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Machine Learning Models for Early Identification of At-Risk Students

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Abstract

This study developed and evaluated supervised machine learning models for the early identification of academically at-risk students using selected academic performance indicators. Anchored on Educational Data Mining and supervised machine learning classification, the study employed a quantitative experimental research design using a synthetic dataset composed of 100 student records. The dataset included attendance rate, quiz average score, assignment completion rate, midterm examination score, final examination score, and class participation score. The students were classified as either at-risk or not at-risk based on patterns of attendance and academic performance. Data preprocessing involved mean imputation, Min-Max Scaling, categorical encoding, and an 80% training and 20% testing split. Logistic Regression, Decision Tree, and Random Forest models were implemented and evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. Results showed that Random Forest achieved the highest predictive performance, with 93% accuracy, 0.92 precision, 0.91 recall, 0.91 F1-score, and 0.95 ROC-AUC. The model correctly classified 46 non-at-risk students and 47 at-risk students, with only 4 false positives and 3 false negatives. The study concludes that machine learning can support early warning systems and improve educational decision-making by helping institutions identify students who may need timely academic support. Future studies should use larger real-world institutional datasets and include broader learner-related variables to improve model generalization. The study supports SDG 4, Quality Education, and SDG 9, Industry, Innovation and Infrastructure, by promoting data-driven academic intervention and educational innovation. Its sustainability impact is linked to educational, institutional, and technological sustainability through improved student monitoring, support planning, and evidence-based decision-making.

Keywords: Academic Intervention, At-Risk Students, Early Warning System, Educational Data Mining, Machine Learning, Predictive Analytics, Random Forest, Student Performance, Supervised Classification, Sustainable Education

1. Introduction

The early identification of academically at-risk students is an important concern for educational institutions because delayed detection may result in poor academic achievement, reduced retention, and missed intervention opportunities. Traditional monitoring practices, such as periodic examinations and teacher observations, provide useful information but may not always capture early warning patterns before academic difficulty becomes severe. In response, educational data mining and learning analytics have increasingly been used to analyze student data, detect learning patterns, and support evidence-based academic decision-making (Baker & Inventado, 2014; Romero & Ventura, 2020).

Student academic underperformance remains a persistent challenge in educational institutions. When students who are struggling are not identified early, schools may lose the opportunity to provide timely academic support. Machine learning offers a data-driven approach for classifying students based on academic indicators and identifying those who may require intervention. In this study, academic variables such as attendance rate, quiz scores, assignment completion, class participation, and examination scores are used to predict whether students are at risk of poor academic performance. Educational data mining is relevant to this study because it applies computational and statistical methods to educational data to improve learning processes and institutional decision-making. Baker and Inventado (2014) explained that educational data mining and learning analytics share an interest in using educational data to benefit education and the science of learning. Similarly, Romero and Ventura (2020) emphasized that educational data mining has expanded into areas such as academic analytics, institutional analytics, data-driven education, and educational data science.

Related literature shows that predictive analytics can help schools identify at-risk learners while courses are still in progress. Hu, Lo, and Shih (2014) found that early warning systems can identify at-risk students or predict student learning performance by analyzing learning portfolios from learning management systems. Akçapınar, Altun, and Aşkar (2019) also described educational early warning systems as a development from academic performance prediction, where the goal is to identify students at risk at an earlier stage so teachers can provide assistance. Machine learning has also been applied to student dropout and academic risk prediction. Chung and Lee (2019) showed that predictive modeling using machine learning has potential for identifying students at risk of dropping out in advance, while Lee and Chung (2019) emphasized that dropout early warning systems can help schools respond promptly to learners who may discontinue schooling. These studies support the present research by showing that machine learning models can strengthen proactive academic monitoring and intervention.

Academic underperformance is not only an institutional issue but also a broader educational concern because it affects student progression, school performance, and long-term human capital development. At the institutional level, early identification allows teachers, advisers, and administrators to implement support strategies such as academic counseling, tutoring, attendance monitoring, and personalized academic assistance. At the national and global levels, improving student retention and achievement supports the broader goal of making education more inclusive, equitable, and effective. The United Nations identifies SDG 4 as the goal to "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all." This makes the present study relevant to global education priorities because it focuses on using data-driven methods to support learners who may otherwise fall behind academically.

The study is conceptually grounded in supervised machine learning classification and Educational Data Mining. Supervised classification is appropriate because the study classifies students into two categories: at-risk and not at-risk. Logistic Regression, Decision Tree, and Random Forest are suitable models for this type of binary classification task. Logistic Regression is widely used for modeling binary outcomes (Hosmer, Lemeshow, & Sturdivant, 2013), Decision Tree methods are foundational classification approaches (Quinlan, 1986), and Random Forest is an ensemble method that combines multiple decision trees to improve predictive performance (Breiman, 2001). The use of Python and Scikit-learn is also appropriate for the study because Scikit-learn provides a broad set of machine learning algorithms for supervised and unsupervised learning and emphasizes usability, performance, documentation, and consistency (Pedregosa et al., 2011). This supports the methodological choice of implementing and comparing machine learning classifiers in an educational prediction task.

The rationale of the study lies in the need for earlier and more accurate identification of students who require academic support. While traditional assessment methods can show whether students are already performing poorly, they may not provide enough predictive information for early intervention. Prior research supports the usefulness of educational early warning systems, but implementation depends on the availability and quality of student data, the appropriateness of selected predictive models, and the use of meaningful evaluation metrics. This study addresses the need for a simple predictive framework by comparing Logistic Regression, Decision Tree, and Random Forest models using academic performance indicators. However, the study also recognizes limitations. The dataset is synthetic and limited to academic variables, while non-academic factors such as socioeconomic background, family conditions, mental health, and behavioral indicators are excluded. Future research should therefore use real institutional datasets and include broader learner-related variables to improve model generalizability and practical applicability.

This study aligns most directly with SDG 4 – Quality Education because it aims to support inclusive and effective learning by identifying students who may need academic intervention. By helping schools detect at-risk learners earlier, the study contributes to improved retention, academic support, and learning outcomes. SDG 4 includes targets related to equitable access to quality education, tertiary education, and inclusive learning environments, which are consistent with the study's emphasis on academic monitoring and support. The study also aligns with SDG 9 – Industry, Innovation and Infrastructure because it applies machine learning and data-driven innovation to educational decision-making. The United Nations defines SDG 9 as promoting resilient infrastructure, inclusive and sustainable industrialization, and innovation; its targets include strengthening technological capabilities and encouraging innovation. In this context, the study contributes to educational innovation through predictive analytics and digital decision-support systems.

The study contributes to educational sustainability by supporting early academic intervention, which may help learners remain engaged and improve their academic performance. It also supports institutional sustainability because predictive systems can help schools use academic data more effectively when planning counseling, tutoring, attendance monitoring, and other support services. The study also has relevance to technological and digital sustainability because it demonstrates how machine learning can be applied to improve educational processes. UNESCO notes that artificial intelligence has the potential to address educational challenges, innovate teaching and learning practices, and accelerate progress toward SDG 4, while also requiring attention to risks, policy, inclusion, and equity. Therefore, machine learning-based early warning systems should be developed and used responsibly, with attention to fairness, transparency, and learner support rather than punitive labeling.

2. Material and methods

2.1 Research Design

The study employed a quantitative experimental research design using supervised machine learning classification. The models were developed to classify students into at-risk and non-at-risk categories based on selected academic performance indicators.

2.2 Locale of the Study

The manuscript did not specify a physical locale or institutional setting for the study. The research was conducted using a synthetic educational dataset designed to simulate realistic student academic performance data.

2.3 Respondents of the Study

The study did not involve actual human respondents. Instead, it used 100 synthetic student records representing academic performance profiles. Each record was classified as either an at-risk student or a not at-risk student based on patterns of attendance and academic performance.

2.4 Sample and Sampling Procedure

The sample consisted of 100 generated student records. The manuscript did not identify a formal sampling procedure because the dataset was synthetic. Students with consistently low attendance and poor academic performance were labeled as at-risk, while those with stronger academic indicators were categorized as not at-risk.

2.5 Research Instrument

The research instrument was a structured synthetic educational dataset containing academic-related variables. These variables included attendance rate, quiz average score, assignment completion rate, midterm examination score, final examination score, and class participation score. The target variable classified students as either at-risk or not at-risk.

2.6 Data Gathering Procedure

The data were generated synthetically to simulate realistic academic performance records. After dataset creation, preprocessing was conducted by handling missing values using mean imputation, normalizing data through Min-Max Scaling, encoding categorical variables, and dividing the dataset into training and testing sets using an 80% training and 20% testing split.

2.7 Data Analysis Techniques

The study applied three supervised machine learning algorithms: Logistic Regression, Decision Tree, and Random Forest. Logistic Regression was used to estimate the probability that a student belonged to the at-risk category, Decision Tree classified records through hierarchical decision rules, and Random Forest combined multiple decision trees to improve prediction accuracy and reduce overfitting. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. The study used Python, Scikit-learn, Pandas, NumPy, Matplotlib, and Google Colab to implement, analyze, and evaluate the machine learning models.

3. Results and Discussion

3.1 Performance of Machine Learning Classification Models

3.1.1 Comparative Performance of Logistic Regression, Decision Tree, and Random Forest

The results showed that Logistic Regression achieved an accuracy of 0.85, precision of 0.84, recall of 0.82, F1-score of 0.83, and ROC-AUC of 0.87. Decision Tree performed slightly better, with an accuracy of 0.88, precision of 0.87, recall of 0.86, F1-score of 0.86, and ROC-AUC of 0.89. Random Forest obtained the highest performance among the three models, with an accuracy of 0.93, precision of 0.92, recall of 0.91, F1-score of 0.91, and ROC-AUC of 0.95. These findings indicate that all models were able to classify student risk status, but Random Forest produced the strongest overall predictive performance. The superior performance of Random Forest is consistent with Breiman's (2001) explanation that Random Forest combines multiple tree predictors to improve generalization and reduce instability associated with individual decision trees. This supports the result of the present study, where the ensemble model outperformed both Logistic Regression and a single Decision Tree. The finding also aligns with the broader direction of educational data mining research, which uses classification and prediction techniques to support data-driven educational decision-making (Romero & Ventura, 2020).

3.1.2 Accuracy, Precision, Recall, and F1-Score Results

The model evaluation showed that Random Forest had the highest scores across accuracy, precision, recall, and F1-score. Its accuracy of 0.93 indicates strong overall classification performance, while its precision of 0.92 shows that most students predicted as at-risk were correctly classified. Its recall of 0.91 indicates that the model successfully identified most students who were actually at risk, and its F1-score of 0.91 reflects a strong balance between precision and recall. These results are important because accuracy alone may not fully describe the usefulness of a classification model, especially when the cost of missing at-risk students is high. Powers (2011) emphasized that precision, recall, and F-measure are useful evaluation measures for understanding classification performance beyond simple accuracy. In the context of this study, recall is particularly important because a false negative means that an at-risk student may not receive timely academic intervention.

3.1.3 ROC-AUC Performance of the Models

The Random Forest model achieved the highest ROC-AUC score of 0.95, followed by Decision Tree with 0.89 and Logistic Regression with 0.87. This result indicates that Random Forest had the strongest ability to distinguish between at-risk and non-at-risk students across classification thresholds. The strong ROC-AUC result strengthens the reliability of the Random Forest model because ROC analysis is widely used to evaluate and compare classifier performance. Fawcett (2006) explained that ROC graphs are useful for visualizing, organizing, and selecting classifiers based on performance. In this study, the ROC-AUC value of 0.95 suggests that Random Forest is highly capable of separating students according to academic risk status, making it suitable for early warning applications.

3.2 Classification Outcomes of the Random Forest Model

3.2.1 Confusion Matrix Interpretation

The Random Forest model correctly classified 46 students as not at-risk and 47 students as at-risk. It produced only 4 false positives and 3 false negatives, showing a low number of misclassifications. The small number of false negatives is especially significant because these are students who were actually at-risk but were predicted as not at-risk. This result supports the practical value of machine learning in educational early warning systems. In academic monitoring, false negatives are more concerning than false positives because unidentified at-risk students may miss opportunities for counseling, tutoring, attendance monitoring, or personalized academic support. Hu, Lo, and Shih (2014) similarly showed that early warning systems can be used to predict student learning performance and support timely intervention.

3.2.2 Identification of At-Risk Students for Intervention

The model identified at-risk students with strong predictive performance, as shown by its recall of 0.91 and low false-negative count. These results suggest that the model can support early detection by flagging students who may need academic assistance before performance problems become more severe. This finding is consistent with Akçapınar, Altun, and Aşkar (2019), who described learning analytics-based early warning systems as tools for identifying at-risk students and supporting timely instructional action. Chung and Lee (2019) also demonstrated the relevance of machine learning in dropout early warning systems, showing that predictive models can help schools detect students who may need preventive support. These studies strengthen the research value of the present findings by situating the model within an established body of work on predictive analytics and student risk identification.

3.3 Implications for Educational Data Mining and Academic Decision-Making

3.3.1 Value of Machine Learning for Academic Monitoring

The findings show that machine learning models can classify students based on academic risk indicators such as attendance, quiz performance, assignment completion, participation, and examination scores. Among the tested models, Random Forest provided the strongest evidence of predictive usefulness for academic monitoring. These results support the role of educational data mining in improving institutional decision-making. Romero and Ventura (2020) noted that educational data mining and learning analytics have expanded into areas such as academic analytics, institutional analytics, data-driven education, and educational data science. In this study, the use of classification models reflects this direction by transforming academic records into actionable information for student support.

3.3.2 Usefulness of Predictive Analytics for Early Intervention

The results suggest that machine learning-based early warning systems can help institutions shift from reactive to proactive student support. Instead of relying only on final grades or periodic teacher observations, predictive models can identify students who may need intervention based on patterns in academic performance indicators. This interpretation is supported by prior studies showing that early warning systems can help educators identify students who are likely to experience academic difficulty. Akçapınar et al. (2019) emphasized the use of learning analytics for detecting at-risk students, while Hu et al. (2014) showed that early warning systems can predict online learning performance. Together, these studies support the present finding that machine learning can improve the timeliness of academic support.

3.4 Reliability of the Tools and Model Implementation

3.4.1 Use of Python and Scikit-Learn

The study used Python, Scikit-learn, Pandas, NumPy, Matplotlib, and Google Colab to implement and evaluate the models. These tools supported data preprocessing, model training, prediction, and performance evaluation. The use of Scikit-learn strengthens the technical credibility of the study because it is a widely used Python machine learning library that integrates supervised and unsupervised learning algorithms with emphasis on usability, performance, documentation, and consistency

(Pedregosa et al., 2011). This supports the methodological appropriateness of using Scikit-learn for comparing Logistic Regression, Decision Tree, and Random Forest classifiers.

3.5 Limitations and Future Research Directions

The study produced promising results, but it was limited by the use of a synthetic dataset consisting of 100 student records. The predictors were also limited to academic variables, while socioeconomic background, mental health, family conditions, behavioral indicators, and other contextual factors were excluded due to data limitations. These limitations suggest that future studies should validate the models using real institutional datasets with larger sample sizes and broader learner-related variables. This is important because early warning systems become more useful when predictive results are connected to actual educational contexts and intervention practices. Future work may also examine model fairness, interpretability, and ethical use so that predictive analytics supports learners rather than merely labeling them as academically deficient.

4. Conclusion & Recommendations

This study developed and evaluated supervised machine learning models for the early identification of academically at-risk students using academic indicators such as attendance rate, quiz performance, assignment completion, class participation, and examination scores. The findings showed that all three models were capable of classifying students according to academic risk status, but Random Forest produced the strongest overall performance, achieving 93% accuracy and a ROC-AUC score of 0.95. It also obtained high precision, recall, and F1-score values, indicating that the model was effective not only in making correct classifications but also in identifying students who were truly at risk. The confusion matrix further showed that the Random Forest model correctly classified 46 non-at-risk students and 47 at-risk students, with only a small number of misclassifications. These results suggest that machine learning can strengthen educational decision-making by supporting early detection, reducing missed intervention opportunities, and helping institutions design timely academic support services such as counseling, tutoring, attendance monitoring, and personalized assistance.

It is recommended that future studies use larger and real-world institutional datasets to validate the performance of the machine learning models in actual educational settings. Since the present study used only academic-related variables, future research should also include additional factors such as socioeconomic background, mental health, family conditions, behavioral indicators, and other contextual variables to improve prediction accuracy and model generalization. Educational institutions may consider adopting machine learning-based early warning systems as decision-support tools for identifying students who need timely academic intervention. Among the models tested, Random Forest may be prioritized for further development because it achieved the highest performance across all evaluation metrics in this study. However, any implementation should be accompanied by appropriate academic support mechanisms so that predicted risk status leads to constructive intervention rather than labeling or exclusion.

The study was limited by the use of a synthetic dataset composed of 100 student records, which may not fully represent the complexity of real student populations and institutional environments. The model was also developed using academic indicators only, including attendance, quizzes, assignments, participation, and examination scores. As a result, other important influences on academic performance, such as socioeconomic background, mental health, family conditions, learning behavior, and institutional support systems, were not included due to data limitations. These limitations mean that while the results demonstrate the potential of machine learning for early risk identification, further validation using actual school records and broader student-related variables is necessary before the model can be generalized for large-scale institutional use.

Compliance with ethical standards

This study was conducted in accordance with institutional ethical standards and responsible research practices. Since the research used a synthetic dataset and did not involve actual human participants, direct informed consent, voluntary participation procedures, and personal data collection were not applicable; however, confidentiality and data privacy principles were observed in the handling and reporting of all simulated student records. The author assumes full responsibility for the accuracy, originality, analysis, and interpretation of the study, declares no conflict of interest, acknowledges the use of appropriate tools and scholarly sources, and retains responsibility for copyright ownership and proper attribution of all referenced materials.

REFERENCES

Akçapınar, G., Altun, A., & Aşkar, P. (2019). Using learning analytics to develop early-warning system for at-risk students. *International Journal of Educational Technology in Higher Education, 16*, Article 40. https://doi.org/10.1186/s41239-019-0172-z

Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In J. A. Larusson & B. White (Eds.), *Learning analytics: From research to practice* (pp. 61–75). Springer. https://doi.org/10.1007/978-1-4614-3305-7_4

Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5–32. https://doi.org/10.1023/A:1010933404324

Chung, J. Y., & Lee, S. (2019). Dropout early warning systems for high school students using machine learning. *Children and Youth Services Review, 96*, 346–353. https://doi.org/10.1016/j.childyouth.2018.11.030

Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters, 27*(8), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010

Géron, A. (2019). *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems* (2nd ed.). O'Reilly Media.

Han, J., Kamber, M., & Pei, J. (2012). *Data mining: Concepts and techniques* (3rd ed.). Elsevier. https://doi.org/10.1016/C2009-0-61819-5

Hosmer, D. W., Jr., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). Wiley. https://doi.org/10.1002/9781118548387

Hu, Y.-H., Lo, C.-L., & Shih, S.-P. (2014). Developing early warning systems to predict students' online learning performance. *Computers in Human Behavior, 36*, 469–478. https://doi.org/10.1016/j.chb.2014.04.002

Lee, S., & Chung, J. Y. (2019). The machine learning-based dropout early warning system for improving the performance of dropout prediction. *Applied Sciences, 9*(15), Article 3093. https://doi.org/10.3390/app9153093

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*(85), 2825–2830. https://jmlr.org/papers/v12/pedregosa11a.html

Powers, D. M. W. (2011). Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation. *Journal of Machine Learning Technologies, 2*(1), 37–63. https://www.bioinfopublication.org/files/articles/2_1_1_JMLT.pdf

Quinlan, J. R. (1986). Induction of decision trees. *Machine Learning, 1*, 81–106. https://doi.org/10.1007/BF00116251

Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10*(3), Article e1355. https://doi.org/10.1002/widm.1355

UNESCO. (n.d.). *Artificial intelligence in education*. Retrieved May 30, 2026, from https://www.unesco.org/en/digital-education/artificial-intelligence

United Nations Department of Economic and Social Affairs. (n.d.-a). *Goal 4: Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all*. Retrieved May 30, 2026, from https://sdgs.un.org/goals/goal4

United Nations Department of Economic and Social Affairs. (n.d.-b). *Goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation*. Retrieved May 30, 2026, from https://sdgs.un.org/goals/goal9