

Student Performance Prediction and Early Warning System

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Abstract – The project utilized machine learning methods to forecast student performance and identify students with potential academic failures. The UCI Student Performance Dataset was utilized in this study. The evaluation tools included Decision Tree, Random Forest, and Support Vector Machine (SVM). To determine their F1-score and ROC-AUC, models were tested for accuracy, precision, and recall. The precision of Random Forest and SVM was 70.89%. In the at-risk group, 53.85% of the students were identified by the Decision Tree, which had the highest recall, and Random Forest's ROC-AUC was 0.6887. Moreover, the Decision Tree had the highest F1-score of 51.85% at that stage. However, the results show that an early warning system cannot accurately deliver a full picture. This application is crucial in locating students who are vulnerable. While the Decision Tree was more accurate, Random Forest was better suited for predictors with a higher likelihood of students being at risk. It is a basic model that can predict student performance, which may be improved in the future by adding behaviorally based information, managing class differences, and connecting predictions with automated support measures. Machine learning is a key factor in determining academic success, and the Early Warning System, Decision Tree, Random Forest, and SVM are used to forecast student performance.

Key Words: *Student Performance Prediction, Machine Learning, Early Warning System, Decision Tree, Random Forest, SVM*

1. INTRODUCTION

Not every student reaches the same level of performance in their study. Several students may encounter issues such as low attendance rates, past academic failure rates (e.g., absenteeism), reduced study time, and limited learning opportunities. Students who have been identified using traditional performance monitoring methods may face difficulties in being identified before their academic performance is affected. With the growing availability of student information, machine learning provides an opportunity to identify patterns by analysing

academic performance, study duration, absences, and demographic information among students. The effectiveness of identifying students at risk depends on the machine learning model employed. An Early Warning System uses these predictions to alert teachers or academic advisors about students who may be at risk. The teacher may not always agree with the prediction, as it operates as an additional source of information for teachers to determine when assistance is required. Using machine learning, the project develops a basic prediction and early warning system to predict student performance. The project examines the ability of three classification models to classify students who may be at risk of academic failure. Additionally, these findings may lead to the development of wider systems that incorporate more behavioural and temporal data.

2. LITERATURE REVIEW

Machine learning is being used more frequently in the educational sector to analyse academic performance and identify patterns. The use of SVM, decision tree, K-nearest neighbours (KNN), and other algorithms allow Ahmed to predict students [1]. The study suggests that students can use supervised machine learning methods to predict academic outcomes by using their data. Alsariera et al. employed machine learning algorithms to forecast student performance through testing. The demonstration showed that decision trees and SVM can generate predictive performance at varying degrees depending on the data and problem.

Another important factor to consider when predicting student performance is the selection of input features. El Guabassi et al. utilized the xAPI-Edu-Data dataset, which includes academic, demographic, and behavioural data [3]. They concluded that student behaviour can be understood not only through academic

information but also through behavioural characteristics. Additionally, Chen et al. utilized machine learning classifiers to detect potential risks in the reading habits of university students [4]. Early signs of academic failure can be observed through learning behaviour.

Additional advanced techniques are also being studied. The prediction of scores using deep learning models that consider feature interactions was suggested by Yang and Bai [5]. Kannan and Raj [6] explored machine learning and deep learning techniques and identified data insecurity and class imbalance as issues. Graph convolutional network models and machine learning were employed by Albreiki et al. [7] to identify students with high risk levels. Predictive analysis can be conducted by examining the associations between students' behavioural traits and their academic performance.

The use of predictive analysis has been applied to early warning systems. Herodotou et al. [8] examined the OU Analyse system utilized at the Open University. Teachers are informed about which students require additional attention through the use of predictive data. While earlier research has demonstrated its usefulness, there are several remaining issues to tackle. A model can be useful in a different educational context while being integrated into essentially the same dataset. Various factors, including data quality, high-precision models, class imbalance, limited observations, and poor data integrity, can influence the outcomes.

The issue of overestimating the future is another matter. An early warning mechanism should, in theory, link prediction with the appropriate response from educators. These observations prompted this project to focus on two interdependent tasks: identifying students at risk and forecasting their performance. The article not only compares machine learning models but also demonstrates how predictions can be utilized in an early warning process.

3. METHODOLOGY

3.1 Data and Target Definition

The experiment relies on the UCI Student Performance Dataset. It contains student records, demographics, academic background, and behavioural data. Initially, the G3 value is used

to grade the students' overall academic performance. The available student information is used to examine factors related to academic performance. The target definition provides the basis for applying the machine learning models in the later stages of the study.

3.2 Data Preparation

The early warning experiment is divided into two versions. Students with G3 of 10 or higher are considered not at risk, while those below the 10-level category are considered at risk. The results are similar. A warning system that focuses on the student's potential need for assistance can be combined with the binary formulation. The modelling pipeline is standardized through one-hot encoding of numerical features, which transforms them into categorical variables. G1, G2, and associated predictor variables are excluded to avoid using information that is directly related to the target.

3.3 Classification Models

The data is then split into 80:20 stratified segments for training and testing. A random number such as 42 is used to ensure reproducibility. The same training and test partitions are applicable to all three models. This allows the performance of the three classification models to be compared using the same data conditions. The models are evaluated under the same testing setup to maintain consistency in the results. The Decision Tree method uses recursion to divide observations based on features and classes that are suitable for prediction at the terminal branches. The model is uncomplicated, unlike other black-box models, and teachers can flag issues without delay once they implement it. Variables can be nonlinear and dependent on arbitrary data, which is achieved by adding more trees. The ensemble baseline SVM is utilized as an alternative classifier. It is not necessary to create multiple trees, but rather to classify the data into classes. The inclusion of integer features is a significant aspect in SVM implementations, and it is particularly useful for managing complex class structures.

3.4 Evaluation Measures

The classifiers are evaluated on five criteria, which are accuracy, precision, recall, F1-score, and ROC-AUC. These factors are used for classification evaluation. The test observations are classified in

the same manner. Precision represents the percentage of at-risk predictions that are accurate. The model can identify the percentage of students with real risks accurately through recall, but this application requires a high level of recall. This is important because the early warning system should be able to identify students who may require additional attention. The evaluation measures therefore help in understanding the effectiveness of the models in identifying at-risk students. Even if perceived as vulnerable, students will not be given lower grades. The impact of missing cases in the early warning system is not limited to reducing accuracy. False alarms can cause unnecessary stress, so teachers and advisors should be aware of them. All the measures are covered in this assessment.

3.5 Early Warning Workflow

The early warning workflow uses the predictions generated by the classification models to identify students who may be at risk. The predicted results can be used to provide information to teachers or academic advisors so that appropriate attention can be given to students who may require support. The workflow connects the prediction stage with the early identification of students who may face academic difficulties. It therefore provides a basic process for using machine learning predictions as part of an early warning system. The system is intended to support teachers rather than replace their judgement. The predictions can be considered as an additional source of information when deciding whether a student may need assistance.

4. RESULTS AND DISCUSSION

4.1 Data and Target Definition

We tested three models, namely the **Decision Tree**, Random Forest, and Support Vector Machine, using a stratified 80:20 train-test split of the same dataset. The models were tested using the same dataset and the same train-test division. The performance of each model was then compared using the evaluation measures described in the previous section. This comparison helps to examine the differences in the results produced by the three models.

TABLE-1: Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
Decision Tree	67.09	50.00	53.85	51.85	0.6372
Random Forest	70.89	61.54	30.77	41.03	0.6887
SVM	70.89	66.67	23.08	34.29	0.6865

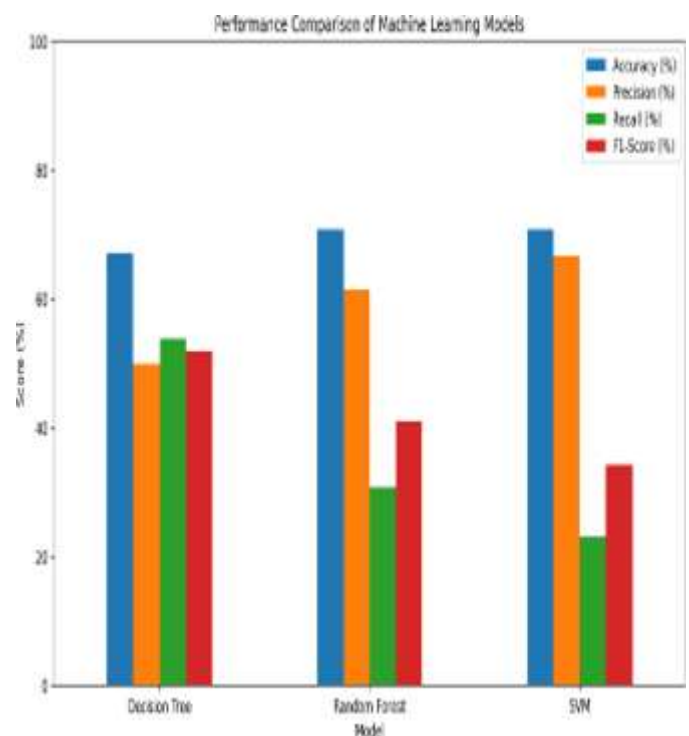


Fig-1: Source: Experimental results obtained using the UCI Student Performance dataset.

4.2 Discussion

Testing Machine Learning models using the UCI Student Performance dataset produced the following results. All three machine learning models were found to have similar performance outcomes, as evidenced by the experimental results. While other metrics were not as accurate, Random Forest and SVM both achieved an accuracy of 70.89%. An early warning system model's reliability cannot be confirmed based on its accuracy alone. ROC-AUC was 0.6887 for Random Forest, while Random Forest had a precision of 61.54 percent.

The model differentiated between the vulnerable and invulnerable groups. SVM's findings revealed that 30.77% of students in the high-risk group were correctly identified. Additionally, SVM achieved a precision of 66.67%, but its recall was only 23.08%. The limited recall by SVM makes it ineffective as a warning system for potential students who may need additional education. Compared to Random Forest and SVM, the accuracy of Decision Tree was 67.09%. Despite this, it obtained 53.85% recall and achieved its highest F1-score of 51.85%. There's a chance that more students in the high-risk group may be involved. It is essential to have an early warning system to pinpoint the students in need of aid, as responding may be slower than usual. You can see how the model of this system depends on what function it serves. Compared to the Decision Tree, students identified by the Random Forest may be less susceptible to danger. Finally, it could be too advantageous. A number of models highlight the need for multiple evaluation measures to establish educational prediction systems. Previous research has indicated that machine learning methods can yield diverse outcomes for different datasets and prediction objectives by prioritizing specific features and predictions. Studies conducted in the past have demonstrated that knowledge of academic and behavioral attributes can help identify students who may not perform well on exams. The results also show that no single model performs equally well across all evaluation measures. Decision Tree achieved the highest recall and F1-score, while Random Forest and SVM achieved higher accuracy. This difference highlights the importance of considering multiple evaluation measures when assessing an early warning system. The findings can therefore be used to understand the different strengths of the three models within the UCI Student Performance dataset. Despite its benefits, the study only has 395 student records. This dataset is quite significant for the analysis, but the limited number of records may affect the generalization of the results.

5. CONCLUSION

It is not a good idea to treat the prediction as isolated data. Additionally, these elements can impact the interpretation of results in models. Instead of relying only on an expected risk assessment, attention should also be given to the student's needs. A machine-learning model is employed in the study to predict

how students will perform and identify students who may need early academic preparation. Using Decision Tree, Random Forest and SVM, experimental techniques were applied to the UCI Student Performance dataset. A precision of 70.89% was achieved by Random Forest and SVM. The Decision Tree had the highest recall, standing at 53.85%, with an F1-score of 51.85%. This demonstrates the importance of using multiple indicators to make an informed decision. The percentage of students at high risk is a better predictor for the Decision Tree than Random Forest and SVM.

The findings show that machine learning predictions can provide useful information for identifying students who may require early academic support. However, the prediction should be considered as a decision-support signal rather than as the only basis for intervention. Teachers are obligated to consider the complete needs of an individual student and provide suitable assistance.

Lack of support for missing students is a significant issue in an early intervention setting. It is suggested that future studies should concentrate on larger and more diverse datasets, such as temporal and behavioral data, class imbalance in prediction models, and connections to structured academic interventions. Decision-support signals can therefore be an important component of machine learning predictions when they are considered together with appropriate academic support.

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