The Thirty-Second International Florida
Artificial Intelligence Research Society Conference (FLAIRS-32)

Using EEG Features and Machine Learning to Predict Gifted Children

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Abstract

Gifted students have a higher capability of understanding and learning. They are characterized by a high level of attention and a high performance in the classroom. Gifted children are defined in this paper as children who have a performance higher than the average group (59.64%). In order to predict gifted students from normal students, we conducted an experiment where 17 pupils have voluntarily participated in this study. We collected different types of data (gender, age, performance, initial average in math and EEG mental states) in a web platform to learn mathematics called NetMath. Participants were invited to respond to top-level exercises on the four basic operations in decimals. We trained different machine learning algorithms to predict gifted students. Our first results show that the decision tree could predict gifted students with an accuracy of 76.88%. Using J48 trees, we noticed also that two relevant features could determine gifted children: the relaxation extracted from EEG headset and the characteristic of strong student. A strong student is defined as a student who obtained a mean higher than the group's mean in the first step evaluation in class.

Introduction

Nowadays, the performance of students in primary school is very different. It varies from an individual to another. Students could be generally divided into three groups: Strong, medium and weak. The weak students have generally a performance under the mean's performance of the class group. The medium students have a performance around the average class group. However, the strong students have a highest performance. A high value of performance could be a sign to characterize gifted, talented or high creativity students. In this paper, we define gifted students as students who obtained a mean score above the group average in some exercises designed for top-level students. According to Zettel (1979), general intelligence usually manifests in Intelligent Quotient (IQ). Gifted students have an IQ of 130 or above. They are characterized by a mean value of attention (around 60%) and slightly weak values of the mental states of attention and workload compared to the weak pupils (Ghali et al. 2018).

In the literature, several studies have been conducted to identify and detect gifted students. Most studies focus on the measurement of intelligence quotient (IQ) with psychometric tests such as the Wechsler Intelligence Scale for Children (WISC) (Weschsler 1949), the Wechsler Abbreviated Scale of Intelligence (WASI) (Weschsler 1999), and Raven's progressive matrices (Raven 1941). However, to our knowledge very few studies have been interested in predicting gifted students using biometric metrics such as electroencephalogram (EEG). In order to answer this point, we propose in this paper to present a comparison of machine learning models able **to predict gifted students** from normal students. These models are built from a collection of a dataset using EEG mental variation states statistics (attention, relaxation and workload) and a complementary information of a student (age, note and initial performance).

The paper is organized as follows. In section 2 we present some related works about the use of machine learning techniques to predict gifted children. Section 3 describes the experiment conducted in a primary school and how we collect data in order to train machine learning models. Finally, section 4 provides a discussion of our results in terms of using machine-learning algorithms to predict gifted students.

Related Works

In the area of educational psychology, many works have been done to predict final marks of students (Romero et al. 2013), student success (Kovacic 2009, Brown 2017), performance (Muammar 2015, Bhaskaran et al. 2017) which are all related to behaviours of gifted students but not the giftedness itself. Curby et al. (2008) identified some features, which play an important role to the prediction of gifted enrollment. They showed that, students enrolled in gifted programming were those with high cognitive ability but also those who showed early task orientations. Pavleković et al. (2010) proposed an intelligent expert system (MathGift) which assist teachers in making decision about a child's gift in mathematics. The system uses cognitive components of gift, personal components that contribute to gift development, strategies of learning and exercising, as well as some environmental factors to estimate giftedness.

Machine learning techniques have a wide use in the prediction and classification of different variables, but their application in the area of educational psychology is still relatively rare. Just a few studies used machine learning to predict giftedness. For example, Pavleković et al. (2011) tried to model a neural network capable of detecting mathematically gifted elementary school students. As input variables they used teachers' assessments of five components of mathematical giftedness, while the output variable was psychologists' assessment whether the child was mathematically gifted or not. Pavlin-Bernardić et al. (2016) also used neural networks to predict students' general giftedness using teachers' and peers' nominations, school grades, earlier school readiness assessment and parents' education. However, they do not include biometric data in their models.

Unlike existing works which focus only on features able to predict achievements of gifted people based on experiments and statistical analysis or using machine learning to build models but not based on biometric data, we propose a model able to predict if a person is gifted or not, based on its answers (performance) on exercises and its EEG data.

Experiment and Data Collection

Definition

We define a gifted child in this paper as a child who obtained a score above the group's mean score in the experiment with NetMath Platform[1] (tasks are designed to high level students and not seen in the classroom). We report a group average score of **59.64%.** So, we consider children who had a score higher than 59.64% as gifted students.

Experiment

In order to detect gifted children using machine learning algorithms, we conducted an experiment where we collected data from 17 pupils (M=10.05; SD=0.42) from a primary school (École Samuel de Champlain, Brossard, Canada). Pupils (4th and 5th grade) are asked to solve math tasks designed for a higher level (6th grade). These tasks are described in detail in our previous paper (Ghali et al. 2018). While they answered to these tasks, we collected electroencephalogram (EEG) data from a Neeuro Senzeband non-invasive EEG headset. This headset allows us to obtain EEG raw data from 4 channels and three mental states measures (Attention, Workload and Relaxation).

Data preprocessing

Data from the previous experiment were collected in a separate csv file for each participant. Data were synchronized with the log file and we extracted for each participant five statistics (mean, median, standard deviation, minimum and maximum) of the three mental states according to each exercise of *Netmath platform*. We also used some complementary data in order to determine if a child is gifted or not, such as the age of the participant, the difficulty of the exercise (from 1 to 3), its score (from 0 to 100), strong student (yes or no if his score is higher than the class average score) and the time he took to answer (in seconds). All these attributes constituted a raw data for each participant with a total of 143 instances for all the participants. Each row is labeled with gifted equal to "Yes" for a specific exercise, if a child scores above the group's mean score and with gifted equal to "No" otherwise. The goal is to predict the value of the gifted (Yes or No) based on the EEG data and other information.

Results

In this section, we describe the results obtained by four different machine learning algorithms: J48 decision tree, Naïve Bayes, Bagging and AdaBoost. We chose only to communicate the best results (accuracy is higher than 65%) obtained from different machine learning algorithms. The choice of those algorithms is based on the fact that we don't have a large dataset and it has been shown that those machine learning techniques work well on few data (Forman et al. 2004, Wu et al. 2008, Bhargava et al. 2013) compared to most recent techniques such as neural networks for example. In a Machine learning point of view, small data requires models that have low complexity (as those we selected) (or high bias) to avoid over-fitting the model to the data. One of the advantages choosing those methods is that, for example with a decision tree, we are able to visually and explicitly represent decisions and able to easily point out features that are important for the prediction (Ali et al. 2012) (which play an important role to the prediction of gifted in our case). To estimate the performance of the models, we used the k cross validation technique with k fixed to 10.

[1] https://www.netmath.ca/fr-qc/

Table1: Accuracy and Root Mean Square Error of Machine learning models on the original dataset

Models	*Accuracy (%)*	*RMSE*
J48 Trees	*65.035*	*0.5612*
Bagging	*69.930*	*0.451*
Ada Boost	***70.629***	***0.4543***
Naïve Bayes	*70.629*	*0.5088*

Table 2: TP, FP and F-measure of Machine Learning Models on the original dataset.

Models	*TP*		*FP*		*F-measure*	
	Y	*N*	*Y*	*N*	*Y*	*N*
J48 Trees	*0.78*	*0.349*	*0,651*	*0.22*	*0.757*	*0.375*
Bagging	*0.88*	*0.279*	*0.721*	*0.12*	*0.804*	*0.279*
Ada Boost	*0.85*	***0.372***	***0.628***	*0.15*	*0.802*	***0.432***
Naïve Bayes	***0.92***	*0.209*	*0.791*	***0.08***	***0.814***	*0.3*

Experiments with our data set resulted in 4 different models able to predict gifted children based on EEG data with one that, we can visually analyze. The models were evaluated based on 5 well known metrics: Accuracy, Root Mean Squared Error (RMSE), True Positive (TP), False Positive (FP) and F-measure. In table 1 and table 2, we report these statistics.

From table 1, we see clearly that Ada Boost is the best model to predict gifted children because it has the highest value of accuracy (70.629%) and the lowest value of root mean square error (0.4543). Naïve Bayes always has good performance but higher RMSE followed by bagging and J48 trees. However, in table 2, we report statistics of TP, FP and F-measure. We highlight in this table (TP and F-measure) the highest values for each class and each machine learning model. For the FP metric, we highlight the lowest value as the more it is low, the better is the model. As we can see, AdaBoost is the best model because it gives a higher value for the two classes (Yes or No) but we notice that the value of the class "No" (students are not gifted) is still very weak

Table 3. Accuracy and Root Mean Square Error of Machine learning models on dataset 3.

Models/dataset3	Accuracy (%)	RMSE
J48 Trees	**76.88**	0.4463
Bagging	74.37	**0.413**
Ada Boost	70.35	0.448
Naïve Bayes	67.83	0.5009

(less than 0.44). This result can be explained by the fact that our dataset is unbalanced. In the total of 143 instances that we have, 100 instances correspond to the class "Yes" while only 43 belong to the class "No".

As the data set is unbalanced, the TP, FP, F-score measures is less than 0.4 for the class gifted= "No". The models built from this data set are biased toward the class that has more instances. Therefore, we applied some techniques that aim to balance dataset. The first technique we had chosen is the penalization of models (Cost-sensitive models (Shi et al. 2015)). It works as follows: we penalize the classification by imposing an additional cost on the models for making classification mistakes on the minority class during training. The penalties can bias the model to pay more attention to the minority class. However, this technique was unsuccessful because the results was not better than using the original dataset. The second technique we used aims at resampling the dataset (Ghosh et al. 2017). With this technique, the models are insured to not be biased toward one class. Thus, we ran other experiments on 3 versions of the original dataset. We obtained those three versions by resampling the dataset as follow:

- For the dataset 1, we used the under-sampling technique. We randomly selected a subset of samples from the class "Yes" as it has more instances, to match the number of samples from the class "No". Thus, we randomly picked 43 out of the 100 examples from class "Yes".
- The remaining 57 examples from class "Yes" added with the 43 examples from class "Yes" form the dataset 2.
- For the third dataset, we used the oversampling technique which consisted of randomly duplicate 57 samples from the class "No" in other to have 100 examples in each class.

We reported for each of the machine learning technique we selected, the best results obtained from one of the 3 datasets we used.

We can already see that results are much better than when we used the original dataset. From table 3, we see that, now **J48** is **the best model** to predict gifted children because it has the highest value of accuracy (76.8%). However, the bagging algorithm has the lowest value of RMSE (0.413). Naïve Bayes do not have good performance compared to the first experiment. We noticed also that in the J48 decision tree we obtained the root node is the feature « Strong » which means it is the best predictor of gifted children. The two second best predictors are the "attention" and the "relaxation".

Conclusions

The present work provides valuable information and results regarding the prediction of gifted children based on EEG data. We present a set of machine learning models able to predict gifted children. We found out that the main features of that prediction were the "strong" factor which is true for a pupil when he obtains a mean higher that the group's mean in the first step evaluation in class, and the "relaxation" factor from the EEG data, whereas a lower value of attention seems to be related to non-gifted student.

Our proposed solutions will help schools to better select children who should follow programs for gifted students in schools. In this preliminary work, we were able to predict gifted students. The results of studies such as ours can be useful to guide research towards a deep analysis on the impact of biometric data on predicting giftedness and also in developing more sophisticated machine learning models to be able to detect gifted persons. The result we drawn are only based on 143 examples which may not be enough to make some conclusions. Our future works therefore aim at enriching and test the models on a larger dataset and validate the assumptions we made in a large scale.

Acknowledgments

We thank FRQNT (Fonds de Recherche du Québec en Nature et Technologies) for supporting this work and Mrs Christine Nadeau to welcoming us in her school.

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