Comparation of Machine Learning Algorithms for ADHD Detection with Eye Tracking

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Abstract. ADHD, or attention deficit hyperactivity disorder, is a persistent pattern of inattention that affects both young people and adults, causing interference with their functioning and overall development. The objective of this study is to develop an efficient diagnostic tool based on machine learning algorithms. The proposed tool utilizes eye-tracking technology to collect data on patients' eye movements while engaging in a concentration game. The eye movement patterns are carefully analyzed and categorized into two groups: patients with ADHD and those without. Initially, a manual classification was performed, followed by the training of algorithms, resulting in F1 scores of 100%, 95.55%, and 60.86% for KNN, ANN, and SVM, respectively. The main goal of this project is to provide a comparation comparison between four machine learning techniques and get base for a diagnostic tool that surpasses the accuracy of current diagnostic methods. By achieving this, it aims to enhance the precision and efficiency of ADHD diagnosis, ultimately improving the quality of care and support provided to individuals with this condition.

Keywords: ADHD · Machine Learning · Eye Tracking · Diagnosis

1 Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is characterized by persistent patterns of inattention and/or hyperactivity that interfere with functioning or development. In ADHD, the inattention aspect of the disorder manifests as distractibility, lack of persistence, difficulty concentrating, and confusion. Hyperactivity involves excessive movement in inappropriate situations or engaging in excessive fidgeting, tapping, or excessive talking. Symptoms of this disorder can range from mild to absent [1].

Individuals with ADHD often exhibit a pattern of hyperactivity or inattention that hinders proper development. Common characteristics of patients with ADHD include frequently not following instructions, inability to complete tasks, being easily bothered or entering a state of denial when faced with mentally demanding tasks that require

J. de J. A. Flores Cuautle et al. (Eds.): CNIB 2023, IFMBE Proceedings 96, pp. 3–13, 2024.
https://doi.org/10.1007/978-3-031-46933-6_1

prolonged effort. Currently, the diagnosis of this disorder is conducted through various medical examinations, such as auditory and visual tests, to rule out other disorders with similar symptoms to ADHD. A crucial stage in the process is completing a checklist to assess ADHD symptoms. It is important to highlight that diagnosis and treatment should be carried out by an interdisciplinary team available in specialized neurology clinics, consisting of different experts in this pathology [1].

Machine learning is a branch of technology to learn various tasks using data analysis and prediction algorithms. This tool in the field of medicine has a wide range of applications that can contribute to diagnosis. The application of this technology is highly beneficial for data mining in medical research and acquiring knowledge to improve health outcomes [2, 3].

Currently, there are already several investigations on different methods for detecting ADHD, such as electroencephalographic signals (EEG), attention and continuous performance test (CPT), as well as patient behavioral activity (BA). These studies employ different metrics than those obtained in this research [4 − 6].

Previously works using eye tracking for detect some disorders, this technique can be using for diagnosis and detection of spectrum autism, neurological disorders or affect for medications. Thus, is because the eye movements are a principal indicator of concentration, distraction and neurological impulses [13, 14].

The objective of this research is to develop a comparation of four popular algorithm of machine learning for detect ADHD that can accurately identify individuals with this disorder. This algorithm relies on a variety of characteristics associated with ADHD, such as inattention and hyperactivity. By analyzing different variables and features of the obtained samples, the algorithm can be a valuable tool in establishing a reliable diagnosis. It is important to emphasize that this diagnosis cannot replace existing evaluations conducted by a trained mental health professional. However, our intention is for it to serve as a supportive tool, providing additional information for clinical diagnosis.

2 Methodology

2.1 Signal Acquisition

For this work, we developed a graphical user interface (GUI) using the Python language. This GUI displayed a central point, and random images appeared around this point at a frequency of 2 Hz. Eye movement signals were acquired using a camera. To do this, participants were required to hold their heads in a static position and look directly at the central point. See Fig. 1.

This investigation was conducted with the participation of sixteen clinically diagnosed ADHD students and sixteen students without indications of this mental disorder, who were asked for their consent and were shown that their data would be anonymous in the research. All participants were between the ages of 18 and 27 and are students of biomedical engineering at the Autonomous University of Chihuahua.

The experiment acquired data for 15 s at a frequency of 12.4 Hz. This work used 80 signals (S_{ADHD}) for the class of ADHD and 80 signals (S_{NOADHD}) for the class of No ADHD. This was for the application of 10 experiments per participant [13]. The

Fig. 1. GUI and a participant for sample collection.

data was divided into two groups: train and test. The train group contained 70% of the signals (*tr*), while the test group contained the remaining 30% (*ts*). In order to perform the algorithms, we use windows 10 with 16 GB RAM memory and using MATLAB 2020b.

2.2 Data Preprocessing

Each signal S^D; D = {tr, ts} has two signals corresponding to the movement of the iris in the axis x and the movement on axis y denoted by $pl = \{x_l, y_l\};\ l = \{1,2,3,\ldots L\}$. Using mapminmax algorithm Eq. (1) where *c* correspond at class c = {ADHD, NOADHD}, *r* represents the number of experiment r = {1,2,3…R} and *i* is the sample i = {1,2,3,… I} on the signal.

$$Norm_{c,r,i}^{D,pl} = \text{mapminmax}\left(S_{c,r,i}^{D,pl}\right) \tag{1}$$

This process was necessary for the variation on the position of the camera during data acquisition.

2.3 Feature Extraction

The feature extraction was necessary for develop the description of each signal. The features selected show a variation with eye movement, for this we used the feature of entropy whit the Eq. (2).

$$H_{c,r}^{D,pl} = Entropy(Norm_{c,r,i}^{D,pl}) \tag{2}$$

Other feature was the energy calculated with the Eq. (3)

$$E_{c,r}^{D,pl} = Energy(Norm_{c,r,i}^{D,pl}) \tag{3}$$

The finish feature was the standard deviation, for this we used the Eqs. (4), where $\overline{Norm_{c,r}^{D,pl}}$ represent the average of the signal $Norm_{c,r}^{D,pl}$ and I represents the number of samples in this signal.

$$\sigma_{c,r}^{D,pl} = \sqrt{\frac{\sum_{i=1}^{I}(Norm_{c,r,i}^{D,pl} - \overline{Norm_{c,r}^{D,pl}})}{I}} \tag{4}$$

Each feature was put into a vector how show in the Eq. (5)

$$V_{c,r}^{D} = [H_{c,r}^{D,x}, H_{c,r}^{D,y}, \sigma_{c,r}^{D,x}, \sigma_{c,r}^{D,y}, E_{c,r}^{D,x}, E_{c,r}^{D,y}] \tag{5}$$

2.4 Support Vector Machine

The algorithm of support vector machine (SVM) using a linear kernel for classification data [7, 8]. In this case, we used a SVM trained into MATLAB with *fitcsvm* function and V^{tr} vectors. The results are shown in the Eq. (6). Where V^{ts} represents the vector for predicting and the subindices are the position agree Eq. (5) and W represent the value of each component calculated from the SVM model.

$$R_{svm} = W_1 * V_1^{ts} + W_2 * V_2^{ts} + W_3 * V_3^{ts} + W_4 * V_4^{ts} + W_5 * V_5^{ts} + W_6 * V_6^{ts} + W_b \tag{6}$$

2.5 Artificial Neural Network

An artificial neural network, or simply a neural network, is a mathematical model based on biological brain networks [9, 10]. The ANN designed contains 6 inputs, 1 hidden layer with 5 neurons and 2 outputs (see Fig. 2). The network's training schedule was carried out using 15 epochs, a validation check of 6, a learning factor of 1×10^{-7} and a minimum error 1×10^{-29}, using the Levenberg-Marquardt backpropagation technique. These numbers were acquired experimentally using vectors of trained group.

2.6 K-Nearest Neighbors

The KNN algorithm, known as K-nearest neighbors, is a machine learning technique used for classification and regression. Its approach is based on identifying the nearest distances between a new sample and a set of training samples, allowing it to make predictions [11].

For this algorithm, is necessary to obtain the training data, which consists of a series of instances with their own features and a class label. This training vector allows training the classification model with the nearest neighbors using the *fitcknn* function in MATLAB, this makes a model calculates the Euclidean distance between the sample data point and the training data. This allows finding the K nearest neighbors to the sample point, where K is a predefined parameter representing the number of closest neighbors to consider for prediction. In this case, the selected value for K was 7.

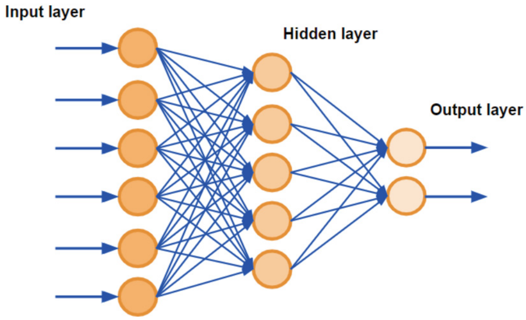

Fig. 2. ANN design with 6 inputs, one hidden layer of 5 neurons with sigmoidal tangential activation function and two outputs.

Finally, the classes to which these K nearest neighbors belong are tallied: ADHD (K_{ADHD}) and non-ADHD (K_{NOADHD}), and the number of identified classes is compared. See Eq. (6)

$$Class = \begin{cases} ADHD \quad if \;\; K_{ADHD} >= K_{NOADHD} \\ NOADHD \; if \qquad otherwise \end{cases} \tag{7}$$

2.7 Naïve Bayes

The Naive Bayes (NB) classifier is a generative learning method that assumes each feature, where the features are independent and do not interact with each other. It is a computationally efficient tool that can handle large datasets with multiple dimensions [12].

The probability of a specific class was calculated using Eq. (7). This equation refers to the random probability of a vector belonging to a patient with ADHD or a patient without ADHD, respectively. The number of vectors for training that agree at class c is denoted by N. Since this number is equal for both classes, the probability is 50%.

$$P_c = \frac{N_{V_c^{tr}}}{N_{V_{ADHD}^{tr}} + N_{V_{NOADHD}^{tr}}} \tag{8}$$

Afterward, statistical values of the mean $((\overline{X}_{c,j}))$ and variance $(\sigma_{c,j}^2)$ were determined with the help of Eqs. (8) and (9), where j represents each characteristic, c corresponds to each of the classes, c = {ADHD, NOADHD}, r represents an experiment and $N_{V_{c,j,r}^{tr}}$ corresponds to the total of data for each characteristic j of the class c.

$$\overline{X}_{c,j} = \frac{\sum^{(} V_{c,j,r}^{tr})}{N_{V_{c,j,r}^{tr}}} \tag{9}$$

$$\sigma_{c,j}^2 = \frac{\sum^{(} V_{c,j,r}^{tr} - \overline{X}_{c,j})^2}{N_{V_{c,j,r}^{tr}} - 1} \tag{10}$$

Subsequently, using Eq. (10), the probability of a new sample belonging to a class was calculated as a function of each characteristic.

$$Pr_c = \left(\prod P(c|j)\right)(P_c) \tag{11}$$

To obtain the priority (Pr_c), the product of the probabilities obtained in Eqs. (10) and Eq. (7) was used with the help of Eq. (11).

$$Pr_c = \left(\prod^{P}(c|j)\right)(P_c) \tag{12}$$

Then, the evidence (Ev) was calculated using Eq. (12), which was used in Eq. (13) to calculate the posteriori (Ps_c) and determine the probability of each class.

$$Ev = \sum^{P} r_c \tag{13}$$

$$Ps_c = \frac{Pr_c}{Ev} \tag{14}$$

Finally, to determine the class to which the sample belongs, the rule presented in Eq. (14) must be followed.

$$Class = \begin{cases} ADHD & if \; Ps_{ADHD} > Ps_{NOADHD} \\ NOADHD \; if & \quad Otherwise \end{cases} \tag{15}$$

2.8 Metric Evaluation

With the remaining 30% of the data, we evaluated the accuracy of each algorithm to assess their performance and reliability. To evaluate these metrics, Eqs. (15), (16), (17) and (18) were used to determine the precision, accuracy, recall and F1 score, as can be seen in the equations the data of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN), which were being obtained with the development of the algorithm, are used. Precision focuses on the proportion of correct positive results, recall focuses on the ability to find all positive cases, accuracy focuses on the proportion of correct predictions overall, and the F1 score combines precision and recall to provide a balanced measure of model performance.

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{16}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{17}$$

$$Recall = \frac{TP}{TP + FN} \tag{18}$$

$$F1 = 2\frac{PrecisionRecall}{Precision + Recall} \tag{19}$$

The development of the eye-tracking algorithm for ADHD diagnosis is a complex procedure that must be carefully elaborated, as it takes into account multiple factors as mentioned before, including data selection and preparation. (See Fig. 3).

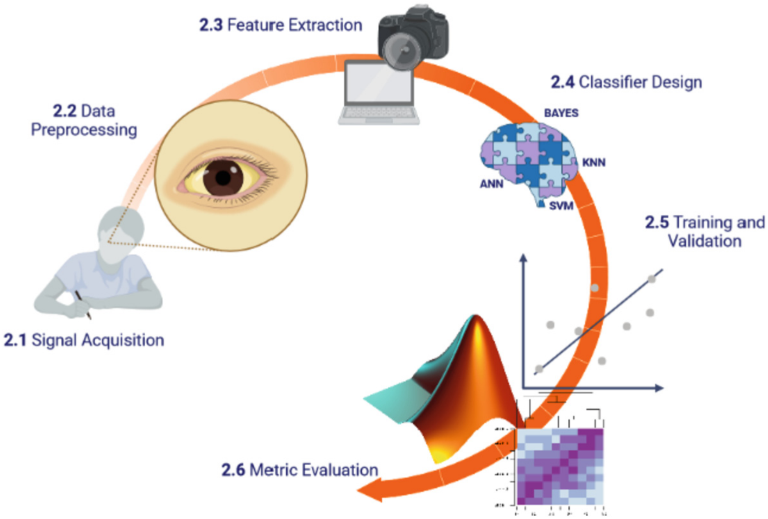

Fig. 3. Diagram illustrating research methodology

3 Results

The designed algorithms of SVM, ANN, Naïve Bayes, and KNN was evaluated using V^{ts} data to obtain our results. Where our SVM is show in Fig. 4. This was our lowest performing algorithm, with an accuracy of 46.66%, precision of 43.75%, recall of 87.50%, and an F1 score of 60.86%.

Next, the results obtained from our artificial neural network can be observed in Fig. 5. The metric results show an accuracy of 95.83%, precision of 96.66%, recall of 93.33%, and an F1 score of 95.55%.

SVM			
Real	ADHD	21	24
	No ADHD	3	0
		No ADHD	ADHD
		Prediction	

Fig. 4. SVM algorithm confusion matrix

ANN			
Real	ADHD	23	1
	No ADHD	1	23
		No ADHD	ADHD
		Prediction	

Fig. 5. Confusion matrix of the artificial neural network

For the Bayesian algorithm, the results are presented in a confusion matrix shown in Fig. 6. The metric results with an accuracy of 93.75%, precision of 93.75%, recall of 87.5%, and an F1 score of 93.33%.

NB			
Real	ADHD	21	0
	No ADHD	3	24
		No ADHD	ADHD
		Prediction	

Fig. 6. Confusion matrix of the Naïve Bayes algorithm

Lastly, our best-performing algorithm, KNN, is presented in Fig. 7. This show 100% accuracy, precision, recall, and F1 score.

KNN			
Real	ADHD	24	0
	No ADHD	0	24
		No ADHD	ADHD
		Prediction	

Fig. 7. Confusion matrix of the KNN algorithm

4 Discussion

The development of an eye tracking algorithm for the diagnosis of ADHD is a promising area of research in the integration of biomedical engineering and psychology. The eye tracking method can provide objective information about attention patterns and gaze control in patients with ADHD, which could improve traditional diagnostic methods based on clinical observations and subjective evaluations. It is important to consider that an eye tracking algorithm for ADHD diagnosis may present significant challenges.

The main advantage of this type of systems is the reduction of time for detection ADHD in comparation with method of recompilation of data from family, clinical history and psychological test. If the tool mentioned on this paper is only a probe, in a future this can be used how a first intervention in case suspicious for a deep analysis agree the results and congruence with a specialist. As mentioned earlier, several studies have been conducted using different methods for ADHD diagnosis. The inclusion of the biomedical engineer in this field offers several important advantages.

Firstly, the eye tracking method provides a continuous and non-invasive measure of visual behavior, allowing for the capture of subtle patterns and important features of eye movement. For example, features such as fixation frequency, duration, movement speed, and deviation from the fixation point demonstrate significant differences between patients with ADHD and individuals without indications of the disorder. Furthermore, it offers advantages in terms of objectivity and standardization, reducing the inherent bias in clinical assessments and improving diagnostic consistency. By automating the process of analyzing eye tracking data, variability is reduced, and the reliability of diagnostic results is increased. Table 1 shows a comparison of metrics obtained from different previously investigated diagnostic methods, highlighting the significant performance difference of the mentioned algorithms.

This approach also has the potential to reduce costs and time in the diagnosis of ADHD. By using eye tracking algorithms and machine learning, a supportive model has been developed to detect individuals with ADHD. This automation allows for a more efficient and rapid evaluation, facilitating early detection and timely intervention.

While further development and validation are required, this project offers an innovative and effective way to objectively assess ADHD and improve the quality of life for affected individuals. The inclusion of biomedical engineering in psychology, through the development of tools such as the eye tracking algorithm, enables interdisciplinary collaboration that drives significant advancements in the diagnosis and treatment of mental disorders, thereby enhancing patient care and well-being.

Table 1. Comparison of accuracy represented in percentage for various methods used in the algorithms.

Algorithm	EEG (%)[4]	CPT (%)[6]	BA (%)[5]	ET (Ours) (%)
SVM	96.4	-	71.9	46.66
ANN	96	89	72.1	95.83
KNN	81.2	-	84	100
NB	-	-	69.8	93.75

The present work is designed to focus on the diagnosis of children, as it is a difficult field to detect ADHD, but it would be introducing another graphical interface that could be suitable for preschool infants. Some of the main changes that would be made in the GUI would be the way in which the images are presented to children, since compared to adults in children it is easier for them to be distracted whether they are patients with ADHD or not, so it would be ideal to present another series of images to be able to evaluate them with eye tracking

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