ADHD EEG signal analysis using Machine Learning

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Abstract – *Traditionally after an EEG(electroencephalogram) test, the data is analysed only by an experienced neurologist(a doctor trained in nervous system disorders) and it takes at least 48 hours for the patient to get their results back. In some cases, it could take days for results to arrive. But with the help of Machine learning and Deep learning this task can be performed in considerably less time with decent accuracy. This will help neurologists to make more informed decisions about a person's EEG data. Once it provides desired accuracy, it could significantly reduce the time taken to analyse EEG signals and thus will prove of great importance to the medical community. Our project involves building an ML model to analyse EEG signals of people suffering from Attention Deficit Hyperactivity Disorder(ADHD) and give results within minutes with maximum possible accuracy. The goal is to find out which data pre-processing techniques and Machine learning algorithms works the best to detect ADHD.*

The first part of the project involves building an ML model with the help of a dataset provided by Ali Motie Nasrabadi on IEEE dataport. We use various feature selection ,component analysis techniques and Machine learning models in order to maximize accuracy. The second part incorporates taking actual readings and testing the model's accuracy on these reading to verify its reliability. This part won't be completed as we are bridled by the pandemic.

Key Words: **Electroencephalogram(EEG), Attention-deficit hyperactivity disorder(ADHD), Machine learning(ML), Deep learning**

1. INTRODUCTION

Attention deficit hyperactivity disorder (ADHD) is a high-cost/high-burden disorder. Early detection and interference may prevent the development of the disorder and reduce its long-term effects. It is a mental health disorder that causes above average levels of overactive and abrupt behaviors. People with ADHD may also have trouble focusing their attention on one task or sitting still for long time. People of all age groups can suffer from ADHD

With the availability of portable non-invasive EEG acquisition devices EEG is gaining popularity for applications including brain-computer interfacing, disease diagnosis, etc.

Brain disorders like dyslexia, ADHD, dementia, sleeping problems, depression. etc, can also be noticed in EEG signal traits. Electroencephalogram (EEG) is nothing but signals representing spontaneous electric potentials on the scalp caused by cerebral neuronal activities. The EEG signals are therefore rich with information about psychophysiological disorder.

Five main constituents of EEG sub-bands are: delta (0–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–28 Hz) and gamma (>28Hz).

1. Alpha waves are related to relaxation and attention. They are present when you are awake.

2. Beta waves are observed in people who are awake. It doesn't matter whether your eyes are open or closed.

3. Theta waves are related to sleep. These waves are normal for all ages during sleep.

4. Delta waves are also related to deep sleep. These waves are normal in adults who are in deep sleep and in young children.

Each of these EEG sub-bands correspond to different types of brain activity. Doctors use information from an EEG to gain insight into brain activity. Dynamism associated with sub-band features indicates attention level, psychological state, or possibility of neurological disorders. EEG electrodes detect cumulative electrical potential contributed by group of neurons. Therefore EEG can be used for disease identification as the values of these bands will be different for people suffering from any brain related disorder. While there are many techniques proposed by past research to detect indicators of brain disorders like dyslexia, epilepsy, seizure etc., EEG is one of the most popular techniques used to assess brain behaviours. With our project, we want to help the medical community by facilitating them with a quick and reliable way to detect brain disorders.

2. Literature survey

2.1 Suprava Patnaik, Nitin Ahire, Sushilkumar Yadav, Vaibhav Patel, Jason Malliss, R.N.Awale,"Novel AUD Likelihood detection based on EEG Classification"

This paper gives an machine learning approach which will classify EEG signals which can be useful for discovering the likelihood of suffering of a person from genetic alcoholism. This paper explains about EEG which is known as electroencephalogram and it is a representation of the electrical activity taking place at the surface of the brain. This paper also explains us about Multilayer Perceptron which is a neural network architecture. It is a sequential non-linear model which is quite popular for its universal approximation ability. It has different layers where one layer represent the input layer which takes the information from external device, another layer can be hidden layers which can be more than one and there is a final output layer where the results are predicted. This paper experiments with the two subjects of different categories which are of range 10-13 years and come from families with no trace of alcoholism and families who have a history of alcoholism. The experiment consists of two electrodes and they are placed at both left and right upper forehead (namely FP1 and FP2), after placing the electrodes those subjects were shown different symbolic images, the pictures were from Snodgrass and Vanderwart standardized set of 260 images. The data which was acquired is in the form of EEG signals and those EEG signals were decomposed into its five sub-bands by using DWT (Discrete Wave Transform). After this decomposition of bands the results where stored in different sub-bands and to find the accuracy of the proposed algorithm 10-fold cross validation is used for training and testing. After a careful observation beta spectrum has the maximum accuracy when both FP1 and FP2 channels were considered.

2.2 Ihsan Ullah[1], Muhammad Hussain[2],*, Emad-ul-Haq Qazi[2] and Hatim Aboalsamh[2],"An Automated System for Epilepsy Detection using EEG Brain Signals based on Deep Learning Approach",

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This paper talks about the detection of Epilepsy by classifying the EEG signals and discovering if a person is suffering from Epilepsy or not using machine learning. This paper explains about EEG, it is the electrical activity taking place at the surface of the brain. The recognition of epileptic and non-epileptic EEG signals is a problem of classification. It involves performing classification after extraction of the discriminatory features from EEG signals. The proposed system for epilepsy detection using EEG brain signals is based on machine learning . Three main modules included are : 1.splitting the input signal into sub-signals using a fixed-size overlapping windows, 2. an ensemble of CNN models, where each sub-signal is classified by the corresponding CNN model, and 3. fusion and decision, the local decisions are fused using majority vote to take the final decision. A Convolutional Neural Network model is structured, where low-level layers have a small number of kernels, and high-level layers contain a large number of kernels. But this structure involves a huge number of learnable parameters .A general deep model needs a huge amount of data for training, but for epilepsy detection problem the amount of data is limited. To tackle this issue, we introduce data augmentation schemes, where each EEG signal corresponding to epilepsy or normal case is divided into overlapping windows (subsignals) and each window is treated as an independent instance to train CNN model. Using copies of the trained CNN model, we build ensemble classifier, where each model plays the role of an expert examining a certain part of the signal. For classification, keeping in view the approach, an input EEG signal is split into overlapping windows, which are passed to different CNN models in the ensemble i.e. different parts of the signal are assigned to different experts (models) for its local analysis. After local analysis, each model provides a decision; and in the end, these decisions are fused . The number of CNN models (experts) in the ensemble depends on the number of windows. For example, in case an input EEG signal is divided into n windows (subsignals), the ensemble will consist of nCNN models. The core component of the system is a CNN model. It is a deep model, which consists of convolutional, batch normalization, ReLU, fully connected and dropout layers.

2.3 Mohammad H. Alomari, Aya Samaha, and Khaled AlKamha,"Automated Classification of L/R Hand Movement EEG Signals using Advanced Feature Extraction and Machine Learning", International Journal of Advanced Computer Science and Applications, Vol. 4, No. 6, 2013

The main aim of the paper is to classify Electroencephalography (EEG) signals associated with left and right hand movements using a hybrid system that uses advanced feature extraction techniques and machine learning algorithms. By using advanced feature technique and machine learning algorithms, left and the right hand movement can be classified by using (EEG) electroencephalography signal. By using the International 10-20 system with 64 electrodes placed on the surface of the scalp the practical reading was taken which consists of 1500 EEG records, which includes several experiments such as opening and closing the corresponding fist consisting of different intervals of time until the target disappears on the screen. As we know that (EEG) electroencephalography signals consist of noise so the filter has to be applied Such as a band pass filter to remove the (DC) direct current, notch filter to remove line noise consisting of 50hz frequency. After removal of noise our aim is to classify left and the right hand movement but (EEG) electroencephalography signals consist of useless data containing movement such as eye and muscle movements. To tackle this problem blind source separation and different algorithms has been used to eliminate eye and muscle movement. Machine learning algorithms such as Neural Networks (NNs) and Support Vector Machines (SVMs) algorithms were used for the purpose of classifying (EEG) electroencephalography signals into right and left hand movements

2.4 Sandheep P, Meljo Poulose, Vineeth S, Subha D P,"Performance analysis of deep learning CNN in classification of depression EEG signals",2019 IEEE Region 10 Conference (TENCON 2019)

This paper gives the approach for classification of depression with the help of EEG signals and deep Convolutional Neural Networks. CNN is known as Convolution Neural Network and it is a deep learning algorithm, it consists of different layers namely an input layer, a pooling layer, a fully connected layer and an output layer. It is mainly divided into processes: forward and back propagation. The experiment was taken on the two subjects first is the person who is normal and second one is the person who is suffering from depression. The electrodes were placed according to the 10-20 standard for gaining the EEG signals. The data was recorded for both the part of the brain (i.e left hemisphere and right hemisphere). The data was recorded when the eyes were closed and eyes were opened. This data was then given as the input to the neural structure where accuracy, sensitivity and specificity were calculated precisely. The deep CNN is trained and from that it is concluded that 99.31% of accuracy is obtained from the right hemisphere and 96.31% of accuracy from the left-hemisphere in determining the depression. It was also observed that the network performance was significantly affected by stride size which was there with the first two layers of CNN, learning rate which is a significant hyper-parameter to be tuned for deep networks for better performance, number of epochs which means after passing the entire dataset forward and backward one epoch is counted and the variation in the training data size.

3. METHODOLOGY

3.1 Dataset

Owing to the pandemic, it wasn't possible for our team to step out and build our own dataset using EEG electrodes to record EEG signals of people suffering for ADHD. Instead we resorted to an online resource(IEEE DATAPORT). This dataset, submitted by Ali Motie Nasrabadi, consists of 61 children with ADHD and 60 healthy controls (boys and girls, ages 7-12)..

EEG recording was performed based on 10-20 standard by 19 channels (Fz, Cz, Pz, C3, T3, C4, T4, Fp1, Fp2, F3, F4, F7, F8, P3, P4, T5, T6, O1, O2) at 128 Hz sampling frequency. Since one of the deficits in ADHD children is visual attention, the EEG recording protocol was based on visual attention tasks. 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 image was randomly selected between 5 and 16, and the size of the pictures was large enough to be easily visible and countable by children. To have a continuous stimulus during the signal recording, each image was displayed immediately and uninterrupted after the child's response. Thus, the duration of EEG recording throughout this cognitive visual task was dependent on the child's performance (i.e. response speed).

3.2. Data Preprocessing

The EEG data recorded are affected by different kinds of artefacts and need to be preprocessed to improve the quality of signals. These artefacts include noise from electrical lines, muscle movement, heart beat, sweating, electrode movement, and so on. The EEG signals have a bandwidth between 0.2 and 100 Hz and are recorded with 128 samples per second. The dataset provided is already preprocessed and thus noise and artefact free.

3.3. Component analysis

Feature elimination: Feature elimination is what it sounds like: we reduce the feature space by eliminating features. Advantages of feature elimination methods are simplicity and maintaining interpretability of your variables. As a disadvantage, though, you gain no information from those variables you've dropped. But by eliminating features, we've also eliminated their benefits.

We perform three kinds of component analysis on our data and the results are stated later in the paper.

1.Principal component analysis

2.Independent component analysis

3.Linear discriminant analysis

3.4. Machine learning algorithms.

EEG signals are subjective and dynamic in nature; therefore often machine learning based methods are used for EEG classification. Plentiful literature are available on EEG classification by using SVM, MLP, Neural Networks, etc. and in the paradigm of impact of meditation, disease diagnosis and so on. SVM is studied in for of its better generalization, insensitive to overfitting and curse-of-dimensionality features. Neural network is used for EEG classification predominantly because of its universal approximation ability. However careful architecture selection and regularization is required. The main aim is to train a Machine Learning model to identify whether a person is suffering from a certain brain disease.

4. RESULTS

The maximum accuracies after applying various ML algorithms is as follows

1.K-nearest neighbors : 69%

2.Support Vector Machines: 72%

3.Random forest: 74%

4.Neural Networks: 84%

Above results have been obtained after performing the algorithms on raw EEG data(after noise and artefact reductions)

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 futile as the final accuracy only plummeted.

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.

5. CONCLUSIONS

Based on the observations so far, we can say that Neural Networks works best of raw EEG data in terms of accuracy.

Feature generation/reduction techniques did not provide any noticeable gain in the final output which in turn proves that all the data columns are highly correlated to the output and thus cannot be ignored.

6. FUTURE SCOPE

Our next step is to perform frequency time analysis on the EEG data in order to extract the most important information from the signals.

Convolutional Neural Networks are proven to be effective when dealing with EEG signals and that is exactly what we will be pursuing in the near future.

REFERENCES

[1] Suprava Patnaik, Nitin Ahire, Sushilkumar Yadav, Vaibhav Patel, Jason Malliss, R.N.Awale,"Novel AUD Likelihood detection based on EEG Classification"

[2] Ihsan Ullah[1], Muhammad Hussain[2],*, Emad-ul-Haq Qazi[2] and Hatim Aboalsamh[2],"An Automated System for Epilepsy Detection using EEG Brain Signals based on Deep Learning Approach",

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[3] Mohammad H. Alomari, Aya Samaha, and Khaled AlKamha,"Automated Classification of L/R Hand Movement EEG Signals using Advanced Feature Extraction and Machine Learning", International Journal of Advanced Computer Science and Applications, Vol. 4, No. 6, 2013.

[4] Sandheep P, Meljo Poulose, Vineeth S, Subha P,"Performance analysis of deep learning CNN in classification of depression EEG signals",2019 IEEE Region 10 Conference (TENCON 2019)

[5] Ali Motie Nasrabadi, Armin Allahverdy, Mehdi Samavati, Mohammad Reza Mohammadi, June 10, 2020, "EEG data for ADHD / Control children", IEEE Dataport, doi: https://dx.doi.org/10.21227/rzfh-zn36