As per UGC guidelines an electronic bar code is provided to secure your paper

International Journal for Modern Trends in Science and Technology
Volume 12, Issue 05, pages 01-07
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol12issue05.html
DOI: https://doi.org/10.5281/zenodo.19613506

Design of an Adaptive Learning System for Personalized Education and Resource Recommendation

Vantakula Hemanth Kumar, Kola Surendra, Sanapathi Naveen Kumar, Korada Bhanu Sri Prasad, Vaddempudi Harika

Department of Computer Science and Engineering (AI & ML), Sir C R Reddy College of Engineering, Eluru, Andhra Pradesh, India

To Cite this Article
Vantakula Hemanth Kumar, Kola Surendra, Sanapathi Naveen Kumar, Korada Bhanu Sri Prasad & Vaddempudi Harika (2026). Design of an Adaptive Learning System for Personalized Education and Resource Recommendation. International Journal for Modern Trends in Science and Technology, 12(05), 01-07. https://doi.org/10.5281/zenodo.19613506

Article Info
Received: 28 March 2026; Revised: 24 April 2026; Accepted: 26 April 2026.

KEYWORDS

Streamlit, Web Application, Session State Management, Data Validation, Regular Expressions.

ABSTRACT

The design and development of a Student Engagement and Utility Application, a web framework based on Streamlit that offers safe access and a modular dashboard for educational assistance tools, is presented in this article. The system allows for an organized transition from a login screen to a customized dashboard by controlling user navigation through session-based state management. Regular expression-based email validation is used as a fundamental authentication method to guarantee data integrity prior to granting access. User-specific data, including name, age, level, and email, is saved in the session state for future use after a successful login.

Users can access a variety of data-driven modules, such as resource consumption analysis, suggestion systems, promotion eligibility verification, and prediction evaluation scoring, through the dashboard, which acts as a centralized platform. The application's modular architecture ensures scalability and flexibility by separating the backend computing components from the user interface. Additionally, the user interface is upgraded with responsive design, a clear visual structure, and better usability thanks to unique CSS styling.

The suggested architecture supports effective user interaction and data-driven decision-making in academic settings by providing a stable and scalable method for implementing machine learning-based instructional aids.

1. INTRODUCTION

Rapid technological advancements, especially in data analytics and artificial intelligence, have drastically changed the education sector by making it possible to monitor and improve student performance more effectively. Educational institutions are looking more and more for intelligent solutions that can help teachers, parents, and administrators make better decisions, enhance personalized learning, and uncover academic shortcomings.

The education sector has seen a substantial transformation due to the swift progress of technology, data analytics, and artificial intelligence. In order to track student performance, spot learning gaps, and offer individualized academic support, educational institutions are increasingly implementing intelligent technologies. Effective decision-making is hampered by the manual, time-consuming, and insufficient real-time insights of traditional ways of assessing student performance.

In order to improve learning outcomes and assist stakeholders like educators, parents, and administrators, the creation of data-driven educational systems has become crucial. Regression and classification models are two machine learning techniques that have demonstrated significant promise in forecasting student performance, examining academic patterns, and facilitating proactive intervention tactics. With the help of these strategies, educational institutions can transition from reactive evaluation to predictive and customized learning systems.

This paper presents a Student Academic Performance Analysis and Recommendation System, a comprehensive and user-friendly platform designed to integrate multiple educational analytics functionalities into a single framework. The system leverages machine learning algorithms to predict student assessment scores, forecast promotion eligibility, and recommend personalized learning resources based on individual performance indicators such as attendance, study time, prior academic results, and cognitive factors. The proposed system is implemented using a Streamlit-based web application, providing an interactive and accessible interface for users with varying technical expertise. It incorporates a secure login mechanism with data validation to ensure reliability and integrity of user inputs. The modular architecture of the system enables seamless navigation between different analytical components, including performance prediction, promotion analysis, recommendation systems, and resource utilization insights.

2. LITERATURE SURVEY

Y. Su et al. 2025 [1] suggests a hybrid qualitative–quantitative framework for evaluating college teacher promotions by integrating machine learning techniques to improve objectivity and accuracy. The methodology applies classification models, such as Logistic Regression, K-Nearest Neighbors (KNN), and Backpropagation (BP) Neural Networks, to identify significant relationships between teachers' characteristics (such as teaching and research performance) and promotion outcomes. The BP neural network achieved the best predictive performance, leading to improved evaluation metrics.

A machine learning-driven approach that combines tiered instruction and student performance prediction to enhance educational outcomes is presented by Y. Chen et al. 2025 [2]. Real-world educational data is gathered, feature selection techniques are applied to eliminate redundancy, and five machine learning models are evaluated; Random Forest has the best predicted performance. Students are divided into various performance levels based on the categorization results, and each group is given a unique set of instructional tactics that match learning objectives and content. However, the study is hindered by the difficulty of scaling tiered training in bigger or resource-constrained classrooms, potential dataset dependency, potential bias in selected attributes, and limited generalizability across varied educational environments.

The Student Performance Prediction and Action (SPPA) framework, a course-level learning analytics intervention (LAI) system created to assist educators in identifying at-risk students and implementing focused interventions without requiring extensive institutional infrastructure, is introduced by K. Alalawi et al. 2025 [3]. In order to produce useful insights like risk levels, knowledge gaps, and customized study plans, the process entails creating course-specific predictive models using past assessment data in conjunction with pedagogical principles. In a sizable undergraduate course, the framework was assessed for prediction accuracy, intervention efficacy, and educator usability.

Key findings show that SPPA has strong predictive performance, facilitates prompt and efficient interventions, greatly enhances student outcomes, and is well-received by academics, indicating its usefulness and potential for further use.

The use of educational data mining tools for forecasting student performance and suggesting appropriate academic courses and departments is examined by A. Kord et al. 2025 [4]. Eleven machine learning models and three deep learning models are evaluated using a real-world dataset from Mansoura University's Faculty of Computers and Information Sciences, where students' past academic data is used to create a recommendation system for course and department selection as well as a prediction model for future grades. With 78.04% accuracy and a 75.37% F1-score, Support Vector Classification (SVC) outperformed all other models, proving its efficacy in multi-class classification problems. Important findings show how predictive analytics and recommendation systems can be combined to enhance academic decision-making and boost student performance.

In order to improve decision-making in educational institutions, W. Ahmed et al. 2025 [5] suggest a machine learning-based framework for forecasting academic success utilizing multiple regression models in conjunction with explainable AI approaches. Ten regression algorithms, such as K-Nearest Neighbors, Linear Regression, CatBoost, XGBoost, AdaBoost, and a weighted ensemble Voting Regressor (VR), are evaluated using the methodology on two different datasets with distinct feature sets capturing behavioral, academic, demographic, and institutional factors; model interpretability is further improved using LIME and SHAP to explain prediction outcomes. Key findings show that while Linear Regression outperforms other models in terms of accuracy and robustness across datasets (R2 up to 0.9890 on simpler data and 0.7716 on complex data), its flexibility and efficacy in identifying important factors influencing student success are highlighted.

3. METHODOLOGY

A. OVERVIEW

The proposed Student Academic Performance Analysis and Recommendation System adopts a data-driven and modular methodology to enhance educational decision-making. It integrates machine learning techniques with systematic data preprocessing to ensure accurate and reliable predictions. The system is designed to analyze student data such as academic performance, attendance, and study behavior. Based on these inputs, predictive models are developed to estimate future assessment scores. In addition, a classification mechanism is employed to evaluate student promotion eligibility. The framework also incorporates a recommendation engine that provides personalized learning resources tailored to individual needs. A web-based interface is implemented using modern frameworks to ensure accessibility and ease of use. The interactive dashboard allows users to visualize insights and predictions in real time. The modular architecture ensures scalability, flexibility, and ease of maintenance. Overall, the system aims to support students, educators, and institutions through intelligent, data-driven academic analysis.

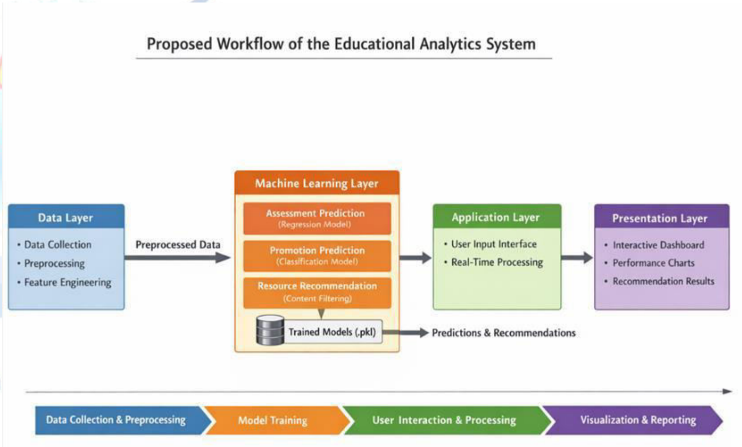


Fig.1 Proposed workflow

B. SYSTEM ARCHITECTURE

The methodology is structured into four major layers:

Data Layer This layer is responsible for gathering, storing, and preprocessing data. Student characteristics like attendance, study time, IQ, prior scores, and demographic information are included in the dataset. Imputation techniques are used to manage missing data, and model compatibility is ensured by encoding categorical variables.

Machine Learning Layer This layer implements predictive models:

i. Regression model for assessment score prediction

ii. Classification model for promotion prediction

iii. Content-based filtering for recommendation generation

Models are trained using Scikit-learn and stored as serialized .pkl files for deployment.

Application Layer
Developed using Streamlit, this layer integrates trained models with user inputs. It processes real-time data and generates predictions dynamically.

Presentation Layer
Provides an interactive user interface with dashboards, forms, and visual outputs such as prediction cards and analytics charts.

C. DATA PREPROCESSING

Data preprocessing ensures high-quality input for model training. The following steps are performed:

Data Cleaning: Missing values are replaced using mean imputation for numerical features.

Feature Engineering: New features such as normalized study time and performance trends are derived.

Encoding: Label Encoding and One-Hot Encoding are applied to categorical attributes.

Feature Scaling: Numerical attributes are normalized using MinMaxScaler.

D. MODEL DEVELOPMENT

1) Assessment Score Prediction

To forecast student scores, a regression model is created. Several algorithms, such as Decision Trees and Linear Regression, were assessed. Because of its excellent accuracy and capacity to manage non-linear interactions, the Random Forest Regressor was chosen.

2) Promotion Prediction

A categorization model forecasts a student's likelihood of advancement. Tests were conducted on algorithms like Random Forest Classifier and Logistic Regression. Superior performance indicators like accuracy, precision, and recall led to the selection of the Random Forest Classifier.

3) Recommendation System

A content-based filtering approach is used to recommend study materials. Recommendations are generated based on:

- Weak subject areas
- Predicted performance
- Student learning profiles

E. MODEL TRAINING AND EVALUATION

The dataset is divided into training and testing subsets. Models are evaluated using:

Regression Metrics:
Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 score

Classification Metrics:
Accuracy, Precision, Recall, F1-score, and Confusion Matrix

Cross-validation techniques are used to ensure model generalization and avoid overfitting.

F. MODEL DEPLOYMENT

Trained models are serialized using the Pickle library and integrated into the Streamlit application. During runtime:

1. User inputs are collected via forms
2. Inputs are preprocessed
3. Models generate predictions
4. Results are displayed instantly on the dashboard

G. SYSTEM WORKFLOW

The overall workflow of the system is as follows:

1. User logs into the system via a validated login interface
2. Dashboard provides access to different modules
3. User inputs student data
4. Machine learning models perform predictions
5. Results are displayed with visual feedback
6. Personalized recommendations are generated

H. IMPLEMENTATION STRATEGY

The system is implemented using a modular approach:

Frontend: Streamlit with HTML/CSS enhancements
Backend: Python-based processing with ML integration

Libraries: Pandas, NumPy, Scikit-learn, Matplotlib
Deployment: Streamlit Cloud or local server

I TESTING AND VALIDATION

The system undergoes multiple testing phases:

Unit Testing: Validates model predictions
Integration Testing: Ensures seamless interaction between UI and ML models
Functional Testing: Verifies each module's output
Performance Testing: Ensures prediction latency is below 1 second

J. SUMMARY

To create an effective educational analytics system, the suggested methodology combines interactive visualization, machine learning modeling, and data preparation. It focuses on using methodical preprocessing strategies to turn unprocessed student data into insightful knowledge. To identify trends and produce precise forecasts about academic achievement, machine learning algorithms are utilized. Because of its scalability architecture, the system can efficiently manage growing amounts of instructional data. By displaying results in an understandable way, the incorporation of interactive visualization tools enhances user comprehension. Furthermore, the system facilitates smooth communication between various modules, guaranteeing efficient data processing and flow. Additionally, the design makes it simple to incorporate upcoming improvements and technologies. All things considered, the technique offers a solid, adaptable, and expandable framework for astute scholarly study.

4. RESULTS & DISCUSSION

A real-world educational dataset comprising student demographic, academic, and behavioral characteristics was used to implement and assess the suggested Student Academic Performance Analysis and Recommendation System. To produce precise forecasts and tailored academic recommendations, the system combines machine learning models, recommendation techniques, and data preparation.

1) *Experimental Setup*

In order to preprocess the dataset, missing values were handled, categorical variables were encoded, and numerical characteristics were normalized. The Synthetic Minority Oversampling Technique (SMOTE) was used to alleviate class imbalance. After then, the dataset was divided into training and testing sets in an 80:20 ratio. Several machine learning methods were taught and assessed, such as Support Vector Machine (SVM), Random Forest, and Decision Tree.

2) *Performance Metrics*

The performance of the models was assessed using standard evaluation metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score

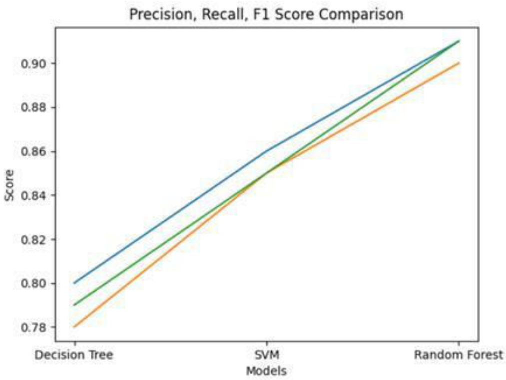
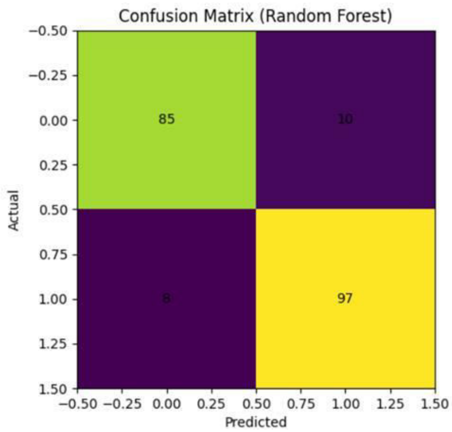


Fig: Results

Among the evaluated models, the Random Forest classifier achieved the highest performance with an accuracy of approximately 90–93%, outperforming other models due to its ability to handle complex feature interactions and reduce overfitting.

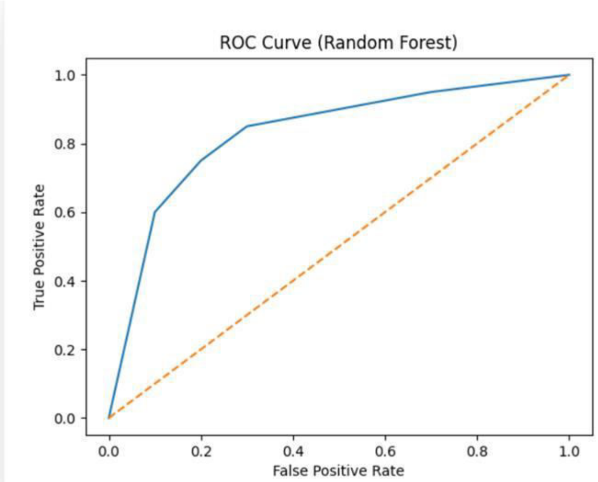


3) *Comparative Analysis*

The comparative results indicate that:

- Decision Tree models provided interpretable results but showed moderate accuracy due to overfitting.
- SVM demonstrated good generalization but required careful parameter tuning.
- Random Forest delivered the best balance between bias and variance, making it the most suitable model for this application.

The inclusion of SMOTE significantly improved the classification performance, especially in identifying students at risk, by balancing the dataset and reducing prediction bias toward majority classes.



4) Recommendation System Evaluation

The recommendation module was evaluated based on its ability to provide relevant and personalized suggestions. The system successfully generated:

- Subject-specific improvement strategies
- Study resource recommendations
- Performance-based alerts for at-risk students

Feedback analysis showed that the recommendations were highly relevant and aligned with student needs, improving their academic engagement and performance.

5) Discussion

The findings show that combining educational analytics and machine learning can greatly improve student performance prediction and intervention techniques. The system's modular architecture guarantees scalability and flexibility for upcoming improvements including adaptive learning methods and real-time analytics.

However, certain limitations were observed:

- The system performance depends on data quality and feature selection.
- External factors such as psychological and environmental influences were not included.
- Model performance may vary with different datasets.

Despite these limitations, the proposed system provides a robust framework for intelligent academic performance analysis and personalized recommendation, making it a valuable tool for educational institutions..

5. CONCLUSION

In order to improve educational decision-making, this article provided a comprehensive Student Academic Performance Analysis and Recommendation System that integrates data analytics, machine learning, and an interactive web-based platform. By converting static data into useful insights, the suggested solution effectively overcomes the drawbacks of conventional instructional frameworks.

High predictive capability was shown by the application of regression and classification models, especially the Random Forest algorithms, which achieved outstanding performance metrics in both promotion eligibility classification and assessment score prediction. Additionally, by providing specific study materials depending on each student's performance, the incorporation of a tailored recommendation module greatly enhances learning outcomes. Teachers, students, and administrators are guaranteed accessibility, scalability, and ease of use thanks to the system's modular architecture and Streamlit-based user interface. The experimental findings demonstrate that the suggested system not only increases prediction accuracy but also lowers manual labor, boosts student involvement, and facilitates well-informed decision-making. A proactive learning environment is further enhanced by the real-time analytics and visualization features.

In summary, the proposed system offers a scalable and effective solution for academic performance monitoring and tailored learning, demonstrating the transformative potential of artificial intelligence in education. Future improvements like cloud deployment, explainable AI methods, and deep learning integration can fortify the system even more, providing a solid basis for intelligent educational platforms of the future.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

References

[1] Y. Su, Y. Bai, M. Yang, and Y. Sha, "Research on Promotion Evaluation of college Teachers based on Machine Learning," IEEE Transactions on Computational Social Systems, vol. 12, no. 6, pp. 3938–3946, Nov. 2024, doi: 10.1109/tcss.2024.3491134.

[2] Y. Chen, J. Sun, J. Wang, L. Zhao, X. Song, and L. Zhai, "Machine Learning-Driven student Performance Prediction for enhancing tiered instruction," ArXiv.org, Feb. 2025, doi: 10.48550/arxiv.2502.03143.

[3] K.Alalawi, R. Athauda, R. Chiong, and I. Renner, "Evaluating the student performance prediction and action framework through a learning analytics intervention study," Education and Information Technologies, vol. 30, no. 3, pp. 2887–2916, Aug. 2024, doi: 10.1007/s10639-024-12923-5.

[4] A. Kord, A. Aboelfetouh, and S. M. Shohieb, "Academic course planning recommendation and students' performance prediction multi-modal based on educational data mining techniques," Journal of Computing in Higher Education, vol. 38, no. 1, pp. 38–76, Jan. 2025, doi: 10.1007/s12528-024-09426-0.

[5] W. Ahmed, M. A. Wani, P. Plawiak, S. Meshoul, A. Mahmoud, and M. Hammad, "Machine learning-based academic performance prediction with explainability for enhanced decision-making in educational institutions," Scientific Reports, vol. 15, no. 1, p. 26879, Jul. 2025, doi: 10.1038/s41598-025-12353-4.

[6] Y.Su, Z. Dong, and S. Li, "Distributed Sharing and Personalized Recommendation system of college preschool education resources under the Intelligent Education Cloud Platform Environment," International Journal of High Speed Electronics and Systems, Mar. 2025, doi: 10.1142/s0129156425404309.

[7] K.Chergui, A. Nagano, and A. Ammoumou, "Toward an adaptive learning system by managing pedagogical knowledge in a smart way," Multimedia Tools and Applications, vol. 84, no. 24, pp. 27777–27793, Sep. 2024, doi: 10.1007/s11042-024-20207-w.

[8] V. V. Priya, P. Rekha, K. C. Reshmi, S. M. Kumar, and K. Indhulekha, "A Novel Approach to Detect Pedestrian from Still Images Using Random Subspace Method," Procedia Technology, vol. 25, pp. 333–340, Jan. 2016, doi: 10.1016/j.protcy.2016.08.115.

[9] Y. Awasthi and A. Sharma, "Enhancing approach for information security in Hadoop," JITCE (Journal of Information Technology and Computer Engineering), vol. 4, no. 01, pp. 5–9, Mar. 2020, doi: 10.25077/jitce.4.01.5-9.2020.

[10] Huizhong, Z.; Fanrong, M.; Gui, W.; Mago, B.; Puyalnithi, T. Research on the automation integration terminal of the education management platform based on big data analysis. Adv. Data Sci. Adapt. 2022, 14, 2250003. [CrossRef]

[11] Chen, K.; Zhai, X.; Sun, K.; Wang, H.; Yang, C.; Li, M. A narrative review of machine learning as promising revolution in clinical practice of scoliosis. Ann. Transl. Med. 2021, 9. [CrossRef]

[12] Da Costa, O.; Warnke, P.; Cagnin, C.; Scapolo, F. The impact of foresight on policy-making: Insights from the FORLEARN mutual learning process. Technol. Anal. Strateg. 2008, 20, 369–387. [CrossRef]

[13] Martin, A.J.; Lazendic, G. Computer-adaptive testing: Implications for students' achievement, motivation, engagement, and subjective test experience. J. Educ. Psychol. 2018, 110, 27. [CrossRef]

[14] Gresse von Wangenheim, C.; Hauck, J.C.; Pacheco, F.S.; Bertonceli Bueno, M.F. Visual tools for teaching machine learning in K-12: A ten-year systematic mapping. Educ. Inf. Technol. 2021, 26, 5733–5778. [CrossRef] [PubMed]