



Application of Classification Algorithms for Attention deficit hyperactivity disorder (ADHD)

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Abstract:

ADHD subtypes are a dubious part of ADHD writing. Most subtypes arrangements are based on social and psychological information yet need biomarkers. Utilizing a multimodal dataset involved EEG information too as self-revealed indications and conduct information, we attempted to foresee the DSM subtypes of every one of our 96 members. Since ADHD has been noted to introduce itself distinctively across sex, we additionally attempted to anticipate sexual orientation. Very still EEG information and social information end up being helpless indicators of the DSM subtypes. In any case, self-revealed manifestations were a rich indicator of ADHD subtype. Also, foreseeing gender utilizing EEG information yielded the most noteworthy deciphering correctness's.

Index Terms: ADHD symptoms, EEG data, Prediction model, Classification algorithms, KNN algorithm.

1. Introduction:

Attention deficit hyperactivity disorder problem (ADHD) is perhaps the most widely recognized neurodevelopmental messes among youngsters what's more, young people. It shows itself through an assortment of intellectual and conduct indications, for example, (yet not restricted to) hyperactivity, need consideration, impulsivity, absence of restraint and reduced working memory. Long haul follow-up examinations uncovered that in 40 to 60% of youngsters with ADHD, the issue continues into adulthood. Subtype arrangement of ADHD has not arrived at agreement inside the writing and examination on the connects of ADHD subtypes show ambiguous discoveries. The most widely recognized gathering of ADHD subtypes (which is likewise the DSM classification) are (1) scatterbrained, (2) hasty/Hyperactive and (3) blended. Those subtypes are for the dominant part in view of rules got from conduct and-self-report information and absence of neurophysiological appraisal is unmistakable. The arrangement of excellent administrations at sensible costs is a critical worry for medical services organizations (emergency clinics, medical services places). Quality assistance incorporates appropriately diagnosing patients and giving successful medicines. Poor clinical choices can have genuine outcomes, which is the reason they should be stayed away from. Clinical tests ought to be kept to a base expense in clinics. Utilizing appropriate PC based choice help frameworks, they can accomplish these objectives.

This venture will expect to examine the forecast capability of subtypes of ADHD between various sorts of estimations, those being social measures, self-revealing measures and electrophysiological (EEG) information. All the more explicitly, Principal parts examination (PCA) will be applied to accomplish measurement decrease and k-closest neighbor grouping will be utilized to foresee the DSM ADHD subtypes as per every information type. An examination of the prescient limit of our 3 information types will be made, also as perceptions about the expected expectation of sex utilizing our dataset. For EEG information, a beneficial examination will be directed to look at forecast capability of ADHD subtypes as indicated by cathode pools (matched by mind locales) for cerebrum motions of interest (estimating otherworldly force).

2. Literature Survey:

Numerous researches on the diagnosis of ADHD symptoms have been published. They used a variety of machine learning techniques to identify the symptoms and came up with different probabilities for each method.

ADHD Symptoms Prediction System is a visual based application that assists users in predicting and treating ADHD symptoms. The application predicts the symptoms name based on the data provided by the patient or user. The system can also be used to obtain precautionary measures such as nearest hospital information. This system is made up of an intelligent system that uses machine learning methods such as KNN. To calculate the probability, the data entered by the patients is compared to some existing datasets. The probability is calculated using the KNN algorithm [1].

Quality service involves appropriately diagnosing patients and providing effective treatments. There are several categorical and numerical data in the available ADHD symptoms database. The proposed method identifies accurate hidden knowledge, such as relationships and patterns related to ADHD symptoms, from a historical ADHD symptoms database. A multilayer perception neural network with backpropagation as the training method is employed in the system. The obtained results indicate that the designed diagnostic method is capable of accurately predicting the levels of ADHD symptoms [4].

Medical KDD(Knowledge Discovery in Dataset) has a lot of potential for identifying hidden patterns in medical data sets. Age, gender, inattention/memory (IM), and hyperactivity/restlessness (HR) etc are among the fourteen features taken from medical profiles that can indicate the chance of a patient getting ADHD symptoms. These characteristics are incorporated into K-means algorithms, MAFLA algorithms, and Decision tree classification in the prevention of stroke using KDD(Knowledge Discovery in Dataset) techniques. The following are the key benefits of this paper: early identification of HC symptoms, accurate values, and therapy at a reasonable cost [5].

Medical data extraction is becoming increasingly important for the prediction and treatment of high death rates due to ADHD symptoms. To avoid making incorrect clinical decisions that have disastrous implications, high-quality services are required. The implementation of proper decision support systems by hospitals helps reduce the cost of clinical tests. The publication discussed how to evaluate multiple research studies on ADHD symptoms prediction and classification using various machine learning and deep learning approaches to determine which strategies are successful and accurate [3].

The paper explained about a novel method of identifying key features using machine learning approaches, which improves the accuracy of brain neurons symptoms prediction. Different combinations of features and numerous well-known classification algorithms are used to introduce the prediction model. The prediction model for ADHD symptoms with the KNN with a linear model yields an improved performance level with an accuracy level of 88.7% [2].

The goal of this research is to use KDD(Knowledge Discovery in Dataset) techniques to provide an effective solution for corrective situations. To diagnose ADHD Symptoms, KDD(Knowledge Discovery in Dataset) classification methods such as decision trees, neural networks, Bayesian classifiers, Support vector machines, Association Rule, and K- closest neighbor classification are utilized. Support Vector Machine (SVM) is the best of these methods [6].

The potential of nine (9) classification systems for predicting ADHD symptoms is explored in this paper. Namely Decision tree, K-NN(K nearest Neighboring)in neural network, SVM, KNN, ANN. In the prediction of ADHD symptoms, the Appropriate algorithm and SVM (support vector machine) are proposed using medical profiles such as an age, sex, inattention/memory (IM), impulsivity/emotional lability (IE) type. Based on these attributes the symptoms can be predicted. In comparison to prior methods, classification-based techniques provide high efficacy and achieve high accuracy, according to the analysis [12].

There are two phases to the proposed system. The automated methodology for the development of weighted fuzzy rules is the initial phase. The second phase includes the creation of a fuzzy rule-based decision-making system. KDD(Knowledge Discovery in Dataset) techniques, attribute weightage, and attribute selection approaches were applied in the first phase. The weighted fuzzy rules are used to design the fuzzy system. The system's performance is compared to that of a neural network-based system in terms of accuracy, sensitivity, and specificity [13].

3. Proposed System:

Many times, we may require immediate medical assistance but are unable to do it due to some reasons. The ADHD symptoms Prediction System is a project that involves online consultation. The technology uses an innovative web system to provide users with immediate guidance on their ADHD conditions. Users can use the application to share their ADHD-related symptoms. It then examines the user's specific information to see if any symptoms could be related to it. The application used some advanced KDD(Knowledge Discovery in Dataset) techniques to determine the most accurate symptoms that could be associated to the patient data. The user can then call a doctor for further treatment based on the results.

Block Diagram



Figure 1: Block diagram of ADHD symptoms prediction

For the symptoms prediction model to be created, the Counselor must enter the patient's information as well as the training data. After the user utilizes the model's services. The symptoms must be entered into the model by the user. The classification algorithm will return the expected results when the user enters the details. For symptoms prediction, we used the K-NN(K nearest Neighboring) algorithm.

Proposed system has 3 major modules

There are three significant modules in the proposed framework. 1. The first is the Pre-Processing module, and the second is the Learning module and third is the Analyzing. Information pre-handling is a cycle of setting up the crude information and making it appropriate for an AI model. It is the first and pivotal advance while making an AI model. 2. The communication of learning begins, in discernments or dataset, similar to training models and direct understanding or direction, to look for plans in dataset and make better decision later on reliant upon the models that we give to outcome. The fundamental point is to allow the PCs adjust therefore without human intervention or help and change exercises properly. 3. Data examination is described as a association of cleaning, changing, and showing data to discover significant information for business dynamic. The inspiration of driving Data Analysis is to eliminate accommodating information from dataset and taking the decision subject to the data assessment.

Merge dataframes (Neuropsy data with df (eeg))

We now need to import the Neuropsydata

```
In [11]: df_neuropsy = pd.read_excel("Neuropsy.xlsx", na_values=".")
print(df_neuropsy.shape)
df_neuropsy.head(5)
```

(100, 15)

```
Out[11]:
```

	ID	Age	Gender	cIM	cHR	cIE	cSC	inat	hyper	Aqtot	Aqaudi	Aqvis	RCQtot	RCQaudi	RCQvis
0	1	21	1	17.0	31.0	29.0	9.0	18.0	20.0	90.0	91.0	92.0	94.0	80.0	110.0
1	3	20	1	10.0	5.0	13.0	1.0	8.0	5.0	27.0	34.0	41.0	25.0	31.0	38.0
2	4	18	1	26.0	17.0	7.0	15.0	23.0	11.0	93.0	89.0	96.0	90.0	92.0	90.0
3	7	23	1	24.0	8.0	6.0	14.0	19.0	3.0	86.0	66.0	112.0	94.0	90.0	100.0
4	10	18	1	NaN	NaN	NaN	NaN	NaN	NaN	98.0	103.0	93.0	92.0	100.0	85.0

Then remove participants (10,18, 52 and 215) because of missing Neuropsy data

Figure 2: Pre-processing Module

I. Pre-Processing Module

- Prediction of output with accurate outcome
- Model evaluation aims to estimate the generalization accurate of a model on future data.
- Methods for evaluating a model's performance are divided into 2 categories: namely, holdout and Cross-validation. Both methods use a test set to evaluate training model performances

KNN with these PCAs

We used the components as features for Knn classification; in order to predict ADHD subtype.

```
In [16]: accuracy, score, pvalue, confusion_matrix, fig_matrix = pre.knn_testing(principalDf, labels)
print('Accuracy:', accuracy)
print("Classification score %s (pvalue : %s)" % (score, pvalue))
print("Confusion matrices:", confusion_matrix)
fig_matrix.show()
```

```
Confusion matrix, without normalization
[[6 4]
 [8 1]]
Normalized confusion matrix
[[0.6 0.4]
 [0.89 0.11]]
Accuracy: 0.3684210526315789
Classification score 0.4933333333333333 (pvalue : 0.5445544554455446)
Confusion matrices: [[0.6 0.4]
 [0.89 0.11]]
```

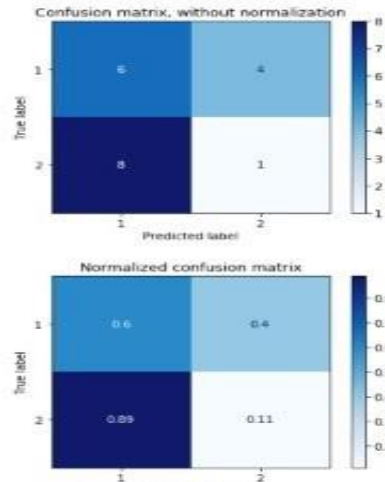


Figure 3: Learning module

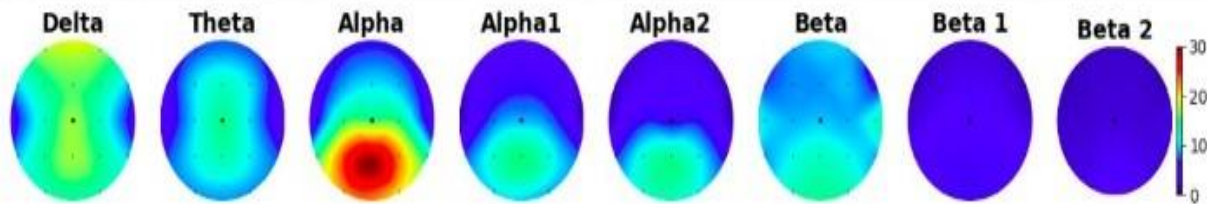
II. Learning Module

- Applying Algorithm of KNN for training the model
- K-Nearest Neighboring (KNN) is one of the simplest algorithms used in Machine Learning for regression and classification problem.
- KNN algorithms use data and classify new dataset points based on similar measure

General scalp plots

They represent our whole sample, not taking gender nor ADHD subtype into account.

```
In [21]: array_topoplot(data, ch_xy); # ";" needed in notebook so it doesn't print in double, maybe remove if on other ide
```



Visualize the distribution difference between the inattentive and combined subtypes

Figure 4: Analyzing module

III. Analyzing module

- Prediction of output with accuracy
- Model analysis aims to estimate the generalization accuracy of a model on future knowledge.
- Methods for evaluating a datasets model's performances square measure divided into a pair of categories particularly, holdout and Cross-validation.
- Both ways use a check set to judge coaching model performance.

4. Results

The project's outcomes are discussed in this section. The current scenario's challenges are described, as well as how the proposed solution is deployed to solve them.

Existing System

Patient symptoms, inventory management, and the generation of simple statistics are all supported by many hospital information systems. Decision support systems are used in some hospitals; however, they are mostly limited. These systems result in issues such as:

- System maintenance is really difficult.
- There's a chance you'll get inaccurate results.
- There is a lack of user-friendliness.
- The processing of the activities takes longer.

Proposed System

The ADHD symptoms Prediction application is a web-based consultation application. Through an automated system online, individuals can receive immediate counseling on their ADHD symptoms. Users can use the application to share their ADHD-related issues. It then examines the user's specific information to see if any illnesses could be associated with it. The following are some of the system's benefits:

- Based on the outcome, the system displays the outcome, as well as the name of a certain doctor for further treatment.
- The technology allows the user to view information about the doctor.
- In highly chances, the system can be used.



KNN without PCAs

```
In [42]: accuracy, score, pvalue, confusion_matrix, fig_matrix = pre.knn_testing_nopca(features, labels)
print('Accuracy:', accuracy)
print("Classification score %s (pvalue : %s)" % (score, pvalue))
print("Confusion matrices:", confusion_matrix)
fig_matrix.show()
```

```
Confusion matrix, without normalization
[[9 1]
 [8 1]]
Normalized confusion matrix
[[0.9 0.1]
 [0.89 0.11]]
Accuracy: 0.5263157894736842
Classification score 0.4533333333333334 (pvalue : 0.7623762376237624)
Confusion matrices: [[0.9 0.1]
 [0.89 0.11]]
```

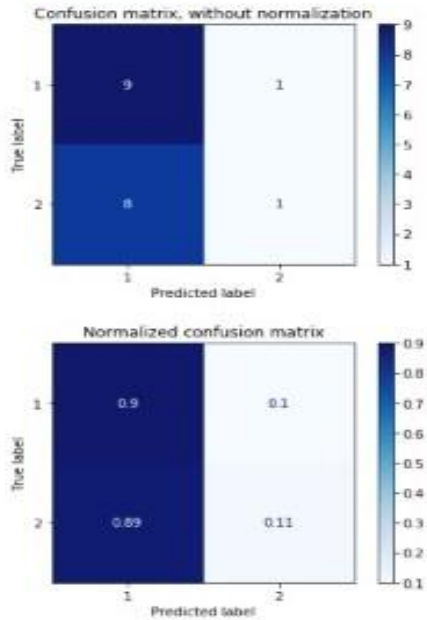


Figure 5: Result of the predicted symptoms

The expected symptoms is shown in Figure 5. For symptoms prediction, the user must fill out all of the required information, after which the system will analyze the symptoms. The user might then seek medical advice for further treatment.

5. Conclusion

ADHD symptoms Prediction, which has traditionally been seen as a required burden at medical offices, healthcare facilities, and wellness centers, can now be totally automated by an efficient online software application. The advantages of deploying this technology benefit everyone involved in the scheduling process, as doctors and users can do their responsibilities more easily and efficiently. The system explores a historical ADHD symptoms database for hidden information. Identifying ADHD symptoms utilizing patient health data will benefit in the long-term improve of human brain. Thus, if the symptoms are discovered at an early stage and treatment is offered as soon as possible, the brain damage rate can be drastically reduced. This system can be further improved and expanded.

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