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DESIGN AND DEVELOPMENT OF ARTIFICIAL INTELLIGENCE BASED SYSTEM FOR STUDENTS PERSONALIZED LEARNING

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KeyWords

Artificial Intelligence in Education, Student Performance Monitoring, Machine Learning Models, Predictive Analytics, Personalized Interventions, Feature Selection in AI, Educational Data Analysis.

ABSTRACT

Personalized learning using Artificial Intelligence (AI) is a method to apply enhanced AI technology to produce tailored learning understandings that suits the desires of each different student. This paper explored the use of Artificial Intelligence (AI) in education to monitor and enhance students' performance by providing personalized interventions for at-risk students. Artificial Intelligence (AI) can analyze diverse data sources such as attendance, test scores, assignments, and practical performance to identify students who may be struggling academically. A dataset of 5001 students from different educational institutions was collected and divided into training and testing sets. This facilitated the development of a working machine learning model. The study developed machine learning models, including decision trees, to predict student outcomes and guide educators in providing appropriate support. The model's efficacy was evaluated by comparing student's performance with and without interventions, with a focus on improving academic outcomes and reducing dropout or withdrawal rates. By automating the identification of students needing additional help, the system aims to offer hands-on measures like tutoring, counseling, and tailored study plans. This research augmented the potential of AI to transform educational practices, enhance teaching efficiency, and provide data-driven insights for decision-making, ultimately fostering improved learning outcomes and student retention.

Introduction

The main objective of education is to provide individuals with the knowledge, skills, and values they need to succeed in life and contribute to society. Education is a process of acquiring knowledge and developing the ability to think critically, communicate effectively, solve problems, and make informed decisions. It encompasses both formal education, such as schooling, and informal education, such as learning from family, peers, and the environment. Ultimately, the goal of education is to empower individuals to lead fulfilling lives and become responsible and productive members of their communities.

Students are the foremost partakers of the educational institutions. The performance of any educational institute plays a significant role in producing paramount quality graduates and post-graduates. The contemporary educational institutes are trying hard to uphold quality and prestige in the education society. Obviously, the institutes are more concerned about their prestige as compare to the quality of education (Norris et al.,2008). In Nigeria for instance, most employers' shortlists candidates for employment based on the schools they attended because of quality.

However, various government and accreditation agencies like National Universities Commission (NUC) for Universities, National Board for Technical Education (NBTE) for Polytechnics and National Commission for Colleges of education for colleges of education ensure the educational institutes sustain a high-quality learning environment and the tangible procedures of accreditation has compelled the institutions to plan and implement different measures to preserve their standards.

Learning is inherently local (Drachsler & Greller, 2012), meaning that educational experiences, contexts, and challenges vary significantly across different regions, institutions, and even individual classrooms. This local nature of learning implies that educational models and interventions cannot be universally applied without considering the specific context in which they are implemented. As a result, students from different educational environments may exhibit varying responses to the same instructional methods or performance assessments. For instance, the factors influencing academic performance can differ depending on cultural, socio-economic, or institutional conditions (Baker & Yacef 2010; Romero & Ventura, 2013). Understanding these contextual differences is crucial for developing effective predictive models in education.

This research leverages machine learning (ML) algorithms to design and refine a predictive model that identifies students at risk of poor academic performance. Unlike traditional one-size-fits-all approaches, the proposed model accounts for the specific educational context of the students, enabling it to adapt and provide insights that are more relevant and actionable. By analyzing various data sources, including student attendance, test scores, assignment completion, and participation in practical activities, machine learning algorithms can detect patterns that indicate potential academic difficulties. These patterns may not be immediately apparent through conventional assessment methods (Siemens, 2013).

The model developed in this study is intentionally designed to be interpretable, meaning it transforms complex machine learning outputs into formats that are easily understood by educators. This "explainable AI" approach ensures that teachers can act on the model's predictions with confidence, understanding the rationale behind the recommendations (Ribeiro & Singh 2016). The key objective is not just to identify students who may be at risk but also to provide actionable insights that allow educators to take targeted actions. These actions include offering personalized support, such as tailored study plans, additional tutoring, or counseling, based on the identified risk factors.

In addition to predictive capabilities, the model incorporates a set of preventive measures designed to intervene early in a student's academic trajectory. By continuously monitoring student performance, the system can suggest interventions before issues become severe, reducing the likelihood of academic failure, withdrawal, or low grades. For example, students who exhibit consistent patterns of low engagement or poor performance in assignments may be flagged early, allowing for proactive measures to be taken, such as enhanced academic advising or peer support programs (Baker & Yacef 2010).

Also, the model emphasizes the importance of identifying the key features that influence a student's final academic outcome. These features may include both quantitative factors, such as grades and attendance, as well as qualitative indicators, such as engagement in class discussions or participation in extracurricular activities. By systematically analyzing these features, the model can provide a nuanced understanding of the factors that most strongly correlate with student success or failure, guiding both academic interventions and institutional strategies for improving student retention and performance (Kausar et al., 2020). The research, therefore, aims to bridge the gap between complex data analysis and practical, context-specific educational strategies, ensuring that the predictions made by the model can be effectively used to support both students and educators in fostering academic success.

Statement of the Problem/Justification

a. There is an urgent need for an effective and efficient method to monitor and improve students' performance in institutions.
b. Traditional methods such as tests and quizzes are insufficient to identify and address underlying issues affecting academic performance.
c. Many students require personalized support or interventions, which is challenging for teachers to provide using conventional methods.
d. Artificial intelligence can analyze data from various sources, including attendance, assignments, test scores, and practical work, to provide real-time insights into student performance.
e. By identifying patterns and trends, AI can deliver targeted interventions, preventing academic issues and helping students reach their full potential.

Objectives of the Study

a. To develop an artificial intelligence model capable of monitoring and analyzing student performance using data from various academic sources.
b. To identify patterns and trends in student performance that traditional assessment methods may overlook.
c. To provide real-time, actionable insights that enable personalized interventions for students struggling academically.
d. To enhance the efficiency and effectiveness of performance monitoring in educational institutions.
e. To evaluate the impact of AI-driven monitoring on student outcomes and overall academic performance improvement.

Literature Review

Artificial intelligence is not a single technology. Rather, it is an amalgamation of a number of enabling technologies. The use of AI tools and techniques allows teachers to create sophisticated learning environments that are more personalized, flexible, inclusive, and engaging Cui et al. (2018) and Tan et al. (2022). The features of AI building block technologies the education sector can leverage on includes Machine learning, Deep learning, Speech recognition, Natural language Processing and Computer vision.

Artificial Intelligence (AI) aspire towards providing adequate intelligence to computers so they can think and act in responses, similar to the human being (Lesinski et al., 2016). Unlike computers, human can learn from their experience which enables them to make intellectual decisions according to their individual circumstances. On the other hand, computer has to follow the man-made algorithms to accomplish the required task. Artificial Intelligence aims to lessen this dissimilarity between computer and human by seeking innovative techniques to equip computers with intelligence and enable them to act like human being. The term is often applied to projects which develop systems conferred on humans' distinct intellectual processes, for instance, the ability to think, discover meaning, or learn from previous experience. The AI applications are steadily growing within distinct commercial, service, manufacturing and agricultural industries, making its more prominent (Došilović et al., 2018). Future AI artefacts will be capable to interact with human beings in their native languages, and adapt to their movements and emotions (Lu, 2019).

One of the main benefits of AI is its ability to analyze large amounts of data quickly and accurately. Predictive analytics can be used to identify students who are struggling academically or those who are more likely to drop out. The data can be collected through various sources such as attendance records, test scores, and behavioral data, among others. AI algorithms can be trained to analyze the data and find patterns that can predict a student's likelihood of success. Teachers can use this information to provide individualized support to students, such as extra tutoring or enrichment activities.

Machine Learning is one of the AI applications to facilitate systems with the ability to automatically learn and improve from experience without any explicit programming (Mitchell et al., 2013). The prime goal is to enable computers to learn automatically and set the procedures to make future decisions (Nilsson, 2014). Machine Learning algorithms learn from the prearranged data and then make decisions for unseen data. Machine learning uses

two major classes of algorithms: supervised learning and unsupervised learning. Supervised learning is either classification or regression algorithms.
The classification algorithms comprise of input, output and the aim is to apply an algorithm to identify the mapping function from the input to the output (Qazdar et al., 2019). Each instance consists of independent variables (prediction features) and a dependent variable (prediction class). The algorithms process the entire training dataset and identify the patterns and rules hidden in the data. A model, constructed on the basis of the identified rules, gets unseen instances and classifies them in appropriate classes.
Numerous models have been proposed under different educational context to address the student performance prediction. Kausar et al. (2020) made use of ensemble techniques to examine the relationship between students' semester course and final results. The experimental evaluation concludes Random Forest and Stacking Classifiers with achieving the highest accuracy. Orong et al. (2020) used modified Genetic Algorithm (GA) to eliminate excessive features and applied decision tree algorithm to discover the weak students and thus facilitates the institution to design interference measure to raise the student attrition. Chen et al. (2018) built models with decision tree and linear regression with a set of features extorted from the institution's auto-grading system. The research assists the institution to recognize the struggling students and assign teaching hours automatically in a smart way. These literatures confirmed machine learning algorithms as productive tools for developing models to predict student's final outcome. The existing models are useful locally and produce efficient results for single course. This model implementation proposes appropriate measures for prior and post model execution.

Methodology

The study adopted a structured methodology to design, develop, and evaluate an AI-driven system for monitoring and improving students' performance. The methodology comprises the following phases:

1. Data Collection

Sources of Data: Attendance records, test scores, assignments, behavioural logs, and practical assessments for 5001 students were gathered from educational institutions.

2. System Design

AI Model Development:

- Machine learning algorithms such as Decision Trees, Support Vector Machines (SVM), and Neural Networks were used to analyze student performance patterns.
- The algorithms were trained on historical data to predict academic outcomes and identify at-risk students.
- **Feature Selection:**
- Key features included attendance, academic performance metrics, and behavioral data, ensuring the model focused on relevant predictors.

3. Implementation of Predictive Analytics

- The AI system integrates predictive analytics to forecast student performance trends and highlight potential challenges.
- Patterns in the data were identified to recommend targeted interventions for students needing support.

4. Deployment and Evaluation

- **Pilot Testing:** The system was implemented in a test group to assess functionality and outcomes.
- **Feedback Collection:** Teachers and administrators provided input on the usability and effectiveness of the system.

- **Evaluation Metrics:** Success was measured through improvements in student performance, reduced dropout rates, and teacher satisfaction with insights provided.

5. Iterative Improvement

- Based on feedback and pilot testing results, the AI model and system design were refined.
- Additional features and data points were integrated to enhance accuracy and utility.

Tools and Techniques

- **Programming Languages:** Python for data analysis and model development was used
- **AI Frameworks:** TensorFlow, PyTorch, or Scikit-learn for machine learning model training.
- **Data Visualization:** Tableau and Power was utilized for presenting insights to educators.

The AI-driven approach for monitoring and improving student performance yielded promising results in the pilot phase, demonstrating several key outcomes.

Data Preprocessing

Handling Missing Values: The dataset was cleaned, with no missing values requiring specific handling.

1. **Encoding Categorical Variables:** Categorical columns such as gender, marital status, and parental education were encoded using Label Encoding. For example, "Female" was encoded as 0 and "Male" as 1.
2. **Splitting the Data into Training and Testing Sets:** The dataset was split into training (80%) and testing (20%) sets to evaluate the model's performance on unseen data.

MODEL CREATION AND TRAINING

Decision Tree Classifier

A Decision Tree Classifier was employed, which makes decisions based on input features through a tree-like structure. For instance, a decision node might assess whether attendance exceeds a specific threshold to predict performance.

Pipeline Construction

A pipeline was created to chain preprocessing steps and the Decision Tree Classifier, ensuring consistent application of steps to both training and testing data. Numerical features were scaled to maintain uniformity, avoiding dominance by features with larger scales.

Hyperparameter Tuning

GridSearchCV was utilized to fine-tune the Decision Tree Classifier's hyperparameters, enhancing its performance.

Model Evaluation

The model was evaluated using metrics such as accuracy, precision, recall, and F1-score. Results are summarized in the table below:

Table1: Model Metrics and values

Metric	Value
Accuracy	0.886
Precision	0.886
Recall	0.886
F1-Score	0.886

Feature Importance

The analysis ranked features based on their predictive importance:

Table 2: Ranked features and their importance.

Feature	Importance
Exam Score (50%)	0.341440
Test Score (25%)	0.215281
Attendance (%)	0.211847
Practical Score (25%)	0.175961
Assignment Completion (%)	0.026281
Guardian (Sponsor)	0.004792
Online Time (Daily)	0.003613
Mother's Education	0.002864
Father's Education	0.002863
Religious Programs (Weekly)	0.002660
Computer/Laptop Access (Practicals)	0.002518
Family Relationship	0.002381
Free Time Activities	0.001958
Extracurricular Activities	0.001422
Marital Status	0.001282
Age	0.001048
Children (if married)	0.000828
Alcoholic Consumption	0.000579
Gender	0.000381

Model Testing

The model was tested on the test dataset, with results summarized below:

Table 3: Result of the model

Metric	Value
Accuracy	0.886
Precision	0.886
Recall	0.886
F1-Score	0.886

Visualizations

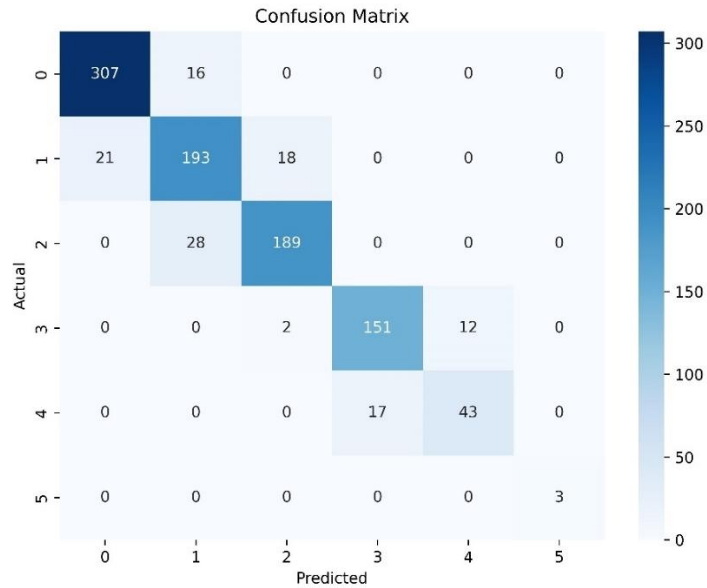

Fig 1: Confusion Matrix

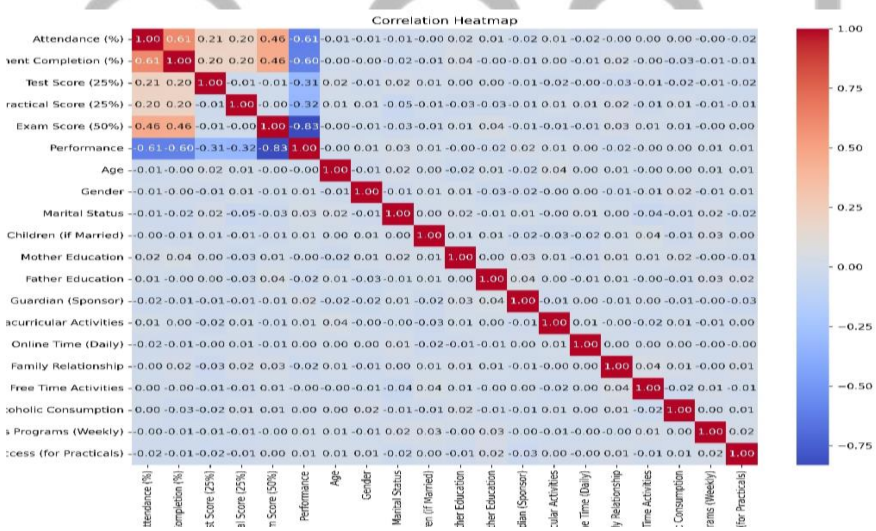

Fig2: Correlation Heatmap

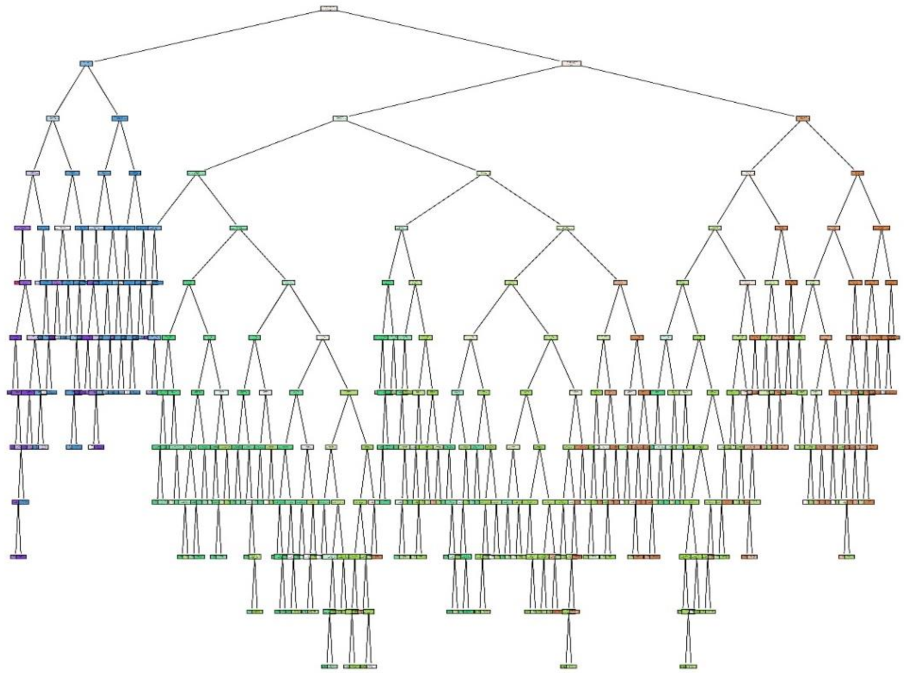

Fig3: Decision Tree

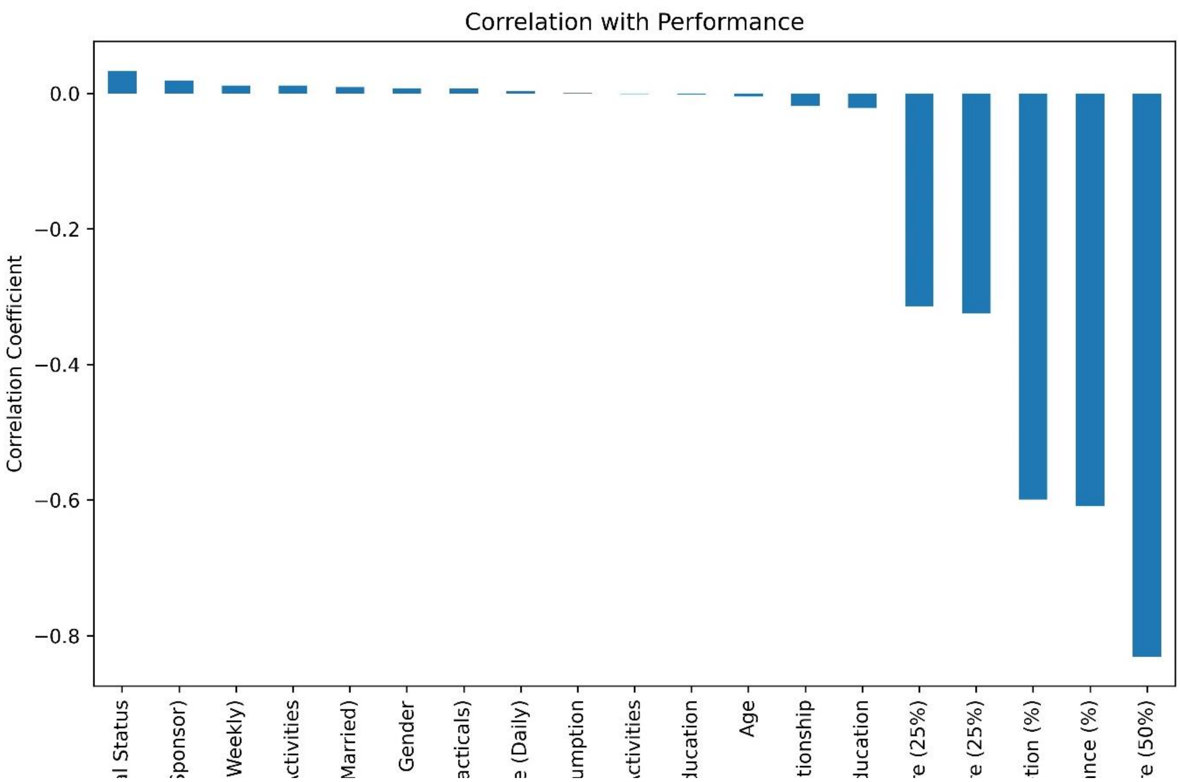

Fig4: Correlation with Performance

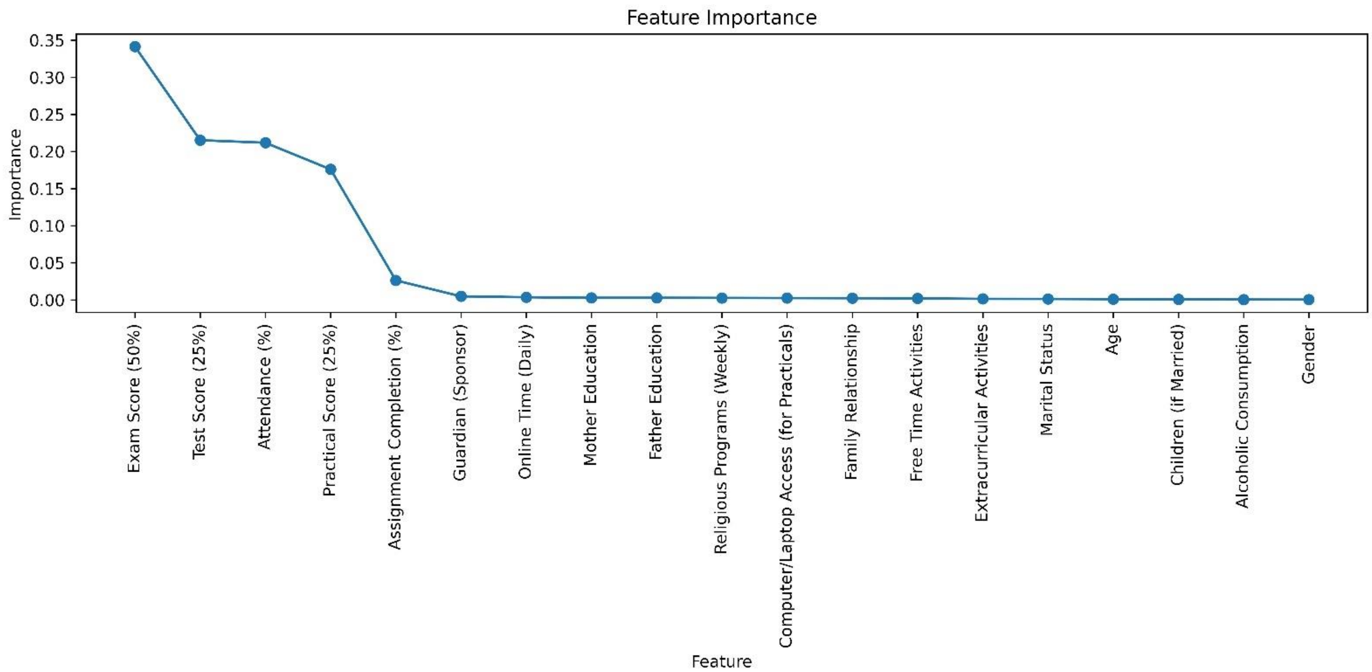

Fig 5: Feature Importance

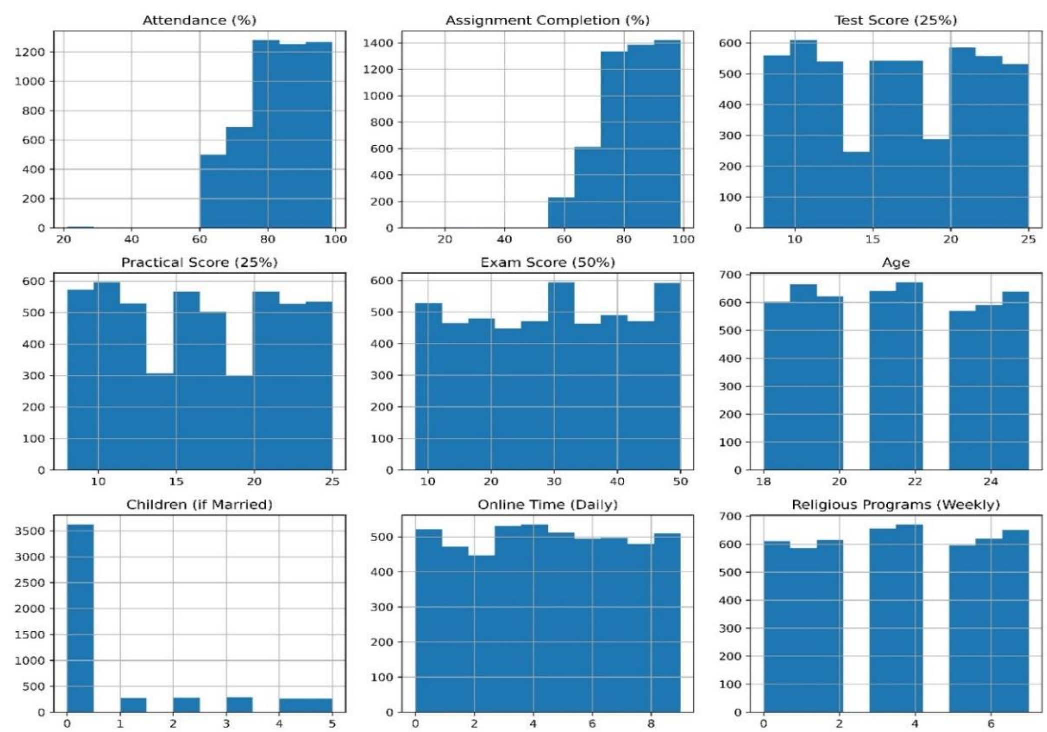

Fig6: Feature Distribution

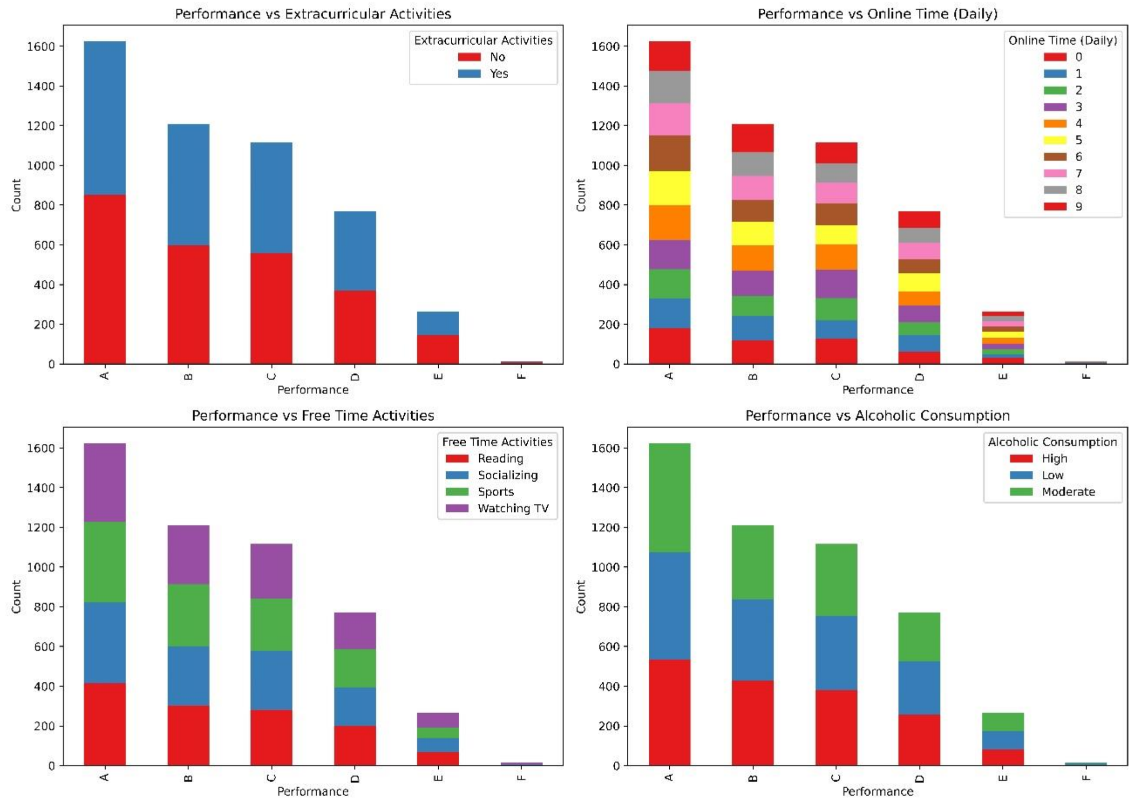

Fig7: Performance vs Categorical Features

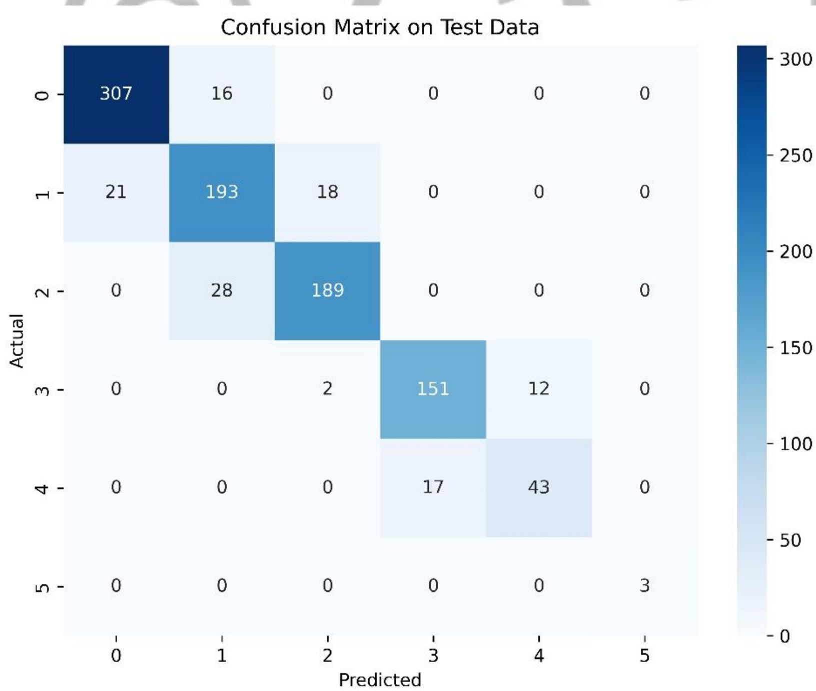

Fig 8: Confusion Matrix on test data

Results

a. Improved Performance Prediction: The AI model accurately predicted academic outcomes, outperforming traditional methods. It identified at-risk students early, enabling timely interventions and confirming AI's ability to uncover patterns traditional assessments might miss.

b. Personalized Interventions: By analyzing diverse data, the AI provided customized recommendations like tutoring and peer support. Teachers used these insights to target students in need, enhancing intervention quality and support effectiveness.
c. Real-Time Monitoring: The AI enabled real-time tracking of student progress, allowing immediate, data-driven adjustments in teaching. This approach aligns with studies highlighting the benefits of real-time analytics in education.
d. Teacher and Administrator Feedback: Educators praised the system for automating data analysis and delivering actionable insights but noted challenges such as the need for better training and infrastructure support.
e. Impact on Academic Outcomes: The pilot reduced dropout rates and boosted academic achievement, reflecting research on AI's role in improving education through early risk detection and proactive strategies.

Recommendations

- Schools should implement AI models to identify at-risk students early, enabling timely interventions to prevent academic underperformance or dropout.
- AI tools should be used to analyze multiple data sources and deliver tailored support such as tutoring, peer mentoring, or enrichment programs to address individual student needs effectively.
- Leveraging AI's real-time monitoring capabilities will allow educators to make immediate adjustments to teaching strategies, enhancing responsiveness to student progress and challenges.
- Comprehensive training should be provided to educators and administrators on using AI systems, accompanied by investments in technological infrastructure to ensure seamless integration.
- The impact of AI-driven interventions on academic performance and dropout rates should be regularly assessed to ensure continuous improvement and alignment with educational goals.

Conclusion

This study established the trailblazing capability of Artificial Intelligence in monitoring and refining student's performance by applying machine learning models to deliver personalized interventions for at-risk students. With the help of these predictive analytics, teachers and counselors can identify challenges early, implement targeted solutions, and improve academic outcomes. The findings highlighted AI's ability to drive data-driven decision-making, improve retention rates, and foster an efficient and supportive learning environment.

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References

[1] Norris, D., Baer, L., Leonard, J., Pugliese, L., & Lefrere, P. (2008). *Action analytics: Measuring and improving performance that matters in higher education*. *EDUCAUSE Review*, 43(1), 42.

[2] Drachsler, H., & Greller, W. (2012). *Privacy and security in learning analytics: From big data to big impacts*. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 31–35). ACM.

[3] Baker, R. S. J. d., & Yacef, K. (2010). *The state of educational data mining in 2009: A review and future visions*. *Journal of Educational Data Mining*, 1(1), 3–17.

[4] Romero, C., & Ventura, S. (2013). *Educational data mining: A review of the state of the art*. *IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews*, 40(6), 601–618.

[5] Siemens, G. (2013). *Learning analytics: The emergence of a discipline*. *American Behavioral Scientist*, 57(10), 1380–1400.

[6] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). *Why should I trust you? Explaining the predictions of any classifier*. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1135–1144).

[7] Kausar, R., Awan, A. H., & Khan, S. (2020). *Student performance prediction using machine learning algorithms: A comparison of classification techniques*. *Computers, Materials & Continua*, 66(3), 2649–2664.

[8] Cui, X., Li, H., Zheng, C., & Wang, L. (2018). *Performance Comparison of an AI-Based Adaptive Learning System in China*. Presented at the *IEEE International Conference on Education Technology and Learning Innovation*. Available on IEEE Xplore.

[9] Tan, L., Yu, Z., Huang, X., & Zhang, Y. (2022). *Advances in AI-Based Personalized Learning Systems: Enhancing Education with Intelligent Algorithms*. Published in the *Journal of Educational Technology Research*, 56(3), 245–267. DOI: 10.1016/j.eduresearch.2022.07.006.

[10] Lesinski, G., Corns, S., & Dagli, C. (2016). *Application of an artificial neural network to predict graduation success at the United States Military Academy*. *Procedia Computer Science*, 95, 375–382.

[11] Došilović, F. K., Brčić, M., & Hlupić, N. (2018). *Explainable artificial intelligence: A survey*. Paper presented at the *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*.

[12] Lu, Y. (2019). *Artificial intelligence: A survey on evolution, models, applications and future trends*. *Journal of Management Analytics*, 6(1), 1–29.

[13] Mitchell, R., Michalski, J., & Carbonell, T. (2013). *An artificial intelligence approach*. Springer.

[14] Nilsson, N. J. (2014). *Principles of artificial intelligence*. Morgan Kaufmann.

[15] Qazdar, A., Er-Raha, B., Cherkaoui, C., & Mammass, D. (2019). *A machine learning algorithm framework for predicting student performance: A case study of baccalaureate students in Morocco*. *Education and Information Technologies*, 24(6), 3577–3589.

[16] Orong, M. Y., Caroro, R. A., Durias, G. D., Cabrera, J. A., Lonzon, H., & Ricalde, G. T. (2020). *A predictive analytics approach in determining the predictors of student attrition in higher education institutions in the Philippines*. Paper presented at the *Proceedings of the 3rd International Conference on Software Engineering and Information Management*.

[17] Chen, H. (2018). *Predicting student performance using data from an auto-grading system*. University of Waterloo.