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Predictions of Academic Performance of Children and Adolescents with ADHD Using the SHAP Approach

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Abstract

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder characterized by inattention and/or impulsivity-hyperactivity symptoms. Through Machine Learning methods and the SHAP approach, this work aims to discover which features have the most significant impact on the students' performance with ADHD in arithmetic, writing and reading. The SHAP allowed us to deepen the model's understanding and identify the most relevant features for academic performance. The experiments indicated that the Raven_Z IQ test score is the factor with the most significant impact on academic performance in all disciplines. Then, the mother's schooling, being from a private school, and the student's social class were the most frequently highlighted features. In all disciplines, the student having ADHD emerged as an important feature with a negative impact but less relevance than the previous features.

Keywords:

Attention-Deficit/Hyperactivity Disorder, Academic Performance, Machine Learning

Introduction

Present in the Diagnostic and Statistical Manual of Mental Disorders (DSM), Attention-Deficit/Hyperactivity Disorder (ADHD) is defined by harmful levels of inattention, disorganization and/or hyperactivity and impulsivity, symptoms that are excessive when compared with other people of the same age and degree of development. Surveys suggest that ADHD occurs in most cultures in about 5% of children and 2.5% of adults, being more frequent in males [1].

The damage caused by ADHD affects the individual's life in several ways. In this context, the school has a fundamental role in human cognitive and socioemotional development. However, due to their peculiar functioning, students with ADHD tend to have significant academic problems, such as learning difficulties, behaviors considered inappropriate to the school environment, difficulties in relationships with colleagues, and considerable educational and social losses. Consequently, schools must adopt appropriate strategies to develop students with ADHD effectively. However, in general, educational institutions have found it difficult to deal with students with the disorder [2]. Given this, due to the difficulties inherent to ADHD and schools' low adequacy to deal with students with the disorder, it is natural to find a general picture of students' low performance.

On the other hand, it is believed that ADHD is not a definitive factor of low performance. Despite the difficulties imposed by the disorder, there are individuals with ADHD who do not have academic deficits [3]. Thus, it is possible that other characteristics enhance or minimize the damage caused by the disorder.

Given the scenario described, it is necessary to raise the characteristics that interfere with students' performance with ADHD. Identifying success cases and understanding what factors led to this positive outcome can help guide actions that benefit other students. Studying low-performance cases, understanding which characteristics influenced this situation can provide subsidies for parents, educators, and other professionals (psychologists, psychiatrists, and neurologists) to direct their actions for better results for students.

The Pediatrics Department of a Brazilian university surveyed 266 people aged between 6 and 18 years, of which 196 were diagnosed with ADHD. This survey generated a database with 225 characteristics of these children/adolescents. A database of students with ADHD is a valuable research source and needs to be the object of study searching for knowledge about this scenario with open questions. At this point, data mining can play an important role, as it often points out relationships that, at first, even experts are unable to perceive.

The advancement of Machine Learning (ML) methods has enabled models that typically achieve high predictive capacity. However, in many scenarios, having a model with high predictive performance only partially solves the problem since understanding the behavior drives decision-making and increases the confidence of the person who will execute it [4, 5]. For this reason, in many contexts, as in the case of the present work, it is essential to provide interpretable models.

SHapley Additive exPlanations (SHAP) is an approach to interpreting predictive models based on cooperative game theory [6]. SHAP helps explain ML models, allows understanding the effects of features in individual predictions in a classification problem.

Therefore, this work aims to discover, through ML methods and the SHAP approach, which features have the most significant impact on students' performance with ADHD in arithmetic, writing, and reading. We believe that a model with an adequate predictive capacity associated with the interpretability resources present in SHAP allows us to view the main features that must be observed and worked on with ADHD students to increase their academic performance.

For each discipline, predictive models were developed based on four ML methods: Decision Tree, Neural Networks, Support Vector Machines (SVM), and Random Forest. The model based on Random Forest obtained the best performance and, therefore, interpretability with SHAP was performed only to it.

Methods

Database description

This research is developed in partnership with the Department of Pediatrics of a Brazilian university. The institution carries out support work for children and adolescents with a previous diagnosis of ADHD. Once the diagnosis is confirmed, patients are monitored at the hospital linked to the institution. The medical team responsible for this monitoring surveyed patients and guardians through manual questionnaires and interviews. This survey gave rise to the database object of this study.

The database contains 266 people (instances) aged between 6 and 18 years. Among them, 196 people are diagnosed with ADHD and 70 have a negative diagnosis for the disorder. The database consists of 225 attributes, including personal, gestational, medical, socioeconomic, parental care, education, family data, and the scores related to the individuals' arithmetic, writing, and reading tests. Figure 1 presents an overview of the database with the types of attributes and their quantities.

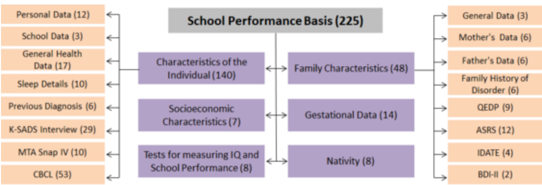

Figure 1 – Attributes description, organized by category

Prediction models development

To improve the quality of the data, we pre-process the database. In summary, the following were accomplished:

1. Transformation of scores obtained in the School Performance Test, which is subdivided into writing, arithmetic, and reading, in the higher and lower classes. The School Performance Test Manual [7] was used to compare students' scores with the average grade of the same state where the test was applied.
2. Exclusion of duplicate attributes (e.g., age in months and age in years) or irrelevant (e.g., name and phone number) to predict school performance.
3. Binarization of non-ordinal nominal attributes, such as the father's marital status and disorders that the student had. That is, each attribute was coded as the presence or absence of the feature.
4. For the missing data, the mode and the median were used as statistical measures to fill in the data.
5. Manual random separation of 15% of the instances of each class to perform the testing step.
6. Balancing the remaining 85% of the data using the SpreadSubsample algorithm present in the WEKA tool. Table 1 shows the number of instances reserved for training and testing in each discipline.
7. The dimensionality reduction of the arithmetic, writing, and reading bases was performed using a genetic algorithm (GA) to improve the models' performance. We chose Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to find the best subset of features maximizing your fitness, in this case, the F-measure. The K-Nearest Neighbors (KNN) classifier was used to measure the F-measure. The GA was implemented in the Python language, using the DEAP library.

Table 1 – Number of instances for training, validation, and testing

Discipline	Training/Validation	Test	
		Higher	Lower
Arithmetic	118	11	29
Writing	100	09	31
Reading	78	08	27

Prediction models development

In the quest to obtain the best predictive capacity in each discipline, models based on four ML methods were developed: Decision Tree, Neural Networks, SVM, and Random Forest. The models were implemented in Python using the Scikit-learn library. The proposal is to develop the interpretability of only the models with the best performance in each discipline.

The Precision, Recall, and F-measure metrics were used to assess the quality of the models. All classifiers were built and validated using the k-fold cross-validation process, with $k = 10$.

Results

We generated models with different ML methods to understand students' profiles with ADHD, to identify the most relevant features in success and low academic performance. Figure 2 presents the results of the test phase of the prediction models. In general, the model based on Random Forest obtained the best results. Occasionally, the other models presented similar or superior results for precision or recall in a given class/discipline. Therefore, we decided to perform the model interpretation with Random Forest for all scenarios.

For the interpretability of tree-based models, SHAP offers the Tree Explainer [6], the algorithm used in the explanation models described below. Figure 3 shows the generated plots. The features mentioned in the description of the experiments are listed in Table 2, as well as the numerical transformation of their values.

Model experiments for Arithmetic

Regarding arithmetic, the model with Random Forest obtained a F-measure of 87% for the lower class and 72% for the higher class, considering that it has a good predictive capacity for performance in that discipline.

Exploring the resources in SHAP, we can see in Figure 3a an overview of the effects of the main features in predicting performance in arithmetic for the lower class. This plot orders the features by their importance. It uses the SHAP values to show the distribution of impacts that each attribute has on the model's output. Each point present on the line for a given feature represents an instance, and therefore a student that has been impacted by that feature. The color represents the value of the feature in the instance (high red, low blue). Considering the central axis of the graph, if an instance is on the right-hand side of a feature line (positive SHAP values), such a feature brings the instance closer to the lower class. Likewise, if the instance is on the left (negative SHAP value), the same feature moves it away from the lower class. It is important to note that the farther from the central axis of the graph, the more significant the impact of that feature for a given instance. The attributes at the bottom of the graph have few points and these are very close to the central axis, which denotes that this attribute has a minor effect on the model.

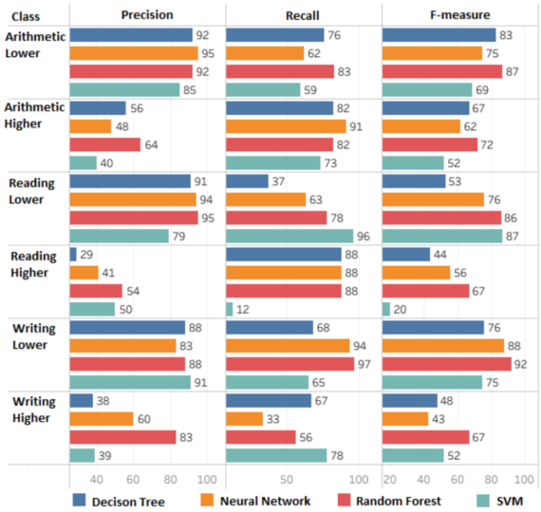

Figure 2 – Models performance evaluation

Table 2 – Features highlighted in the explanation models

Feature	Domain
Mother_schooling/ Father_schooling	1 to 4 years(0), 5 to 8 years(1), Incomplete HS(2), Complete HS(3), Incomplete graduation(4), or Complete graduation(5)
Social class	Poor(0), Vulnerable(1), Middle class(2) or High class(3)
Raven_Z	-3.58...2.41
ADHD (if the patient has ADHD)	Yes(1) or No(0)
School Year	Early childhood education(0), First year(1), Second year(2), Third year(3), Fourth year(4), Fifth year(5), Sixth year(6),Seventh year(7),Eighth year(8), Ninth year(9) or High school(10)
Height	1,06...1,72
Mother_age	22...67
School_type	Public school (0) or Private school(1)
Sex	Male(0) or Female(1)

Thus, it is possible to perceive that the Raven_Z is the feature of a more significant influence in predicting the student's performance in arithmetic. The clear separation on the line of this feature from the red dots on the left of the central axis and the blue dots on the right shows that low values in the Raven_Z test tend to lower arithmetic performance. Raven_Z is a widely used intelligence (IQ score).

Also, analyzing the attributes with the most relevant impact, the positive and notable influence of highly schooled mothers, high-class families, and studying in a private school is noteworthy. Finally, the graph confirms that the student having ADHD is a complicating factor for school performance in arithmetic, although it is preceded in importance by other features.

To deepen the behavior of a given feature, SHAP has the graph shown in Figure 3b. In this case, it was decided to explore the effect of the Raven_Z test score for the lower class in arithmetic since this proved to be the most relevant attribute to predict performance in the discipline. It can be seen that negative scores contribute to the instance belonging to the lower class (positive SHAP values).

The same plot optionally allows relating another attribute. In this case, we chose to observe the distribution of Raven_Z scores to the ADHD attribute, in which the red dots refer to students with the disorder and the blue dots refer to students without the disorder. It is noticed that in the highest scores of Raven_Z the presence of students with or without ADHD. On the other hand, in the lowest scores, there is a predominance of students with the disorder.

Figure 3c allows us to visualize the features that led to the prediction of a particular student as lower performance in arithmetic. The features that drive the prediction for the chosen class (lower) are shown in red, those that distance the prediction for this same class are in blue. It is noted that the low level of schooling of parents and the fact that they are from a public school brings students closer to the lower class. On the other hand, having a good score on the Raven_Z test distance him from the lower class.

Model experiments for Writing

For writing, the model reached the F-measure of 92% for the lower class and 67% for the higher class, representing a meaningful result for the lower class but a predictive capacity with limitations for the class higher.

The impacts of the main features related to writing performance can be seen in Figure 3d. Again, Raven_Z appears as the most relevant feature, in which low score values contribute to lower performance prediction. As in arithmetic, attributes such as type of school, mother's education, social class, and having ADHD appear with prominence and similar behavior for writing, although in different orders of importance. The sex attribute emerges with significant importance. According to the graph's explanation, being male approaches the prediction of lower performance and the female sex contributed to the instances being predicted as being of the higher class.

Figure 3e shows the plot of the mother's schooling for writing. It is possible to note that mothers with lower schooling levels contribute significantly to student performance prediction as lower. The behavior of this feature in arithmetic is similar.

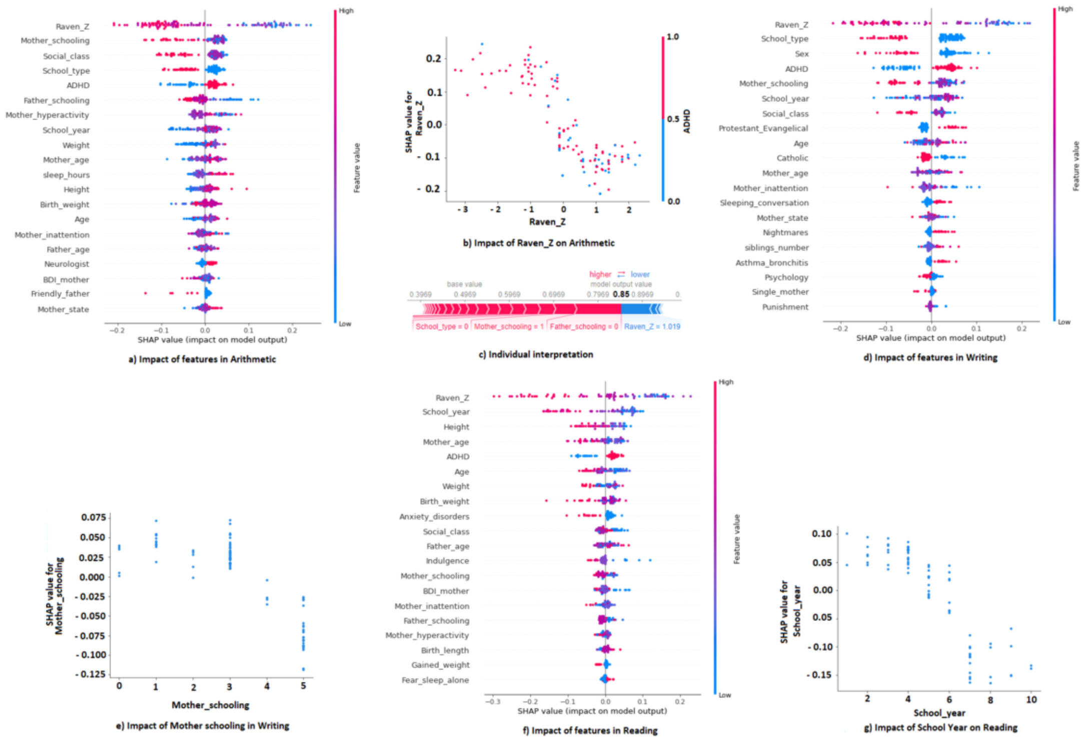

Figure 3 – Interpretability plots

Model experiments for Reading

The model's behavior for reading obtained 86% for the lower class and 67% for the higher class, showing a more significant predictive capacity for the lower class.

Figure 3f shows that the Raven_Z test score was once again the most relevant feature for the model with similar behavior as the other disciplines since high test scores indicate better performance in reading.

The school year is the second most important feature for reading. Through Figure 3g, it is possible to interpret that the student improves his reading performance over the years.

It is reasonable to assume that the student's height attribute among the most relevant is possibly related to the school year. Naturally, over the years, the tendency is to have higher height values.

Finally, we observe the relevance of the feature mother's age, which being the child of older mothers contributes to the student's performance.

Discussion

Some aspects common to the three disciplines can be observed. Regardless of the discipline, the model has a greater predictive capacity for lower performance. Although the ideal would be to have high rates for both classes, the model behaved very well for the lower class is considered satisfactory. Understanding students' profiles with low performance to direct reflections and actions to this group were the factors that motivated the creation of the database by the specialists.

The interpretability resources pointed to the Raven_Z test score as the most important feature in predicting academic performance in all scenarios. Low scores on the Raven_Z contribute a lot to the prediction for the lower class.

The influence of features related to the student's mother, such as education or age, appears in all disciplines. The model considers a positive impact on mothers with complete or incomplete graduation. The other lower levels of schooling almost always harm performance. In arithmetic, the father's schooling showed relevance but with less importance than the mother's.

The explanation model presents attributes such as social class and school type as important for predicting performance. Such features added to the mother's schooling build a framework where the best economic conditions and school and family support are essential in individuals' academic lives, especially in students with ADHD. They need the support of various natures for their development process. On the other hand, it is important to reflect on individuals who do not have such favorable attributes and still have to live with complications resulting from the disorder.

The behavior of the attribute school year caused questioning, as it presented a somewhat divergent behavior in the disciplines since, for reading, the advancement of school years positively affects performance, and for arithmetic and writing, the initial years contribute to higher performance. It is necessary to deepen the understanding of this attribute's behavior, considering the need to maintain a critical view of both the original and explanation models.

Interestingly, attributes related to comorbidities commonly related to ADHD and medication use did not appear among the relevant features in the studied scenarios.

Conclusions

This research sought to recognize individuals with ADHD profile in an academic environment by identifying the features of the most significant impact on student performance in the arithmetic, writing, and reading disciplines. Some ML methods were tested and the Random Forest proved to be the most suitable for the scenario in question.

For reflections and actions to be performed, it is necessary to understand the model's decisions, especially understanding how the attributes influenced the prediction process. Thus, the use of the SHAP approach for interpretability proved to be helpful. Its resources allowed to deepen the model's understanding and identify the relevant features for academic performance.

The experiments indicated that the student's IQ, represented in the database studied by the Raven_Z IQ test, is the factor with the most significant impact on academic performance in all disciplines. Then, the mother's schooling, being from a private school, and the student's social class were frequently highlighted attributes. This result indicates that the school and family support around the student positively influences their academic performance. In all disciplines, the student having ADHD emerged as an important attribute with a negative impact, but in general, less relevant than the previous features.

Finally, bringing together the explanations from the interpretability resources used, it is possible to assess that ADHD is indeed a complicating factor for academic performance, but other attributes can minimize or enhance its impact. In the ML field, it was possible to realize that the interpretability features allow exploring the models substantially more profitable.

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