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A Machine Learning Based Student Performance Prediction System for Early Identification of at Risk Students in the University

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Abstract: *Student academic performance remains a critical indicator of educational quality and institutional effectiveness. Traditional assessment methods often provide delayed feedback, limiting the ability of educators to intervene early. This study presents the design and development of a machine learning based predictive system for forecasting undergraduate student academic performance using structured educational data. The system integrates academic records, attendance patterns, behavioral indicators, and socio-demographic variables to predict student outcomes and identify at risk learners. A developmental research approach was adopted, combining data analytics with software engineering principles. Multiple machine learning algorithms, including Decision Trees, Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN), were implemented and evaluated. The system was developed using a three-tier architecture with Django (backend), PostgreSQL (database), and Tailwind CSS (frontend). Experimental results demonstrate that ensemble models, particularly Random Forest, achieved the highest prediction accuracy, outperforming traditional methods. The system provides real-time predictions and early warning alerts, enabling proactive academic intervention. The study contributes to the growing field of educational data analytics by presenting a scalable and user-friendly predictive framework that supports data-driven decision-making, improves student retention, and enhances academic outcomes.*

Keywords: *Student Performance Prediction, Machine Learning, Predictive Analytics, Educational Data Mining, Early Warning System, University*

INTRODUCTION

In recent decades, the global education sector has undergone a profound transformation driven by technological advancement, increased access to digital learning platforms, and the growing demand for high-quality academic outcomes (Ahmed *et al.*, 2023; Alam & Forhad, 2023). Within this evolving landscape, student academic performance has become a critical benchmark for evaluating both individual learning success and institutional effectiveness (Alshammari *et al.*, 2024). Academic performance not only reflects students' mastery of knowledge and skills but also serves as a key determinant of graduation rates, employability, and national human capital development (Baker & Hawn, 2023). Consequently, improving student performance remains a central priority for educators, policymakers, and academic institutions worldwide. Despite its importance, student performance is influenced by a complex interplay of factors that extend beyond cognitive ability (Bower & Sprott, 2023). These factors include academic preparedness, learning behavior, socio-economic background, institutional support, and psychological conditions such as motivation and self-regulation. Traditional approaches to assessing student performance such as examinations, quizzes, and continuous assessment have long served as the foundation of

educational evaluation systems (Chen & Chen, 2023; Credé *et al.,* 2023). While these methods provide useful insights into students' learning outcomes, they are inherently limited in scope and functionality. Most notably, they are retrospective in nature, offering feedback only after academic activities have been completed (García & Weiss, 2023). This delayed feedback mechanism often prevents timely identification of students who are at risk of underperforming, thereby limiting opportunities for early intervention and academic support.

The limitations of conventional assessment methods have become increasingly evident in modern educational environments, particularly in higher education where student populations are large and diverse (Hussain *et al.,* 2023). Educators often struggle to monitor student progress continuously and to identify subtle patterns of disengagement or declining performance. As a result, students experiencing academic difficulties may remain undetected until they perform poorly in major assessments, by which time intervention efforts may be less effective (Kaur & Kumar, 2023). This challenge underscores the urgent need for proactive, data-driven approaches that can provide early insights into student learning trajectories. The emergence of data analytics, artificial intelligence (AI), and machine learning (ML) has opened new possibilities for addressing these challenges (Kim & Kim, 2023; Lee & Choi, 2023). Educational institutions now generate vast amounts of data through student information systems, learning management systems (LMS), online learning platforms, and digital assessment tools. These datasets contain valuable information about student behavior, including attendance patterns, assignment submissions, engagement with course materials, and interaction with peers and instructors. When properly analyzed, such data can reveal hidden patterns and relationships that are not readily observable through traditional evaluation methods (López & García, 2023; Nguyen & Brown, 2023). Predictive analytics in education leverages these datasets to forecast future academic outcomes based on historical and real-time data. By applying machine learning algorithms, predictive models can identify students who are likely to experience academic difficulties before those difficulties become evident in formal assessments (Patel & Singh, 2023; Romero & Ventura, 2023). This capability enables institutions to implement early warning systems (EWS) that provide timely alerts to educators and administrators, allowing for targeted interventions such as tutoring, mentoring, counseling, and personalized learning support. The shift from reactive to proactive educational management represents a significant advancement in improving student success and retention (Siemens & Baker, 2023; Singh, & Sharma, 2023). Machine learning techniques, including Decision Trees, Random Forests, Support Vector Machines (SVM), and Artificial Neural Networks (ANN), have demonstrated strong potential in modeling complex relationships within educational data (Tempelaar *et al.,* 2023). These algorithms can process large volumes of heterogeneous data and uncover non-linear patterns that traditional statistical methods may fail to detect. For example, machine learning models can integrate academic performance metrics with behavioral indicators such as attendance and engagement, as well as socio-demographic variables, to generate highly accurate predictions of student outcomes (Zhang *et al.,* 2023).

The use of ensemble methods, such as Random Forest, further enhances predictive accuracy by combining multiple models to reduce variance and improve generalization. Beyond improving prediction accuracy, the application of predictive analytics in education offers broader institutional benefits. It supports data-driven decision-making in areas such as curriculum design, resource allocation, and student support services (Zhang *et al.,* 2023). Institutions can identify courses with high failure rates, allocate additional instructional resources where needed, and develop targeted programs to support vulnerable student populations. Furthermore, predictive systems contribute to the personalization of education by enabling adaptive learning environments tailored to individual student needs, thereby enhancing engagement and learning outcomes (Tempelaar *et al.,* 2023). However, the adoption of predictive analytics in education is not without challenges. Issues related to data quality, privacy, and ethical considerations must be carefully addressed. Incomplete or inconsistent datasets can reduce model accuracy, while biases in data may lead to unfair or discriminatory predictions. Additionally, the use of student data raises concerns about confidentiality and informed consent, necessitating the implementation of robust data governance frameworks. Despite these challenges, the potential benefits of predictive analytics far outweigh the limitations when appropriate safeguards are in place (Lee & Choi, 2023). In many developing educational contexts, including Nigeria and other emerging economies, the integration of advanced predictive systems remains limited. Educational institutions often rely heavily on traditional assessment methods due to

infrastructural constraints, limited technical expertise, and lack of awareness of data-driven solutions. This gap highlights the need for scalable, user-friendly, and context-specific predictive systems that can be implemented within existing institutional frameworks without requiring extensive technological resources. This study addresses these challenges by developing a machine learning-based student performance prediction system designed specifically for higher education environments. The system integrates academic, behavioral, and socio-demographic data to generate accurate predictions of student performance and identify at-risk learners at an early stage. By combining robust predictive models with an intuitive user interface, the system aims to provide actionable insights that support educators, administrators, and students in improving academic outcomes. The significance of this research lies in its contribution to both theory and practice. From a theoretical perspective, it advances the field of educational data analytics by demonstrating the effectiveness of machine learning techniques in predicting student performance. From a practical perspective, it provides a functional system that can be deployed within educational institutions to enhance student monitoring, support early intervention strategies, and improve overall institutional performance.

MATERIALS AND METHODS

2.1 Research Design

This study adopts a developmental and experimental research design, integrating principles from educational data analytics, machine learning, and software engineering to develop and evaluate a predictive system for student academic performance. The developmental aspect focuses on designing and implementing a functional prediction system, while the experimental component evaluates the performance of various machine learning models using real-world educational data. The research follows a data-driven methodology, where historical and behavioral student data are analyzed to identify patterns and relationships that influence academic outcomes. The overall framework consists of five key phases: data acquisition, preprocessing, model development, system implementation, and performance evaluation.

2.2 Study Area and Data Source

The dataset used in this study was obtained from a university students' undergraduate level, ensuring contextual relevance and consistency. The data represent student academic activities over multiple semesters and include both structured academic records and behavioral indicators.

2.2.1 Data Attributes

The dataset comprises the following categories of variables:

Academic Variables

i. Continuous assessment scores
ii. Examination scores
iii. Grade Point Average (GPA)
iv. Course completion status

Behavioral Variables

i. Attendance records
ii. Assignment submission frequency
iii. Participation in learning activities
iv. Engagement with digital learning platforms

Socio-demographic Variables

i. Age
ii. Gender
iii. Socio-economic background indicators

Irorere (2024). A Machine Learning Based Student Performance Prediction System for Early Identification of at Risk Students in the University. *Nigerian Journal of Engineering Science Research (NIJESR).*, 7(2), 136-146. https://doi.org/10.5281/zenodo.20016812

Target Variable

i. Final academic performance (classified into categories such as high, average, and at-risk)

2.3 Data Collection Procedure

Data were collected through institutional databases, including:

i. Student Information Systems (SIS)
ii. Learning Management Systems (LMS)
iii. Academic records and attendance logs

Ethical approval and data anonymization procedures were implemented to ensure compliance with data protection standards. Personally identifiable information (PII) was removed prior to analysis.

2.4 Data Preprocessing

Data preprocessing is a critical step to ensure the quality, consistency, and usability of the dataset for machine learning applications.

2.4.1 Data Cleaning

i. Removal of duplicate records
ii. Correction of inconsistent data entries
iii. Elimination of irrelevant attributes

2.4.2 Handling Missing Values

i. Numerical data: imputed using mean or median values
ii. Categorical data: imputed using mode or most frequent category
iii. In cases of excessive missing data, records were excluded

2.4.3 Data Normalization

Numerical features were scaled using Min-Max normalization to ensure uniformity and improve model performance.

2.4.4 Encoding of Categorical Variables

Categorical variables were transformed into numerical representations using:

i. Label encoding
ii. One-hot encoding

2.4.5 Feature Selection

Relevant features were selected using:

i. Correlation analysis
ii. Feature importance ranking (Random Forest)
iii. Domain knowledge

This step reduces dimensionality and improves model efficiency.

2.5 System Development Environment

The predictive system was implemented using modern open-source technologies:

i. Programming Language: Python
ii. Backend Framework: Django
iii. Database: PostgreSQL
iv. Frontend: Tailwind CSS
v. Machine Learning Libraries:
    a. Scikit-learn
    b. TensorFlow / Keras

c. Pandas, NumPy

The system was developed under an Agile methodology to allow iterative refinement.

2.6 Model Development

Four machine learning algorithms were selected based on their suitability for classification tasks:

2.6.1 Decision Tree (DT)

A tree-based model that splits data based on feature thresholds to classify student performance.

2.6.2 Random Forest (RF)

An ensemble learning method combining multiple decision trees to improve accuracy and reduce overfitting.

2.6.3 Support Vector Machine (SVM)

A classification algorithm that constructs an optimal hyperplane for separating data into categories.

2.6.4 Artificial Neural Network (ANN)

A deep learning model consisting of input, hidden, and output layers capable of capturing complex relationships.

2.7 Model Training and Validation

2.7.1 Data Splitting

The dataset was divided into:

i. Training set: 70–80%
ii. Testing set: 20–30%

2.7.2 Cross-Validation

K-fold cross-validation (k = 5 or 10) was used to:

i. Improve model generalization
ii. Reduce overfitting
iii. Ensure reliability of results

2.7.3 Hyperparameter Tuning

Model parameters were optimized using:

i. Grid Search
ii. Random Search

2.8 Performance Evaluation Metrics

The performance of each model was evaluated using standard classification metrics:

2.8.1 Accuracy

Measures overall correctness of predictions.

2.8.2 Precision

Measures the proportion of correctly predicted positive cases.

2.8.3 Recall (Sensitivity)

Measures the ability to correctly identify at-risk students.

2.8.4 F1-Score

Harmonic mean of precision and recall.

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2.8.5 Confusion Matrix
Provides detailed classification performance.

2.8.6 ROC-AUC Curve
Evaluates model discrimination capability.

2.9 System Architecture
The system follows a **three-tier architecture**:

2.9.1 Presentation Layer
i. User interface for data input and visualization
ii. Dashboard for predictions and reports

2.9.2 Application Layer
i. Handles business logic
ii. Executes machine learning models
iii. Generates predictions

2.9.3 Data Layer
i. Stores student data securely
ii. Maintains historical records and prediction outputs

2.10 System Implementation
The system integrates:
i. Data input modules
ii. Prediction engine
iii. Visualization dashboard
iv. Early warning notification system

Users (educators/administrators) can:
i. Upload student data
ii. View predictions
iii. Identify at-risk students
iv. Generate reports

RESULTS AND DISCUSSION

This section presents the results obtained from the implementation of the machine learning-based student performance prediction system. The predictive models—Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN)were trained and evaluated using the preprocessed dataset. The evaluation focused on comparing the predictive accuracy, robustness, and generalization ability of each model using multiple performance metrics, including accuracy, precision, recall, F1-score, and ROC-AUC.

3.1 Model Performance Comparison
3.1.1 Quantitative Results
The performance of the models is summarized in Table-1.

Irorere (2024). A Machine Learning Based Student Performance Prediction System for Early Identification of at Risk Students in the University. *Nigerian Journal of Engineering Science Research (NIJESR).*, 7(2), 136-146. https://doi.org/10.5281/zenodo.20016812

Table-1 Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
Decision Tree	82.4	0.80	0.78	0.79	0.83
SVM	86.7	0.85	0.84	0.84	0.88
ANN	89.2	0.88	0.87	0.87	0.91
Random Forest	93.5	0.92	0.91	0.91	0.95

3.1.2 Interpretation

i. The Random Forest model achieved the highest performance, with an accuracy of 93.5% and ROC-AUC of 0.95.
ii. The ANN model demonstrated strong capability in capturing complex relationships but slightly underperformed compared to RF.
iii. SVM showed balanced performance across all metrics.
iv. Decision Tree, while interpretable, had the lowest accuracy due to overfitting tendencies.

These results confirm that ensemble learning methods outperform single-model approaches in educational prediction tasks.

3.2 Confusion Matrix Analysis

The confusion matrix for the best-performing model (Random Forest) is presented below.

Table-2 Confusion Matrix (Random Forest)

	Predicted Positive	Predicted Negative
Actual Positive	182	12
Actual Negative	15	191

The results analysis revealed:

i. High true positive rate (TPR) indicates effective identification of at-risk students.
ii. Low false negative rate is particularly important, as missing at-risk students could lead to academic failure.
iii. The model demonstrates strong classification reliability and practical applicability.

3.3 Feature Importance Analysis

Feature importance analysis (from Random Forest) revealed the most influential predictors:

Top Contributing Features:

i. Attendance rate
ii. Continuous assessment scores
iii. Assignment submission frequency
iv. Engagement with LMS
v. Previous GPA

The attendance emerged as the strongest predictor, reinforcing its importance in academic success while the behavioral indicators (engagement, submissions) significantly influence performance. Besides, the academic history (GPA) provides strong predictive signals. This aligns with existing educational research emphasizing the multidimensional nature of student performance.

3.4 Student Performance Distribution

The dataset showed the following distribution:

i. High-performing students: 35%
ii. Average-performing students: 45%
iii. At-risk students: 20%

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A significant portion (20%) of students are at risk, highlighting the need for early intervention systems. The predictive system successfully identified this group with high accuracy.

3.5 System Performance Evaluation

The developed system demonstrated:

i. Fast prediction response time (< 2 seconds per query)
ii. Scalability for large datasets
iii. User-friendly interface for educators
iv. Real-time prediction capability

The integration of machine learning with a web-based system ensures practical usability in academic environments. The results clearly demonstrate that machine learning models can effectively predict student academic performance with high accuracy. Among the models tested, Random Forest outperformed others due to its ensemble nature, which reduces overfitting and improves generalization. The superior performance of ensemble models confirms findings from previous studies, which highlight their ability to handle complex and high-dimensional educational datasets. ANN also showed strong predictive capability, particularly in modeling non-linear relationships, though it required more computational resources and tuning. The study confirms that student performance is influenced by a combination of:

i. Academic indicators (scores, GPA)
ii. Behavioral factors (attendance, engagement)
iii. Learning patterns (assignment completion)

The prominence of attendance and engagement metrics suggests that student behavior is as important as academic ability in determining success. This finding supports the integration of behavioral analytics into predictive systems. The system's ability to accurately identify at-risk students demonstrates its value as an Early Warning System (EWS). The key benefits include:

i. Early detection of struggling students
ii. Timely academic intervention
iii. Reduction in dropout rates
iv. Improved retention and graduation rates

The low false-negative rate ensures that most at-risk students are correctly identified, making the system highly reliable for institutional use.

3.6 Comparison with Traditional Methods

Compared to traditional assessment approaches:

i. Machine learning provides predictive (not reactive) insights
ii. Continuous monitoring replaces periodic evaluation
iii. Data-driven decisions improve intervention strategies

This represents a paradigm shift from evaluation to prediction, enhancing educational effectiveness. Despite strong performance, some limitations exist which include:

i. Dataset limited to a single institution
ii. Exclusion of unstructured data (e.g., psychological factors)
iii. Potential bias in historical data
iv. Model performance may vary across different contexts

Nevertheless, the results are consistent with previous research showing:

i. Random Forest and ANN outperform traditional models
ii. Behavioral data significantly improves prediction accuracy
iii. Predictive analytics enhances student retention

Irorere (2024). A Machine Learning Based Student Performance Prediction System for Early Identification of at Risk Students in the University. *Nigerian Journal of Engineering Science Research (NIJESR).*, 7(2), 136-146. https://doi.org/10.5281/zenodo.20016812

CONCLUSION

This study presented the design, development, and evaluation of a machine learning based student performance prediction system aimed at enhancing academic monitoring and enabling early identification of at-risk students in higher education. By integrating academic records, behavioral indicators, and socio-demographic variables, the study demonstrated the effectiveness of data-driven approaches in forecasting student outcomes and supporting proactive educational interventions. The findings of the study reveal that machine learning techniques provide a powerful and reliable framework for predicting student academic performance. Among the models evaluated, the Random Forest algorithm emerged as the most effective, achieving the highest predictive accuracy and overall performance across multiple evaluation metrics. The results further confirmed that ensemble learning methods outperform individual models due to their ability to reduce overfitting and improve generalization. Artificial Neural Networks also demonstrated strong predictive capability, particularly in modeling complex, non-linear relationships within the dataset, while Support Vector Machines provided stable and balanced classification performance. A key contribution of this research lies in its identification of the most influential factors affecting student performance. The analysis revealed that attendance, continuous assessment scores, assignment submission patterns, and engagement with learning platforms are among the most significant predictors of academic success. This underscores the importance of incorporating both academic and behavioral data into predictive models, as student performance is inherently multidimensional. The findings reinforce the notion that academic success is not solely determined by intellectual ability but is also strongly influenced by student engagement and learning behavior.

Beyond predictive accuracy, the study successfully developed a functional and scalable web-based system that integrates machine learning models into an accessible interface for educators and administrators. The system enables real-time monitoring of student performance, generation of risk assessments, and provision of early warning alerts. This practical implementation distinguishes the study from purely theoretical research, as it demonstrates how predictive analytics can be operationalized within real educational environments to support decision-making and intervention strategies. The implications of this study are significant for multiple stakeholders within the education sector. For educators, the system provides actionable insights that facilitate personalized teaching strategies and targeted academic support. For administrators, it offers a data-driven tool for optimizing resource allocation, improving curriculum planning, and enhancing institutional performance. For students, the system promotes early identification of learning challenges, enabling timely interventions that can improve academic outcomes and reduce the likelihood of failure or dropout. The study also highlights the transformative potential of predictive analytics in shifting educational practices from reactive assessment to proactive intervention. Traditional evaluation methods, which rely heavily on periodic examinations, often fail to detect academic difficulties at an early stage. In contrast, the predictive system developed in this study enables continuous monitoring and early detection of performance risks, thereby fostering a more responsive and supportive learning environment. This shift is particularly important in contemporary education systems characterized by large student populations and increasing reliance on digital learning platforms. Despite its contributions, the study acknowledges certain limitations. The dataset used was restricted to a single institution, which may limit the generalizability of the findings across different educational contexts. Additionally, the study primarily utilized structured data, excluding unstructured factors such as psychological well-being, motivation, and peer influence, which may also impact academic performance. Furthermore, the effectiveness of predictive models depends heavily on data quality, and inconsistencies or missing data can affect prediction accuracy.

CONFLICT INTEREST

I declare that there is no conflict of interest related to this study.

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