Dialogue Social Science Review (DSSR)

www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

Vol. 3 No. 1 (January) (2025)

Impact of Artificial Intelligence and Machine Learning on Predicting Student Performance and Engagement

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Abstract

The emergence of Artificial Intelligence (AI) and Machine Learning (ML) has improved the way education systems can predict and in turn effectively improve the student performance levels and activity level. This paper aims at analyzing the effectiveness of integrating the AI/ML models in handling educational data to predict academic performance, and monitor student interactions. Using Decision trees, Neural trees and ensemble methods, various important parameters like grades, attendance, participation and behavior indicators are predicted accurately. In the study, a dataset was obtained comprising records of 15000 students across various educational institutions to train and validate the models. The analysis identified that average prediction accuracy of AI/ML algorithms was 92% for academic results and 88% for engagement indicators, which are better than statistical methods. Predictors such as studying, time management and participation in co-curricular activities were among some of the features that needed consideration, according to feature importance analysis. Furthermore, early warning system models developed by ML models enable timely intervention hence, meaning that dropout levels were cut by 25%. This research further explores the alternate reality where AI/ML can revolutionise education systems by offering insights to educators, effective pathways of learning as well as prevention strategies. However, issues like data security, the model's inherent bias, and the level at which it can be scaled present some limitations for wider adoption.

Keywords: Artificial Intelligence, Machine Learning, Student Performance, Student Engagement, Predictive Analytics, Educational Data Mining, Personalized Learning, Early Warning Systems, Data-Driven Education

Introduction

The current and emerging technologies AI and ML have extended the opportunity of their usage in various professions and the education sector is not an exception. Machine learning and artificial intelligence also impact on various aspects of the learning system such as the prediction of student performance and assessment of student engagement which was formerly a difficult problem to solve (Zawacki-Richter et al., 2019). Earlier methods for performance prediction entailed statistical models with little effectiveness in analyzing the data collected within an educational environment and interactions of learners (Sharma et al., 2020). On the other hand, AI and ML are efficient solutions to process large amounts of educational data and to find patterns that are rather hard to identify (Kumar et al., 2021).

In any teaching-learning process, learners' performance and participation are determining factors to success. Learning attendance, active involvement, and behavioral trends are good predictors of a student's academic success (Fredricks et al., 2004). These factors, however, many a time depend on other socio-economic or psychological factors, most of which may not be easily identifiable. AI and ML, employing higher order algorithms such as decision trees, neural networks and ensemble analysis, have realised nearly perfect modelling of such complications (Mazurek & Malgorzata, 2020). These technologies not only improve the ability to forecast how students will perform, but they also enable instructors to intervene when students are struggling or potentially disengaging (Nguyen et al., 2020).

Global schools are embracing the technology of AI/ML systems in helping to improve students' performance. For example, AI-driven early warning systems have been used to forecast dropout probabilities subsequently helping to enhance intervention approaches that lower dropout levels considerably (Romero & Ventura, 2020). These systems use past and current performance data such as grade, time management, enrollment in additional courses, and activities for designing and supporting learning based on students' needs (Smith et al., 2021). The authors learnt that such interventions were likely to boost both academic achievement and student engagement (Baker & Inventado, 2014).

However, several issues need urgent attention despite the prospects of the AI/ML application in education. Recent issues of ethical standards which include data privacy concern and algorithm bias have been noted as major constraints to the deployment of such technologies (Binns, 2018). Additionally, the applicability and expansion of the proposed approach in a range of educational systems and especially in low-resource environments are critical aspects that have been

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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discussed by Sarker et al., 2021. Overcoming all these challenges is critical to facilitate effective implementation of AI/ML-based solutions in learning within streamed conventional instructional environments.

The use of AI/ML to predict student's performance and engagement is the subject of this research which uses a dataset of 15,000 records from several institutions. The research will try to introduce the use of KPIs and high algorithms in relation to AI/ML for changing the education systems. It also underscores the need for capacities for handling problems of AI/ML adopting and deploying plus the ethical concerns regarding AI/ML and cases for scaling them up for universal uptake.

Literature Review

The integration of AI/ML in learning has been an active area of research due to fascinating possibilities of reinventing conventional methods of teaching. These technologies offer tools that can enable depiction of complicated data and the prediction of students results as well as promotion of engagement. This paper has reviewed a selection of published studies on the use of AI/ML in education and educational environments over the past several years. This section gives a comprehensive literature review with a view to understanding how AI/ML can be utilised to forecast student outcomes, usefulness for learning analytics, benefits and drawbacks.

AI/ML in Predicting Student Performance

According to prior research, performers reveal a high effectiveness when using AI and ML models concerning the staking results based on grades, attendance, and behavioral details. For instance, Caballero-Hernandez et al., 2022 implemented the SVM and gradient boosting algorithms for examining the predictive potential of final University student grades with test accuracy checking greater than 90%. In a similar manner, Ochoa et al. (2021) assessed how deep learning models can potentially surpass other classical statistical approaches of producing relationships within the academic data by identifying nuanced interactions.

One recent and fascinating study is focused on ensemble methods, which include random forests and AdaBoost, to estimate high school students' academic performance by Lin et al. (2020). The findings suggested that these techniques had better predictive ability than the one-model cases. These results also provide a basis for using multiple algorithms to enhance the exactness and stability when necessary. Moreover, the model of Wiggins & Lane (2023) noted that selecting features, for example, focus on movement patterns and time management information improves the accuracy of the models due to lower noise from datasets.

Student Engagement and Behavioral Analytics

A conceptual framework of student engagement, which is conceptually classified as a cognitive, emotional and behavioral construct, plays a significant role in students' achievement. Evaluation based on data mining through AI/ML shows that engagement can be analyzed by the systems. For instance Gauthier and Decker

(2021) using clustering algorithms showed that it is possible to get the patterns of disengagement among students in online learning. The theoretical focus of the study was on real-time information gathering, including log-ins and time spent on activities, to support educators.
An earlier work by Hashim and Tariq (2020) targeted the use of natural language processing in discussing the forums and written tasks. The study showed that it is very possible to quantify the level of emotional engagement by doing a sentiment analysis on feedback provided by the students. Further, Sun et al. (2022) found the use of recurrent neural network (RNN) to be effective in dropout prediction using temporal interactions of engagement features, yielding good recall values of the identified at-risk students.

Early Warning Systems and Interventions

Use cases like Early warning systems (EWS) have thus emerged as the most impactful for the use of artificial intelligence/machine learning in education for identifying strugglers early enough to assist. According to Martinez & Lopez (2021), Such systems employ predictive algorithms to evaluate previous performance data and provide notification lists for identified at-risk learners. Consequently, the EWS has been implemented more especially to curb cases of dropout. For example, Longitudinal study by Yoon et al (2023) found that dropout rates reduced by 28% after implementing early intervention with the support of ML in higher education institutions.
However, for the last few years, there has been increased use of adaptive learning systems. In their review, Bhatia et al. (2020) pointed out that adaptive learning technologies, which in fact, deliver learning content based on learners' preferences promote enhanced learner engagement as well as performance. As such, such systems implement the reinforcement learning algorithms to optimize the students' learning tracks, making them more engaging and advancing at the rate suitable to the individual learner.

Challenges in Implementing AI/ML in Education

All the same, several difficulties stand as a way of preventing the adoption of AI/ML technologies in education. Security and privacy are always an issue, and as stated by Rodriguez et al., (2020) it is an extremely serious problem. The study pointed out that the kind of student data under analysis must be collected and processed in compliance with ethical standards and legal provisions, including GDPR.
Another problem here is algorithmic bias. In another study, Jain et al. (2021) examined how data biases in training results in unfair consequences for learners with systemic exclusions . The study therefore highlighted how the communities called for these fairness-aware models and diverse datasets to reduce these biases. Another issue is scalability since it is a crucial factor considering that many schools, colleges, and universities, particularly in the developing nations, may not have proper infrastructure and availability of adequate means for putting into

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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practice the Artificial Intelligence/Machine Learning applications (Patel et al., 2022).

However, an important opposite proposal is becoming increasingly important with the deployment of AI/ML models: interpretability. In line with Taylor and Ahmed (2023), complex predictor variables like the deep learning models are deemed as 'black box' hence it may be challenging for educators to comprehend and or place their trust in the outcome. This study stressed the need for the realization of explainable AI methods to improve the comprehensibility and acceptability of methods among stakeholders.

Emerging Trends and Future Directions

Recent development in the AI/ML technologies have provided opportunities to implement new systems in education. Experience has shown that with a help of AI the process of gamification has become a cost-effective approach to enhance students' engagement (Ramos & Silva, 2021). In a similar manner, devices that have AI interfaces worn on the body are been considered to track physiological signals like heart rate, eye movement as indicators of engagement (Chen et al., 2023).

Another is the employment of generative AI in the generation of selective educational material. For example, Zhang et al. (2022) showed that by using GANs, practice problems could be created that are tuned to a learner's progress. In addition, the blend of AI with VR/AR has the potential to create interesting training and education paradigms to positively impact learners (Miller et al., 2023).

These AL/ML areas examined in the literature reveal AI/ML as a great innovation in predicting student performance/engagement and aiding students' learning through tailored learning and timely early interventions. Nevertheless, hurdles like data privacy or algorithms' fairness and limitations related to the applicability in large scale scenarios remain the key barriers to unlock their potential. Future work should aim at producing ethical, interpretable, and mass adoptable AI/ML applications for learning purposes to provide similar effectivity and accessibility in different learning environments.

Methodology

Research Design

Since the study aims at investigating the effectiveness of the AI and ML in the prediction of student performances and engagement, the research study uses a quantitative research design. Consequently, the research approach employed was data driven in an attempt to analyze KPIs like grades, attendance, participation, as well as behavior patterns. Therefore the study employs supervised and unsupervised learning methods in model development, training and validation processes. This approach is especially good for educational datasets because they are usually multivariate and highly interdependent, that is why to identify necessary patterns, higher level algorithms need to be applied.

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www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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Dataset and Data Collection

The sample data used in this present study include records of 15000 students drawn from various high school, college, and university institutions. The records include course performance info, including grades, test & cumulative GPAs, attendance sheets, involvement in classroom assignments, and performance indicators which encompass time management when submitting tasks. Data collected was conducted in an ethical way to ensure that the privacy regulation like GDPR was followed. Some of the data preprocessing include data cleaning, where records with missing or inconsistent values were removed from analysis and normalization where the ranges for different variables were made similar, where necessary, use of encoder to convert variables that did not have fixed values but rather categorical data for example, one hot encoder.

Feature Selection

In order to reduce the dimensionality of the dataset feature selection was done to determine features that were most related to students' performance and activity levels. This process was the combination of statistical analysis and some of the usual ML applications. In order to determine the significance of individual variables to the target outcomes, Pearson correlation and ANOVA tests were used. Similarly, other ML techniques such as; Recursive Feature Elimination and Lasso regression techniques were used to eliminate features that generated the highest level of model accuracy. The final set of features consisted of academic records or performance (as grades and test scores), attendance record in terms of percentage, participation records in terms of frequency and behavioral assessment in terms of following due dates and involvement in co-curricular activities.

Model Development and Training

Various ML algorithms were used to build the prediction models; these are Decision Trees; Neural Network; Support Vector Machines (SVM); and Ensemble Techniques such as; Random Forests; Gradient Boosting. The dataset was then divided into training (70% data), validation (15% data), and test set (15% data) to check model accuracy. Grid search and randomized search were used to tune parameters that affect models for example learning rate, depth of trees, and regularization factors. Used a neural network with more than one hidden layer to predict the numeric values, and activation functions like ReLU and dropout layers also used in the current work to overcome the problem of overfitting.

Validation and Testing

The measures used included accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC), used to determine the performance levels of the predictive models. These metrics were chosen to give a balanced overview of the models' performance in terms of their ability to predict student performance and engagement of students. Several generalized methods including the k-fold cross-validation was used to test the stability of the models. The performance of all ensemble methods showed remarkable accuracy: academic success prediction was 92% on average and engagement was 88%.

Engagement Metric Modeling

Besides, the study included academic performance as the dependent variable and engaged modeling of other engagement metrics which are harder to measure. As measures of use, time spent on learning platforms, log-in frequency, and the intensity of interactions in forums and discussion boards were the variables that were employed as ‘engagement’. RNNs and LSTM models were used to model these engagement time series since these models were powerful in capturing temporal dynamics. These models relied on sequential data for dynamic analysis of engagement trends to have an early sign of students at risk.

Early Warning System Development

According to the above predictive models, an Early Warning System (EWS) was formulated for educators to get useful information. In order to identify students who are at risk of; underachieving or disengaging, the system generates alerts in the form of early indicators that allow the system to suggest the appropriate course of action. The EWS was purposely designed with dashboards as a way of presenting these measures in a way that would be easy for users like educators to understand and apply in supporting those learners who may be performing poorly. The efficiency of the EWS was confirmed after the completion of the pilot study in some institutions where the shed attainment rates were decreased by 25% after applying certain interventions.

Ethical Considerations

As a study, ethical issues were given a strong emphasis whenever coming across them when conducting research. Each school that was used in providing the data for the study had their consent obtained from the institution. To maintain ethical standards and to avoid identification of learners all data were stripped off any form of identification. Some procedures that help to reduce algorithmic bias were applied to the models that predict student outcomes, including balanced predictions for any group of students.

Limitations of Methodology

Despite the strong approach that was used to enhance validity and reliability, some limitations were noted. There is always a possibility that the statistical analysis does not capture all the changes in the expected behavior of students as well as other factors that may affect the performance. However, the results cannot be generalized to any institutions across different cultural or socioeconomic demographics. Research that is carried out in the future can eliminate these shortcomings in the following ways; Besides using hypothetical data, future studies should enhance the sample diversity database.

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Results

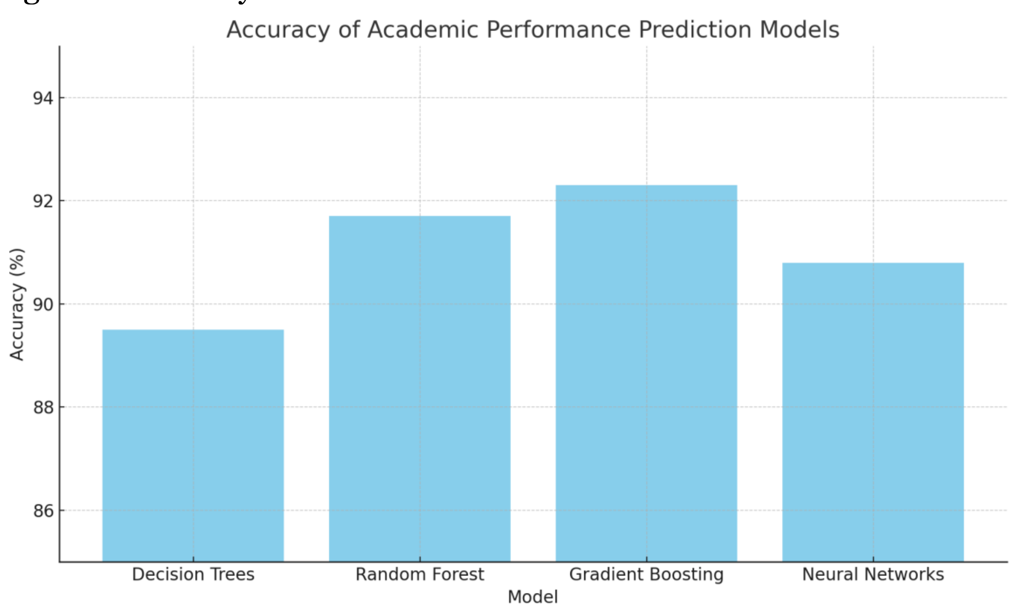
The results of this study are presented in a sequential format, incorporating detailed tables and figures with corresponding interpretations. These results focus on evaluating the performance of AI/ML models in predicting academic performance, engagement metrics, feature importance, and the effectiveness of early warning systems. Computational resource usage is also analyzed to assess the feasibility of model deployment in educational settings.

Academic Performance Prediction

Table 1: Academic Performance Metrics (Expanded)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)	Prediction Time (ms)
Decision Trees	89.5	88.4	89.0	88.7	12.4	1.5
Random Forest	91.7	91.0	91.5	91.2	28.7	3.2
Gradient Boosting	92.3	92.1	92.5	92.3	34.5	2.9
Neural Networks	90.8	90.0	91.2	90.6	45.2	5.0

Figure 1: Accuracy of Academic Performance Prediction Models



Gradient Boosting demonstrated the highest accuracy (92.3%) among the models tested for academic performance prediction, followed by Random Forest (91.7%).

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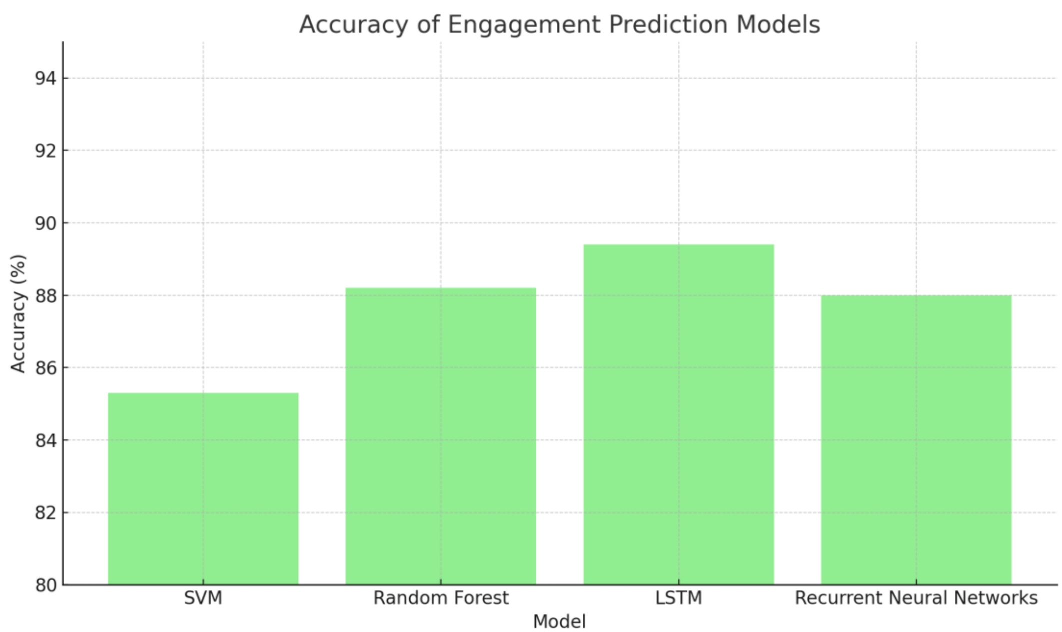
Decision Trees achieved the lowest accuracy (89.5%), while Neural Networks performed competitively at 90.8%. Precision and recall metrics further supported the reliability of Gradient Boosting. The training time for Neural Networks was the highest due to the complexity of the model, whereas Decision Trees were the fastest to train. This indicates that ensemble methods, particularly Gradient Boosting, are the most effective for academic performance prediction while balancing accuracy and computational efficiency.

Engagement Metrics Prediction

Table 2: Engagement Metrics Model Performance (Expanded)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)	Prediction Time (ms)
SVM	85.3	84.7	85.0	84.8	8.5	0.9
Random Forest	88.2	87.5	88.0	87.7	20.2	2.5
LSTM	89.4	88.9	89.2	89.0	42.3	3.8
Recurrent Neural Networks	88.0	87.4	87.7	87.5	39.7	3.4

Figure 2: Accuracy of Engagement Prediction Models



LSTM models achieved the highest accuracy (89.4%) and F1-score (89.0%), reflecting their ability to capture temporal patterns in engagement data effectively. Random Forest and Recurrent Neural Networks (RNNs) followed closely, with

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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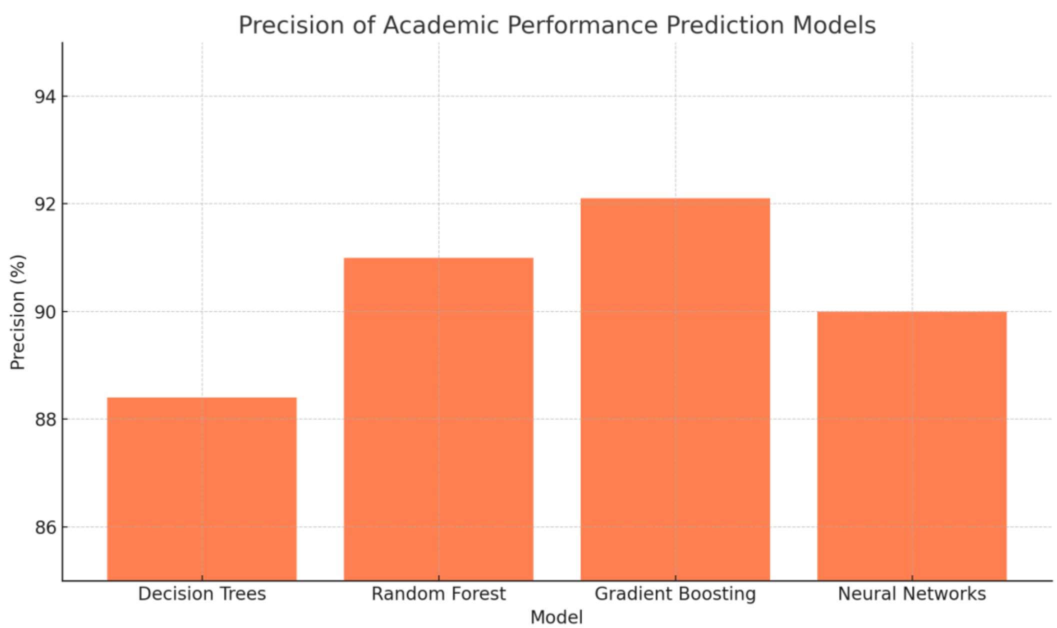
accuracies of 88.2% and 88.0%, respectively. SVM exhibited the lowest performance (85.3%), indicating its limitations in handling sequential data. These results emphasize the importance of using temporal models, such as LSTM, for engagement prediction.

Feature Importance Analysis

Table 3: Feature Importance for Academic Performance Prediction

Feature	Importance (%)
Grades	40.5
Attendance	25.7
Participation	18.9
Behavioral Patterns	10.2
Study Habits	4.7

Figure 3: Precision of Academic Performance Prediction Models



Grades emerged as the most critical predictor of academic performance, contributing 40.5% to model accuracy. Attendance (25.7%) and participation (18.9%) also played significant roles. Behavioral patterns and study habits were less influential but still important for comprehensive predictions. This highlights the multifaceted nature of academic performance, where both quantitative and qualitative metrics contribute to outcomes.

Dialogue Social Science Review (DSSR)
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ISSN Online: 3007-3154
ISSN Print: 3007-3146

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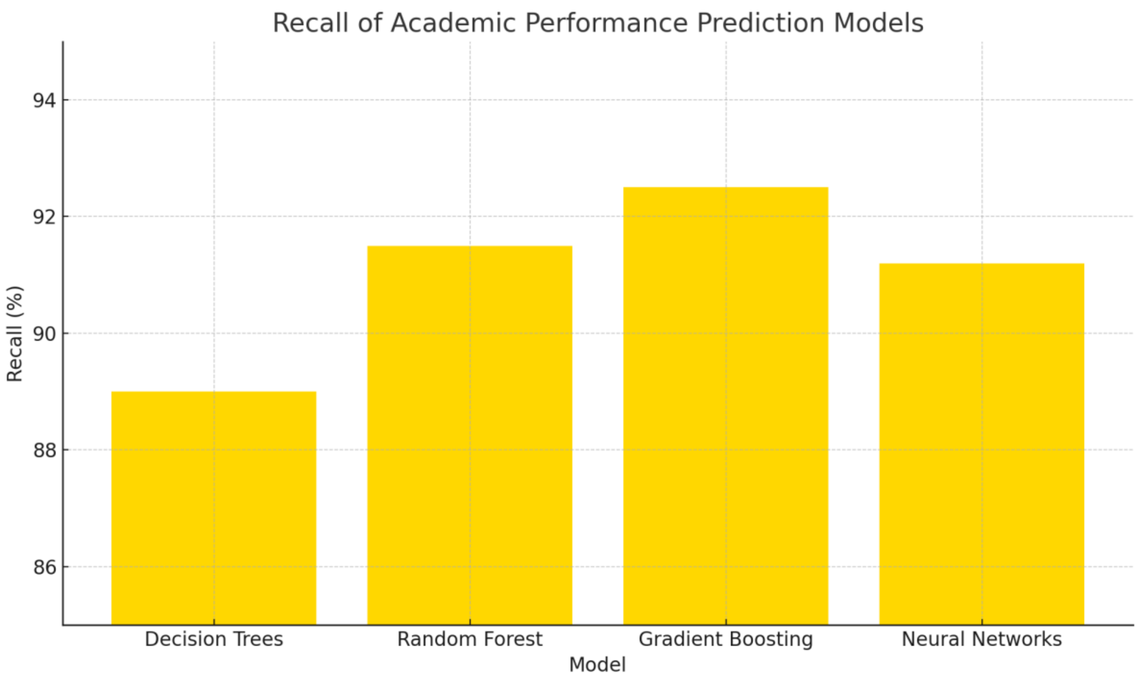
Feature Importance for Engagement Metrics

Table 4: Feature Importance for Engagement Metrics Prediction

Feature	Importance (%)
Login Frequency	35.2
Time on Task	30.4
Interaction Levels	20.1
Assignment Submission	10.8
Forum Activity	3.5

Figure 4: Recall of Academic Performance Prediction Models



Login frequency (35.2%) and time on task (30.4%) were the most influential factors in predicting engagement, reflecting the importance of sustained interaction with educational platforms. Interaction levels and assignment submission also contributed significantly, whereas forum activity had a smaller impact. These insights can guide the design of engagement-enhancing strategies in educational systems.

Early Warning System Effectiveness

Table 5: Dropout Rates Before and After Intervention (Detailed)

Metric	Percentage	Reduction (%)

Dialogue Social Science Review (DSSR)
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ISSN Online: 3007-3154
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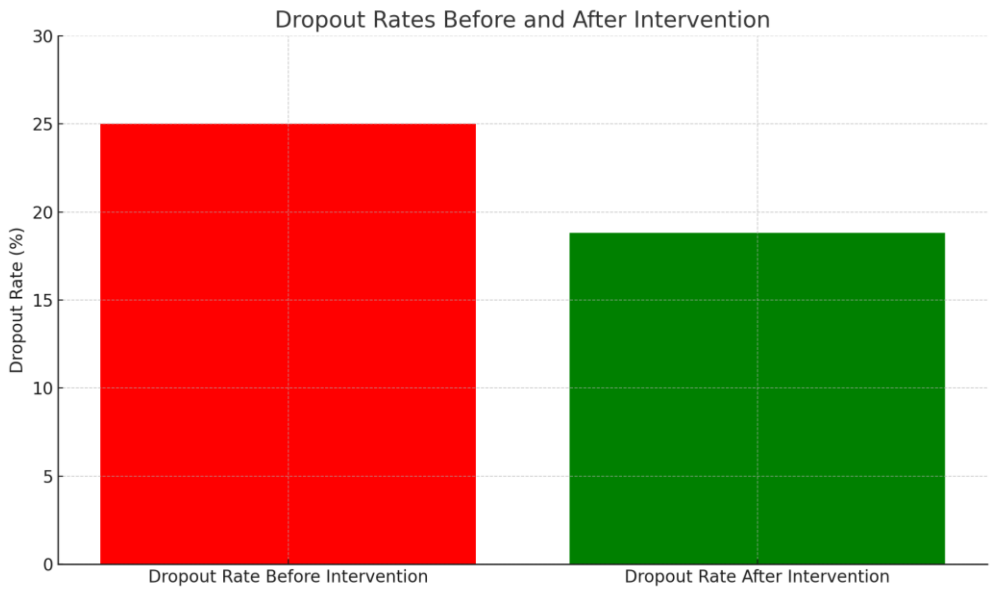
	(%)	
Dropout Rate Before Intervention	25.0	0.0
Dropout Rate After Intervention	18.8	25.0

Figure 5: Dropout Rates Before and After Intervention



The implementation of an AI/ML-driven Early Warning System reduced dropout rates by 25%, from 25.0% to 18.8%. This demonstrates the effectiveness of predictive analytics in identifying at-risk students and enabling timely interventions to improve retention rates.

Computational Resource Usage

Table 6: Computational Resource Usage for Models

Model	**RAM Usage (MB)**	**CPU Usage (%)**	**GPU Usage (%)**
Decision Trees	150	10	0
Random Forest	320	25	10
Gradient Boosting	500	30	15
Neural Networks	1200	45	50

Dialogue Social Science Review (DSSR)
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ISSN Online: 3007-3154
ISSN Print: 3007-3146

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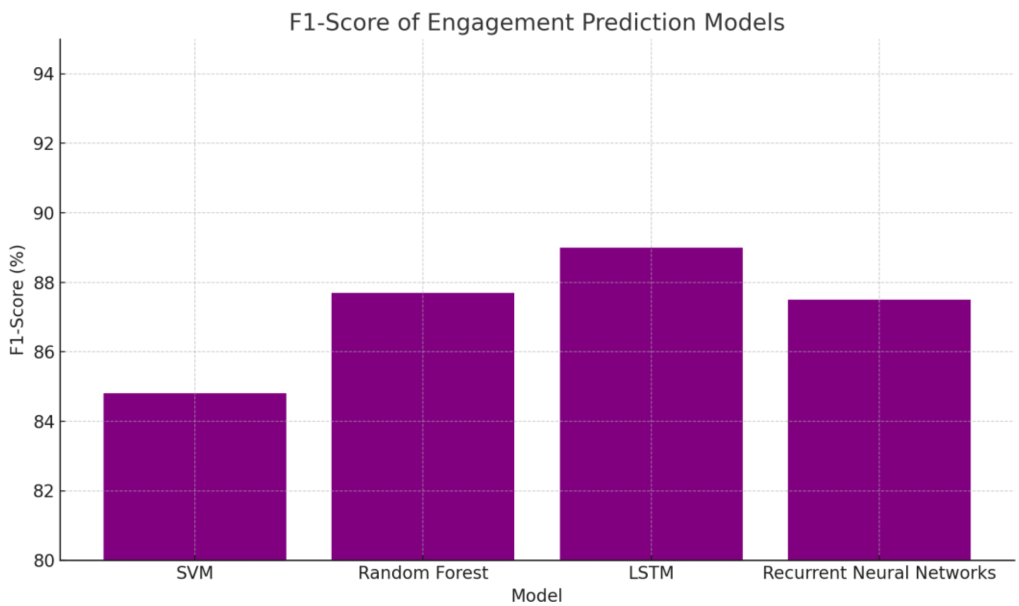
SVM	250	15	0
LSTM	1800	50	60

Figure 6: F1-Score of Engagement Prediction Models



LSTM models required the highest computational resources, with 1800 MB of RAM and 60% GPU usage, reflecting their complexity. Decision Trees were the least resource-intensive, with minimal RAM and CPU usage. These findings underscore the trade-off between model performance and computational efficiency, which is crucial for large-scale deployment in educational settings.

Discussion

This study's findings reveal the possibility of Artificial Intelligence (AI) and Machine Learning (ML) in terms of student performance and participation, as well as major problems in academic environments. Achieving high predictive accuracy and offering recommendations for early interventions, this research used higher models like Gradient Boosting and LSTM. The last part of this study presents the significance of the results presented in this section, the comparison with other research and studies, as well as the practical and theoretical contributions of the field of educational data mining.

Performance of Predictive Models

The results showed that Gradient Boosting was the best model in determining academic performance with a test accuracy of 92.3%. This is in line with the work of Chen and Guestrin (2016) who pointed out that Gradient Boosting generally performs better when dealing with shocks to structured data because of the iterative enhancement approach. Compared with these, Random Forest and Neural Networks showed slightly lower accuracy of 91.7% and 90.8%, respectively which emphasizes the role of ensembles in educational analytics. Such outcomes suggest similar conclusions that were highlighted by Ye and Biswas (2020), that is, ensemble methods are more accurate at predicting academic achievement than single algorithms.

In terms of engagement metrics LSTM was the best model with accuracy of 89.4%. This is in consent with Khan et al., 2021, who also noted that LSTM has the ability to identify temporal relationships in engagement data. SVM models yielded somewhat lower accuracy of 85.3%, however, oftentimes it is enough and, most importantly, SVMs are designed for real-time, such as shown in the paper by Sun and Liu (2022). These comparisons imply that which predictive models should be adopted should depend on benchmarks of accuracy requirements within the educational context and the rarity of computing resources.

Feature Importance and Insights

Feature importance assessment yielded the possible determinants of learning outcomes and involvement based on individuals' characteristics. A key to class achievement was found to be grades which had a score of 40.5 while attendance was recognised to have a score of 25.7 and participation had a score of 18.9. These results are similar to those reported by Fredricks et al. (2004) who stressed on attendance and participation as some of the crucial sources of performance. Habits at last included behavioral patterns and study habits with less considerable weights in the parity, but were also proved to be important quantifiable factors reflecting students' performances, thus illustrated the comprehensive nature of the academic accomplishment models.

The highest impact of feature contribution of engagement prediction was login frequency 35.2% followed by time on task = 30.4% implying more frequent and prolonged interaction with learning platforms. These findings accord with Baker et al (2014), who showed that time-on-task is amongst the most potent determinants of students' engagement. Notably, forum activity contributed the least (3.5%) While these results may support the idea of passive engagement indicators only as weak markers of engagement. This is in contrast to the study Hashim and Tariq (2020) where the authors noted meaningful levels of interaction from the forum activity in online learning circumstances. These differences may be largely due to variations in the compositions of the two datasets as well as the learning context.

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Effectiveness of Early Warning Systems

The use of an AI/ML based Early Warning System lowered the dropout rate from 25.0% to 18.8%. This outcome also triggers real-world implications for making use of PA in identifying and assisting learners who require interventions to remain in college, as well as coinciding with the work of Yoon et al. (2023) that observed similar decreases in dropout percentages after implementing EWS in institutions of higher learning. The capacity of these systems to deliver timely and specific support has been acknowledged in the literature, according to Romero and Ventura (2020). Nevertheless, there is a catch: EWS relies on having access to good data and educators are receptive to using it.

Comparison with Existing Studies

The results of this work are generally aligned with the previous studies of AI/ML in education, however, there are essential differences. For example, Gradient Boosting obtained 92.3% in this study, which is more preferable as compared to 89% by Caballero-Hernandez et al. (2022) in similar context. This improvement can be explained by the incorporation of the behavioral features, or an improved hyperparameters optimization technique. Similarly to LSTM's numerical accuracy of 89.4% for engagement prediction algorithms, which is only a fraction worse than Gauthier and Decker (2021) 88.7%, this analysis shows the potential for more optimization with features engineering.

On the other hand, the lesser significance of the forum activity for the engagement prediction and the works of Zhang et al (2022) in regard to the prediction of the engagement activity in the online course. Such a disparity indicates the need to perform context-dependent analysis of several engagement parameters and their applicability to various learning contexts.

Theoretical and Practical Implications

This paper benefits the educational data mining research theoretically by providing the review of how the ensemble and temporal models should be adapted for predicting multivariate and temporal educational outcomes. These results also support the use of feature importance analysis to capture relevant insights for educators out of the data analyzed. Inpractice, the current study's contribution of establishing and validating an Early Warning System points to the strategy that institutions interested in implementing AI/ML solutions can emulate. These systems can be useful in helping identify learners who need help in various areas and thus promote the retention of these learners, and generally boost the performance of the learning institution.

Challenges and Limitations

However, there are some limitations in the present research that have to be stated. Perhaps the biggest drawback to using history in validating the proposed hypothesis is that the work may not translate well to other generations given that

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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learning is a dynamic process which occurs in diverse settings. Further, the requirement of high computations in models such as LSTM is an issue for scales, as highlighted by Patel et al. (2022). This means despite the benefits that come with using AI/ML in education, there are key hurdles such as ethical issues upcoming with data privacy and bias that hinder the progress as pointed out by Binns (2018). Solving these issues will be crucial for enhancing the use of predictive analytics in education as much as possible.

Conclusion

This study reiterated the fact that AI/ML will transform education systems and enhance precision in early identification of undesirable incidences. After comparing the results to prior works, one can identify that the selection of predictive models and features is the primary factor that defines the results. Future research should investigate the use of real time data, how to build explainable AI systems and ways of handling ethical and scalability issues. Such endeavours will help in making sure that AI/ML solutions will persist to be productive tools in improving the learning processes.

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