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EEG Based Identification of Learning Disabilities using Machine Learning Algorithms

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Abstract

A learning disability (LDs) is a comprehensive word used for various learning problems. Children with learning disabilities are not sluggish or intelligently retarded. Learning disability is a neurological condition that is characterized by a vague understanding of words and poor reading skills. It affects many school-aged children, with fellows being more likely to be involved, placing them at risk for deprived academic concerts and low self-esteem for the rest of their lives. Our research entails developing a machine learning model to analyse EEG signals from people with learning difficulties and provide results in minutes with the highest level of accuracy. In this research, we have used Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) methods were used for component analyse of the dataset. For classification purposes we have used Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), K-nearest neighbours (K-NN), Decision Trees and XGBoost, etc., different types of algorithms. The goal is to determine which data pre-processing approaches and machine learning algorithms are the most effective in detecting learning disabilities.

Keywords: Electroencephalography • Learning disability • Feature extraction • Classification algorithms • Machine learning

Introduction

A learning disability is caused by a nervous condition [1]. For a child with a learning disability, reading, writing, spelling, forming things, and so on can be hard [1]. It has nothing to do with the IQ of a child [2]. The children, however, can be aided in discovering their potential and determining future career decisions with the correct identification and assistance. Machine learning is now used in a variety of businesses to anticipate future events. Two of the most useful applications of machine learning include predicting learning impairments in children and determining the underlying causes. Learning difficulties can be caused by a variety of factors [1,2]. A learning handicap affects one's capacity to grasp knowledge. It's tough to comprehend the nature of these disabilities. However, there has been substantial progress in mapping some of the challenges that learning impairment types face, as well as specific brain regions and structures.

If a person has a visual, hearing, or motor impairment, it is not considered a learning disability. Mental retardation, emotional instability, or cultural issues are not considered learning disabilities [3].

Electroencephalography (EEG) is one of the newer approaches being investigated for identifying specific brain activation patterns in learning disabilities [1-5]. Electroencephalography detects electrical activity present in our brain with the help of metal caps (electrodes) that are placed on our scalp by using 10-20 system as shown in Figure 1. Even when you are sleeping, electrical impulses interact between your brain cells. This activity appears as wavy lines on an EEG recording.

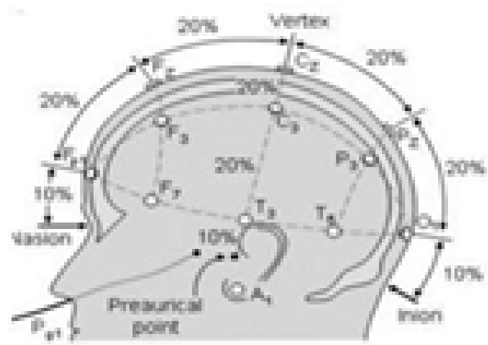

Figure 1. 1-10-20 system for EEG sampling [2]

Machine learning is being used to predict future events in a variety of sectors. The most useful areas of machine learning applications are predicting learning problems in children, diagnosing the actual disability, and determining how early it may be recognized. In this research comprises creating a machine learning model that will assess a data set obtained from the EEG signals of different learning difficulties like dyslexia and ADHD (attention deficit hyper disorder) and offer accurate results in minutes.

Methods

Problem statement

Identify and evaluate the most commonly practiced techniques used to classify the EEG data associated with learning disabilities, and to evaluate the accuracy for various machine learning algorithms and identify which model is well suited for the specified dataset.

Dyslexia: The primary step is to identify the procedure is to demeanor a user survey and get information from them. In traditional dyslexia diagnosis techniques, psychologists assess participants' behavior throughout uniform exams, such as writing or writing skills along with, phonological awareness, and working memory [1,5]. Low results on these tests are used to identify dyslexics. However, because people's symptoms vary, these methods are frequently time-intense and unsuccessful for a large group of people. As a result, academics are increasingly turning to machine learning techniques, which are less time intense and low-cost.

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ADHD: ADHD patients may also have trouble focused on a solo task or sitting ideal for long time period. Anyone of any age can be affected by ADHD. EEG signal features can detect dyslexia, ADHD, dementia, sleeping problems, depression, and other brain illnesses. EEG headsets monitor brain activity by placing electrodes in an array along the user's or research subject's scalp.

Proposed system

Data collection: Due to the pandemic situation, it was not anticipated for us to build our dataset using sampling of EEG signals of people woe for LDs. Instead, we search for an online benchmark data resource [6-13]. The first dataset carries the information of dyslexic and non-dyslexic students which is available on Skit Learn. For dyslexia identification the dataset we have selected is unbiased dataset of 28 dyslexic and 21 non dyslexic (25 male and 24 female). For the test purpose memory, vocabulary, speed, visual discrimination, audio discrimination feature is selected to discriminate between dyslexic and non-dyslectic persons. And the second dataset for ADHD and non-ADHD students was submitted by Ali Motie Nasrabadi, it consists of unbiased data of 61 children with ADHD and 60 healthy controls (boys and girls, ages 7-12) on IEEE data port. For ADHD identification, on the basis of EEG recordings, children with ADHD and children without ADHD are classified [14]. The data is broken down into four sections: ADHD part 1, ADHD part 2, Control part 1 and Control part 2. Each portion is made up of a number of mat files, each of which corresponds to a person's EEG data. In the task, a set of pictures of cartoon characters was shown to the children and they were asked to count the characters. The number of characters in each copy was arbitrarily selected from 5 to 16 in numbers, and the magnitude of the copy/pictures was big sufficient to be simply observable and countable by children Thus, the duration of EEG recording throughout this cognitive visual task was dependent on the child's performance (i.e., visual attention and response speed).

Pre-processing, feature extraction and feature selection: The dataset must be preprocessed and screened previously applying machine learning algorithms. This entails converting the data into a number or qualitative/textual format. To locate useful attributes and eliminate nulls, pre-processing is utilized. Following the initial processing step, the feature elimination/extraction technique, in which relevant features are recognized and a variety of standards is assigned. Here each frequency channel band is a feature and the threshold value of each wave is their respective frequency as stated.

We accomplish three types of component analysis on this dataset and the outcomes are specified later in this paper.

- Principal component analysis
- Independent component analysis
- Linear discriminant analysis

System training and classification

ML algorithms: Random Forest Classifier, Decision Tree Classifier, Linear Regression, XGB Classifier, Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), and are among the algorithms employed after the component analysis (Figure 2).

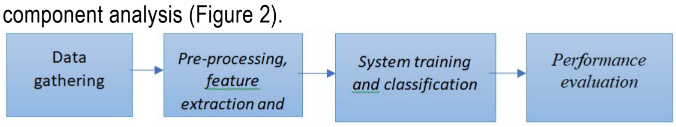

Figure 2. Proposed system [5]

Performance evaluation: In the performance evaluation, Python-based tools are employed. In this scenario, accuracy score is utilized to assess the performance of machine learning-based on detection of LDs systems.

Results

Dyslexia

Following Table gives the accuracy score for different ML based algorithms (Table 1) (Figure 3).

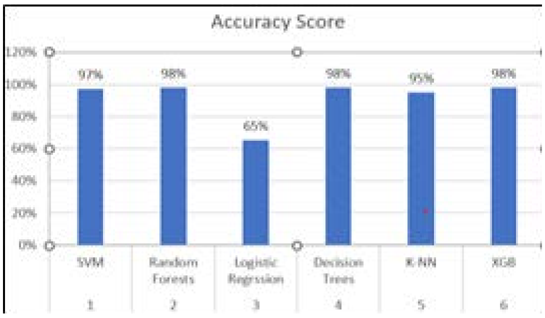

Figure 3. Model Accuracy Score for Dyslexia

Table 1. Model Accuracy Score for Dyslexia

S. No	Algorithm	Accuracy Score
1	Support Vector Machine	97%
2	Random Forests	98%
3	Logistic Regression	65%
4	Decision Trees	98%
5	K-NN	95%
6	XGB	98%

ADHD

The following table and graph gives the accuracy score for different ML based algorithms (Table 2) (Figure 4).

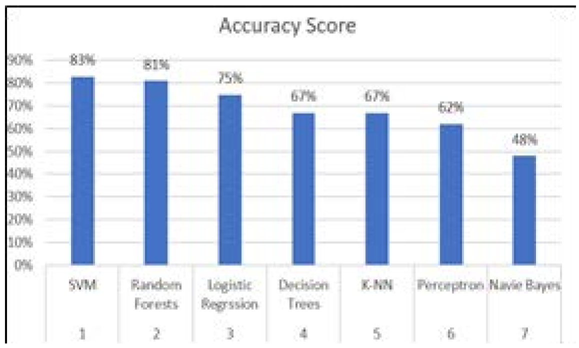

Figure 4. Model Accuracy Score for ADHD

Table 2. Model Accuracy Score for ADHD

S.No	Algorithm	Accuracy Score
1	Support Vector Machine	83%
2	Random Forests	81%
3	Logistic Regression	75%
4	Decision Trees	67%
5	K-NN	67%
6	Perceptron	62%
7	Navie Bayes	48%

Dyslexia

Figure 5 shows the topographic map of a child diagnosed with Dyslexia and a normal child.

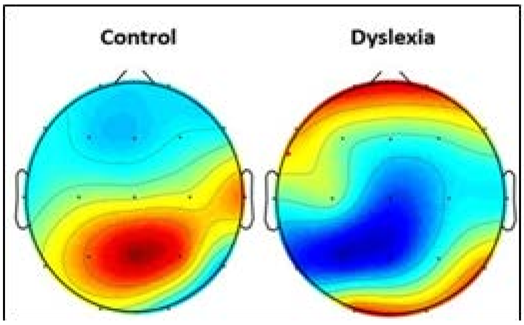

Figure 5. Topographic map of dyslexia children

ADHD

Figure 6 shows the topographic map of a child diagnosed with ADHD and a normal child.

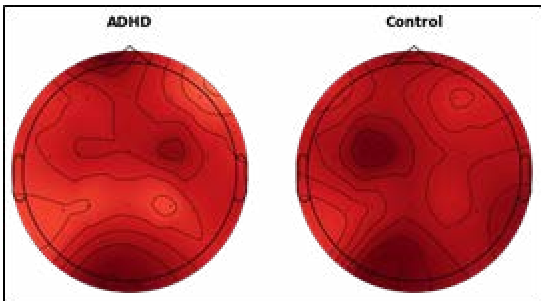

Figure 6. Topographic map of ADHD children

Discussion

The basic idea of our project is to increase the accuracy of the learning disability assessment and reduce the time used for learning disability assessment. Machine learning is used in wide variety of fields and applications where certain outcomes have to be predicted.

Machine learning outcomes it allows the software applications to learn and become more accurate in predicting outcomes. A comparison of machine learning algorithms is used for a particular data set to discover which one produces accurate prediction results. We tried to find which Machine Learning algorithm works best for identifying specific disability. After the outcomes obtained, it is understood in what way inventively the machine learning models classifies dyslexia and ADHD datasets.

By reducing features using various feature elimination techniques such as Variance threshold, correlation matrix, recursive elimination, we observed no significant increase in the test accuracy. Feature generation of degree 2 was performed on the 19 columns leading to a total of 210 columns out of which best 30 were selected. Even this proved useless as the final accuracy only fallen. After selecting the best 8 features out of the 19, only 61% of accuracy was obtained which proves that all of the features are substantially correlated to the output and they cannot be ignored. For the tomographic graphs, the following inferences are made.

From Figure 5 topographic mapping of dyslexic brain electrical activity revealed four discrete regions of difference between the two groups involving both hemispheres, left more than right. Aberrant dyslexic physiology was not restricted to a single locus but was found in much of the cortical region ordinarily involved in reading and speech.

From the Figure 6 we can accomplish that visual cortex region of both ADHD and normal children were activated. In a normal (control) child we can see the left side of the head (central lateral sensory motor area) (F3-Fp1) lighting up. This indicates the child is responding to the visual stimulus. However, for a child with ADHD, this region doesn't seem to light up. This is because of visual attention is one of the deficits in ADHD children, therefore they are slower to respond to visual stimulus in comparison to normal children.

Conclusion

The result shows that the accuracy of the Support Vector Machine (SVM) is better in both the cases for identifying the learning disabilities which is 97% and, 83% for dyslexia and ADHD respectively learning disabilities as compared to other algorithms mentioned over here.

Future Scope

Here we have considered accuracy as only parameter to identify the learning disabilities in future we are using precision, recall and F1-score to be considered along with the accuracy score for better results. Although the technique achieves reasonable accuracy and success rates, it has room for improvement. In this case, data after many bases (e.g., pictures, text, games, and scans) it may be integrated for improvement and the prediction models' performance. Text as comprehension, arithmetic, including calculation and problem resolving and written expression, including writing, predicting and structure Games like KINLDD which provides a gesture-based interface, computer-based video-game type tests like word identification, word attack that measure children's reasoning attributes while they are using their motorized skills to relate with the game. Scans such as MRI and CT scan may be accommodating in diagnosis a traumatic brain injury or other nervous damage that may be at least part of the cause for a learning disability. These proposed tools can rummage-sale to grow a combined and user-friendly instrument that is extremely precise in classifying the syndromes, and propose the correct way and maximum suitable instructional events to paternities and tutors. In many cases, more than two classes are required. As a result, we're interested in investigating different algorithms whose learning may be extended to several classes in order to achieve two goals boosting efficiency in terms of training and testing time frames, and enhancing accuracy by uncovering information concealed in interclass interactions.

Ethical Approval

We will conduct ourselves with integrity, fidelity, and honesty. We will openly take responsibility for my actions, and only make agreements, which we intend to keep. We will not intentionally engage in or participate in any form of malicious harm to another person or animal.

Competing Interests

The authors did not have any Competing interests.

Authors' Contributions

The first draft of the manuscript was written by Nitin Ahire and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Availability of Data and Materials

The datasets are freely available on the IEEE data port (https://ieee-dataport.org/open-access/eeg-data-adhd-control-children) and Kaggle dataset (https://www.kaggle.com/datasets)

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