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Enhancing Academic Performance through Machine Learning: A Comprehensive Study of Student Academic Tracking Systems

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Abstract

The rapid advancement of technology has created new opportunities to enhance education, with machine learning (ML) emerging as a transformative tool. This study presents the development and evaluation of a comprehensive academic tracking system designed to monitor and categorize students based on performance metrics, while also providing functionality beyond simple grade reporting. Unlike traditional systems that serve primarily as repositories for academic scores, the proposed system offers integrated tools for tracking attendance, monitoring academic progress, managing assignments, and generating early alerts for at-risk students. Developed using Python for backend logic, React for frontend implementation, and MySQL for secure data management, the web-based platform was designed to improve real-time access and usability for both students and educators. The system incorporates a multifaceted methodology to analyze a wide range of student-related factors, including demographic data (e.g., age, gender, socioeconomic background), academic performance (e.g., grades, attendance), and behavioral indicators (e.g., participation and assignment submissions). The model classifies students into low, average, and high-performing groups using machine learning techniques, enabling more targeted interventions. When tested with real academic data from tertiary institutions in Nigeria, the proposed system demonstrated superior accuracy and efficiency in tracking and predicting student performance compared to existing solutions. These findings underscore the system's potential to support data-driven decision-making in educational environments and to enhance learning outcomes through early identification and personalized support strategies.

Keywords: Machine Learning; Student Performance; Academic Tracking Systems; Classification; Educational Data Analysis

INTRODUCTION

Student performance serves as a vital indicator of the quality of education delivered by an institution. The various teaching approaches employed by educational institutions aim to cultivate students who are skilled, confident, and capable of handling the practical demands of their academic disciplines. With technological advancements, many institutions are adopting innovative tools to enhance student success, thereby improving both the academic standing of the institution and contributing to national educational progress (Brown *et al.*, 2019).

Historically, education has often adhered to a standardized, one-size-fits-all methodology. This approach, while widespread, does not account for the individual differences in learning styles and needs among students (Smith & Colby, 2020). Some students thrive in independent learning environments, while others benefit more from personalized guidance or peer interaction (Johnson, 2021). Recognizing these diverse learning preferences, educational institutions are increasingly turning to technology to create more personalized educational experiences that cater to individual student needs, thereby boosting academic performance (Mayer, 2022).

The rapid advancement of technology presents new opportunities to improve education, with machine learning (ML) emerging as a promising solution (Nguyen, 2021). Machine learning, a branch of artificial intelligence, enables systems to learn from data and improve over time without being explicitly programmed. By analysing large datasets, machine learning algorithms can identify patterns and trends that can inform educational decisions (Jordan & Mitchell, 2015). When integrated into student tracking systems, machine learning has the potential to transform how educators approach teaching and learning (Baker & Inventado, 2019).

Machine learning-powered tracking systems offer a range of benefits, including personalized learning experiences and data-driven decision-making. These systems can analyse data such as grades, assignments, attendance, and demographics to predict student performance, identify at-risk students early, and provide targeted support (Hernandez *et al.*, 2020). The insights generated by these systems help educators tailor their teaching methods to meet the specific needs of each student, thereby enhancing overall academic achievement (Kim & Park, 2021). This study aims to explore the development and application of machine learning in academic tracking systems, demonstrating how these technologies can revolutionize education by fostering personalized learning and improving student performance.

The prevalent use of the one-size-fits-all teaching methodology in many educational institutions has led to significant underperformance among students. This approach fails to account for individual learning styles, resulting in students who may pass exams through rote memorization without truly understanding the material. Consequently, these students often struggle with problem-solving and practical applications of their knowledge.

Additionally, there is a need for longitudinal studies that assess the long-term impact of ML on academic performance. While short-term improvements have been documented, the sustained effects of ML-driven interventions on student learning, retention, and overall academic success are not yet fully understood (Zhu *et al.*, 2018). Longitudinal research could provide valuable insights into how these technologies influence educational trajectories over time.

Another significant contribution of ML in academic tracking is the personalization of learning. Machine learning algorithms can adapt to individual student needs by analysing their learning behaviours and preferences. This enables the creation of tailored educational experiences that optimize each student’s learning potential (Zhu *et al.*, 2018). For instance, intelligent tutoring systems (ITS) use ML to provide real-time feedback and customized learning paths based on a student's progress, thereby enhancing engagement and academic achievement (Nye, 2015).

Moreover, ML-driven academic tracking systems offer continuous assessment and feedback, providing educators with actionable insights into student performance throughout the learning process. These systems can dynamically adjust to new data, allowing for more accurate and up-to-date tracking of student progress (Kuh *et al*., 2015). This real-time data analysis contrasts with traditional systems, which often rely on end-of-term assessments that may not reflect a student's ongoing needs and challenges.

However, the implementation of ML in academic tracking is not without challenges. Issues such as data privacy, ethical considerations, and the need for high-quality, consistent data inputs are critical concerns that must be addressed to ensure the effective and responsible use of these technologies (Hao *et al*., 2020). Despite these challenges, the potential benefits of ML in enhancing academic tracking systems are vast, offering a more nuanced and supportive approach to student learning and success.

Machine learning (ML) offers transformative benefits in enhancing academic performance by enabling more personalized, data-driven, and proactive approaches to education. One of the most significant advantages of ML is its ability to facilitate personalized learning experiences. By analysing vast amounts of data on student behaviour, learning patterns, and performance, ML algorithms can tailor educational content to meet the individual needs of students, thereby optimizing their learning outcomes (Zhu *et al*., 2018). This personalized approach ensures that students receive the right support at the right time, whether through customized assignments, adaptive learning platforms, or intelligent tutoring systems (ITS) that adjust to their pace and learning style (Ma *et al*., 2014).

Another benefit of ML in education is its ability to predict student performance and identify at-risk students before they fall behind. Predictive analytics powered by ML can analyse factors such as attendance, engagement, and historical performance to forecast academic outcomes and suggest timely interventions (Wolff *et al*., 2013). This proactive approach helps educators address potential issues early, reducing dropout rates and improving overall student success. ML also enhances the efficiency and effectiveness of educational assessments. Traditional assessments often rely on periodic testing, which may not accurately reflect a student's ongoing learning progress. In contrast, ML can provide continuous assessments by monitoring and evaluating student performance in real time (Kuh *et al*., 2015). This allows educators to make data-driven decisions that improve teaching strategies and better support student learning.

Additionally, ML reduces the administrative burden on educators by automating routine tasks such as grading and generating reports (Hwang *et al*., 2020). This automation frees up time for instructors to focus on more critical tasks, such as mentoring and personalized instruction. Despite its numerous benefits, the integration of machine learning in education is not without challenges and limitations. One of the primary concerns is the quality and availability of data. Machine learning models rely heavily on large datasets to function effectively. However, in many educational settings, data can be incomplete, inconsistent, or biased, which can lead to inaccurate predictions and unfair outcomes (Slade & Prinsloo, 2013). Ensuring high-quality data and addressing biases in datasets are critical for the successful implementation of ML in education.

Another challenge is the ethical implications of using ML in educational settings. Concerns about privacy, data security, and the potential for misuse of student data are significant issues that need to be addressed (Hao *et al*., 2020). For instance, there is the risk that predictive models could inadvertently reinforce existing biases or lead to unfair treatment of certain groups of students. Furthermore, the deployment of ML systems in education requires substantial technical infrastructure and expertise, which may be lacking in some institutions. This can create disparities between well-resourced schools that can afford to implement these technologies and underfunded institutions that cannot (Holmes *et al*., 2019). The digital divide may be exacerbated if ML-driven educational tools are not accessible to all students.

Finally, there is the concern that over-reliance on ML and automation could diminish the human element of education. While ML can provide valuable insights and efficiencies, it cannot replace the role of teachers in providing emotional support, mentoring, and fostering critical thinking and creativity (Luckin *et al*., 2016).

Related Work

Machine learning (ML) has emerged as a powerful tool in the field of education, particularly in academic tracking systems, where it offers the potential to transform how student performance is monitored, analysed, and improved. Unlike traditional academic tracking methods that primarily rely on static metrics such as grades and attendance, ML algorithms can process vast amounts of data to uncover hidden patterns and trends that can predict student outcomes, identify at-risk students, and suggest personalized interventions (Baker & Inventado, 2014).

One of the key applications of ML in academic tracking is predictive analytics, where algorithms are used to forecast student performance based on historical data. For example, by analysing factors such as previous grades, attendance records, and engagement with learning materials, ML models can predict which students are likely to struggle and recommend timely interventions (Wolff *et al.*, 2013). These predictive models allow educators to move from reactive to proactive strategies, addressing issues before they result in academic failure or dropout.

The study to investigates the use of machine learning methods, such as neural networks and support vector machines, to forecast academic achievement and student retention has been proposed (Liu et al., 2022). It draws attention to the possibilities of these methods in learning environments. This study utilises the application of machine learning methods, including Support Vector Machines and neural networks, to predict student retention and academic success. It demonstrates the potential of these strategies in educational settings. Another study considers the use of Machine Learning Techniques for Predicting Student Performance (Mohammed et al., 2023). This study offers a system that uses machine learning to predict students' academic performance based on a number of variables, with the goal of improving educational results through early interventions.

A group of researchers proposed the implementation of a Graph Transformer for Student Performance Prediction in Collaborative Learning (Peng, et al., 2023). The authors present a graph transformer framework designed to predict student performance in collaborative learning settings. The methods involved modeling student interactions within teams, however, the study provides insights into how collaboration impacts academic outcomes.

A Deep Learning technique for Student Performance Prediction in Online Courses with challenges based on a global perspective has been proposed (Abdallah et al., 2024). The study concentrates on online education. This study proposes the use of deep learning techniques, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks with Long Short-Term Memory (RNN-LSTM), to predict student performance. The study highlights the effectiveness of these models across diverse datasets.

Other researchers employed the use of Machine Learning techniques for Predicting Students' Academic Performance and Study Strategies Based on Their Motivation" (Orji & Vassileva, 2022). This study explores the use of machine learning models to predict academic performance and study strategies by analyzing key motivational attributes. This study proposed Random Forest as a tree-based model that can provide excellent prediction in terms of performance.

Existing Systems and Knowledge Gap

Current academic systems focus predominantly on grading students and calculating GPAs, but they overlook critical features that could enhance student performance, such as personalized teaching strategies and real-time feedback mechanisms. In many existing systems, there is no provision for immediate feedback after lectures, which prevents both instructors and students from understanding whether the material was effectively communicated and comprehended. This lack of feedback makes learning more challenging, particularly for students who may struggle with traditional teaching methods.

The problems faced by current academic systems can be summarized as follows:

i. Insufficient and inconsistent data availability: Data that could be used to personalize learning or predict student success is often incomplete or not utilized effectively.

ii. Suboptimal student performance and preventable dropouts: Many students are not reaching their full potential, leading to higher dropout rates that could be avoided with better support systems.

Neglect of diverse learning styles: The current systems do not account for individual learning preferences, which disproportionately affects students who may need additional support. While the application of machine learning (ML) in academic performance tracking and education has shown promising results, several gaps in existing research remain. These gaps highlight areas that require further investigation to fully realize the potential of ML in enhancing education.

One significant gap is the limited exploration of how ML models can be effectively integrated into diverse educational settings. Much of the existing research focuses on controlled environments or specific academic institutions, often overlooking the challenges of scaling these technologies in varied and resource-constrained settings (Holmes *et al.*, 2019). There is a need for more research on the implementation of ML in different cultural, socio-economic, and educational contexts to ensure that these technologies are adaptable and beneficial across diverse populations (Luckin *et al.*, 2016).

Another gap is the insufficient focus on the ethical and social implications of ML in education. While some studies address concerns related to data privacy and bias (Slade & Prinsloo, 2013), there is still a lack of comprehensive frameworks that guide the ethical use of ML in academic tracking systems. More research is needed to develop and evaluate strategies that mitigate potential harms, such as reinforcing existing inequalities or infringing on student privacy (Hao *et al*., 2020).

Moreover, current research often emphasizes the technical aspects of ML, such as algorithm development and data analysis, but less attention is given to the pedagogical implications. For instance, how ML-driven insights can be effectively integrated into teaching practices and curriculum design remains underexplored (Woolf, 2010). Further research is needed to bridge the gap between ML-generated data and actionable educational practices that can be implemented by educators to improve student outcomes.

Lastly, the lack of research on student and teacher perceptions of ML in education represents a significant gap. Understanding how educators and learners perceive and interact with these technologies is crucial for their successful adoption and effectiveness. Research in this area can help identify potential barriers to acceptance and use, as well as provide guidance on how to design ML systems that are user-friendly and aligned with the needs of both students and educators (Holmes *et al*., 2019).

System Development Strategies and Implementation

This research employs a multifaceted methodology aimed at capturing a comprehensive understanding of the factors influencing student performance in Nigeria's tertiary institutions. The data collection process involves the use of a developed student tracking system that compiles extensive information on students, including demographic data (e.g., age, gender, socioeconomic background), academic records (e.g., grades, attendance), and behavioural indicators (e.g., class participation and assignment submission). In addition, qualitative inputs from instructors are incorporated, providing valuable insights into student engagement and performance that may not be fully captured through quantitative data alone. This extensive dataset forms the foundation for the subsequent analytical steps.

Advanced statistical techniques, such as regression and multivariate analysis, are employed to identify relationships and trends within the data, while machine learning algorithms, including decision trees, random forests, and neural networks, are applied to predict student performance and identify those at risk of academic failure or dropout. The study also integrates qualitative methods, such as semi-structured interviews with educators and students, and surveys to gather broader perspectives on the academic environment. Data triangulation is used to cross-verify findings from different sources, ensuring the robustness and validity of the results. Furthermore, pilot testing of the predictive models and interventions is conducted in selected institutions to refine the methods before full-scale implementation. Ethical considerations, including informed consent and data anonymization, are strictly adhered to throughout the research process. This comprehensive approach ensures a holistic understanding of the factors impacting educational outcomes and the development of effective interventions tailored to the Nigerian context.

METHODS

The structure of the design phases and the relationships between each component were explained by the system architecture. Synergy exists between two or more components or phases, starting with data collection and continuing through processing, training, testing, and the predection module. The system is designed in a few steps. When designing the system, the following factors will be considered:

a. **Data Collection:** Real-time data collection is crucial to increasing the precision and dependability of student performance tracking. The collection includes student grades, attendance rates, assignment submissions, and involvement in extracurricular activities, among other academic records. To ensure that we have the most up-to-date and dynamic insights on student progress, this data is automatically gathered from various sources within the higher institutions. The Student Achievement Tracking System (SATS) continuously learns about patterns in student performance, academic involvement, and areas that may require improvement by using these real-time data sets. This helps teachers make better decisions and improve learning outcomes.

b. **Dataset Creation:** In order to refine the dataset and guarantee optimal performance and accuracy in student performance analysis, data pre-processing is crucial. Pre-processing methods aid in the organization, improvement, and cleaning of the data, reducing errors and boosting its usefulness for academic prediction tests.

c. Feature Analysis: One of the most important jobs in this study is feature analysis. Tahis is important because utilizing every element complicates the method for predicting student achievement. Consequently, the characteristics of each feature are identified in order to choose more important aspects for the system's training.

d. Data Processing: There is a wide range of values for various features. Thus, a narrower range of data is processed. Before being used, data are normalized. For the training process, the data is subsequently separated into training and testing sets.

e. System Training and Testing: Various machine learning techniques are employed to train the system. The system is trained on the training set and tested on the testing set. The benefits and drawbacks of various system vary. A superior metrics analysis is guaranteed when all the methods' for the system development are available.

f. System Performance Evaluation: Lastly, the system's performance is assessed. Because the most accurate systems perform best during real-time predictions, performance determines the system's qualitative characteristics and dependability.

System Development Strategies

The goal of the Student Achievement Tracking System (SATS) is to efficiently track and predict trends in student achievement. It is made to be adaptable and appropriate for various educational settings and curricula. In contrast to conventional evaluation techniques that rely on fixed reports and manual tracking, this system provides real-time insights through data-driven analytics.

To assess crucial academic metrics including grades, attendance, and participation in extracurricular activities, SATS uses predictive modelling approaches. Teachers can identify pupils who may be having difficulties and act quickly with the use of sophisticated data processing and visualization technologies. All things considered, this technique simplifies performance evaluation and is a useful tool for raising student achievement levels.

Explored Algorithms

There are various algorithms used for student academic performance prediction system, prominent among which are Support Vector Machine, Naïve Bayes, Convolutional

Neural Network, Random Forest, etc. However, this paper employed the use of k-nearest neighbor and matrix factorization.

i. **K-Nearest Neighbor**

This is a classification-based algorithm that could be used to classify student academic performance instances based on their relationship or distance in relation as observed in the proposed student academic performance matrices.. This is illustrated in figure 1.

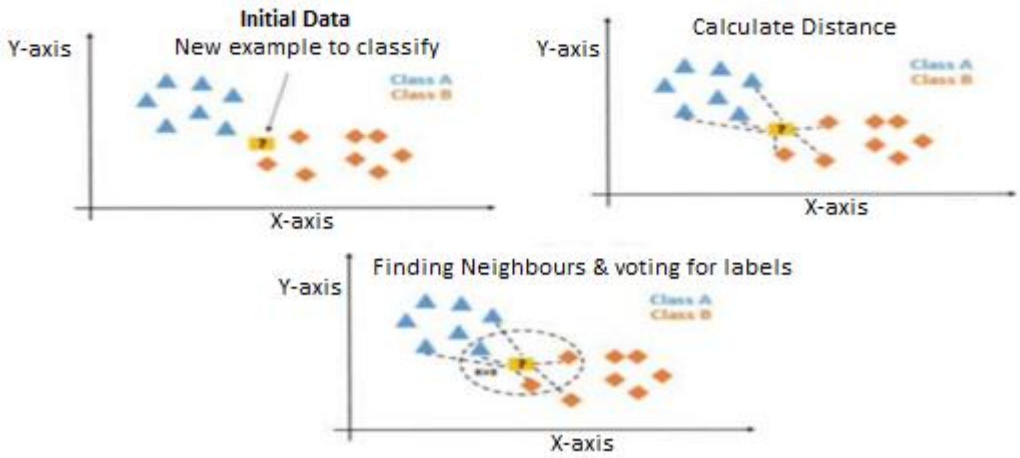

Figure 1: Structure of K-Nearest Neighbour

The distance between class A and B of the strata is known as Euclidean Distance. This is used to predict academic performance based on unique features or behavior. It is used in this research for students' academic performance classification into most common types or classes. There is also performance record which seems to exist on their own which are grouped and are none-linear strata of academic records which will require a special random approach to their classification and prediction algorithm. The K-Nearest Neighbor is modeled to mimic trend in the academic performance rating behaviour of the selected data. There is opening on the e-academic performance record page from which certain targeted data are collected for the machine learning purpose. This includes grades, attendance records, assignment scores and participation in extracurricular activities which determine how prepared the students are to face their studies.

The adjectival keywords in the review body are usually targeted by the machine learning algorithm to determine the rate at which the performance system is managed or mismanaged by the administrators. Keywords such as (low, very low, moderate, high, very high) were targeted in the body content of the review to speculate and predict student performance.

ii. Matrix Factorization

Matrix factorization requires a breakdown of actual student academic prediction classifier matrix into two, having one as the upper triangle (U) while the other as a lower triangle (L). What this implies is that the Upper (U) and Lower (L) angles of the matrix represent different classes of student academic performance but with common general class. This is mostly used in collaborative filtering methods in academic performance assessment algorithms.

Dataset Information and Analysis

The dataset used in this paper is made up of incidences representing the academic record in higher institutions. The dataset comprises of 25,208 rows and 10 columns collected between the period of 12-02-2019 and 30-12-2024 with the following columns: grades, attendance records, assignment scores and participation in extracurricular activities, overall performance rating, review headline, review body, and review date respectively. Review_headline shows the title of the review, review_body contains the context of the review, and review_date is the date the review was written. For the purpose of this assessment, we concentrated on the curated dataset of some selected higher institutions in Nigeria which we believe would provide a greater percentage of concrete and quantitative assessments.

Feature Extraction

The dataset provides some features which are not needed for the purpose of training this system. In this regard, student id, performance_rating, review_date are selected as they are most useful to this evaluation, and the rest were cast-off. The dataset was examined for missing values, and they were found to be all complete. Furthermore, grades made up of alphanumeric values of object datatype were transformed to integer values to help lessen feature complications. Dataset preprocessing was performed to convert or encode data to a state that machine can deconstruct so easily for its algorithm. The essence is to normalize the data before experimenting with it.

A step took to normalize the dataset was to transform the student_id column of object datatype made up of alphanumeric values to a unique integer value to reduce the complexity and to avoid irregularity in the process during the classification process and date of reviewing its timestamp equivalent. Some students have over reactively provided high performance ratings and least failure ratings while some have rated low. To normalize these ratings for those kinds of students, data of students who have rated 40 failure and more were considered.

RESULTS AND DISCUSSION

Streamlit was used to create a web-based Student Achievement Tracking System that offers an interactive platform for tracking student performance. Through an API, the system obtains up-to-date information on exam results, attendance logs, assignment submissions, and engagement levels. Students, instructors, parents, and administrators may all effectively obtain performance insights thanks to the structured dashboard that presents the processed and gathered data.

The system utilizes historical data and trend analysis to highlight students at risk of academic difficulties. By monitoring declining grades, irregular attendance, and reduced participation, the system provides actionable insights to educators, supporting timely interventions.

Simulation

The system is developed in order to train the data collected based on features embedded in academic performance records as variables. The dataset was preprocessed and trained. Supervise and Single Value Decomposition (SVD) is used to disintegrate the original matrix and latent factor that helps in generating the assessment ratings. In order to achieve good accuracy in this assessment, we presented carefully selected features as part of the post-processing. Table 1, figures 1 and 2 represent data sample, performance rating output, and mean distribution of performance rating respectively.

Table 1: Data sample

S/N	Student_id	perf_id	assessment_id	grade_rating	timestamp
0	IMT001	239456	135130	5	116589300
1	IMT002	356811	365210	5	11522000
2	IMT003	543189	531270	1	11481100

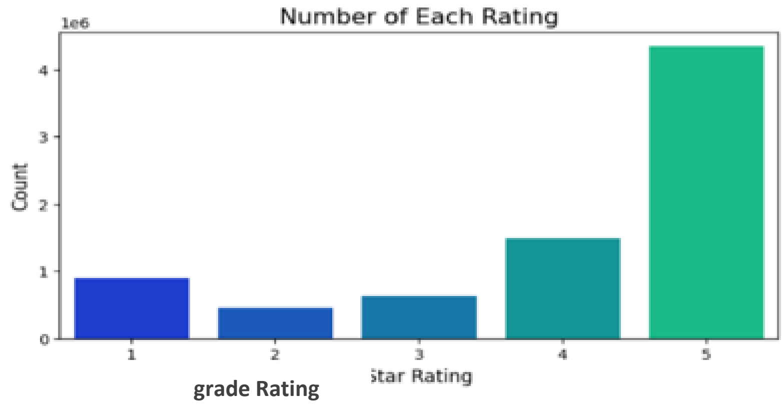

Figure 2: Academic performance Rating Output

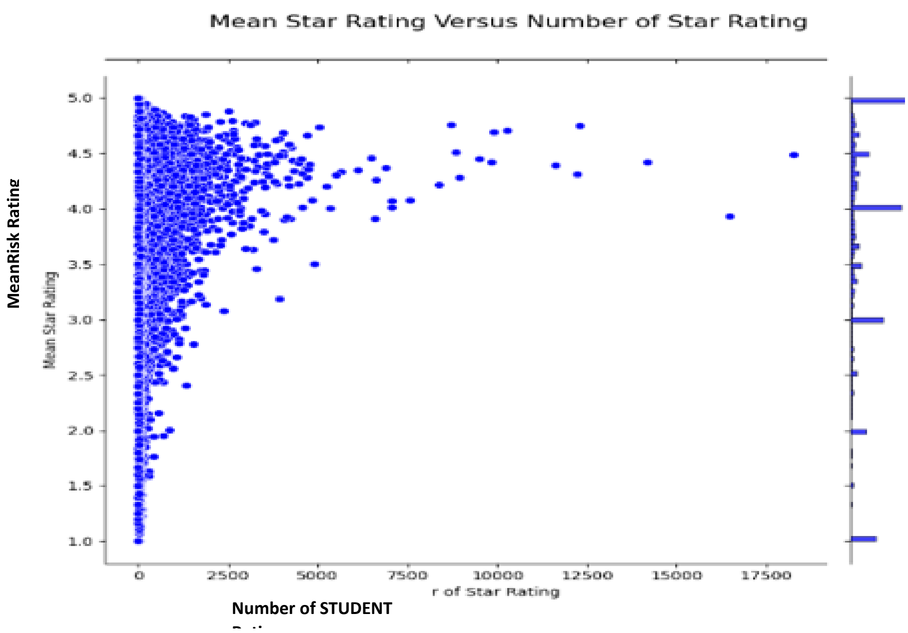

Figure 3: Mean Distribution of student Rating

The prediction is done using collaborative and content-based learning. The training data from this system contains 20,200 observations.

Performance Evaluation

In predictions, accuracy metrics are generally applied for system valuations, Root Mean Square Deviation (RMSD) also known as Root Mean Square Error (RMSE) is used to determine the distinction between the predicted values and the assessment of the actual values as shown in equation 1 (Bush, et al., 2018).

$$\text{RSME} = \sqrt{\frac{1}{n}} \sum_{i=1}^{n}(|xi - yi|)\text{RSME} = \sqrt{\frac{1}{n}} \sum_{i=1}^{n}(|xi - yi|) \tag{1}$$

The proposed system makes predictions according to user behavior by predicting student performance evaluation. The four potential outcomes of the predictions are:

● True-Positive: this indicates situations where the outcome of the system correctly predicted the student performance as positive.

● False-Positive: represents situation where the system falsely predicted the scores outcome as positive.

● False-Negative: this implies in situations where the system predicted the performance outcome as negative.

● True-Negative: this indicates situations where the outcome of the system correctly predicted the student academic performance as negative.

Precision (P) calculates the fraction of the accurate positive predictions on the total numbers of predictions thus:

$$P = \frac{True\ Positives}{True\ Positives + False\ Positives} P = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{2}$$

Recall (R) is used to calculate the fraction of the positive predictions against the sum of the true positive values. The true positives here are the combination of the true positives and false negatives as shown in equation 3:

$$R = \frac{True\ Positives}{True\ Positives + False\ Negatives} R = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{3}$$

This paper explored both collaborative and content-based prediction. The collaborative filtering had RMSE of 4.42 and the hybrid assessment produced RMSE and MAE of 0.32 and 1.20 approximately. Figure 5 shows the classification report of the proposed system.

	precision	recall	f1-score	support
1	1.00	1.00	1.00	9
2	1.00	0.25	0.40	8
3	0.50	1.00	0.67	6
4	1.00	1.00	1.00	42
5	1.00	1.00	1.00	136
accuracy			0.96	201
macro avg	0.90	0.85	0.81	201
weighted avg	0.99	0.96	0.96	201

Figure 4: Classification report of the proposed system

The train data shows a consistency in predicting student academic performance in higher institution.

Figure 6 shows an accuracy of 0.96 which is very significant. This means the accuracy of the system is relatively high.

CONCLUSION

This study investigates the transformative power of machine learning in improving academic achievement via improved student tracking systems. As educational institutions try to improve student outcomes, traditional techniques sometimes fail to consider individual learning requirements. This study emphasizes the transition from conventional techniques to more individualized, data-driven educational experiences made possible by the use of machine learning. By analysing student data, these systems can forecast performance, identify at-risk pupils, and deliver tailored treatments that are tailored to each student's individual learning style.

The study highlights the transformative potential of machine learning in education. Beyond basic grade monitoring, comprehensive academic tracking systems, driven by machine learning, can provide valuable insights to enhance teaching methods and support student success. The research aims to showcase how educational institutions can utilize these tools to elevate their academic performance and contribute to overall educational advancement.

The system, when implemented in real time, will assist higher institutions in closing the knowledge gap regarding the prediction of student academic performance which will add value to the educational sector.

We recommend access to critical data be made available for research in this direction in order to effectively improve the existing student academic performance so as to ensure that an informed decision-making process is achieved and to assist the schools in identifying and managing student performance records.

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