Attention! Data Helps Diagnoses: A machine learning approach to predicting ADHD

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Abstract

Objective

- Create a machine learning model to predict whether an individual has ADHD.

Purpose

- To improve the efficacy of ADHD diagnoses, resulting in fewer undiagnosed adults and earlier interventions.

Method

- We used a **machine learning classification algorithm (*k*-nearest neighbors)** to predict whether an individual has ADHD based on several features (e.g., presence of comorbid conditions).

Results

- **k = 8** optimized model performance. Overall, the model was acceptable with an average of 77% sensitivity, 78% accuracy, and 80% specificity.

Conclusions

- Machine learning models can be used by practitioners to enhance speed and accuracy of diagnoses. More work should be done to improve the performance of these models.

Introduction

Attention-Deficit/Hyperactivity Disorder

- A neurodevelopmental disorder often beginning in childhood characterized by irregular attention spans and hyperactive/impulsive behavior.

Factors and consequences of late recognition

- ADHD is frequently misdiagnosed as other conditions (e.g., anxiety, depression).
- Symptoms change throughout the lifespan. More recognizable and stereotypical symptoms present in children fade in adulthood, making diagnosis harder with age.
- Negative stigma can lead to missed symptoms by parents and teachers, who classify symptomatic behavior as "laziness" or "lack of effort".
- Although symptoms change with age, negative outcomes do not. Undiagnosed adults struggle with: academic/occupation performance, unstable relationships, financial burdens, and substance abuse.

Current barriers in diagnosis

- Missed diagnoses are not expected to decrease due to existing problems with mental health treatment, including physician bias (diagnosing comorbid conditions) and patient difficulty in making treatment sessions to get diagnosed.

Method

Dataset

- HYPERAKTIV (Hicks et al., 2021) is a public dataset obtained from the Open Science Framework (OSF) platform.

Sample

- N = 103, n = 93 (18-67 years old, 51 with ADHD, 52 controls (all with 1 or more psychiatric disorders).
- 10 participants were excluded from our analysis due to missing responses to one or more variables.

Feature selection

Variables

ADHD : Presence of Attention Deficit/Hyperactivity Disorder (0=no, 1=yes).

ASRS : Adult ADHD Self-Report Scale; an 18-item screening tool evaluating current severity of ADHD symptoms. Higher scores = more symptoms.

SEX : 0 (Female), 1 (Male)

ANXIETY : Presence of anxiety disorder (0=no, 1=yes)

DEPRESS : Presence of depression (0=no, 1=yes)

BIPOLAR : Presence of bipolar disorder (0=no, 1=yes)

SUBSTANCE : Potential drug or alcohol addiction

MED : Whether patient is medicated or not

	ADHD	ASRS	SEX	ANXIETY	DEPRESS	BIPOLAR	SUBSTANCE
ASRS	.53***	-					
SEX	0.05	-0.07	-				
ANXIETY	-.21*	-0.03	0	-			
DEPRESS	0.08	-0.09	-0.1	0.07	-		
BIPOLAR	-0.09	.23*	-0.04	0.14	-.53***	-	
SUBSTANCE	0.13	-0.03	.26*	0.14	0.05	-0.06	-
MED	-0.14	-0.19	0.16	.22*	0.15	0.09	0.06

Table 1: Bivariate correlations amongst study variables.

k-Nearest Neighbors:

- A supervised machine learning algorithm used to classify data based on the status of “nearest neighbors”. The k-value indicates how many neighboring points are used for classification.
- 80% of the data were used to train the model and 20% were used as a testing set to evaluate the model's performance. The seed was set prior to analysis to make the results reproducible.
- We tested the model using k-values of 1-10 and found k = 8 to be the best fit for our model.
- We focused on the sensitivity of the model (as opposed to accuracy and specificity). This meant maximizing the correct prediction of people who truly had ADHD.

Results

Model Evaluation

- The model (where k=8) accurately predicted the presence of ADHD (or not) 78% of the time, misdiagnosing 4 out of 18 individuals.
- Results per metric were between 40-85%, but k-values between 4-8 appeared the most stable across performance criteria.

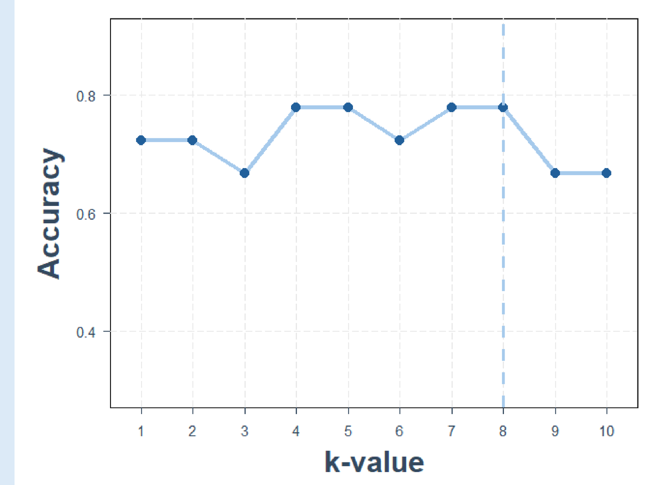

Figure 1. Model accuracy (% of all correct predictions).

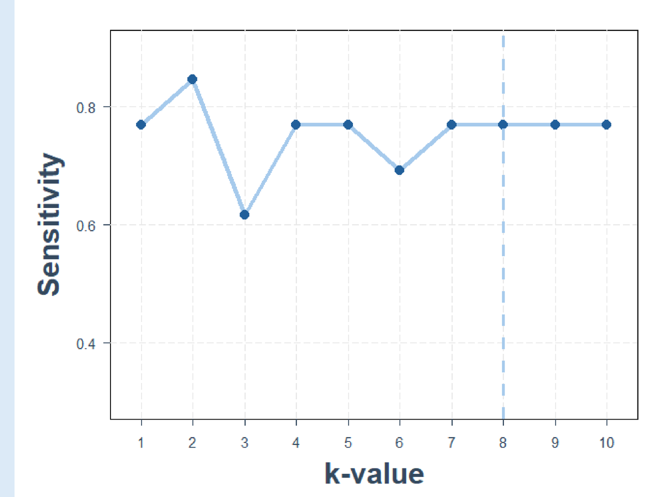

Figure 2. Model sensitivity (% of all correct predictions out of total true positives).

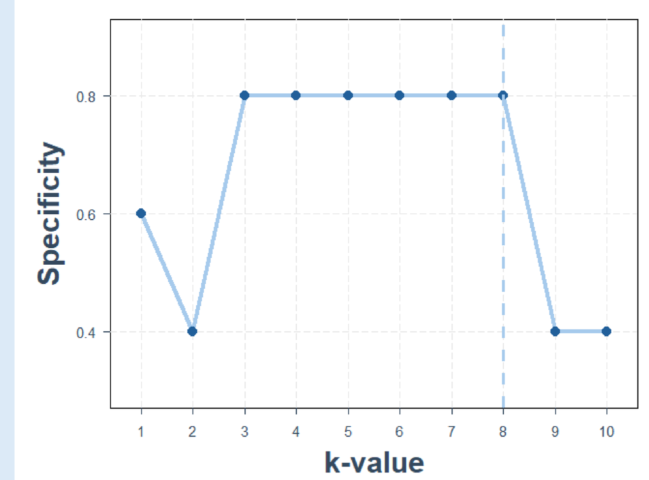

Figure 3. Model specificity (% of all correct predictions out of total true negatives).

Classification on the testing set.

k = 8		
Prediction	Actual	Outcome
1	1	TRUE
0	0	TRUE
1	0	FALSE
0	0	TRUE
0	0	TRUE
1	1	TRUE
1	1	TRUE
0	1	FALSE
0	1	FALSE
1	1	TRUE
0	1	FALSE
1	1	TRUE
1	1	TRUE
1	1	TRUE
1	1	TRUE
1	1	TRUE
1	1	TRUE
0	0	TRUE

		Predictions	
		Negative	Positive
True Values	Negative	True Negative (n = 4)	False Positive (n = 1)
	Positive	False Negative (n = 3)	True Positive (n = 10)

Figure 4: Confusion matrix for the k = 8 model.

k	Accuracy	Sensitivity	Specificity
1	0.72	0.77	0.6
2	0.72	0.85	0.4
3	0.67	0.62	0.8
4	0.78	0.77	0.8
5	0.78	0.77	0.8
6	0.72	0.69	0.8
7	0.78	0.77	0.8
8	0.78	0.77	0.8
9	0.67	0.77	0.4
10	0.67	0.77	0.4

Discussion

Conclusions

- Even simple machine learning methods such as this one show potential for supporting current mental health diagnostic procedures.
- Use of a predictive model can reduce the time needed to obtain an official diagnosis.

Limitations

- Small sample size and missing data: The original sample size (*n* = 103) was small and dropped to *n* = 93 after listwise deletion, impacting both model training and evaluation. We had to exclude other possible features with high missingness to prevent further loss in sample size.
- Limited access to public data: Datasets with patient information are often restricted for public use, making further modeling a challenge.
- Relying on diagnoses as truth: There is no objective test or cutoff for ADHD. We had to rely on clinician assessment of ADHD as "truth", which is known to vary within and between clinicians.

Future Directions:

- A larger sample size and including additional features (e.g., race/ethnicity, employment, relationship status) would improve model performance.
- Future efforts should strive to simplify diagnostic measures and model features. (For example, anxiety symptoms would be easier, cheaper, and faster to obtain than an anxiety diagnosis.). This would make diagnosis more efficient/accessible.
- Previous studies used features such as heart rate, EEG recordings, and real response-time data. This may be difficult and costly to obtain, making the use of behavioral measures and questionnaires a point of consideration for future studies.
- Other machine learning models might perform better than KNN. Other possibilities include:
  - Logistic Regression
  - Random Forest
  - Support Vector Machines (SVM)
  - Decision Trees

References

Scan the QR code to view referenced literature, supplemental readings, and a PDF version of this poster!