Detecting ADHD in Adults in Ninety Seconds Using Eye Movements Recorded via Web-Cam

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Abstract: Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder that can be present in both children and adults. This paper addresses the use of eye movements recorded by a web-cam to detect ADHD in adults (n=440). In this study, 237 adults with self-reported ADHD and 203 adults without self-reported ADHD read approximately 90 seconds of text while a web camera recorded their eye-movements. Using a 3:1 training/test split, a logistic regression classifier was able to predict ADHD with an accuracy of 82%. The 90-second duration is considerably shorter than other ADHD screenings and is promising as a low-cost approach for assessing ADHD risk.

Keywords: Attention Deficit Hyperactivity Disorder, ADHD, Machine Learning, Logistic Regression, Adults

Introduction

Adults with ADHD often struggle with paying attention, impulsive behavior, and hyperactivity. These symptoms can make activities requiring focus difficult. Studies have shown that the analysis of eye movements while focused on an activity such as reading can be used to accurately detect ADHD in individuals (De Silva et al., 2019; Lev et al., 2020.) Research has shown that tracking eye-movement while reading is highly informative for understanding cognitive processes (Rayner 1998).

According to the Diagnostic and Statistical Manual of Mental Disorder (DSM-5), to be diagnosed with ADHD, adults must show five symptoms of inattention or hyperactivity-impulsivity (American Psychiatric Association, 2013.) The ICD-10 uses a similar classification for ADHD. Although ADHD is typically onset in childhood and persisting into adulthood, studies have shown that it can be misdiagnosed (Kooji et al., 2010), especially in females (Walters 2018.) Despite the symptoms being similar to childhood ADHD they can present themselves differently in adults. The high number of undiagnosed cases of adult ADHD highlights the need for quick and reliable screening devices that are easily available to the public.

Machine learning has shown promise as a way to identify ADHD in individuals (Tenev et al., 2014; Christiansen et al., 2020.) Studies have used such algorithms to successfully identify individuals with ADHD at a high-level of accuracy. Unlike past attempts at studying individuals with ADHD, expensive equipment is no longer needed to accurately measure eye-movements (Valliappan et al., 2020; Aljaafreh et al., 2020.)

Participants

Adults (n=440) volunteered to read text on their computers while their web camera recorded their eye movements. Prior to the reading, participants reported their reading difficulty with the option of choosing ADHD, dyslexia, or none. Participants were at least 18 years old but no other characteristics about them were known. This limitation is discussed further in this paper.

Materials and design

Two passages are presented to the participant, one at a 500 Lexile score level the other a 1400 Lexile score level, set in two fonts; First Lexend Deca and then Lexend Zetta. Lexend Deca is a normally spaced font while Lexend Zetta is a very widely spaced font. Therefore each participant is exposed to passages of text at 500 Lexile in Deca Font, 500 Lexile in Zetta Font, 1400 Lexile in Deca Font, 1400 Lexile in Zetta Font. The lines of text were four lines for 500 Lexile Deca, five lines for 500 Lexile Zetta, six lines for 1400 Lexile Deca and six lines on 1400 Lexile Zetta.

While the participant is reading the lines, the MediaPipe Face Detection library is used to detect face landmarks. Only data from one eye is kept. Using the right eye, three nodes are identified: the Inner Palpebral Fissure, the Pupil, and the Outer Palpebral Fissure. From the recorded data of the right eye, x and y coordinates are normalized using the inner palpable fissure as a reference point.

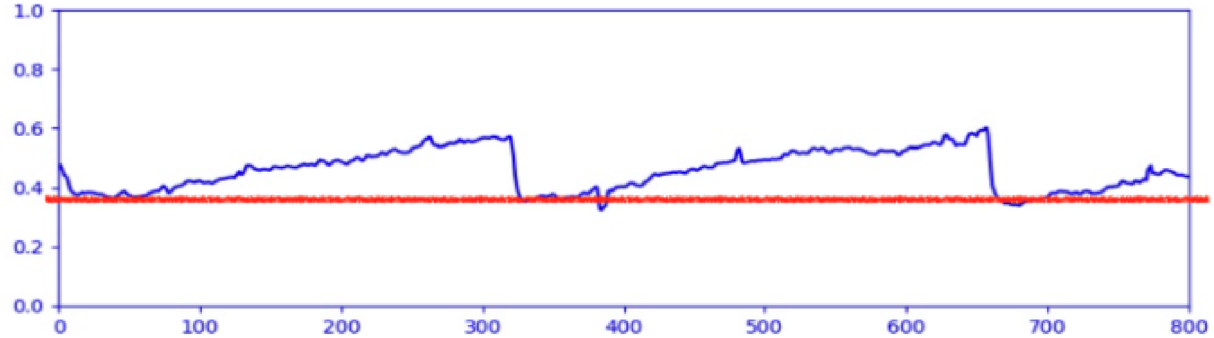
Methods

The normalized data was analyzed to identify patterns in the eye movements of readers. There are clear distinctions among self-reported ADHD, dyslexia, and readers with no reading difficulties, which can be seen when graphed. Figure 1 shows the pattern of a typical reader without ADHD or dyslexia.

From the normalized data, two features were identified that correlate with self-reported ADHD status. Two thirds of participants (n=294) were used in the training set. A logistic regression classifier was used where the outcome was self-reported ADHD status using the two identified features as predictors.

The remaining 146 participants were used in the test set. The fit-model was applied to the test set and checked for accuracy against the participants' self-reported ADHD status.

Figure 1



Example of a neurotypical reader where the y-axis represents the location of the eye while reading and the x-axis represents the frame number.

Results

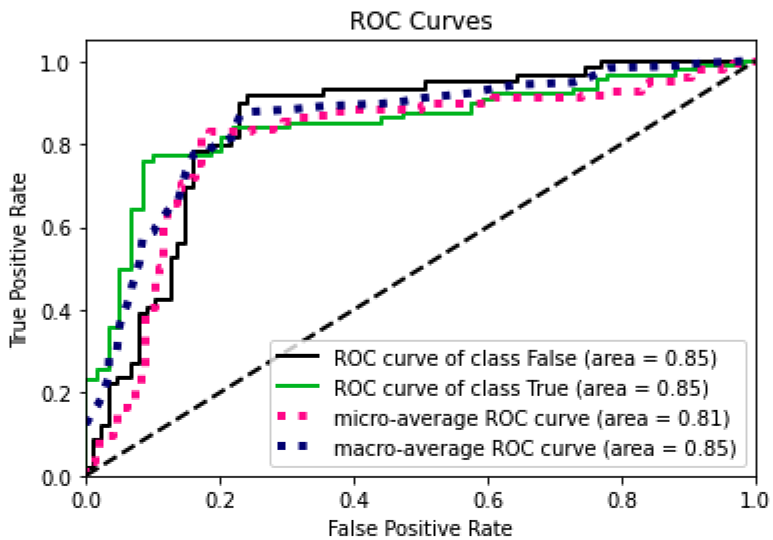
Table 1 shows the confusion matrix. The accuracy of the model was 82% with a specificity of 90%.

Table 1

N=146	Predicted: No	Predicted: Yes
Actual: No	TN = 53	FP = 6
Actual: Yes	FN = 21	TP = 66

The Receiver Operating Characteristic (ROC) is shown in Figure 2, with an area under the curve (AUC) of 0.85. Both the accuracy and the AUC show the high reliability of the model in predicting ADHD risk.

Figure 2



Discussion

Other approaches to detecting ADHD via eye-movement data have shown similar accuracy but with a longer test duration (De Silva et al., 2019).

There are a number of limitations of this study that help to inform future study but do not take away from the reliability of this model. For example, the model has not been tested in languages other than English, such as Spanish or in languages that do not use the English alphabet.

Future iterations of this study will collect covariates such as age and sex, which will improve the precision of the estimates.

Declaration of interest statement

The authors are employed by Readable Technologies, a company that uses the model in this paper to screen customers for ADHD.

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