

Predicting Academic Performance of Students from Formative Assessment Methods using Machine Learning Algorithms

Jayadev Gyani

Asst.Professor, Dept. of Computer Science, College of Computer and Information Sciences, Majmaah University, Al Majmaah-11952, Saudi Arabia, je.gyani@mu.edu.sa

Abstract

Predicting the academic performance of students is always an interesting area of research for academicians. Different inputs were considered to predict the academic performance of students in several research publications. If predictions are made too early, accuracy of results will be affected as the performance of the students depend upon several factors during the semester the student is studying. We are postponing the predictions until the middle of the semester to have better monitoring and control of the students for the final grades. We use key formative assessment methods to predict the performance of the students at the end of the semester. We used popular machine learning classification methods Naïve Bayes, Random Forest, and Support Vector Machine (SVM) to predict the end of the semester performance.

Keywords:

Grade Prediction, Machine Learning, Naïve Bayes, Random Forest, Support Vector Machine

1.Introduction

Academic Grade prediction is an interesting problem for academicians at the university level for several years. Many researchers have attempted to predict the grades in upcoming exams using previous semester subject grades which are related to that subject. Dropout of students was predicted using previous semester grades based on nationality, gender, and background.

Several researchers attempted academic performance prediction using machine learning. Predictive analytics is used to derive key performance indicators for all education levels, one of them being student grades. These grades can be used to monitor the academic performance of the students^[1]. Predicting the academic level of

students helps identify the weak students and to support those students to overcome educational challenges^[2]. Predicting student performance became an important goal for educational institutes which will help students at risk and to maintain their retention by providing learning resources in turn improving university reputation^[3]. The evaluation and development of prediction of college students are the prime area of student management in universities. The prediction of grades of students' future academic performance is of great importance in strengthening education management^[4]. In higher education, several students struggle to complete various courses because of the lack of support offered to students who need special focus. Predicting the grades in the courses will enable the instructors to assist those students^[5]. Grade prediction of

students for their future courses will help in advising the students to take up personalized course plans based on their performance^[6]. The role of a tutor is to prevent the dropout of students in courses which they have taken and at the same time to improve their performance. The information hidden in the student academic data can be effectively used for personal guidance^[7]. Educational Data Mining can be used to observe interesting patterns and knowledge in educational organizations^[8]. Every institute's primary concern is to improve the graduation rate of students. To achieve this, students' future grade prediction in the next enrolment became a priority issue^[9]. We attempted to predict the academic grade performance using the formative assessment methods of the same semester for the first time in the literature. This study helps teachers to counsel the students who are going to be performing "Poor" in the upcoming final exam as per the prediction. It gives a fair chance to the students who are unable to perform in the formative assessment methods due to their background, medical, or any other reasons.

To improve the teaching-learning process, teachers need to indicate their students about their performance at regular intervals in the continuous evaluation process. However, some assessment methods will impact their end-semester grades and will be considered as indicators of their end-semester grades. Several assessment methods are used during the teaching-learning process such as Assignments, Quizzes, Class Tests, Exercises, Mid Term Tests,

Puzzles, Surprise Tests, Case Studies, and Homework assignments. Some assessment methods reflect the students' cognition level and others may depend on their interaction with other students and the regularity of their attendance.

Our outcome of the research was very interesting as we could predict the performance of the students using two formative assessment methods Mid and Quiz scores with the highest accuracy of 87.72% using Naïve Bayes classification.

2. Literature Survey

Many researchers attempted to predict the grades of students using different techniques. However, all the grade predictions are based on the previous course grades. In the present work, we are predicting end-term grade performance using the formative performance in the same semester.

Sweeney et al.^[9] predicted next term semester grades using Factorization Machine and collaborative filtering algorithms. They modeled the grade prediction system as a recommender system. Saa^[8] has shown that personal and social factors in the previous semester will affect the grades in the next semester. The author constructed a survey with multiple questions containing personal and social factors and predicted students' performance from these factors. Rovira et al.^[7] predicted student dropout rate in the first year to know the possibility of students seeking admission in second or third years from the first-year data and modeled as a binary classification problem and compared popular classification techniques in machine learning such as Gauss-

ian Naïve Bayes, Support Vector Machine, Logistic Regression, Random Forest and Adaptive Boosting. They also predicted the grades using previous academic year grades using the linear regression model. Iqbal et al.^[5] used Collaborative Filtering, Matrix Factorization, and Restricted Boltzmann Machines to analyze the data collected from the university in Pakistan. They predicted the GPA scores of students using these techniques. They evaluated the models using repeated random sample cross-validation. They claim that the predicted GPA scores can be used to warn students who are scoring low. Morsy et al.^[6] developed a Cumulative Knowledge-based Regression Model to predict the grades of the courses which the students going to take. They found that the knowledge learned in the past courses will affect grades in future taking courses. X. Zhang et. al.^[4] used Naive Bayes, Decision Tree, Multilayer Perceptron, and Support Vector classification models to predict students' academic performance. In their study, the multi-layer perceptron model has demonstrated powerful effectiveness, which achieved 65.90% accuracy on the training set and 62.04% accuracy in the test set. L. M. Abu Zohair et. al.^[3] proved the possibility of training and modeling a small dataset size and the feasibility of creating a prediction model with a credible accuracy rate. This work focused on identifying the key indicators in the small dataset, which will be utilized in creating the prediction model, using visualization and clustering algorithms.

A. E. Tatar et al.^[2] made a study using Student records populated from Imam Abdulrahman bin Faisal University(IAU) learning management system containing features of three different nature: the demographic features, the pre-college features, and the college records including enrolment information and college performance. They used two approaches one is based on the previous semester courses and the other one is based on the cumulative performance from the date of joining the college. They observed that the prediction performance improved as more semesters were included in the cumulative model and reached up to 94.9%. Using the first approach after term1 they got an accuracy of 65.6% using the Logistic regression method.

S. D. A. Bujang et al.^[1] predicted students final grades based on their previous course performance records in the preceding semesters' performance records. They used SMOTE (Synthetic Minority Oversampling Technique) to handle the imbalanced datasets and then grades were predicted in the next semester.

3. Present Work

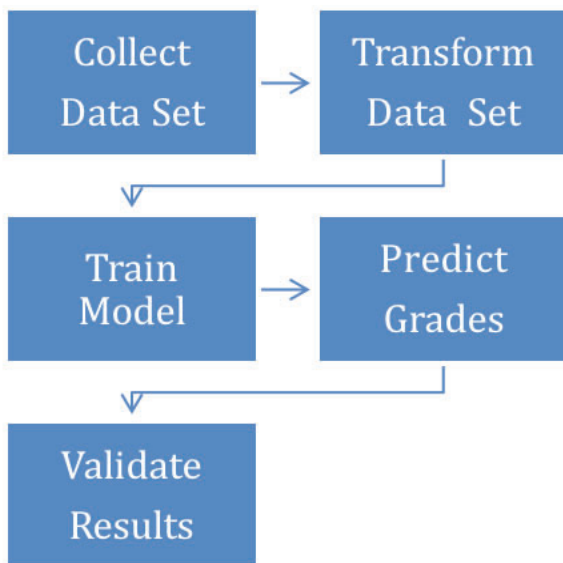
In this paper, we have taken data of 194 students data collected from various academic semesters which include Mid Term, Quiz marks, and End Semester Grades in 10 subjects namely Programming Languages, System Administration, Software Engineering, System Integration, Programming in C++, Software Modeling and Analysis, Parallel and Distributed Computing, Software Evolution, Software Architectures,

and Low-Level Software Design.

The collected data set contains Subject Code, Mid Term Marks, Quiz Marks, and End Semester Grades. We transformed the data by eliminating subject codes and mapped the Grades A+, A, B+, B, C+, C to the label “Good” and D+, D, and F to the label “Poor”. Now predicting the end semester performance became a binary classification problem by identifying the students’ performance as “Good” or “Poor” on the test data set.

The steps in the grade performance prediction process are shown in Fig. 1.

Fig. 1. Steps in grade performance prediction



3.1 Data Set

The Student Grade data set contains three fields Mid (Number), Quiz(Number), and Grade(Label). The range of Mid Marks is 0-20. The range of Quiz marks is 0-10 and the Grade can be “Good” or “Poor”. A few rows of the data set are shown in Table 1. We have chosen the Mid Term Exam and Quiz exam as the students need to write these exams with reasonable preparation.

Table 1. Sample rows in Data Set

Mid	Quiz	Grade
18	7	Good
20	9	Good
19	9	Good
19	4	Good
17	7	Good
13	5	Poor
19	9	Good
17	7	Good
11	6	Poor
14	7	Poor
18	9	Poor

These exams focus on the fundamentals of subjects. We observed that the other assessment methods such as Assignments, Case Studies, and Exercises will allow enough time to solve the problems. So, the most influencing factors for the end semester grades will be Mid Term and Quiz exams. Our results strongly indicate the influence of these assessment methods on the end-semester grades. Formative assessment methods are used to evaluate the students’ performance during the semester. These assessment methods will give an overview of the strengths and weaknesses of the students.

The density estimate of Mid Score and Quiz scores are shown in Fig. 2. and Fig. 3.

Fig. 2. Density estimate of Mid Score

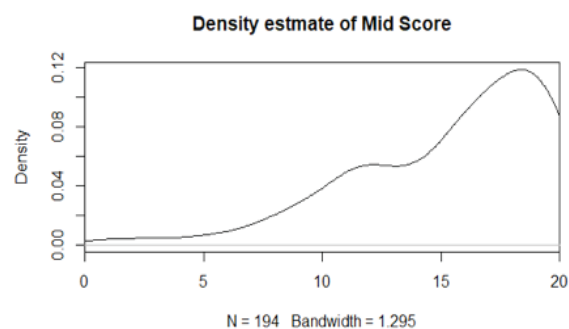
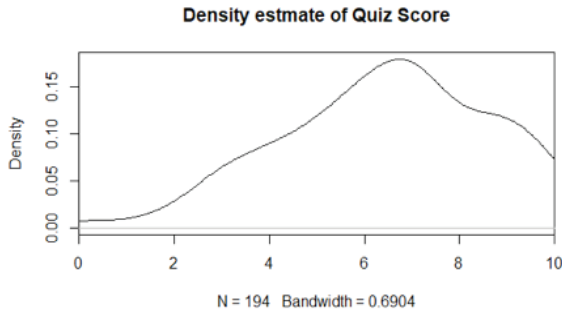


Fig. 3. Density estimate of Quiz Score



The density estimates of Mid score and Quiz scores show that the data is distributed in the range and not skewed. It is important to have the data distributed when the data set size is limited otherwise it may lead to overfitting.

3.2 Experimental Results

We used the Split Validation technique to predict the labels using three popular Machine Learning-based Classification Algorithms Naïve Bayes, Random Forest, and Support Vector Machine (SVM). Then we compared the predicted labels with available labels and found very interesting results. We implemented all three models in R Language. On 194 student records, split validation was used, so 137 records were used for training the models and 57 records with known labels were used for testing and validation. Naïve Bayes gave the highest accuracy of 87.72% whereas Random Forest gave an accuracy of 82.46% and Support Vector Machine gave an accuracy of 85.96% as shown in Table 5.

In each of the Figures below dots represent false predictions and triangles represent correct predictions. When the academic performance is predicted, the students who are labeled as “Poor” will be focused more

to perform well in the coming assessment methods.

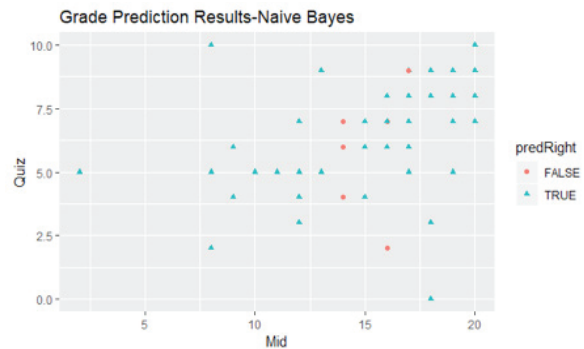
3.2.1 Naïve Bayes Classification

Naive Bayes is based on the Bayes Theorem. It predicts the membership probabilities of each class for a data point that belongs to a particular class. The class with the highest probability is taken as the expected class.

Table 2. Confusion Matrix and Statistics

Prediction	Reference	
	Good	Poor
Good	35	5
Poor	2	15

Fig. 4. Naïve Bayes Prediction



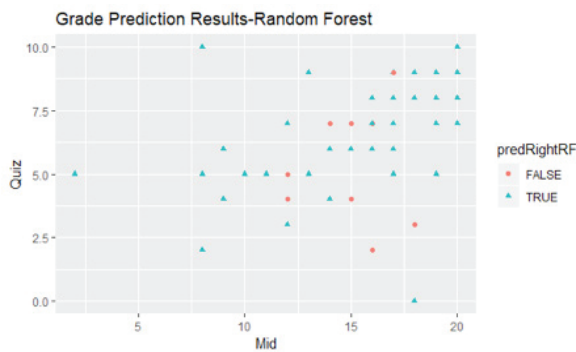
3.2.2 Random Forest

The Random Forest algorithm is a collection of several decision trees. This algorithm chooses random samples from training data for constructing the trees and extracts a random subset of features during splitting of the nodes. During training, each tree in Random Forest learns from randomly selected samples. During testing, prediction from each tree is taken and the average of all these predicted values is considered as the final prediction.

Table 3. Confusion Matrix and Statistics

Prediction	Reference	
	Good	Poor
Good	33	6
Poor	4	14

Fig. 5. Random Forest Prediction



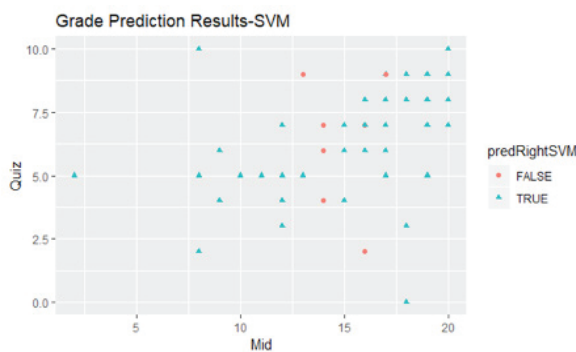
3.2.3 Support Vector Machine (SVM)

A support vector machine is a supervised learning model which can identify two basic classes from the set of labeled data. The function of SVM is to detect a hyperplane that can distinguish between two classes.

Table 4. Confusion Matrix and Statistics

Prediction	Reference	
	Good	Poor
Good	34	5
Poor	3	15

Fig. 6. SVM Prediction

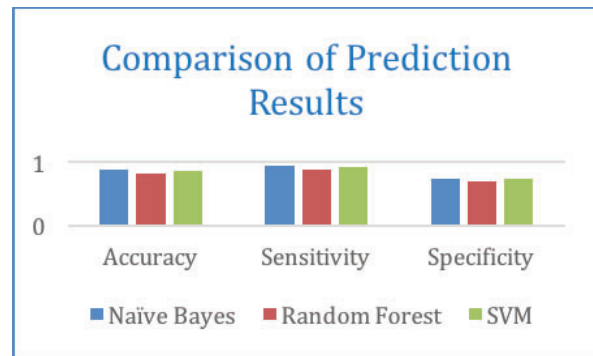


3.2.4 Comparison of Results

Table 5 Comparison of Prediction Results

Model\Parameter	Accuracy	Sensitivity	Specificity
Naïve Bayes	0.8772	0.9459	0.7500
Random Forest	0.8246	0.8919	0.7000
SVM	0.8596	0.9189	0.7500

Fig. 7. Comparison of Prediction Results



Accuracy (ACC) is the ratio of the number of all correct predictions to the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0. Sensitivity (SN) is the ratio of the number of correct positive predictions to the total number of positives. It is also called recall (REC) or true positive rate (TPR). The best sensitivity is 1.0, whereas the worst is 0.0. Specificity (SP) is the ratio of the number of correct negative predictions to the total number of negatives. It is also called true negative rate (TNR). The best specificity is 1.0, whereas the worst is 0.0.

Execution Environment:

Core i7, 4GB RAM, 256GB HDD, Windows OS, R version 4.0.2

Time of execution of each model:

Naïve Bayes: 0.4 sec

Random Forest: 3.3 sec

SVM: 0.63 sec

4. Conclusion and Future Work

Our present work is useful in advising the students for improving their performance before final exams. When the academic performance is predicted, the students who are labeled as “Poor” will be focused more to perform well in the coming assessment methods. Many related works are using past semester grades to predict the present grades, but our approach reduces the error in prediction as we are using the formative assessment results of the same semester. Our experimental setup considered only the data related to the College of Computer and Information Sciences, Majmaah University. However, it can be extended to other universities in Saudi Arabia.

Conflict of Interest

The author has no conflict of interest.

Acknowledgment

The author would like to thank the anonymous reviewers for their suggestions for improvement. The author would like to thank the Deanship of Scientific Research, Majmaah University, Saudi Arabia to use the formative assessment scores of my courses vide Approval No. MUREC-Jan.29 /COM-2019/16.

References

- [1]S. D. A. Bujang et al., “Multiclass Prediction Model for Student Grade Prediction Using Machine Learning,” in *IEEE Access*, vol. 9, pp. 95608-95621, 2021, DOI: 10.1109/ACCESS.2021.3093563
- [2]A. E. Tatar and D. Dü³tegor, “Prediction of academic performance at undergraduate

graduation: Course grades or grade point average?”, *Appl. Sci.*, vol. 10, no. 14, pp. 1_15, 2020

[3]L. M. Abu Zohair, “Prediction of student’s performance by modeling small dataset size”, *Int. J. Educ. Technol. Higher Educ.*, vol. 16, no. 1, pp. 1_8, Dec. 2019, DOI: 10.1186/s41239-019-0160-3

[4]X. Zhang, R. Xue, B. Liu, W. Lu, and Y. Zhang, “Grade prediction of student academic performance with multiple classification models,” in *Proc. 14th Int. Conf. Natural Comput., Fuzzy Syst. Knowl. Discovery (ICNC-FSKD)*, Jul. 2018, pp. 1086_1090

[5]Z. Iqbal, J. Qadir, A. N. Mian, and F. Kamiran, “Machine learning based student grade prediction: A case study”, arXiv preprint arXiv:1708.08744, 2017

[6]S. Morsy and G. Karypis. “Cumulative knowledge-based regression models for next-term grade prediction”, In *Proceedings of the 2017 SIAM International Conference on Data Mining*, pages 552–560. SIAM, 2017

[7]Rovira S, Puertas E, Igual L (2017), “Data-driven system to predict academic grades and dropout”, *PLoS ONE* 12(2): e0171207. doi:10.1371/journal.pone.0171207

[8]A. A. Saa, “Educational data mining & students’ performance prediction”, *International Journal of Advanced Computer Science & Applications*, 1:212–220, 2016

[9]M. Sweeney, J. Lester, and H. Rangwala, “Next-term student grade prediction”, In *BigData (Big Data)*, 2015 IEEE International Conference, pages 970–975. IEEE, 2015