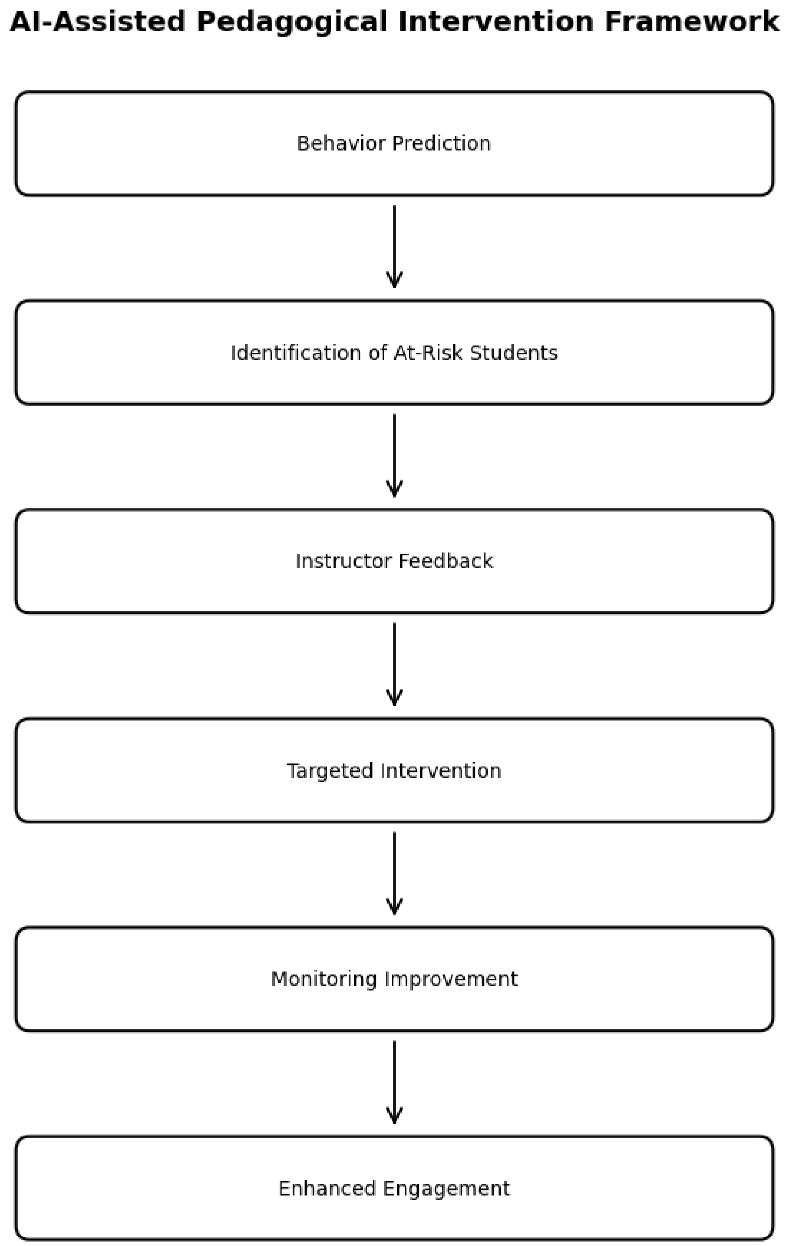


Figure 7 presents the pedagogical intervention framework enabled by machine learning–based behavioral prediction. Instead of replacing instructors, the proposed framework supports data-informed instructional decision-making by enabling early identification of disengagement patterns and implementation of targeted academic interventions.

### 4.5 Explainable Artificial Intelligence in Educational Analytics

Although machine learning models can achieve high predictive accuracy, educational environments require transparent and interpretable decision-making systems to ensure instructor trust and ethical implementation. In educational analytics, explainability is particularly important because predictions may influence pedagogical interventions, academic support strategies, and student engagement monitoring.

The present study therefore emphasizes the importance of Explainable Artificial Intelligence (XAI) for interpreting behavioral prediction outcomes. Among the investigated models, Decision Trees and Random Forests provide comparatively higher interpretability because feature importance rankings can identify the variables most strongly influencing behavioral engagement prediction.

Feature importance analysis indicated that final examination performance, consistency indicators, learning gains, and mid-term assessment scores were among the most influential predictors of student engagement and behavioral classification. These findings are pedagogically meaningful because they align with established educational theories linking academic consistency and progressive assessment improvement with learning engagement and motivation.

The integration of explainable machine learning approaches can assist instructors in understanding the underlying behavioral patterns associated with at-risk students rather than relying solely on black-box prediction outputs. Transparent educational AI systems may therefore improve trust, accountability, and fairness in AI-assisted instructional decision-making.

Future work may incorporate advanced XAI techniques such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and attention-based interpretability frameworks to further investigate behavioral prediction mechanisms and support personalized learning strategies.

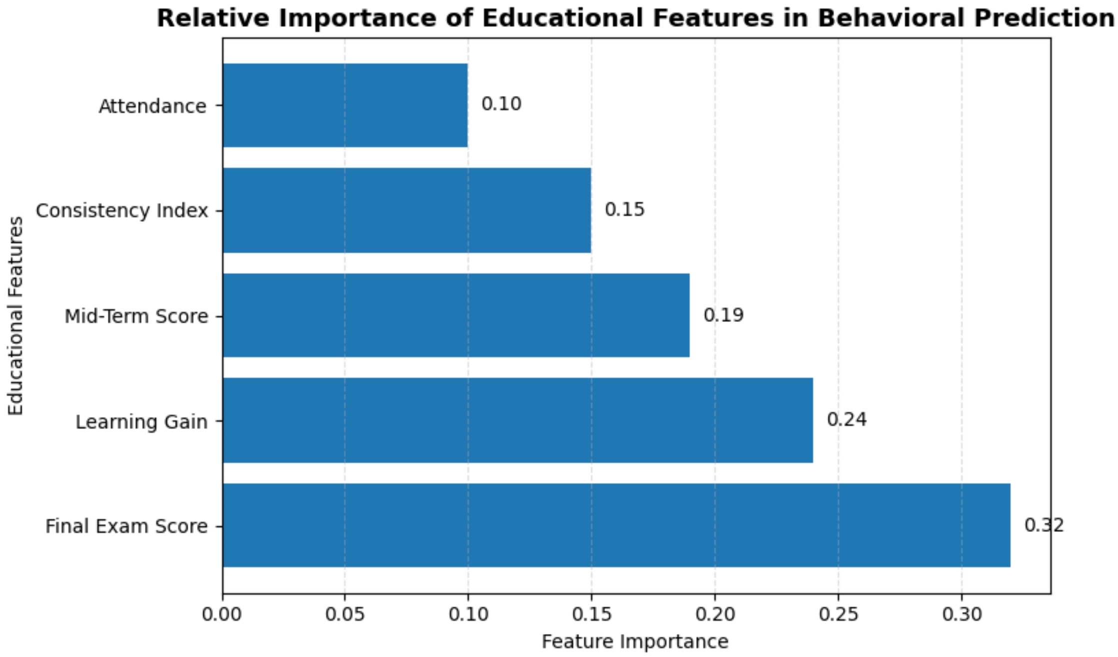


Figure 8. Relative Importance of Educational Features in Behavioral Prediction

Figure 8 illustrates the relative contribution of educational features to behavioral prediction performance. Final examination score and learning gain exhibited the highest influence on engagement classification, indicating that academic progression and consistency are strongly associated with student behavioral patterns. Attendance and consistency indicators also contributed meaningfully to prediction capability, supporting the importance of sustained classroom participation in educational analytics frameworks.

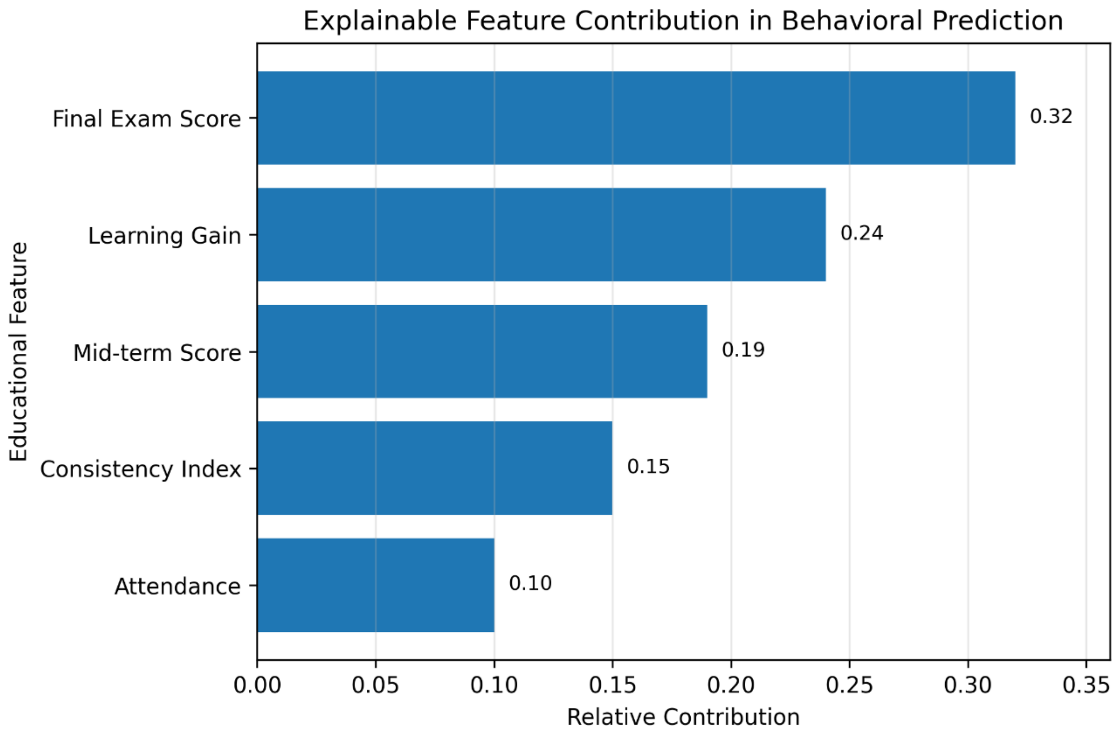


Figure 9. Explainable Feature Contribution in Behavioral Prediction

Figure 9 shows that final examination score and learning gain contributed most strongly to behavioral classification. Mid-term score and consistency index also played important roles, while attendance contributed comparatively less but remained pedagogically meaningful. These results support the use of explainable AI because instructors can identify which educational indicators influence model predictions.

### 4.6 Critical Discussion of Machine Learning Performance

The proposed framework is intended to support instructors rather than replace human educational judgment. Machine learning predictions should therefore be interpreted as decision-support indicators rather than deterministic evaluations of student capability. Ethical implementation of educational AI requires transparency, fairness, confidentiality, and avoidance of algorithmic bias during pedagogical decision-making processes.

The comparative analysis of machine learning algorithms demonstrated that the Random Forest classifier achieved the highest predictive accuracy among the investigated models. This superior performance can be attributed to the ensemble-learning mechanism of Random Forest, which combines multiple decision trees to reduce variance and improve generalization capability. Educational datasets frequently contain nonlinear relationships, noisy behavioral indicators, and overlapping engagement patterns; therefore, ensemble-based classifiers are often more robust than single-model approaches in such environments.

Although Decision Tree classifiers provided comparatively lower prediction accuracy, they offered higher interpretability and transparency. In educational contexts, interpretability is critically important because instructors must understand the reasoning behind behavioral predictions before implementing pedagogical interventions.

Transparent models may therefore improve instructor trust and support ethical implementation of educational artificial intelligence systems.

The Support Vector Machine (SVM) classifier demonstrated strong predictive capability due to its effectiveness in handling nonlinear educational data distributions through the Radial Basis Function (RBF) kernel. However, SVM performance remains sensitive to hyperparameter selection and dataset scaling, which may influence classification stability in small educational datasets.

The Artificial Neural Network (ANN) model achieved competitive accuracy but did not outperform the Random Forest classifier. This limitation may be associated with the relatively small dataset size used in the present study. Deep learning models generally require substantially larger datasets to fully exploit their representation-learning capability and avoid overfitting. In educational analytics applications involving limited classroom datasets, ensemble-learning methods may therefore provide better performance stability than deep neural architectures.

The obtained findings are consistent with previous educational data mining studies reporting strong performance of ensemble-learning approaches for predicting academic engagement and student performance. The results further demonstrate that machine learning models can support early identification of at-risk students, improve educational monitoring, and contribute toward data-informed instructional decision-making within engineering education environments.

Despite the promising results, the present study has several limitations. First, the dataset size was relatively small and limited to a single engineering course, which may affect generalizability across broader educational contexts. Second, behavioral prediction was based primarily on academic and classroom indicators without incorporation of psychological, emotional, or socio-economic variables that may also influence engagement patterns. Future studies involving multi-institutional datasets, multimodal learning analytics, and longitudinal educational monitoring may further improve predictive robustness and educational applicability.

# 5. Conclusion

This presented study uses machine learning models in order to predict student behavior and class engagements. Several learning algorithms were compared.

Among the investigated models, the Random Forest classifier achieved the highest predictive performance with an accuracy of 91.8%.

Statistical analysis revealed learning progression with an increase in mean academic performance from 85.2 in the mid-term assessment to 95.83 in the final evaluation. The reduction in standard deviation and the large values of Cohen's d size suggests meaningful educational improvement.

From a pedagogical perspective, the developed framework contributes transparent and interpretable educational decision-making rather than relying on black-box prediction systems.

In spite of these findings, there are several drawbacks including use of small data size and evaluations based on s single course. Future work should there fore take into account larger cohort of classes across different courses taught at various levels at different institutions incorporating real time data from monitoring systems to support next-generation smart learning environments.

# Declarations

**Competing interests:** All Authors declare that they have no competing interests in publication of this work.

**Funding information:** The authors did not receive support from any organization for the submitted work.

### Author contributions

The author solely contributed to the conceptualization, methodology development, data collection, data curation, software implementation, formal analysis, visualization, investigation, validation, writing of the original draft, reviewing, editing, and supervision of the present study.

### Use of Artificial Intelligence Tools

Artificial intelligence–based language and visualization tools, including ChatGPT (OpenAI), were used to assist in language refinement, figure generation, formatting improvement, and structural organization of the manuscript. All scientific interpretation, data analysis, methodological development, validation of results, and final manuscript content were critically reviewed and verified by the authors. The authors accepts full responsibility for the accuracy, originality, and integrity of the presented research work.

### Ethical Considerations

The present study was conducted in accordance with institutional ethical guidelines for educational research involving anonymized academic data. The research protocol was reviewed and approved by the Institutional Research Ethics Committee of Tecnológico de Monterrey under Protocol ID: P-EIC-202601-005.

All student-related information used in this study was anonymized prior to analysis to ensure confidentiality and privacy protection. No personally identifiable information was collected, stored, or disclosed during the investigation. The dataset consisted only of academic and behavioral indicators derived from routine classroom and learning management system (LMS) activities.

The study involved minimal risk because no medical, psychological, or invasive procedures were conducted. The analysis was limited to educational performance and engagement data obtained during normal academic activities. Data handling procedures complied with institutional ethical standards and educational research policies.

The machine learning models developed in this work were used exclusively as decision-support tools intended to assist instructors in identifying learning trends and at-risk students. The models were not used for automated grading, disciplinary decisions, or exclusion of students from academic activities

## 9. References

[1] Siemens, G., & Long, P. (2011). Penetrating the Fog: Analytics in Learning and Education. EDUCAUSE Review, 46, 31-40.

[2] López-Meneses, E.; Mellado-Moreno, P.C.; Gallardo Herrerías, C.; Pelícano-Piris, N. Educational Data Mining and Predictive Modeling in the Age of Artificial Intelligence: An In-Depth Analysis of Research Dynamics. *Computers* 2025, *14*, 68. https://doi.org/10.3390/computers14020068.

[3] Lou, Y., Colvin, K.F. Performance prediction using educational data mining techniques: a comparative study. Discov Educ 4, 112 (2025). https://doi.org/10.1007/s44217-025-00502-w

[4] Papadogiannis, I.; Wallace, M.; Karountzou, G. Educational Data Mining: A Foundational Overview. *Encyclopedia* 2024, *4*, 1644-1664. https://doi.org/10.3390/encyclopedia4040108

[5] Lu, Y.; Yeom, S.; Maktoubian, J.; Rahman, M.M.; Kim, S.-H. Improve Student Risk Prediction with Clustering Techniques: A Systematic Review in Education Data Mining. *Educ. Sci.* 2025, *15*, 1695. https://doi.org/10.3390/educsci15121695

[6] Lou, Y., Colvin, K.F. Performance prediction using educational data mining techniques: a comparative study. Discov Educ 4, 112 (2025). https://doi.org/10.1007/s44217-025-00502-w

[7] Yuan Y, Xu H, Krishnamurthy M, Vijayakumar P. Visualization analysis of educational data statistics based on big data mining. Journal of Computational Methods in Sciences and Engineering. 2024;24(3):1785-1793. doi:10.3233/JCM-230003

[8] Garcia, M.B. Text mining as an educational evaluation methodology: analyzing textual data extracted from online learning environments. Learning Environ Res 28, 685–709 (2025). https://doi.org/10.1007/s10984-025-09547-y

[9] Vaheed, S., Pratap Singh, R., Nayak, P., Mallikarjuna Rao, C. (2022). Student's Academic Performance Prediction Using Ensemble Methods Through Educational Data Mining. In: Bhateja, V., Satapathy, S.C., Travieso-Gonzalez, C.M., Adilakshmi, T.

(eds) Smart Intelligent Computing and Applications, Volume 1. Smart Innovation, Systems and Technologies, vol 282. Springer, Singapore. https://doi.org/10.1007/978-981-16-9669-5_20

[10] Lin, Y., Chen, H., Xia, W. et al. A Comprehensive Survey on Deep Learning Techniques in Educational Data Mining. Data Sci. Eng. 10, 564–590 (2025). https://doi.org/10.1007/s41019-025-00303-z

[11] McCarthy, R.V., McCarthy, M.M., Ceccucci, W. (2022). What Do Descriptive Statistics Tell Us. In: Applying Predictive Analytics. Springer, Cham. https://doi.org/10.1007/978-3-030-83070-0_3

[12] Wen Xiao, Ping Ji, Juan Hu, A survey on educational data mining methods used for predicting students' performance, Vol. 4, No.5, e12482 https://doi.org/10.1002/eng2.12482

[13] Romero, C., Ventura, S. Educational data mining and learning analytics: An updated survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 2024, 14(2), e1514. https://doi.org/10.1002/widm.1514

[14] Klašnja-Milićević, A., Ivanović, M., Budimac, Z. Learning analytics and educational data mining: Current challenges and future research directions**.** *IEEE Transactions on Learning Technologies*, 2024, 17, 1–14. https://doi.org/10.1109/TLT.2024.3364127

[15] Pardo, A., Siemens, G., Jovanovic, J., Dawson, S. From learning analytics to actionable intelligence: A review of prediction models in education. *Computers & Education*, 2024, 207, 104927. https://doi.org/10.1016/j.compedu.2024.104927

[16] Hassan, S.-U., Waheed, H., Aljohani, N.R., Ali, M. Machine learning–based early warning systems for student performance prediction: A systematic review. *IEEE Access*, 2024, 12, 32241–32260. https://doi.org/10.1109/ACCESS.2024.3360982

[17] Ifenthaler, D., Yau, J.Y.-K. Utilising explainable artificial intelligence to support learning analytics and educational data mining. *British Journal of Educational Technology*, 2024, 55(2), 586–603. https://doi.org/10.1111/bjet.13363

[18] Kumar, A., Singh, R., Dwivedi, S. Hybrid machine learning models for predicting student academic performance in smart learning environments. *Expert Systems with Applications*, 2025, 241, 122522. https://doi.org/10.1016/j.eswa.2024.122522

[19]Alamri, A., Almaiah, M.A., Al-Rahmi, W.M. Learning analytics and educational data mining in higher education: Trends, challenges, and future research agenda. *Education and Information Technologies*, 2024, 29, 1897–1923. https://doi.org/10.1007/s10639-023-12088-1

[20] Krouska, A., Troussas, C., Virvou, M. Deep learning approaches in educational data mining for student performance prediction: A review. *Neural Computing and Applications*, 2024, 36, 11291–11312.https://doi.org/10.1007/s00521-023-09102-7

[21] Wang, J.; Sun, Y.; Tian, S. Deep Learning for Student Behavior Detection in Smart Classroom Environments. *Information* 2025, *16*, 949. https://doi.org/10.3390/info16110949.

[22] Sheng, X., Li, S. & Chan, S. Real-time classroom student behavior detection based on improved YOLOv8s. S ci Rep 15, 14470 (2025). https://doi.org/10.1038/s41598-025-99243-x.

[23] Bayan Alnasyan, Mohammed Basheri, Madini Alassafi, The power of Deep Learning techniques for predicting student performance in Virtual Learning Environments: A systematic literature review, Computers and Education: Artificial Intelligence, Volume 6,2024,100231,ISSN 2666 920X,https://doi.org/10.1016/j.caeai.2024.100231.

[24] Althaqafi, T., Saleem, F. & AL-Ghamdi, A.AM. Enhancing student performance prediction: the role of class imbalance handling in machine learning models. Discov Computing 28, 79 (2025). https://doi.org/10.1007/s10791-025-09576-4.

[25] Wang J, Yu Y. Machine learning approach to student performance prediction of online learning. PLoS One. 2025 Jan 14;20(1):e0299018. doi: 10.1371/journal.pone.0299018. PMID: 39808634; PMCID: PMC11731722.

[26] Su YS, Lin YD, Liu TQ. Applying machine learning technologies to explore students' learning features and performance prediction. Front Neurosci. 2022 Dec 22;16:1018005. doi: 10.3389/fnins.2022.1018005. PMID: 36620438; PMCID: PMC9817150.

[27] Zhuang, P. (2024). Classroom Learning Behavior Analysis and Grade Prediction Based on Data Mining. In: Paas, F., Patnaik, S., Wang, T. (eds) Recent Trends in Educational Technology and Administration. EduTA 2023. Learning and Analytics in Intelligent Systems, vol 38. Springer, Cham. https://doi.org/10.1007/978-3-031-60777-6_22

[28] Qiu, F., Zhang, G., Sheng, X. et al. Predicting students' performance in e-learning using learning process and behaviour data. Sci Rep 12, 453 (2022). https://doi.org/10.1038/s41598-021-03867-8

[29] Balcioğlu, Y. S., & Artar, M. (2023). Predicting academic performance of students with machine learning. Information Development, 41(3), 896-915. https://doi.org/10.1177/02666669231213023 (Original work published 2025)

[30] Wang H, Gao C, Fu H, Ma CZ, Wang Q, He Z, Li M. Automated Student Classroom Behaviors' Perception and Identification Using Motion Sensors. Bioengineering (Basel). 2023 Jan 18;10(2):127. doi: 10.3390/bioengineering10020127. PMID: 36829621; PMCID: PMC9952181.

[31] Trabelsi, Z.; Alnajjar, F.; Parambil, M.M.A.; Gochoo, M.; Ali, L. Real-Time Attention Monitoring System for Classroom: A Deep Learning Approach for Student's Behavior Recognition. *Big Data Cogn. Comput.* 2023, *7*, 48. https://doi.org/10.3390/bdcc7010048

[32]M. M. Elsaid Khoudier *et al.*, "Prediction of student performance using machine learning techniques," *2023 5th Novel Intelligent and Leading Emerging Sciences Conference (NILES)*, Giza, Egypt, 2023, pp. 333-338, doi: 10.1109/NILES59815.2023.10296766.

[33] Luo, Y., Cui, Y. (2024). Improving Students' Achievement Prediction in Blended Learning Environments with Integrated Machine Learning Methods. In: Khine, M.S. (eds) Machine Learning in Educational Sciences. Springer, Singapore. https://doi.org/10.1007/978-981-99-9379-6_9

[34] Almalawi, A.; Soh, B.; Li, A.; Samra, H. Predictive Models for Educational Purposes: A Systematic Review. *Big Data Cogn. Comput.* 2024, *8*, 187. https://doi.org/10.3390/bdcc8120187

[35] Albreiki, B.; Zaki, N.; Alashwal, H. A Systematic Literature Review of Student' Performance Prediction Using Machine Learning Techniques. Educ. Sci. 2021, 11, 552. https://doi.org/10.3390/educsci11090552

[36] Arizmendi, C.J., Bernacki, M.L., Raković, M. et al. Predicting student outcomes using digital logs of learning behaviors: Review, current standards, and suggestions for future work. Behav Res 55, 3026–3054 (2023). https://doi.org/10.3758/s13428-022-01939-9

[37] Alruwais, N.; Zakariah, M. Student-Engagement Detection in Classroom Using Machine Learning Algorithm. *Electronics* 2023, *12*, 731. https://doi.org/10.3390/electronics12030731

[38] Shi, S., Gao, J., Wang, W. (2021). Classroom Teaching Behavior Analysis Based on Artificial Intelligence. In: Wang, W., Wang, G., Ding, X., Zhang, B. (eds) Artificial Intelligence in Education and Teaching Assessment. Springer, Singapore. https://doi.org/10.1007/978-981-16-6502-8_3

[39] Chen, H.; Zhou, G.; Jiang, H. Student Behavior Detection in the Classroom Based on Improved YOLOv8. *Sensors* 2023, *23*, 8385. https://doi.org/10.3390/s23208385

[40] Zhao, L.; Ren, J.; Zhang, L.; Zhao, H. Quantitative Analysis and Prediction of Academic Performance of Students Using Machine Learning. *Sustainability* 2023, *15*, 12531. https://doi.org/10.3390/su151612531

[41] R. Fu, T. Wu, Z. Luo, F. Duan, X. Qiao and P. Guo, "Learning Behavior Analysis in Classroom Based on Deep Learning," *2019 Tenth International Conference on Intelligent Control and Information Processing (ICICIP)*, Marrakesh, Morocco, 2019, pp. 206-212, doi: 10.1109/ICICIP47338.2019.9012177.

[42] Asselman, A., Khaldi, M., & Aammou, S. (2023). Enhancing the prediction of student performance based on the machine learning XGBoost algorithm. Interactive Learning Environments, 31(6), 3360–3379. https://doi.org/10.1080/10494820.2021.1928235

[43] Luo, Y., Han, X. & Zhang, C. Prediction of learning outcomes with a machine learning algorithm based on online learning behavior data in blended courses. Asia Pacific Educ. Rev. 25, 267–285 (2024). https://doi.org/10.1007/s12564-022-09749-6

[44] Nnadi, L.C.; Watanobe, Y.; Rahman, M.M.; John-Otumu, A.M. Prediction of Students' Adaptability Using Explainable AI in Educational Machine Learning Models. *Appl. Sci.* 2024, *14*, 5141. https://doi.org/10.3390/app14125141

[45] Wen, X.; Juan, H. Early Prediction of Students' Performance Using a Deep Neural Network Based on Online Learning Activity Sequence. *Appl. Sci.* 2023, *13*, 8933. https://doi.org/10.3390/app13158933

[46] Sun, B., Wu, Y., Zhao, K. et al. Student Class Behavior Dataset: a video dataset for recognizing, detecting, and captioning students' behaviors in classroom scenes. Neural Comput & Applic 33, 8335–8354 (2021). https://doi.org/10.1007/s00521-020-05587-y

[47] Namoun, A.; Alshanqiti, A. Predicting Student Performance Using Data Mining and Learning Analytics Techniques: A Systematic Literature Review. *Appl. Sci.* 2021, *11*, 237. https://doi.org/10.3390/app11010237

[48] Zhu, W., Yang, Z. Csb-yolo: a rapid and efficient real-time algorithm for classroom student behavior detection. J Real-Time Image Proc 21, 140 (2024). https://doi.org/10.1007/s11554-024-01515-8

[49] Yağcı, M. Educational data mining: prediction of students' academic performance using machine learning algorithms. Smart Learn. Environ. 9, 11 (2022). https://doi.org/10.1186/s40561-022-00192-z

[50] Lin, L.; Yang, H.; Xu, Q.; Xue, Y.; Li, D. Research on Student Classroom Behavior Detection Based on the Real-Time Detection Transformer Algorithm. *Appl. Sci.* 2024, *14*, 6153. https://doi.org/10.3390/app14146153

[51] Shou, Z.; Xie, M.; Mo, J.; Zhang, H. Predicting Student Performance in Online Learning: A Multidimensional Time-Series Data Analysis Approach. *Appl. Sci.* 2024, *14*, 2522. https://doi.org/10.3390/app14062522

[52] Khoudi, Z., Hafidi, N., Nachaoui, M. et al. New Approach to Enhancing Student Performance Prediction Using Machine Learning Techniques and Clickstream Data in Virtual Learning Environments. SN COMPUT. SCI. 6, 139 (2025). https://doi.org/10.1007/s42979-024-03622-6

[53] Beseiso, M. Enhancing Student Success Prediction: A Comparative Analysis of Machine Learning Technique. TechTrends 69, 372–384 (2025). https://doi.org/10.1007/s11528-025-01044-6

[54] She, Y. (2025). Machine Learning Applications in the Field of Student Performance Prediction. In: Virvou, M., Paas, F., Patnaik, S. (eds) New Paradigm in Digital Classroom and Smart Learning. DCSL 2024. Learning and Analytics in Intelligent Systems, vol 54. Springer, Cham. https://doi.org/10.1007/978-3-031-98607-9_4

[55] Lalitha, R., Vaithilingam, C.A., Abdul Karim, S.A. (2024). Analyzing and Improving Student Learning Behaviour in the Classroom Using Machine Learning Techniques. In: Abdul Karim, S.A. (eds) Intelligent Systems Modeling and Simulation III. Studies in Systems, Decision and Control, vol 553. Springer, Cham. https://doi.org/10.1007/978-3-031-67317-7_26

[56] Bhoot, R., Singh, S.I. (2024). Analysis and Prediction of Students' Performance Using Machine Learning. In: Khanra Jha, S., Shenoy, M.V., Bhattacharyya, T., Seshaiyer, P. (eds) Perspective and Strategies on Newage Education and Creative Learning. ICON BITS 2023. Springer Proceedings in Humanities and Social Sciences. Springer, Singapore. https://doi.org/10.1007/978-981-97-3701-7_3

[57] Mbunge, E., Fashoto, S., Mafumbate, R., Nxumalo, S. (2022). Diverging Hybrid and Deep Learning Models into Predicting Students' Performance in Smart Learning Environments – A Review. In: Ngatched, T.M.N., Woungang, I. (eds) Pan-African Artificial Intelligence and Smart Systems. PAAISS 2021. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 405. Springer, Cham. https://doi.org/10.1007/978-3-030-93314-2_12

[58] Chen, J. et al. (2022). Student Behavior Analysis and Performance Prediction Based on Blended Learning Data. In: Memmi, G., Yang, B., Kong, L., Zhang, T., Qiu, M. (eds) Knowledge Science, Engineering and Management. KSEM 2022. Lecture Notes in Computer Science(), vol 13369. Springer, Cham. https://doi.org/10.1007/978-3-031-10986-7_48

[59] Balaji, P.; Alelyani, S.; Qahmash, A.; Mohana, M. Contributions of Machine Learning Models towards Student Academic Performance Prediction: A Systematic Review. *Appl. Sci.* 2021, *11*, 10007. https://doi.org/10.3390/app112110007

[60] Feng, C., Liu, J., Wang, J. et al. BISAP: A student academic performance prediction model based on the fusion of classroom behavior images and educational information. Educ Inf Technol 30, 7457–7483 (2025). https://doi.org/10.1007/s10639-024-13085-0

[61] Zhan, Z., Shen, T. Development of a prediction model for student teaching satisfaction based on 10 machine learning algorithms. Sci Rep 15, 36547 (2025). https://doi.org/10.1038/s41598-025-19039-x

[62] Alkan, B.B., Kuzucuk, S., Alkan, N. et al. Using machine learning to predict student outcomes for early intervention and formative assessment. Sci Rep 15, 39797 (2025). https://doi.org/10.1038/s41598-025-23409-w

[63] Marín, Y.R., Huatangari, L.Q., Tuesta, J.N.A. et al. Analysis of factors affecting the academic performance of university students using machine learning. Sci Rep 15, 44027 (2025). https://doi.org/10.1038/s41598-025-28870-1

[64] Ngoc Anh, B.; Tung Son, N.; Truong Lam, P.; Phuong Chi, L.; Huu Tuan, N.; Cong Dat, N.; Huu Trung, N.; Umar Aftab, M.; Van Dinh, T. A Computer-Vision Based Application for Student Behavior Monitoring in Classroom. *Appl. Sci.* 2019, *9*, 4729. https://doi.org/10.3390/app9224729

[65] R. Alshabandar, A. Hussain, R. Keight and W. Khan, "Students Performance Prediction in Online Courses Using Machine Learning Algorithms," *2020 International Joint Conference on Neural Networks (IJCNN)*, Glasgow, UK, 2020, pp. 1-7, doi: 10.1109/IJCNN48605.2020.9207196.