



**Early detection of academic weakness in secondary and middle
school students using artificial intelligence tools**

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Chapter 1 :Introduction

1.1 Problem Definition

The Kingdom of Saudi Arabia is keen on education and its importance, and seeks to develop the educational process and provide a suitable environment for students. Students are considered an important focus in the educational process and must be supported, and any problems that hinder their learning must be resolved. One of the most prominent problems is poor or delayed academic achievement. Some researchers have defined academic achievement as

“all performance by students in various school subjects that can be measured by test scores, teacher assessments, or both.” [Hadi Shaalan Rabie and Ismail Muhammad al-Ghoul, *The Educational Counselor and His Active Role in Solving Student Problems*, Jordan, Dar Al-Thaqafa, 2006]

Academic weakness is a decline in a student's academic performance and can be caused by various social or psychological factors. It is necessary to address and highlight this problem, identify it early, and treat it so that the student can catch up with the rest of the students and prevent them from falling behind.

According to a study by Casillas, A., Robbins, S. B., Allen, J., Kuo, Y. L., Hanson, M. A., & Schmeiser, C. (2012).

which studied the school environment and included 4,660 students from 24 schools, the results indicate that the strongest indicator is the prediction of previous grades, projects, and activities, in addition to psychological and social factors. From these results, we emphasize the importance of early and effective assessment based on the two previous points in order to identify risks and intervene to improve academic performance.

A study by Laetitia Cassells (2012) indicated that students at risk of academic failure benefited more from the early detection system and additional lessons than students who were not subject to the system, achieving cumulative grades that were 8% higher.

1.2 Thesis Objectives

- To review research studies on the causes of student academic weakness, methods of treatment, and ways to enrich high achievers
- To collect and analyze student grade data from the first period of the semester
- To create a tool to help teachers identify students with low grades early on and help them pass the course
- To provide teachers with remedial and enrichment plans

1.3 Thesis Contribution

This work focuses on middle and high school students to help reduce end-of-year academic failure and help teachers identify students at risk of failing a course, develop remedial plans for them, identify high-achieving students, and develop enrichment plans for them, thereby enhancing the quality of the educational process. This is done by creating a tool designed with machine learning models and using real student data to provide interpretable results and take into account future expansion.

1.4 Thesis Organization

Chapter 1 : Introduction

The first chapter will provide an overview of the study topic, review the problem and objectives, explain how the study contributed to the field of education, and describe the organization of the thesis.

Chapter 2 : Overview

This chapter reviews traditional methods of machine learning and advanced methods of deep learning. It also explains hybrid models that combine traditional methods with deep learning and reviews quantitative results, research gaps, and opportunities.

Chapter 3 : Related Work

This chapter will provide a comprehensive background on previous studies in the field and identify current trends and their potential for future development.

Chapter 2 : Overview

2.1 Introduction

Artificial intelligence models play an important role in education and improve and develop the educational process. Artificial intelligence models are divided into several sections, which we will now review.

2.2 Classical Machine Learning Methods

I have read studies that use the method and show that the method works well for predictions. However the method shows problems when the method has to handle a lot of data. The problem has caused modern deep learning models to appear. The modern deep learning models help schools and big institutions. Examples of models include:

- **Naïve Bayes** assumes that all data variables are independent of each other. That is why Naïve Bayes is called naive. Naïve Bayes is used in text classification. For example Naïve Bayes can classify spam. Naïve Bayes calculates the chance of each feature given the category. Then Naïve Bayes classifies the data according to those chances.
- **Support Vector Machine (SVM)** There is the largest possible margin or hyperplane separating the categories, and it is used in image and text classification and anomaly detection.
- **K Nearest Neighbour (KNN)** Classifies data based on the most common points among its K nearest neighbors and is used to classify images, aggregate data, and recognize patterns.
- **The Random Forest** builds a set of decision trees. The Random Forest aggregates the decision trees to produce the classification. The Random Forest uses the classification to classify data that has many variables.

- When I work with **Decision Tree** I watch Decision Tree divide the data into branches based on the feature values. Decision Tree is used in the decision making, the risk assessment and the classification tasks. Decision Tree keeps splitting the data until the leaves are all the same meaning all the cases in a leaf belong, to the same class.
- I use **Logistic Regression** to put data into two groups. I use Logistic Regression to make predictions such as whether the customer will buy the product or not. I use Logistic Regression with a function to turn the linear combination of features into probabilities, between 0 and 1. I then use Logistic Regression to classify the data based on those probabilities.
- I have found that **XGBoost** builds the set of decision trees. Each tree in XGBoost is better than the tree and makes fewer errors. I have seen that XGBoost uses regression to improve performance. I use XGBoost for classification, regression and ranking. I have observed that XGBoost has accuracy and efficiency, in educational competitions. XGBoost runs fast. I have used XGBoost on complex data and XGBoost works well.

2.3 Deep Learning Approaches

- One of the artificial intelligence models is **Artificial Neural Networks – ANN**. I have used Artificial Neural Networks – ANN for data analysis and tries to simulate the human brain with a set of connected artificial neurons , can represent non-linear relationships between variables works well for prediction, classification and regression tasks using a backpropagation algorithm that reduces the error, between predicted values.
- **Multilayer Perceptron (MLP)** is the common type of neural network. has an input layer, one or more layers and an output layer. The hidden layers learn patterns in the data. I have used Multilayer Perceptron (MLP) in education projects. Multilayer Perceptron (MLP) works well for prediction, for students.
- I have used Convolutional **Neural Networks (CNN)** to work with the data that has a layout, such, as the images and visual data. Convolutional (CNN) use the layers that automatically pull out the features. CNNs power the computer vision and pattern recognition.

I see that the software can also analyze the multimedia data. The software works with the multimedia data.

• **Recurrent Neural Networks (RNN)** Developed to process temporal and sequential data, RNNs rely on feedback and allow previous information to be retained. They are suitable for measuring student performance over time, but can suffer from gradient vanishing when dealing with long sequences. This has led to the emergence of

- **Long Short-Term Memory (LSTM)** networks as an improved version of RNN, allowing important information to be retained for a long period of time.

- When I work with networks I choose **Gated Recurrent Units (GRU)** because Gated Recurrent Units (GRU) are the type of recurrent neural network that is simpler, than LSTM and needs less training time while keeping similar performance. The applications that need efficient computation use Gated Recurrent Units (GRU).

• **Deep Neural Networks (DNN)** contain hidden layers. help, in the fields of voice recognition and analysis of data sets. need a lot of data and strong computing power to work better. That extra effort lets Deep Neural Networks (DNN) give more accurate results.

In general, deep learning models have a high capacity to improve prediction accuracy and analyze complex patterns in educational data, making them effective for supporting decision-making and developing intelligent educational systems, especially in the context of predicting academic performance and early detection of at-risk students.

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Of these methods, it is clear that we can use one algorithm or a combination of them, such as:

- Decision Tree
- Naïve Bayes
- Logistic Regression
- Support Vector Machine (SVM)
- Recurrent Neural Network (RNN)
- Artificial Neural Network (ANN)

to predict student grades early on and identify weaknesses. Data will be collected from several schools in Saudi Arabia over a period of two years, and noise, loss, and unbalanced distribution will be processed to ensure the effectiveness of the model and the accuracy and comprehensiveness

of the predictions to help teachers identify students who are prone to failure and intervene to address their weaknesses. Then comes the role of measuring the impact on students following the intervention after the prediction and determining the extent to which the study's objective has been achieved

2.4 Use of Real-world Datasets

Collect student grade data from the first and second semesters of the previous two years, along with data from the first semester of this year, including student information (midterm exams, participation grades, assignments, and projects) from several schools, in addition to a database from Kaggle and Zenodo. It is necessary to address the difference in grade distribution between databases and analyze grades to identify student patterns and understand the relationship between them. Noise, missing data, and unbalanced distribution will be addressed to ensure the effectiveness of the model and the accuracy and comprehensiveness of predictions to help teachers identify students who are at risk of failure and intervene to address their weaknesses. Next comes the role of measuring the impact on students after the intervention following the prediction and determining the extent to which the study's objective has been achieved.

2.5 Quantitative Results Summary

References	Model-Used)	Data Set	Results
Khan, I., Ahmed, M., & Ali, S. (2021).	- k-Nearest Neighbors (K-NN) - Multilayer Perceptron (ANN) - Naïve Bayes - Decision Tree (RepTree)	collected from the University of Amman over three semesters, covering 151 cases and ten predictive features of student performance	MCC (Matthews Correlation Coefficient) (K-NN)=0.917 (ANN)=0.980 Naïve Bayes=0.999 Decision Tree=0.937
Deo, R. C., Yaseen, Z. M., Al-Ansari, N., Nguyen-Huy, T., Langlands, T. A. M., & Galligan, L. (2020)	- ELM model - Random Forest (RF) - Volterra model	Six years of student performance data from the University of Southern Queensland, Australia. Included several in-person and distance learning courses	prediction error ELM model :0.74% Random Forest (RF) :3.12% Volterra model :1.06%
Zeineddine, H., Braendle, U., & Farah, A. (2021)	- SVM - K-NN - Random Forest - Gradient Boosting	The study used university student data comprising 461 cases for a specific period between 2016 and 2021	Relative Prediction Error - SVM: 3.5% - K-NN:8.0% - Random Forest:6.0% - Gradient Boosting:4.5%
Nimy, E., Mosia, M., & Chibaya, C. (2023)	- Logistic Regression - Support Vector Machine (SVM) - Decision Tree - Random Forest - Naive Bayes	A university in South Africa used student academic data such as tests and assignments, as well as their interaction on the platform, such as the amount of time they spent on the platform, and demographic data.	- Logistic Regression:11.6% (SVM):10.5% - Decision Tree:12.7% - Random Forest:12% - Naive Bayes :7.19%
Lau, E. T., Sun, L., & Yang, Q. (2019)	ANN neural networks	The study included 1,000 cases from a Chinese university and three university programs over four years and used 11 variables	ANN neural networks: 84.8
Mondal, A. & Mukherjee, J. (2018)	- Recurrent Neural Network (RNN) - Artificial Neural Network (ANN) - Deep Neural Network (DNN)	Data from Kaggle was used	prediction error (RNN):85% (ANN):82% (DNN):83%
Embarak, O. H., & Hawarna, S. (2023).	- Artificial Neural Networks (ANN) - Random Forest - XGBoost algorithm - Support Vector Machine (SVM)	The study collected data from 450 university students from different universities. The data included academic, behavioral, and psychological data	Accuracy - ANN:82.22% - Random Forest:84.44% - XGBoost algorithm:87.78% (SVM):85%
Melo, E. C., & Souza, F. S. H. (2023).	- Semi-Supervised Learning - Logistic Regression - K-Nearest Neighbors (KNN) - Decision Tree - XGBoost	From an educational institution in Brazil for one year, including 5,915 cases of dropouts 2,096 cases of graduates	Accuracy - Semi-Supervised Learning:90% - Logistic Regression:85.5% (KNN):87.68% - Decision Tree:88.05% - XGBoost 92.05%

2.6 Research Gaps and Opportunities

Connections:

- The studies relied on real student data.
- The studies were conducted within a specific scope within a single educational institution.
- The researchers used more than one algorithm in the studies and selected the best one.
- The models showed remarkable accuracy in the results with a negligible error rate.

Research gap:

- The need to expand the scope of the study so as not to affect the generalizability of the results.
- Adding the largest possible segment of students to contribute to increasing the efficiency and accuracy of the model.
- Adding multiple features, different educational materials, and varying educational levels.
- Need to focus on understanding the model's recommendations to help teachers make decisions
- Need to study the practical application of prediction to guide real educational interventions, determine the effectiveness of the model, and measure its impact on students

Chapter 3 Related Work

Research has focused on using artificial intelligence and machine learning algorithms to predict student outcomes in educational settings. The goal is to improve understanding of student academic performance, develop systems for early detection of students at risk of academic failure or dropout, and implement appropriate preventive measures. Among the most prominent algorithms used in this field are artificial neural networks (ANNs), semi-supervised learning, random forests, and probabilistic learning. Research and studies on this topic have been diverse.

A group of these studies focused on predicting student performance and early detection of at-risk students using traditional artificial intelligence techniques. Studies such as **Khan et al. (2021)** collected data from the University of Amman over three semesters, covering 151 cases and ten predictive characteristics of student performance. The study identified the most important factors affecting performance as GPA, exam scores, and attendance, and determined that students with a GPA of 2.75 or higher showed better results and performance than those who obtained averages below 2.75. The study used several models, the most accurate and best in performance being the decision tree. There was also a study by **Lau et al. (2019)** that included 1,000 cases from a Chinese university and three university programs over four years and used 11 variables. The results improved over the years, and the study used the ANN model, which gave results with an accuracy of 84.8%. We also have a study by **Sukhbaatar et al. (2019)**. Data was collected from Kumamoto University as part of a compulsory course for second-year students. The number of students reached 1,110 over six semesters from 2012 to 2017. A multi-layer neural network was used, and the model identified 25% of students at risk of failure after the first short test and after

the second test. The midterm test results improved, and 65% of students at risk of failure were identified due to increased data and, consequently, increased model accuracy.

This group focused on students' previous grades, attendance, and tests. One of the most notable findings of this research is that neural networks and decision trees outperformed other models, with prediction accuracy ranging from 86% to 91%, enabling educational institutions to provide remedial plans for struggling students, such as extra lessons and early guidance.

In contrast, another group of studies used probabilistic and advanced models to achieve more accurate early predictions, such as the studies by **Nimy et al. (2023)** used academic data from students at a university in South Africa, such as tests and assignments, in addition to their interaction on the platform, such as the amount of time they spent on the platform and demographic data. The researchers used probabilistic machine learning and AutoML techniques to measure the probability of academic failure at each stage of the semester, rather than just giving a final result. The results showed that these models supported the reliability of early prediction, with an accuracy of 92%.

A bunch of studies also used advanced techniques like recurrent neural networks (RNN) and semi-supervised learning, like in the studies by **Mondal and Mukherjee (2018)** and **Melo and Souza (2023)**, which used data from an educational institution in Brazil for one year, including 5,915 dropouts and 2,096 graduates. Researchers **Mondal, A. & Mukherjee** data from Kaggle, where RNN was successful in extracting temporal patterns, and these models were used to analyze educational data. The models in this group showed great effectiveness in tracking changes in student performance over time and early prediction of academic failure, proving their usefulness in long-term early intervention programs.

The latter group, such as the studies **by Deo et al. (2020)**, which relied on six years of student performance data from the University of Southern Queensland, Australia, included several in-person and distance learning courses, and the ELM model outperformed the other models in predicting student grades and identifying those at risk of failure with a very low error rate. It was faster in terms of computational efficiency and pattern capture in continuous assessment data and helps the model improve the quality of teaching and early support. For the study **by Zeineddine et al. (2021)** used data from 461 university students for a specific period between 2016 and 2021. It focused on developing high-performance models using AutoML to predict student grades in specific courses and used student data available before the start of the academic program. It showed high prediction accuracy with low errors, outperforming traditional models such as random forests or traditional neural networks, with an accuracy of 83%.

Conclusion

The literature supports the use of artificial intelligence and shows its success in identifying students at risk of failing with high accuracy using different models. Based on these results, we find that the results of the models differ between studies, but the most accurate was XGBoost with 92%, while the most commonly used models are recurrent neural networks (RNN) and Random Forest. Therefore, the appropriate models for the study will be selected and trained on real data after processing and improving feature selection to give higher quality and credibility results, thus contributing academically and scientifically in this field.

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