# Evaluating various machine learning methods for predicting students' math performance in the 2019 TIMSS

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**ABSTRACT**

The growth of a country strongly depends on the quality of its educational system. All over the world, the education sectors are experiencing a fundamental evolution of their mode of operation. The greatest challenge for education today is the low success rate of learners and the abandonment of education in institutions at a premature age. Early prediction of student failure can help administrators provide timely guidance and supervision to enhance student success and retention. We propose a performance prediction model based on students' social and academic integration using several classification algorithms. This study involves a comparative analysis of five algorithms: logistics regression, k-nearest neighbors (K-NN), support vector machine (SVM), decision tree, and random forest. They were applied to a set of data from TIMSS 2019 in Morocco, to determine their effectiveness in predicting student performance using prediction models such as logistics regression, KNN, SVM, decision-tree, and random forest, decision-makers can make data-driven decisions to enhance educational strategies and improve outcomes in mathematics education.



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## 1. INTRODUCTION

Evaluation is now an essential social practice. In its form, it is more usual and probably the most widespread. Evaluation leads to a value judgment on the performance of individuals or social groups for the collection of information and decision-making. In education, many assessment systems (programme for international student assessment (PISA), trends in international mathematics and science study (TIMSS), and progress in international reading literacy study (PIRLS)) experienced spectacular development in recent years, their purpose is to measure, evaluate, and influence the characteristics, behaviors, and results of an education system to enable the implementation of the general policy of this system.

The system of assessment TIMSS is a study that compares students' academic level in their fourth year of primary school and their second year of college in math and science. It is a system made up of exams and questionnaires intended to identify the learning environment. The study includes several questionnaires for students, parents, teachers, and administrators of the participating schools. These studies allow for both the assessment of students' levels of learning as well as the gathering of information on factors related to the learning environment that may have an impact on students' levels of learning. Examples of these factors include the educational resources available at the school, the student’s attitudes toward these subjects, instructional strategies, and the family environment. TIMSS covers several content areas in mathematics (numbers, geometry, algebra, data) and several content areas in science (life sciences, physical sciences, earth sciences). It also covers three cognitive domains (knowledge, application, and reasoning) [1], [2]. Predicting student performance is a complex task due to the increasing amount of data available regarding the results of student assessment systems. However, the application of machine learning can assist teachers and decision-makers in predicting student performance, thereby facilitating decision-making to enhance pedagogical performance.

The objective of this research document is to develop predictive models using a classification algorithm to anticipate the success or failure of mathematics tests based on students' social vulnerability and measurable characteristics of their social environment at school, at home, as well as their surroundings. Five classifiers, such as logistic regression, k-nearest neighbour (KNN), support vector machine (SVM), decision trees, and random forest, are adopted to predict students' performances and classify them as either successful or unsuccessful in mathematics tests. In analyzing the literature on predicting student performance, two major variables are highlighted: features and prediction methods. There has been a lot of research into the attributes that have been commonly employed in predicting student achievement. Commonly utilized criteria include cumulative grade point average (CGPA) and internal assessment.

The second part of the literature on predicting student performance concerns the prediction method. In data mining, prediction modeling is typically used to predict student performance. The techniques can vary from classification, regression, or categorization [3]. The most popular are classification algorithms according to predictive modeling techniques such as decision trees, Naïve Bayes, KNN, neural networks, logistic regression models, and many others, which can be used by many researchers [4]. Several works are interested in the comparison of these techniques, particularly in the prediction of student performance. The work of [5] adopts classifiers such as the decision tree, KNN, and rule learners to predict student performance based on their personal and academic characteristics. On the other hand, [6] proposed a model of student performance predictors using classification techniques, which was found to be satisfactory, with the overall accuracy of the tested classifiers being above 60%.

The paper is organized in the following way, first section introduction: this section provides an overview of the research topic, including the background and motivation for the study, it also outlines the main research questions and objectives of the paper. Section 2 methodology describes the study's research design and methodology, as well as information on the sample population, data collecting, and analysis procedures. Section 3 result and discussion: this section presents the findings of the study and includes relevant data and statistics. It also discusses any patterns or trends that were identified mentions the implications of the findings for the field and suggests areas for future research.

## 2. RELATED WORK

There has been a lot of research done on forecasting student performance, with many interesting methods and tools for attaining goals, obtaining knowledge, making judgments, and providing recommendations. Some of the information used as a source for this article is described below. A study investigating factors influencing software correctness found that data mining in educational contexts often employs two primary types of data analysis methods: predictive model-based approaches and descriptive model-based methods. Predictive methods typically utilize supervised learning techniques to estimate unknown values of the dependent variable, while descriptive models rely on unsupervised learning to uncover patterns elucidating the underlying structure of the data [7], [8].

Bydžovská and PopeĺnskÝ [9], researchers explored the application of a collaborative filtering approach for predicting a student's performance at the outset of a study period based on their academic track record. This approach involves mapping a student's learning journey across various grades in courses they have completed to identify students with similar characteristics. The study leveraged historical data stored in Masaryk University's information system and demonstrated that this approach was just as effective as conventional machine learning methods like SVM.

In a separate research endeavor, authors proposed the development of methods using historical datasets of student performance within a specific course to evaluate individual student achievements [10]. Their proposal centered around decentralized linear models and low-rank matrix factorization. The research evaluated the effectiveness of this technique using a dataset from the University of Minnesota spanning 12.5 years, revealing that focusing on course-specific data could enhance the accuracy of grade predictions.

Khan and Ghosh [11], constructed a model using an experimental dataset comprised of Portuguese students participating in two different courses: mathematics (395 cases) and Portuguese (a Portuguese language course; 659 instances). This data was collected and evaluated by Paulo Cortez and Alice Silva from the University of Minho in Portugal [7]. Three decision tree algorithms, namely J48, RepTree, and Hoeffding tree (VFDT), were utilized in this research. The results affirmed that the J48 algorithm demonstrated the highest effectiveness in categorizing and forecasting students' inclination to pursue higher education and their prospects for success in their courses [12], [13].

Thai-Nghe *et al.* [14], a new method for extracting educational data using recommender systems is proposed, with a focus on forecasting student achievement. This strategy was validated by comparing recommender system techniques to classic regression methods such as logistic regression or linear regression. The use of recommender system methods like matrix factorization to predict future student performance in a classroom setting is an addition tothis work.

## 3. METHOD AND MATERIALS

### 3.1. Student data

In Morocco, the education system includes a six-year primary cycle, a three-year college secondary cycle, a three-year qualifying secondary cycle, and higher education. This study will consider the data collected from TIMSS 2019 in Morocco for student’s grades and will focus on the mathematical test, the student answers a set of questions related to mathematic problems for example ("are you learning quickly in mathematics?" and "how many books do you have in your home?"). Table 1 lists the questions that have an impact on the mathematics test.

Table 1. Description of variables

| Attribute | Description |
|---|---|
| AGE | Student’s age |
| ASBG01 | Student’s sex |
| ASBG03 | Often speak (lang of the test) at home |
| ASBG04 | Number of books in your home |
| ASBG05C | Own room |
| ASBG05D | Internet connection |
| ASBG05E | Mobile own |
| ASBG08 | About how often absent from school |
| ASBG09A | Tired |
| ASBG09B | Hungry |
| ASBM02B | Wish I had not studied math |
| ASBM02C | Math is boring |
| ASBM03A | The teacher expects to do |
| ASBM03B | The teacher is easy to understand |
| ASBM04A | Students do not listen |
| ASBM04B | Disruptive noise |
| ASBM04C | Too disorderly to work |
| ASBM04D | Wait a long time to quiet |
| ASBM04E | Students interrupt tch |
| ASBM04F | Keep telling rules |
| ASBM05A | Usually do well in math |
| ASBM05B | Harder for me than for others |
| ASBM05C | Just not good at math |
| ASBM05D | Learn quickly in mathematics |
| ASBM05E | Math makes me nervous |
| ASBM05H | Mathematics harder for me |
| ASBM05I | Math makes me confused |

### 3.2. Size and precision of the sample

In this research, 7,440 students answered a questionnaire on several areas of mathematics and social content. We extracted 27 features that have an impact on success in a math test. This study used a score of 375 to split the class of students into two classes (pass or fail) in the math test. After analyzing the database, we noticed that 48.1% have problems in learning mathematics, while 51.9% do not find problems or difficulties in learning this last as shown in Figure 1. It seems that only half of the students were able to pass the exam, which is still a positive outcome to some extent. However, our goal should be to minimize the number of students who fail. It seems that only half of the students were able to pass the exam, which is still a positive outcome to some extent. However, our goal should be to minimize the number of students who fail.

### 3.3. Experimentation setting

The study is carried out on a Windows system using the Jupyter Notebook and the Python programming language. The hardware configuration of the machine includes a 64-bit Windows 10 operating system, an Intel Core (TM) i5-7300U CPU @ 2.60GHz, 2.71 GHz, 16.0 GB of RAM, and an Intel UHD

Graphics 620 GPU. Notably, TensorFlow, a deep learning framework, is being run in its CPU-only edition, particularly version 1.8.0, due to the absence of a GPU-supported version.

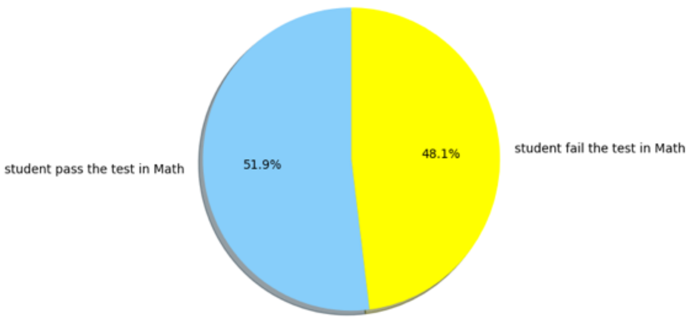


Figure 1. Proportion of students passing and failing math

### 3.4. Measurements and covariates

The machine learning and deep learning algorithms employed to forecast student learning performance were derived from Anaconda. The study's input factors pertain to students' actions when working on exercises and assignments. The performance of several machine learning algorithms was assessed using metrics like accuracy, precision, recall, and F1-score.

### 3.5. Objectif of papier

This study delved into the effectiveness of employing machine learning techniques to assist both a mathematics instructor and the ministry in predicting student performance throughout the academic year and providing tailored educational support. The exploration of machine learning's potential in this context aimed to enhance the accuracy of predictions and improve the efficiency of support mechanisms. By leveraging advanced computational methods, this research sought to contribute valuable insights into the practical applications of machine learning within the educational domain, fostering a more proactive and targeted approach to student success.

### 3.6. Preparation data

#### 3.6.1. Features sculling

Feature scaling is an essential preprocessing procedure in machine learning, encompassing the adjustment of a dataset's features to fit within a designated range. The primary objective of feature scaling is to standardize the scale and magnitude of all features, thereby enhancing the accuracy and stability of the learning algorithm. In the first stage, we attempted to remove all records containing the most incorrect responses. In the second step, we attempted to normalize the data (transform the raw input values into values that machine learning algorithms can use more readily) [15], [16].

$$\frac{col - mean(col)}{\max(col) - \min(col)} \tag{1}$$

Where mean: the mean or the average.

#### 3.6.2. Correlation

In our research, an essential step involved exploring the relationships among various features through the application of heat map methods. Figure 2 visually represents these relationships, specifically illustrating the connections between different features and the status of students. The utilization of a heat map allows for a comprehensive and intuitive understanding of the interplay between diverse factors, shedding light on potential patterns or correlations that may influence student outcomes.

#### 3.6.3. Discussion of results

From this heatmap, we can draw a quick conclusion about which features have the most impact on student status:

Three most impactful features (positively):

- The student’s feeling that the effort he is making is not enough to succeed in mathematics has a positive effect on his success in tests.
- The number of hours taught mathematics has an impact positive.
- The student's feeling of challenge in front of learning mathematics has a positive impact on his success in this test.

Tow most impactful features (negatively):
- The student's feeling that he is slow learning mathematics hurts this test.
- Age is a feature that also negatively impacts student performance in math.

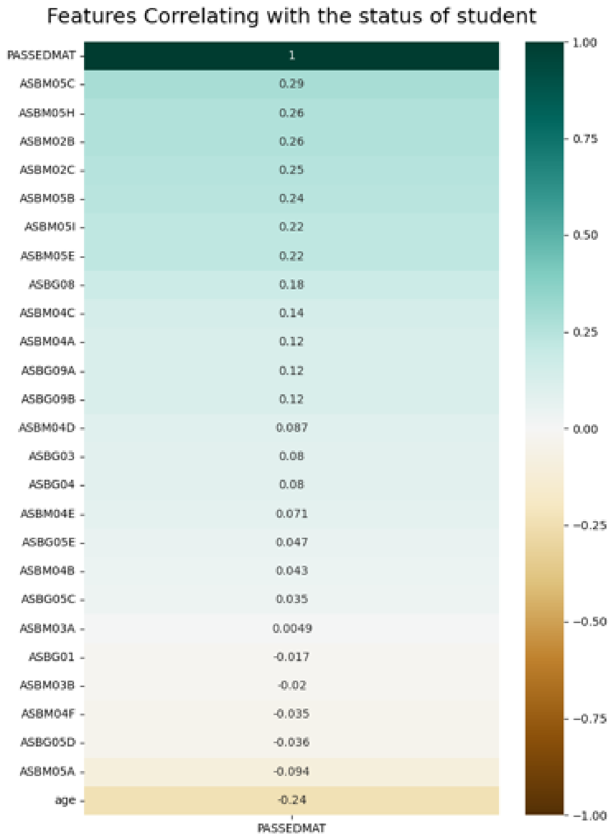


Figure 2. Features correlating to the status of the student

### 3.7. Predicting math test score

To accommodate the condensed dataset consisting of nine parameters, five distinct predictive models were employed: logistic regression, KNN, SVM (with a linear kernel), decision tree, and random forest. Table 2 displays the refined hyperparameters, with the optimal values indicated within brackets. For any hyperparameters not specified in Table 2, default values from the scikit-learn library [17] were applied.

Table 2. Optimal hyper-parameters following a thorough grid search

| Method | Hyper-parameter | Values |
|---|---|---|
| Logistic regression | C (Regularization) | 0.01, 0.1, 1,8,10 (8) |
| KNN | Number of neighbors | 1,5,10,15,20,25 (18) |
| SVM | C (Regularization) | 0.001, 0.01, 0.1, 1,10 (0.1) |
| | Class weights | 0 to 1 |
| Decision-tree | Maximum depth | 1 to 10 (8) |
| | Minimum samples split | 2 to nVars+1 (6) |
| Random forest | Maximum depth | 1 to 10 (8) |
| | Number of estimators | 200 |
| | Minimum samples split | 2 to nVars+1 (6) |

### 3.8. Use of logistic regression algorithms for prediction of math score

A statistical technique for assessing a set of data where one or more independent factors affect the result is called logistic regression. It is utilized to forecast a binary result (in this case, passing or failing a math examination) from a set of independent variables. In this study, we used 80% of the data for training and 20% for testing (5,952) students for training and 1,488 for testing). The results presented in Table 3 are modeled using a logistic function [16], [17].

Table 3. Mathematics achievement evaluation using logistic regression

| | Precision | Recall | F1-score | support |
|---|---|---|---|---|
| ( ) 0.0 | 0.66 | 0.59 | 0.62 | 669 |
| ( ) 1.0 | 0.67 | 0.73 | 0.70 | 789 |
| Accuracy | | | 0.66 | 1,488 |

The analysis of the results highlights a precision of 66% for predicting failures (class 0.0) and 67% for success (class 1.0). While the model has successfully identified a significant proportion of outcomes, the 59% recall for failure underscores a certain limitation. The balanced F1-score metric provides a nuanced view of performance. Overall, the 66% accuracy indicates correct predictions for about two-thirds of the test set, emphasizing potential areas for improvement, including the choice of the "c" (regularization) parameter for the logistic regression model.

### 3.9. Use of K-nearest neighbor's algorithms for prediction of math score

The KNN machine learning method predicts the class or value of a new data point by comparing it to the KNN in the training dataset. KNN identifies these nearest neighbors and makes predictions through majority or average voting, involving the calculation of distances between data points. The choice of the parameter k is crucial, as it plays a central role in determining the algorithm's performance [18]–[20]. In our case, the number of nearest neighbors chosen is set to 18 presented in Figure 3. For a more detailed precision analysis, the results of the KNN method are presented in Table 4.

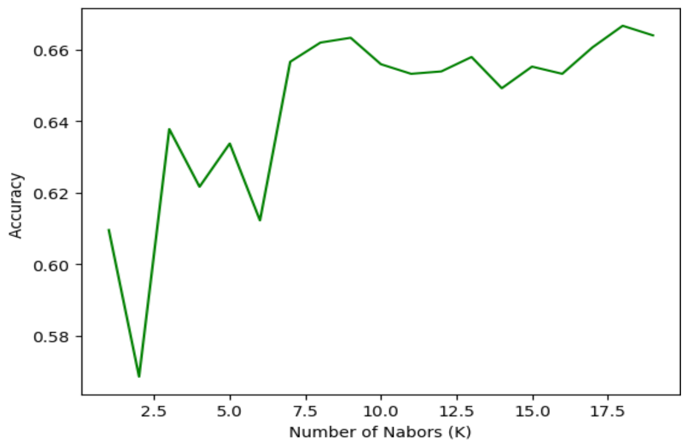


Figure 3. Changes in accuracy with K values

Table 4. K-nearest neighbors performance metrics for mathematics achievement

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| ( ) 0.0 | 0.66 | 0.62 | 0.64 | 699 |
| ( ) 1.0 | 0.68 | 0.72 | 0.70 | 789 |
| Accuracy | | | 0.67 | 1,488 |

The classification results reveal precision scores of 66% for class 0.0 and 68% for class 1.0. The model achieved recall rates of 62% for class 0.0 and 72% for class 1.0. Balancing precision and recall, the F1 score stands at 64% for class 0.0 and 70% for class 1.0. With an overall accuracy of 67%, the model demonstrates effectiveness in correctly predicting outcomes for about two-thirds of the test set.

### 3.10. Use of support vector machine algorithms for prediction of math score

SVM is a popular discriminant approach and a powerful machine-learning classification model. It has a superior generalization ability than other classification models in data mining. It also has a set of advanced theoretical approaches for dealing with non-linearly separable data. The specific procedure for linearly separable situations is to locate the line with the greatest sum of distances from nearby points to separate for linearly inseparable cases, the kernel function is required. SVM is most useful in two situations. The first type of data is linearly separable, and the second type of data is linearly inseparable [18]‒[20].

Table 5 show SVM performance metrics for mathematics achievement. The precision metrics indicate 64% accuracy for class 0.0 and 69% accuracy for class 1.0 in the classification results. The model attained recall rates of 66% for class 0.0 and 67% for class 1.0. Balancing both precision and recall, the F1-score reaches 65% for class 0.0 and 68% for class 1.0. Demonstrating an overall accuracy of 67%, the model effectively predicts outcomes correctly for approximately two-thirds of the test set.

Table 5. SVM performance metrics for mathematics achievement

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| ( ) 0.0 | 0.64 | 0.66 | 0.65 | 699 |
| ( ) 1.0 | 0.69 | 0.67 | 0.68 | 789 |
| Accuracy | | | 0.67 | 1,488 |

### 3.11. Use of random-forest algorithms for prediction of math score

A versatile method used for both classification and regression tasks is random forest. Multiple decision trees are combined in this ensemble learning technique to produce predictions. Random Forest builds many decision trees using random subsets of the training data and characteristics. Individual predictions are made by each tree, and then the group predictions are combined by voting or averaging [18], [21], [22].

Table 6 show random forests performance metrics for predicting mathematics achievement. The classification results show precision scores of 67% for class 0.0 and 68% for class 1.0. The model achieved a recall rate of 61% for class 0.0 and 73% for class 1.0. The F1-score, which balances precision and recall, is 64% for class 0.0 and 71% for class 1.0. The model achieves an overall accuracy of 68%, demonstrating its ability to reliably anticipate outcomes for around two-thirds of the test set.

Table 6. Random forests performance metrics for predicting mathematics achievement

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| ( ) 0.0 | 0.67 | 0.61 | 0.64 | 699 |
| ( ) 1.0 | 0.68 | 0.73 | 0.71 | 789 |
| Accuracy | | | 0.68 | 1,488 |

### 3.12. Use decision-tree algorithms for the prediction of math scores

Classification and regression tasks frequently use decision trees. It resembles a flowchart because each internal node corresponds to a feature, each branch to a set of instructions, and each leaf node to the result. The algorithm creates branches that maximize information gain or decrease impurity by recursively splitting the training data based on the chosen attributes [23]‒[25].

Table 7 show decision tree performance metrics for predicting mathematics achievement. Class 0.0 and class 1.0 precision scores, according to the categorization results, are 67% and 69%, respectively. Balanced F1-scores for classes 0.0 and 1.0 are 65% and 71%, respectively, with recall rates of 63% and 73% for each class. The model successfully predicts outcomes for almost two-thirds of the test set, with an overall accuracy of 68%. In the above Figure 4, the decision tree was obtained after training.

Table 7. Decision tree performance metrics for predicting mathematics achievement

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| ( ) 0.0 | 0.67 | 0.63 | 0.65 | 699 |
| ( ) 1.0 | 0.69 | 0.73 | 0.71 | 789 |
| Accuracy | | | 0.68 | 1,488 |

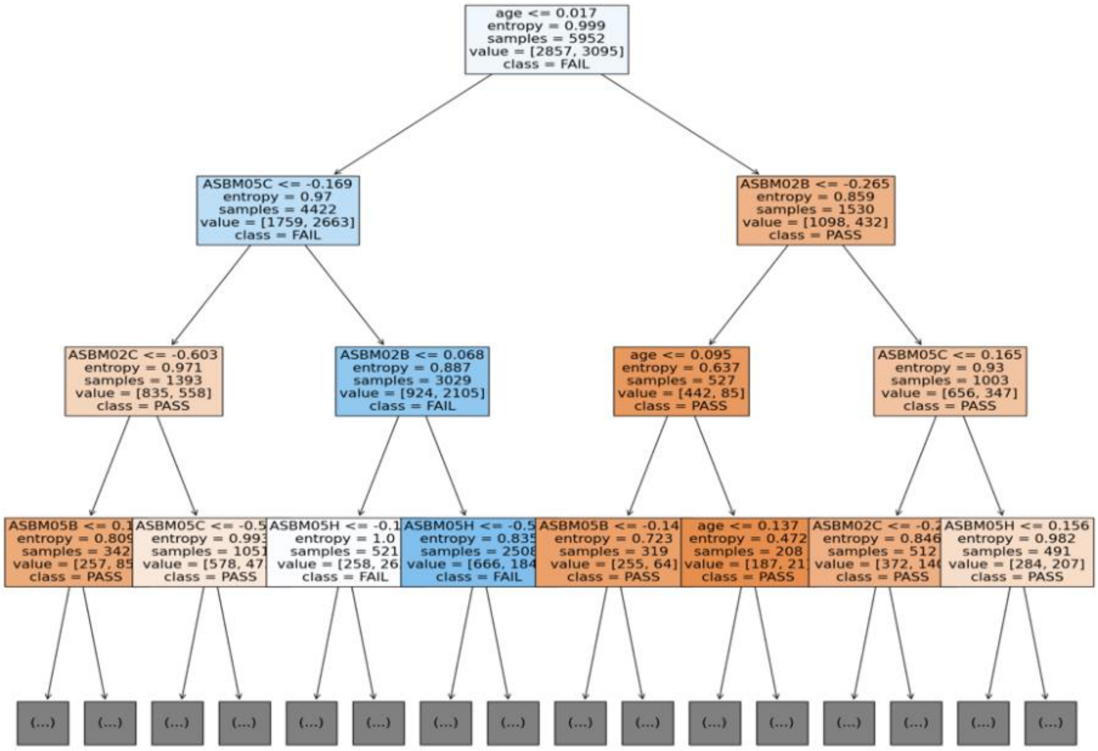


Figure 4. Decision trees for pass and fail classes in math tests

## 4. RESULTS AND DISCUSSION

The results for the performance of selected classification algorithms (accuracy, precision and recall) are summarized and presented in Table 8. When comparing the results of the different algorithms, it is evident that SVM, random forests, and decision trees outperform logistic regression and KNN in terms of accuracy, precision, recall, and F1 score. These three algorithms achieve consistently high precision and recall scores, ranging from 0.68 to 0.69 for class 1 precision and 0.73 for class 1 recall. Additionally, they exhibit high F1 scores and superior levels of accuracy, ranging from 0.67 to 0.68. On the other hand, logistic regression and KNN have slightly lower performance, with precision, recall, F1, and accuracy scores ranging from 0.66 to 0.67. Therefore, if the goal is to achieve the best overall performance, it is recommended to use SVM, random forests, or decision trees for predicting the math score.

Table 8. Comparison of model accuracy

| No. | Model | Percentage accuracy | Precision | Recall |
|---|---|---|---|---|
| 1 | Logistic regression | 66 | 0.66-0.67 | 0.59-0.73 |
| 2 | KNN | 67 | 0.66-0.68 | 0.62-0.72 |
| 3 | SVM | 67 | 0.64-0.69 | 0.66-0.67 |
| 4 | Random forest | 68 | 0.67-0.68 | 0.61-0.73 |
| 5 | Decision tree | 68 | 0.67-0.69 | 0.63-0.73 |

When comparing the results of the different algorithms, it is evident that SVM, random forests, and decision trees outperform logistic regression and KNN in terms of accuracy, precision, recall, and F1 score. These three algorithms achieve consistently high precision and recall scores, ranging from 0.68 to 0.69 for class 1 precision and 0.73 for class 1 recall. Additionally, they exhibit high F1 scores and superior levels of accuracy, ranging from 0.67 to 0.68. On the other hand, logistic regression and KNN have slightly lower performance, with precision, recall, F1, and accuracy scores ranging from 0.66 to 0.67. Therefore, if the goal is to achieve the best overall performance, it is recommended to use SVM, random forests, or decision trees for predicting the math score.

## 5. CONCLUSION

In conclusion, it is crucial to consider key strategies to improve mathematics achievement. First, fostering a proactive learning approach significantly improves students' subject knowledge and deepens their understanding of mathematical concepts. Second, incorporating practical teaching techniques, such as work examples, makes mathematics more accessible and relevant, allowing students to recognize the value and usefulness of the subject in real-world situations. Finally, the exploitation of the results of this study allows decision-makers and teachers to predict the future mathematical performance of students, thus facilitating adjustments to teaching methods, strategies, programs, and planning within educational establishments. teaching through the integration of machine learning techniques such as SVM, random forests, or decision trees.

## REFERENCES


[1] M. O. Martin and I. V. Mullis, *TIMSS 2019 assessment frameworks*. Amsterdam: International Association for the Evaluation of Educational Achievement, 2017. [Online]. Available: https://eric.ed.gov/?id=ED596167

[2] I. V. S. Mullis, M. O. Martin, G. J. Ruddock, C. Y. O. Sullivan, and C. Preuschoff, *TIMSS 2011 assessment frameworks*. Amsterdam, 2011. [Online]. Available: https://timssandpirls.bc.edu/timss2011/downloads/TIMSS2011_Frameworks.pdf

[3] A. M. Shahiri, W. Husain, and N. A. Rashid, "A review on predicting student's performance using data mining techniques," *Procedia Computer Science*, vol. 72, pp. 414–422, 2015, doi: 10.1016/j.procs.2015.12.157.

[4] B. K. Baradwaj and P. Saurabh, "Mining educational data to analyze students' performance," *International Journal of Advanced Computer Science and Applications*, vol. 2, no. 6, pp. 63–69, 2011.

[5] D. Kabakchieva, "Predicting student performance by using data mining methods for classification," *Cybernetics and Information Technologies*, vol. 13, no. 1, pp. 61–72, Mar. 2013, doi: 10.2478/cait-2013-0006.

[6] C. Anuradha and T. Velmurugan, "A comparative analysis on the evaluation of classification algorithms in the prediction of students performance," *Indian Journal of Science and Technology*, vol. 8, no. 15, 2015, doi: 10.17485/ijst/2015/v8i15/74555.

[7] P. Cortez and A. Silva, "Using data mining to predict secondary school student performance," in *15th European Concurrent Engineering Conference 2008, ECEC 2008 - 5th Future Business Technology Conference, FUBUTEC 2008*, 2008, pp. 5–12.

[8] Z. Khoudi, M. Nachaoui, and S. Lyaqini, "Identifying the contextual factors related to the reading performance of Moroccan fourth-grade students from a machine learning-based approach.," *Education and Information Technologies*, Jun. 2023, doi: 10.1007/s10639-023-11881-8.

[9] H. Bydžovská and L. Popelínský, "The influence of social data on student success prediction," in *ACM International Conference Proceeding Series*, 2014, pp. 374–375. doi: 10.1145/2628194.2628199.

[10] A. Polyzou and G. Karypis, "Grade prediction with models specific to students and courses," *International Journal of Data Science and Analytics*, vol. 2, no. 3–4, pp. 159–171, Dec. 2016, doi: 10.1007/s41060-016-0024-z.

[11] A. Khan and S. K. Ghosh, "Student performance analysis and prediction in classroom learning: a review of educational data mining studies," *Education and Information Technologies*, vol. 26, no. 1, pp. 205–240, Jan. 2021, doi: 10.1007/s10639-020-10230-3.

[12] N. Z. Salih and W. Khalaf, "Prediction of student's performance through educational data mining techniques," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 22, no. 3, p. 1708, Jun. 2021, doi: 10.11591/ijeecs.v22.i3.pp1708-1715.

[13] M. Mursalin, Y. Zhang, Y. Chen, and N. V Chawla, "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier," *Neurocomputing*, vol. 241, pp. 204–214, Jun. 2017, doi: 10.1016/j.neucom.2017.02.053.

[14] N. Thai-Nghe, L. Drumond, A. Krohn-Grimberghe, and L. Schmidt-Thieme, "Recommender system for predicting student performance," *Procedia Computer Science*, vol. 1, no. 2, pp. 2811–2819, 2010, doi: 10.1016/j.procs.2010.08.006.

[15] M. Y. Kiang, D. M. Fisher, J.-C. V. Chen, S. A. Fisher, and R. T. Chi, "The application of SOM as a decision support tool to identify AACSB peer schools," *Decision Support Systems*, vol. 47, no. 1, pp. 51–59, Apr. 2009, doi: 10.1016/j.dss.2008.12.010.

[16] F. J. Ferri, P. Pudil, M. Hatef, and J. Kittler, "Comparative study of techniques for large-scale feature selection* *This work was suported by a SERC grant GR/E 97549. The first author was also supported by a FPI grant from the Spanish MEC, PF92 73546684," in *Machine intelligence and pattern recognition* 1994, pp. 403–413. doi: 10.1016/B978-0-444-81892-8.50040-7.

[17] P. Fabian *et al.*, "Scikit-learn: machine learning in python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[18] P. Wang, E. Fan, and P. Wang, "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning," *Pattern Recognition Letters*, vol. 141, pp. 61–67, Jan. 2021, doi: 10.1016/j.patrec.2020.07.042.

[19] A. Sun, E.-P. Lim, and Y. Liu, "On strategies for imbalanced text classification using SVM: a comparative study," *Decision Support Systems*, vol. 48, no. 1, pp. 191–201, Dec. 2009, doi: 10.1016/j.dss.2009.07.011.

[20] Z. Rustam, D. A. Utami, R. Hidayat, J. Pandelaki, and W. A. Nugroho, "Hybrid preprocessing method for support vector machine for classification of imbalanced cerebral infarction datasets," *International Journal on Advanced Science, Engineering and Information Technology*, vol. 9, no. 2, p. 685, Apr. 2019, doi: 10.18517/ijaseit.9.2.8615.

[21] J. Zeffora and S. Shobarani, "Optimizing random forest classifier with Jenesis-index on an imbalanced dataset," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 26, no. 1, p. 505, Apr. 2022, doi: 10.11591/ijeecs.v26.i1.pp505-511.

[22] B. Bina, O. Schulte, B. Crawford, Z. Qian, and Y. Xiong, "Simple decision forests for multi-relational classification," *Decision Support Systems*, vol. 54, no. 3, pp. 1269–1279, Feb. 2013, doi: 10.1016/j.dss.2012.11.017.

[23] A. Khalaf, "Selection of best decision tree algorithm for prediction and classification of students' action," *American International Journal of Research in Science, Technology, Engineering & Mathematics*, vol. 16, no. October, p. 26, 2016.

[24] M. H. B. M. Razali, R. B. Saian, Y. B. Wah, and K. R. Ku-Mahamud, "A class skew-insensitive ACO-based decision tree algorithm for imbalanced data sets," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 21, no. 1, p. 412, Jan. 2021, doi: 10.11591/ijeecs.v21.i1.pp412-419.

[25] M. Better, F. Glover, and M. Samorani, "Classification by vertical and cutting multi-hyperplane decision tree induction," *Decision Support Systems*, vol. 48, no. 3, pp. 430–436, Feb. 2010, doi: 10.1016/j.dss.2009.06.004.

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