Identifying Key Predictors of Filipino Students' Mathematics Performance in PISA 2022 Using the Random Forest Machine Learning Algorithm

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Abstract: *Filipino students are still struggling with mathematics, as seen in the results of both the 2018 and 2022 Program for International Student Assessment (PISA) results, where the Philippines is currently ranked 76th out of 81 countries in the test. While there is a slight increase in the average test score from 2018 to 2022, the country still lags behind the global OECD average. Several studies have already utilized the 2018 Philippine PISA data using machine learning algorithms, and this research continues by using the 2022 data to understand the key predictors of Filipino students' mathematics performance. Using the Random Forest (RF) algorithm, the study was able to identify three main themes based on personal and contextual factors that have contributed to the low performance of Filipino students in mathematics: (1) learning access and support; (3) socio-environmental stressors; and (3) mindset and motivation. The model was able to achieve an 83.3% accuracy and 82.4% precision score for the prediction model. Further research is needed to compare the 2018 and 2022 results using advanced machine learning techniques and must be continued in subsequent Philippine PISA scores in the next years to track progression and improvements.*

1. Introduction

The Philippines continues to struggle in the education sector, currently facing numerous crises that ultimately lead to a decline in student performance in mathematics. In both iterations of the Program for International Student Assessment (PISA) results in 2018 and 2022, the Philippines is below the Organization for Economic Cooperation and Development (OECD) average of 358 for mathematics proficiency, garnering a score of 353 in 2018 and only a slight improvement in 2022 with a score of 355 [1]. This ranks the Philippines 76th out of 78 countries in 2018 and 81st out of 81 countries in 2022. The Philippines' proficiency level in mathematics, science, and reading is low regardless of social status, residence, gender, and school type [2], but private schools have performed better than public schools [3]. The Philippines' best students are only comparable to an average student in neighboring Asia-Pacific countries such as Thailand, Vietnam, Malaysia, and Brunei [1].

This research continues upon the previous research studies that have utilized machine learning techniques to profile Filipino students on their mathematics [3], science [4], and reading proficiency [5] scores. Using machine learning techniques, specifically the Random Forest (RF) algorithm for this research, allows analysis of the data in a multi-level analysis based on different features available from the PISA dataset. In turn, complex relationships and factors will be identified. Moreover, by using the updated 2022 data, new insights will be drawn that can help in determining the causes of declining student performance. Recommendations of this study benefit the community of students, educators, and policymakers in improving the current educational landscape in the Philippines.

This study investigates the personal and contextual factors that contribute to the low performance of Filipino students in mathematics based on the 2022 PISA data using the Random Forest algorithm, a machine learning technique that builds multiple decision trees for classification. Specifically, the study can achieve the following:

1. Analyze relevant student, family, and school-level variables associated with low mathematics proficiency.
2. Apply the Random Forest algorithm in classifying student performance levels in mathematics using the 2022 PISA data; and
3. Identify the themes that contribute to the proficiency scores of the students in mathematics.

2. Related Literature

The Philippines' PISA scores are widely discussed by researchers and educators in the Philippines due to their disappointing results. Using the 2018 PISA results, several research studies have used five machine learning algorithms—logistic regression, Multilayer Perceptron (MLP), Support Vector Machines (SVM), decision trees, and RF—to profile students' performance in mathematics [3], [6], science [4], and reading proficiency [5], [7]. In [3] for mathematics, their RF model has achieved 79% accuracy, and 69% precision was achieved for public school students, while 79% accuracy and 81% precision were achieved for private school students. [3] have noted important factors that contribute to the low proficiency in mathematics: resource limitations, lower aspirations in the future in terms of getting a college degree or having a high-paying job, and lower importance of schooling. Another paper has used SVM, garnering an 82% accuracy, to identify the best performing students in mathematics based on the 2018 PISA data from 12 Asia-Pacific countries, including the Philippines [6]. In [4] for science, they achieved a 74% accuracy and 74% precision for their RF model, and the most important variables include reading metacognitive awareness, experiences in the classroom, and motivational experiences. In [5] for reading proficiency, the highest accuracy score belonged to the SVM model, achieving an 81%, while the highest contributors include difficulty in reading, bullying, and work mastery. Another study [7] focusing on Filipino students' reading achievement also uses RF and highlights variables concerned with personal and contextual characteristics such as reading difficulty, socioeconomic status, and repeating a grade. It is evident that solving the crises in each subject area demands multi-faceted responses, as each has its own problems. Moreover, while no study links all three subject areas and the common factors that influence their proficiency, there is a need to understand that some of the factors cannot be solved in the classroom and need the participation of all stakeholders for the betterment of a student in the future.

3. Methodology

The study uses the Random Forest algorithm to create a prediction model that categorizes a Filipino student's mathematics score—whether high or low—using the 2022 PISA data and uses the model to identify the key predictors of mathematics performance from the dataset. The following subsections discuss the dataset (3.1), including its cleaning and normalization; (3.2), and the Random Forest algorithm, including its hyperparameters and evaluation (3.3).

3.1. Dataset

The 2022 PISA data[1] is used for this study, which is publicly available to download. As stated in the PISA 2022 report [8], the PISA 2022 surveys 15-year-old students from Grade 7 and above to take the test, and this cycle was impacted by the COVID-19 pandemic due to unforeseen school closures. The cognitive tests for PISA 2022 include mathematics, science, reading proficiency, creative thinking, and financial literacy. A total of 6631 Filipino students have participated in the PISA dataset. Only the Student Dataset is used for this study, which comprises 684 variables.

Since RF needs structured numerical input, cleaning the dataset is essential to allow it to capture meaningful patterns and to ensure that the results are statistically reliable and interpretable. A combination of manual and automated cleaning was performed on the dataset. Variables with 50-100% missing values were removed. Variables that were not numerical or Boolean were not included. Moreover, feature selection was done by removing variables with high pairwise correlation ($|\rho| > 0.75$) to minimize multicollinearity and redundancy. Imputation was also applied to substitute values inside columns with partially missing values. For this, mean imputation was used to supply the missing values, where the mean of the column was used as a substitution. The transformation of categorical variables into their numeric counterpart was performed manually. After the cleaning process, a total of 414 variables and 6630 rows remained.

Once the data had been cleaned, data normalization was performed to adjust numerical data. Dichotomous questions and those that use frequency and the Likert scale were transformed. Continuous numerical variables were normalized using Min-Max scaling to make the values in the [0,1] range. Moreover, one-hot encoding was used to transform categorical variables. The AVERAGE variable was transformed into a binary target for the classification task, where Class 1 pertains to the low performers (AVERAGE < 357.7) and Class 0 for the high performers (AVERAGE ≥ 357.7).

After cleaning the data, the dataset was divided into an 80/20 split for the training and testing data, respectively. 5304 rows were included for the training, while 1326 rows are solely for testing the model.

3.2. Random Forest Algorithm

The Random Forest algorithm is a machine learning technique that uses multiple decision trees, which consist of nodes to represent the decisions, and the branches connect the nodes to split the decision, indicating its flow [9]. One of the main motivations for using the Random Forest algorithm is its best results from [3], along with its ease of implementation. Moreover, using the Random Forest algorithm allows for determining the key variables that contribute the most in making a decision for classification. The machine learning model was coded using the Python programming language and uses the package scikit-learn to create the Random Forest model. Visualizations use the seaborn and matplotlib packages.

To determine the best parameters to be used for the Random Forest algorithm, Grid Search was employed, which exhausts possible combinations to determine the parameter that would return the highest results from the metrics. Table 1 shows the values that are considered in the Grid Search, and all possible combinations of these values will be used to identify which of them will produce the highest evaluation metric scores. The maximum depth values are taken from [3] while the other values are arbitrarily chosen.

Table 1. Hyperparameter values for Grid Search.

[1] https://www.oecd.org/en/data/datasets/pisa-2022-database.html

Hyperparameter	Description	Values
Number of estimators	Number of decision trees in the forest	10, 50, 100, 200, 500
Maximum depth	Maximum depth of the nodes inside the decision tree	4, 5, 6, 7, 8, 9, 10, 11, 12, 15, 20, 30, 40, 50, 70, 90, 120, 150
Minimum samples split	Minimum number of samples before splitting a node in the tree	2, 5, 10
Criterion	Criterion measures the quality of the split of a node. "gini" refers to Gini index where it measures the probability of being incorrect from a random element; "entropy" measures how much randomness is in the data labels	"gini", "entropy"

3.3. Evaluation

The model was evaluated on four metrics: accuracy, precision, recall, and F1 score. The accuracy (3.3.1) measured the proportion of correctly predicted instances—true positive (TP) and true negative (TN)—divided by the total number of instances. Precision (3.3.2) measured to the number of correctly identified positive cases. Recall (3.3.3) measured how many positive cases are correctly classified. Lastly, the F1 score (3.3.4) combined the Precision and Recall scores to get its harmonic mean.

$$accuracy = \frac{TP + TN}{Total} \tag{3.3.1}$$

$$precision = \frac{TP}{TP + FP} \tag{3.3.2}$$

$$recall = \frac{TP}{TP + FN} \tag{3.3.3}$$

$$f_1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right) \tag{3.3.4}$$

4. Results and Discussion

Table 2 shows the results after the Grid Search for the Random Forest model, where the model was able to achieve 83% accuracy, 82% precision, 78% recall, and 80% F1 score based on the hyperparameters stated below.

Figure 1a shows the confusion matrix of the model using the best hyperparameters, and Figure 1b shows the Area Under the ROC Curve (AUC), which is another metric to determine the effectiveness of the Random Forest classifier in distinguishing between Class 0 and 1. The AUC-ROC curve explains how well the RF classification model identifies whether a student from the training data is considered above or below average. The model achieved a 0.92 AUC score, which indicates good performance of the model when considering all possible thresholds.

Table 2. Evaluation scores of the Random Forest model after grid search.

Metric	Score	Hyperparameters
Accuracy	0.8333	
Precision	0.8241	Criterion: "gini" Maximum depth: 12 Minimum samples split: 10 Number of estimators: 500
Recall	0.7793	
F1 score	0.8011	

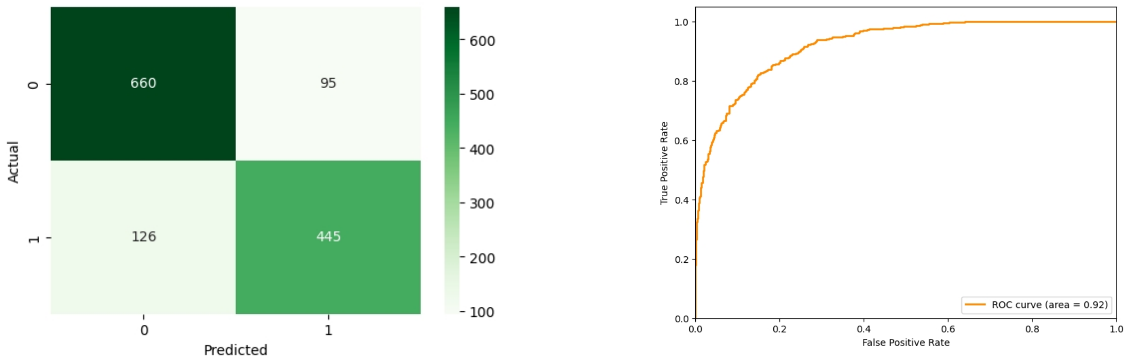

Figure 1. (a) Confusion matrix of the Random Forest model using the best hyperparameters; **(b)** Area under the ROC curve for the Random Forest model.

To determine the most important variables from the dataset that influence whether a learner performs good or not, the Shapley Additive Explanations (SHAP) values are used. These attribute each feature a contribution to the prediction by computing the average marginal effect of including that feature across all possible feature subsets. Figure 2 show the top 15 features based on the degree of significance, while Table 3 show the name and variable label from the PISA 2022 codebook.

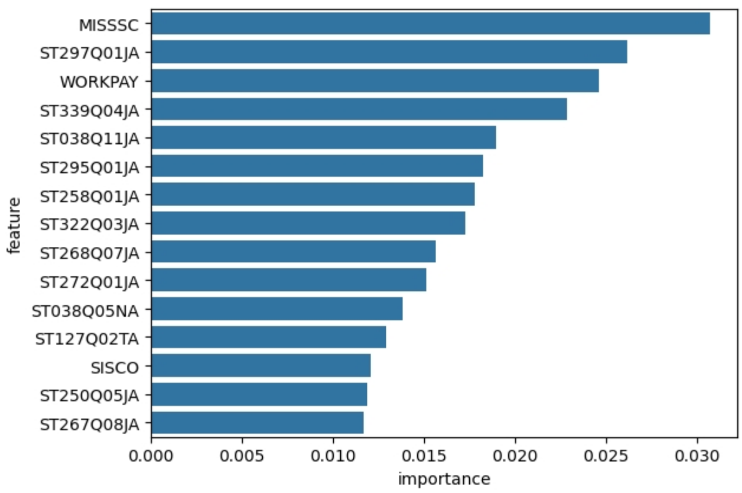

Figure 2. Most important variables based on the computed SHAP values

Table 3. Top 15 variables and their label based on the PISA 2022 codebook

Name	Variable Label
MISSSC	Missing school for more than 3 months
ST297Q01JA	[Additional math instruction] received: One-on-one tutoring with a person
WORKPAY	Working for pay before or after school
ST339Q04JA	Agree/disagree: Creativity can only be expressed through the arts (e.g. drawing, music, or writing)
ST038Q11JA	In past 12 months, how often: I gave money to someone at school because they threatened me.
ST295Q01JA	How many days/wk after school: Eat dinner
ST258Q01JA	In the past 30 days, how often did you not eat because there was not enough money to buy food?
ST322Q03JA	How often: I keep my [digital device] near me to answer messages when I am home.
ST268Q07JA	Agree/disagree, I want to do well in my mathematics class.
ST272Q01JA	On a 1-10 scale, rate the quality of mathematics instruction this school year? Quality of mathematics instruction?
ST038Q05NA	In the past 12 months, how often: I was threatened by other students.
ST127Q02TA	Have you ever repeated a [grade]: At [ISCED 2]
SISCO	Clear idea about the future job
ST250Q05JA	Which of the following are in your [home]: Internet access (e.g. Wi-fi) (excluding through smartphones)
ST267Q08JA	Agree/disagree: The teachers at my school are mean towards me.

From the top 15 features, three main themes emerge: (1) learning access and support; (2) socio-environmental stressors; and (3) mindset and motivation.

The first theme pertains to the learning access and support of the learners, which includes the chronic absenteeism of students as well as their received support in tutoring. The top predictor (MISSSC) has the highest impact among the variables in the study, where students often fall behind if they do not go to school. This is supported by [10], where absenteeism in Filipino students also has a negative relationship with parental involvement. Another study [11] also supports this, where academic performance is affected as well as social interaction with peers and teachers. It is important to note that the PISA 2022 data was collected during the COVID-19 pandemic; thus, missing school for months may have occurred. There are DepEd memoranda from different regions that support home visitation to help cope with the situation [12], [13] which allows teachers to conduct visits to learners that has missed school for a period of time. While effects of the chronic absenteeism are detrimental to the student, school interventions can only do so much with the efforts of the teachers and more student support such as programs for easing poverty, lessening expensive projects that will push-out students, and providing basic school resources [14] which will enable them to regularly attend school. Moreover, as shown in the results that one-on-one tutoring (ST297Q01JA) is a key predictor of mathematics performance, this can be adopted in schools for students to minimize the gaps on learning competencies.

Related to this is the variable ST127Q05NA (*Have you ever repeated a grade*), which puts emphasis that early interventions to prevent students from repeating a grade are necessary to prevent lasting effects on the learner. In the Philippines, a learner repeats a grade if a student did not meet expectations (final grade of less than 75) in three or more learning areas according to a DepEd memorandum [15]. While there are no available data from the past few years about student repetition in public schools, there is data from the EDCOM II [16] that suggests that the dropout rates are declining. Further research is needed to investigate the effects of grade repetition of Filipino students, especially in basic education, since these years serve as foundations for their succeeding years in school.

Instructional support for learning, from the variables ST297Q01JA (*One-on-one tutoring*), which is the top 2 of the variables, and ST272Q01JA (*Quality of mathematics instruction*), emphasizes the quality of education and its support that the learners receive. This may indicate that a direct focus on the student enhances their performance, or it may suggest that struggling students are in much more need of one-on-one tutoring to improve their performance. Nevertheless, tutoring in the Philippines has been supported by literature such as peer tutoring [17], [18] and tutorial programs [19]. Additionally, a meta-analysis supports peer tutoring that exhibits positive effects on mathematics performance [20]. Teachers may adopt strategies in one-on-one tutoring based on results of formative and summative assessments and encourage parents and guardians to support their children at home.

On the quality of mathematics instruction, this can also go in two directions where students who receive a higher quality will receive better performance, rather than those who do not. However, the Philippines' mathematics performance in the 2022 PISA suggests that there is room for improvement in addressing the quality of instruction. For instance, the EDCOM II [16] reports that 62% of high school teachers do not teach their original major, and a lack of structured professional growth after graduation and employment to improve the content of their lessons and better ways on how to deliver it. A study recommends the streamlining of quality assessment or assurance (QA) in teaching educational institutions to ensure quality in education major graduates and harmonization of standards and reinforcement in teacher education [21].

Socio-environmental stressors refer to the external hindrances to the learner that they may or may not have agency to control. The top 3 variable WORKPAY (*Working for pay before or after school*) creates competing demands for the student as they must balance studying and working at the same time, which competes with the learner's need to survive and learn at the same time. This relates to an earlier study about school dropout in the Philippines, where one of the main factors includes students being employed or looking for work and a lack of family income to send them to school [14]. Additionally, ST295Q01JA (*Eating dinner*) and ST258Q01JA (*Not enough money to buy food*) suggest that nutrition is an indicator of mathematics performance in school. In the literature review by [22] from Philippine studies, findings suggest that students with better nutrition often relates to good academic performance. This is a complex problem that requires multifaceted support not only from the education sector but from the family and society at large.

While bullying did not have the highest impact in the model, concepts related to it, such as ST038Q11JA (*Giving money due to threats*) and ST038Q05NA (*Threatened by other students*) are among the top 15. This calls for a school environment that is nurturing and a safe space for students to thrive. The EDCOM II Year 2 report has an extensive discussion about bullying in the Philippines, where the Philippines ranks first among the countries in the PISA 2018 results [16]. Research papers such as [23], [24] also discuss bullying in the Philippines, where both papers call to action on a holistic approach in solving bullying within the school environment due to its complex nature. While [23], [24] discuss bullying using the 2018 PISA data, a deeper investigation is needed to address these concerns about bullying both on the national and local levels in Philippine municipalities.

Surprisingly, the variable ST267Q08JA (*Teachers being mean)* is also included, which may indicate that teachers, as the forefront of the creators of safe spaces in classrooms, should also be mindful of how they interact with students to establish the positive environment they are trying to cultivate. For instance, a study by [25] shows that students who interact with teachers who exhibit excessively controlling approaches to teaching (e.g., physical and verbal abuse) are moderately associated with them being bullied by their peers, and the study highlights the importance of supportive relationships within the school community. Learners should feel a sense of safety and belonging in school and the classroom to improve their performance, especially under the influence of teachers who hold power over the classroom.

Other variables related to the second theme include competing stressors such as the presence of digital devices while studying (ST322Q03JA) and the availability of Internet access (ST250Q05JA), which suggest that digital devices and the Internet have an impact on studying, especially in the post-pandemic era where students are accustomed to digital learning. A similar study that uses the 2022 PISA data reveal that while having a device helps in academic performance, its excessive use can lead to detrimental effects in their academic performance due to it becoming a distraction to learning and suggests interventions such as limiting screen time and proper app usage [26].

Mindset and motivation relate to the student's mathematics performance in terms of their agency and identity in school. For instance, the variable ST268Q07JA (*I want to do well in my Mathematics class*) is important as students should aspire to become better in class to achieve a better performance. Future mindset is also taken into consideration based on the variable SISCO (*Clear idea about future job*). Creativity (ST339Q04JA) is also included in this theme, which is interesting as a mindset about the arts also impacts mathematical performance. This can be interpreted as a holistic and well-rounded approach to education that improves performance, requiring an equal appreciation and interconnectedness of different disciplines.

5. Conclusion

This research uses machine learning to identify the key predictors in the low proficiency scores of Filipino students in the 2022 PISA mathematics test. Using the Random Forest algorithm, the model is able to achieve 83.3% accuracy for the prediction model, which can be used to predict a Filipino student's proficiency. The model identifies missing school for more than three months, one-on-one tutoring, and working for pay as the top predictors based on the variables of the 2022 PISA test. Moreover, themes are identified based on the top 15 predictors: (1) learning access and support, which includes variables for chronic absenteeism and instructional support; (2) socio-environmental stressors, such as nutrition, bullying, and digital devices; and (3) mindset and motivation in mathematics and the future.

Recommendations of this study include a risk assessment tool that can be used by teachers to allow them to identify a student's proficiency outside of test scores, as the factors identified in the study also contribute to their well-being and performance in school. In terms of the model, other machine learning algorithms can also be explored, and their performance compared with the Random Forest and evaluate whether the model is still appropriate to be used in this classification task. Using other machine learning algorithms can also help in identifying key predictors and can be used to compare and contrast with the results of this paper to see the common variables that were identified.

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