Development of blink rate detecting glasses for student attention monitoring

SAM-EE: Student Attention Monitoring for Educational Enhancement

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Abstract

Lack of attention, often exacerbated for students diagnosed with ADHD, can lead to students falling behind in class and achieving less than what they are capable of. To help students become aware of their attention patterns in particular classes and receive personalized coping strategies, a wearable device (the SAM-EE: Student Attention Monitoring for Educational Enhancement) has been developed to measure blink rates. The device consists of a pair of glasses with an attached camera which displays a graph of blink rates via a web application. The SAM-EE system can accurately report differing blink rates that correlate with attentiveness. This prototype serves as a discreet method for supplying students, counselors, and teachers with information about classroom inattention which can help optimize students' learning experiences.

1.0 Introduction

Everyone has experienced how hard it is to remain attentive in educational environments for extended periods of time. But did you know that moments of lost concentration can affect you for years to come? According to a study supported by a grant from the National Institute of Mental Health, children who struggled with inattentiveness during their childhood have lower academic performance for up to ten years later in life than their peers who were attentive in their early education (*Attention-Deficit/Hyperactivity Disorder in Children and Teens: What You Need to Know*, n.d.). While classroom inattentiveness is "the most immediate and persisting issue for students and teachers," it has been normalized and ignored by many academic institutions (Newman 1992). While all students are vulnerable to the negative effects of inattention, the issue affects certain demographics more than others. A study done by Camp et al. exploring the effect of inattention on various demographic groups, showed a larger academic progress impact for women (Camp 2021). Without intervention, these women will fall behind their male counterparts, thereby creating an inequality. However, if they are given a tool to monitor their own inattention trends, they can become more aware of their habits and make appropriate changes.

1.1 Background

1.1.1 ADHD Community

While inattention affects all students to some degree, people with ADHD especially struggle with this issue. ADHD (attention deficit hyperactivity disorder) is a neuropsychiatric disorder which can make the completion of daily tasks difficult (Camp 2021). The symptoms of ADHD can range from inattentive behavior to hyperactive behavior. Currently, ADHD is diagnosed in childhood through DSM-5, a standard classification for mental disorders (Camp 2021). Teachers and parent questionnaires and student transcripts are also used for ADHD diagnosis. It is estimated that 6.1 million children in the United States are diagnosed with the disorder, and 80% of them still experience symptoms into adolescence (Camp 2021). The large number of people affected by ADHD means that inattention is a problem for many students across the globe.

Women with ADHD may also be disproportionately affected by classroom inattention. Women with ADHD are significantly underdiagnosed in comparison to men, meaning that they also receive less treatment. The treatment ratio between men and women is 9:1 (Bruchmüller et al., 2012). This lack of diagnosis and treatment stems from the fact that most women have the inattentive type of ADHD while most men have the hyperactivity type (Camp et al., 2021). It is much easier for adults to notice symptoms of hyperactivity than it is for them to notice signs of inattentiveness, which are usually presented more quietly (M. Paine, personal communication, September 23, 2022). Additionally, ADHD in women is most commonly diagnosed between the ages of 14-16 (Camp et al., 2021). On the other hand, ADHD is most commonly diagnosed in men by the age of 12. This difference in diagnosis age of ADHD results in male students having more time to get treatment before crucial educational years of their life. By the time most women are diagnosed, they are already well into their high school years. Women with ADHD need effective ways of coping with their inattention.

1.1.2 Detecting inattention

Recent research has shown how blink frequency is connected to attention. A study done on detecting driver inattention has found that drivers tend to blink less when faced with a visual workload in order to take in as much information as possible from the scene (Khatib et al., 2020). However, when a cognitive task was added to the visual stimulus, drivers' blink rate increased. These observations on blinking and attention in drivers can be applied to classrooms. For example, a visual workload in the classroom could be a slideshow or video which is being played in class. An example of an added cognitive task would be if students had to watch the slideshow/video while taking notes. The correlation between blink rate and attention is a promising way of measuring student inattention in the classroom.

In addition to blinking, other eye movements like saccades can also be helpful biomarkers, or characteristics of the body which can be measured (Center for Drug Evaluation and Research). Eye saccades are when a person's eyes move quickly from one point of fixation to another. Researchers can use these rapid eye movements to study cognition, memory, and motor control (R. J. Leigh 2004). Saccades can occur both reflexively (looking towards a loud noise) or due to remembered sequences (looking at different keys while playing a song on the piano). Saccades are very short movements. Even the biggest saccade lasts less than 100 ms. Saccades can also occur in the horizontal, vertical, and diagonal directions (R. J. Leigh 2004). On the neurological level, saccades occur when a burst/pulse of activity is sent to the reticular formation of the brain stem. The properties of saccades, like speed and duration, are determined by these burst neurons. Eye saccades are also more likely to occur for people who are more "prone to distractibility," like individuals with ADHD (A. L. Breeden 2016). These individuals have a looser connection between brain activity and involuntary movements, making them more likely to experience saccades (A. L. Breeden 2016).

1.1.3 Existing Blink and Attention Detecting Technology

Blink detecting Technology: Blink and eye movement detecting glasses on the market today aren't specifically catered to the needs of students and are very expensive. The company Pupil Labs has many models of eye-tracking glasses for both researchers and consumers (*Eye Tracking Technology - Gain Insight Into Human Behavior - Pupil Labs*, n.d.). Those interested in researching eye movements such as gaze, blinks, pupil diameter, and fixations can preorder a pair for around $6,400. These glasses use an infrared sensor to detect blinks but only provide raw data to the researcher. The app associated with the glasses doesn't suggest any correlation between eye movements and attention levels. For consumers, Pupil Labs has the Pupil Invisible line available to purchase for around $6,400. These glasses use machine learning to measure user gaze patterns and are most likely used by companies to determine customer response to marketing strategies. The price of Pupil Labs' eye tracking glasses make them impractical for widespread use by students trying to track their attention patterns.

Attention detecting technology: Since blink detecting glasses aren't very accessible, researchers are having to manually count blinks using video footage. Both Chiou and Tseng 2015 and Recarte et al. 2008 studied the connection between number of blinks and attention levels. However, they had to review video footage to determine how many times a subject blinked. Since an affordable blink-counting device doesn't exist on the market, researchers cannot determine blink rates in real-time, thereby slowing down and limiting their experiments.

1.2 Literature Review

A study conducted in 2015 by Chuang-Kai Chiou and Judy C.R. Tseng describes a smart classroom utilizing wireless sensors (Chiou and Tseng 2015). The project included a management system for the environment (e.g. turning air conditioner on when it's too hot), the instruction mode (to assist teachers switch between learning modes), and learning behavior (to let students know when they are inattentive). Physical characteristics of students were measured, including chatting, blink rate, body temperature, CO_2 concentration, pulse, and head movement. In this classroom, each desk had a camera attached to it in order to take data on the students' various movements. Students' attention was ranked on three levels: attentive, inattentive, and very inattentive. On each desk, an LED light would indicate to a student which attention level they are on. If more than half the class is inattentive or very inattentive, then an alarm would sound in order to alert the teacher as well. This paper shows that active feedback from sensors detecting student actions can improve students' attention spans. At the same time, the multi-sensor, classroom based solution described leaves significant room for the development of discreet, individual student attention monitoring.

A 2014 study conducted for *Vision Research,* an international journal for the functional aspects of vision, studied the oculomotor movement patterns in subjects with ADHD, seeking to show that eye blinks could be used to diagnose ADHD. Measurements were taken of pupil diameters, microsaccades, and blinking rates of three test groups: subjects with medicated ADHD, unmedicated ADHD, and no ADHD. Blink rates were found to be correlated with attention, specifically connecting anticipated stimuli with a high blink rate. Additionally, since the difference between an inattentive and attentive blink rate is around 20 blinks per minute and the difference between ADHD and non-ADHD subjects is 1.2 blinks per minute (Recarte et al., 2008), adjusting for ADHD blink differences is not necessary.

1.3 Project Statement

Female high school students need a way of knowing when and why they are inattentive in class so as to learn to implement beneficial personal coping methods to aid their focus. Female student's inattentive symptoms often go unrecognized and therefore untreated. Our solution, SAM-EE (student attention monitoring for educational enhancement), tracks the inattentiveness of students throughout the school day based on blink rates, which are indicative of attention levels (Chiou and Tseng 2015). This data will allow all students to understand what times of day, environments, and teaching styles affect attentiveness. It could also provide teachers with the knowledge of when a student is struggling with attention, and how they can adjust their skill sets to accommodate students' needs.

2.0 Methods

Software, hardware, and a web app (collectively the SAM-EE device) have been developed to measure blink rates and communicate results to the user. In order for blinks to be detected, images of the student's eye are taken and analyzed using the python library OpenCV. A pair of glasses contain a camera and photoresistor, which serve as a prototype for a non-intrusive, discreet final product. A web application allows the student to control the various functions of the glasses. SAM-EE components were tested for reliability and the full device was operated in a classroom environment.

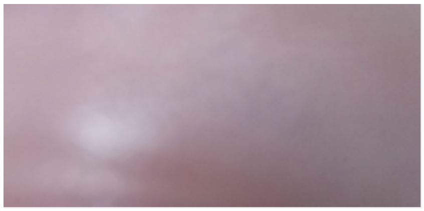
2.1 Blink Rate Detection

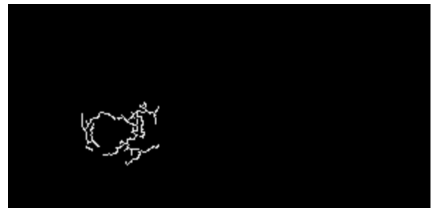
Eye state (open/close) detection: Canny Edge Detection is a method in the OpenCV python library suite that can detect high contrast lines in an image (*OpenCV: Canny Edge Detection*, n.d.). Canny Edge Detection implements image smoothing (to remove extrema) before selecting threshold brightness values for use in detecting edges. Figure 1 shows the product of the edge detection algorithm on a closed and open eye.

Figure 1: Edge detection example for open and closed eyes

OPEN

CLOSED





Using the edge detection image, a count of the number of white pixels can be used to determine an open/closed state for the eye.

Sampling Rate Requirement: The typical person's blink duration, the amount of time that the eye lid is closed, lasts about 300 milliseconds (Kwon et al., 2013). Blink rates of five blinks per second, an extremely fast blink rate, would mean a blink could occur every 200 milliseconds. By detecting if the eye is open or closed every 30 milliseconds, differences in blink rate and duration can be differentiated.

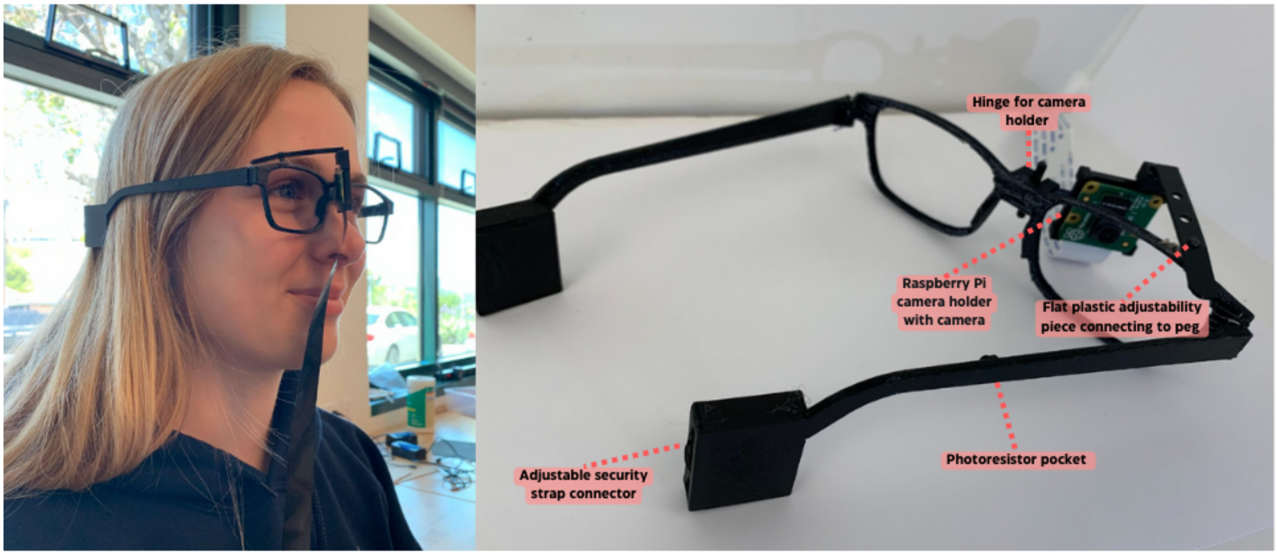
Blink Detection Algorithm: The blink detection algorithm uses the detected state (open/closed) along with a timestamp to determine if a blink has occurred. Added features take into account sleeping (eye closed for too long) and different durations of blinks, resulting in a count of total blinks per 20 second interval. The detailed blink counting algorithm is shown in Appendix 7.2

2.2. Hardware Development

Customized glasses were developed with a camera position adjacent to the bridge of the glasses. The glasses support a Raspberry Pi Camera Module that has a clear view of one eye. Camera position is adjustable on the glasses to accommodate eye position, size, and shape variability in each person. The design of the glasses was developed on TinkerCad to be 3D printed, using the Original Prusa i3 MK3. The glasses were printed with 100% infill to provide a rigid support for the camera.

Additionally, a photoresistor was placed on the temple of the glasses to detect when the glasses were being worn (the photoresistor is fully blocked by the wearer's head).

Figure 2: SAM-EE Glasses Prototype (shown on student model and with key elements labeled)



A small peg on top of the glasses rim can connect with the flat plastic piece, allowing the angle of the camera to adjust.

When developing the hardware of the glasses, student mobility was considered. In order for the glasses to detach from a monitor, it must be attached to a power bank. In the future, the power bank and two small circuit boards will fit inside a fanny pack as it is more comfortable and less visually disruptive than having all of the attachments directly placed on the glasses.

2.3 Web Application Development

A web application provides a user-friendly experience with SAM-EE. The application was made with PyWebIO, a python library which allows developers to create web apps fully in python (*PyWebIO - Build Full Stack Web App With Python*, n.d.).

Figure 3: Web application - Instructions

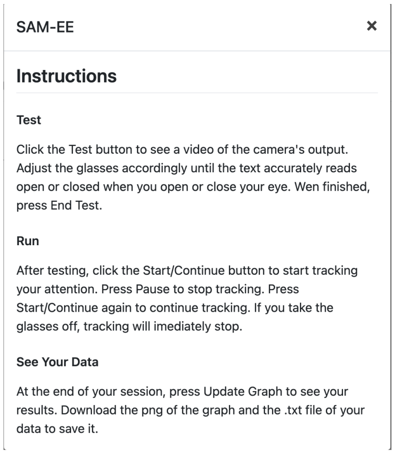


Figure 4: Web Application - main display

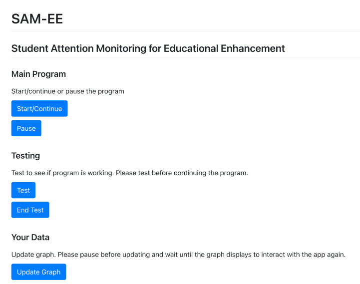
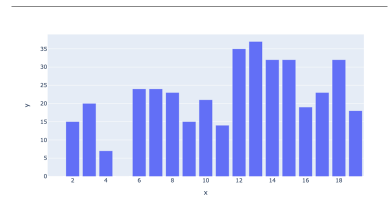


Figure 5: Web Application - Data



The web application consists of an instruction pop-up, the ability to start/stop blink detections, a display of the eye image in real time (used to position glasses), and a view data option for display of blink rate results. In addition to the graphing feature of the app, blink rate raw data is output.

2.4 Component Validation

Eye state (open/closed) detection and transforming an eye state list to blink rates were verified. In experimental trials, the device was used to verify a correlation between blink rate and attention levels.

2.4.1 Edge detection

Eight trials were conducted to verify that detected blinks using Canny Edge Detection and actual blinks were consistent. In each trial, the test subject would calibrate eye position, followed by a timed session. During the trial session, subject blinks were counted manually by an observer for comparison with the software result.

2.4.2 Rate graph

Two trials were conducted to verify that the web application correctly translated a list of open/closed eye states into a “blinks per 20 seconds” rate. During the trials, a student wore the glasses and was told to blink very quickly for 20 seconds, very slowly for the next 20 seconds, and a medium amount for the last 20 seconds. To confirm that the software was working correctly, the graph output from the test was analyzed qualitatively.

2.5 Blink Rate - Attention Validation

A series of tests were conducted to evaluate the correlation between attention levels and blink rates.

2.5.1 Short interval tests

Students were instructed to sit in front of a piece of cardboard in front of a window for six minutes. Before the trial started, the glasses were centered using the "Test" feature of the app. The Method 1 validation test followed a silence - talking - silence sequence, while Method 2 followed a talking - silence - talking sequence. During the talking sections of the experiment, a group member approached the students and asked personal questions to engage them, then left them alone to stare at the cardboard for the "silence" portions of the test.

2.5.2 Full class tests

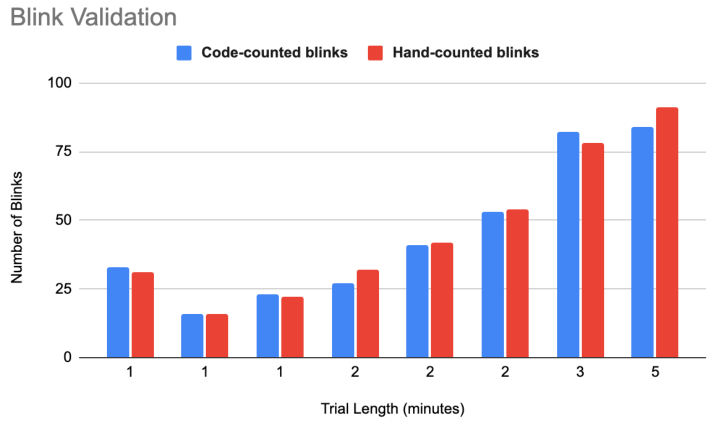
Two trials were conducted to evaluate SAM-EE use for an extended 75 minute class. At the beginning of the class, the student aligned the glasses with the "Test" feature of the web application. Once the glasses were centered on the eye, the program was started. The test feature wasn't turned off for the duration of the class so that the student could occasionally check the monitor and see if the glasses were still centered. Throughout the class, the student was told to keep a log of the different activities the teacher led and the student's attention level during these activities.

3.0 Results

3.1 Edge Detection Validation

Eight trials were completed with eight different students as shown to compare hand-counted blinks with edge detection-counted blinks. Manual and software blink counts ranged between 84 - 100% accuracy (as shown in Figure 6).

Figure 6: Comparison of Code Counted Blinks with Manual Counted for 8 trials



This range of accuracy was considered adequate since an inattentive blink rate is around 20 blinks per minute and an attentive blink rate is around 60 blinks per minute (Recarte et al., 2008). Therefore, there is a big enough difference that, even with ≈ 80% accuracy, an attentive blink rate won't be mistaken for an inattentive one.

3.2 Attentive/Inattentive Validation

Results from the blink rate/attention correlation test (described in 2.4.3) are shown in Figures 7 and 8.

Figure 7: Method 1 Average of blink rates between induced inattentive/attentive states

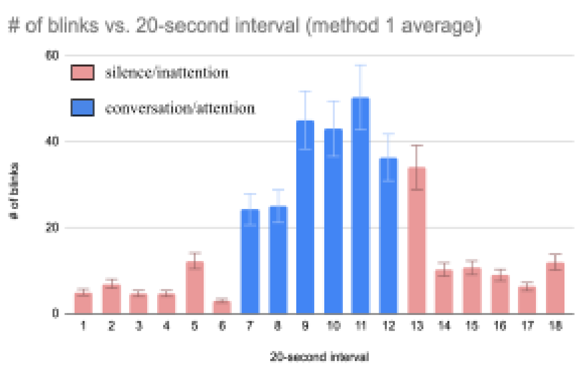
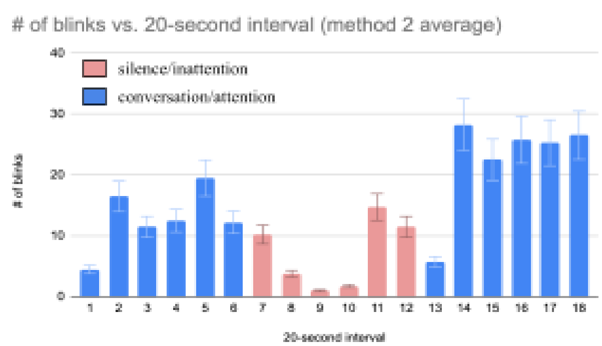


Figure 8: Method 2 Average of blink rates between induced inattentive/attentive states

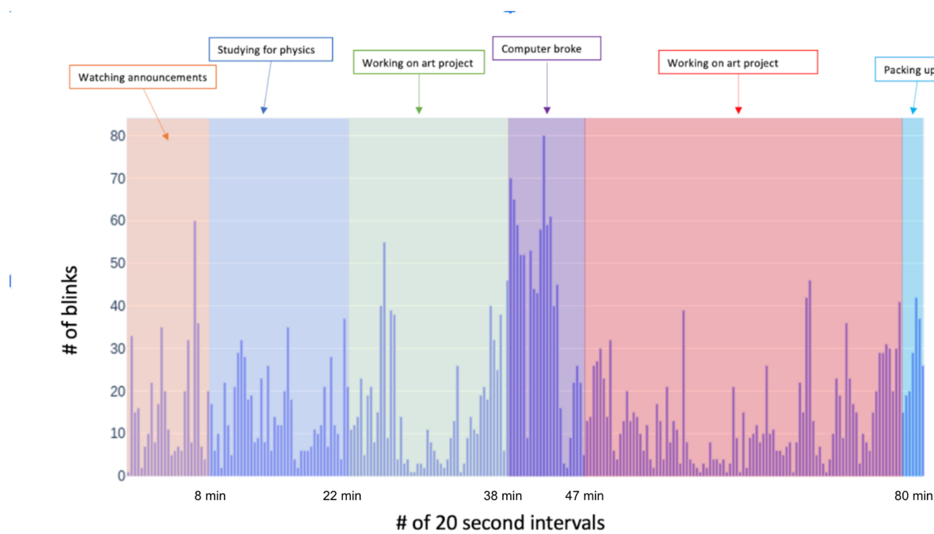


For both Method 1 (silent - conversation - silent) and Method 2 (conversation - silent - conversation) blink rates vary noticeably when a student is in conversation or left in silence. Higher attention levels (when the student is being talked to) result in greater blink rates, while lower attention levels (when the student is told to daydream) show lower blink rates. The graphs shown here use average blink rates from all twelve trials conducted. The error bars represent the worst-case 16% uncertainty based on the software's eye state detection ability described in section 3.1.

3.4 Full Class Validation

Two trials were conducted to evaluate SAM-EE use for an extended 75 minute class.

Figure 9: Blink rates with related activity labels for Student #1 during 75 minute class session



Each highlighted color area in Figure 9 represents an activity that the student recorded on their class log. The bar graph shows the blink rate the student experienced through each activity. The 75 minute class was an independent study time, allowing work on a variety of activities. See Figure 10 for blink rate/attentiveness correlation through the entire class.

Figure 10: Student 1 list of activities (including classification and ideal blink rates) and associated attention levels throughout class period

activity	classification	theoretical attentive blink rate	student self-reported attention level
watching announcements	visual	low	medium
studying for physics	cognitive	high	high
working on art project	visual	low	high
computer broke	visual + cognitive	high	medium

working on art project	visual	low	medium-high
packing up	visual + cognitive	high	medium

A second student trial was completed, with results shown in Figure 13, Appendix 7.2.

4.0 Discussion

4.1 Blink rate and attentiveness correlation

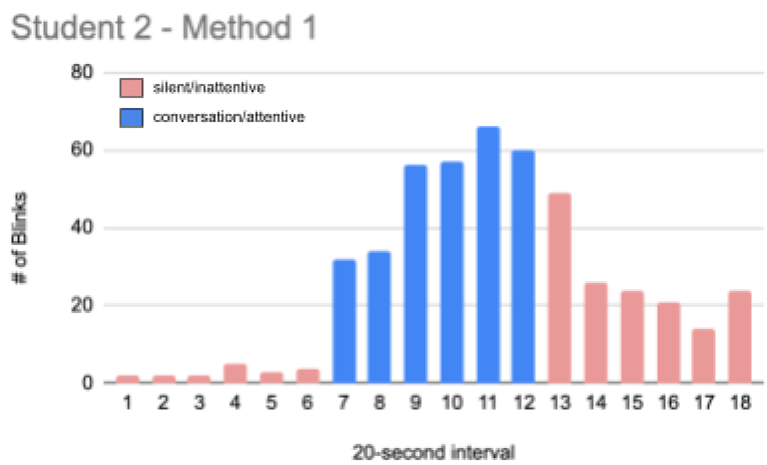
Figures 7 and 8 in 3.2 demonstrate that blink rates are indicative of attention levels (blink rates decreased in silent, uninteresting settings and increased in engaging settings). Measuring blink rates in the classroom is an effective way to gauge student attention and the SAM-EE glasses are able to provide this service.

However, detecting attention in a real classroom setting is more difficult than in the talking/daydreaming test in the lab since the activities the student engages in can be either visual, cognitive, or both. An “attentive” blink rate varies with each of these activity types. Therefore, attention levels can’t be determined by just a high or low level of blinks. When a student is attentive while completing a visual task, they should have a low blink rate. However, when a student is attentive while completing a cognitive task, a high blink rate is expected. If the student is working on a visual and cognitive task and is attentive, their blink rate should be higher than if it was just a visual task. For example, the red highlighted section of Figure 9 shows when this student was working on their art project, which is classified as a visual task. Therefore, a low blink rate would be correlated with an attentive state. Since the student logged that their attention level during this activity ranged from a 5-9 (one being least attentive, ten being most attentive), the relatively low blink rates seen on the graph seem accurate. On the other hand, the blue highlighted section of the same graph represents when the student was studying for a physics test (cognitive task). From around the 51st to 63rd interval, the student’s blink rate declines dramatically. Since studying for a test is a cognitive task, a decrease in blink rate corresponds to a lapse in attention. The student reported that their attentiveness level through this task was 7-8, but could have been distracted during these few minutes (which is exactly the type of attention lapse SAM-EE is designed to detect).

4.2 SAM-EE System Limitations

While conducting some of the experiments comparing blink rate and attentiveness, surprisingly large blink rates outside of the 16% expected error were occasionally recorded.

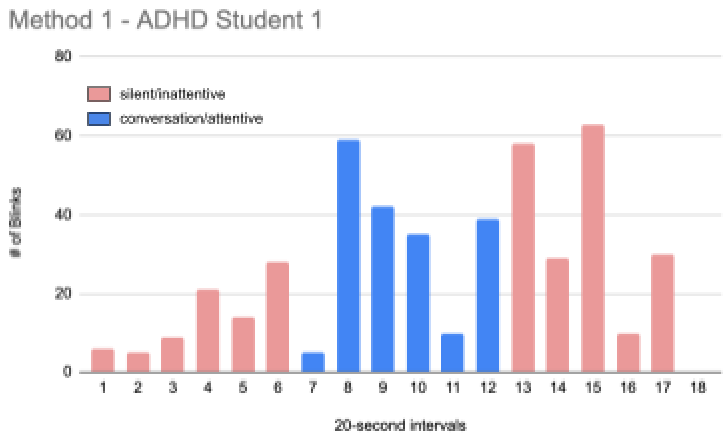
Figure 11: Method 1 high blink count error example



In Figure 11, it can be seen that the student's blink rate during their conversation reached the unrealistic rate of 65 blinks per 20 seconds, meaning the edge detection software was classifying the student's open eye as a closed one on multiple occasions. Watching the video recording of this trial showed the student adjusting her glasses while having the conversation. This adjustment moved the camera so that it wasn't centered on her eye and subsequently counted many more closed eyes than accurate. Another student participating in the experiment began looking down at the table in front of her. This action caused the software to categorize her downcast eyes as closed eyes, thereby contributing to a high blink rate. Both of these examples show the importance of either maintaining consistent camera placement and developing software to account for camera shifting.

4.3 Attentiveness and ADHD

Figure 12: ADHD Student Trial



The Method 1 experiment (silent - conversation - silent) explained in 2.4.3 was repeated on a student who is diagnosed with ADHD (see Figure 12). Although the experiment followed the same stare at cardboard - talk - stare at cardboard sequence, this student's graph looks very different. Throughout all time intervals, this student's blink rate oscillated from high to low very rapidly even when physical conditions did not change. For example, the student's blink rate from the eleventh to twelfth 20-second interval changed drastically even though she was still having a conversation with a group member. Although the connection between ADHD, attentiveness, and blink rate is not yet known, there is a different result in validation between students who have ADHD and don't have ADHD.

4.4 User Interpretation

The student using the product, knowing the class or classes they were in when they wore the glasses, can see when they were attentive and in what setting. For example, if the student notices a spot of interest in the graph and wants to know what class it took place in, they could look at the time stamp on the graph. If that spot was three hours into the test, the student would know what class they were in during the third hour of wearing the product, then further analyze the spot. The student could also check their attentiveness throughout the class since the SAM-EE system counts blinks in real time. In addition, if the data is made available to school counselors, they could also help the student with their inattentiveness. For example, if the school counselor sees a drop in attention during the third hour, they know that the student needs help adjusting their behavior during the class that took place at that time. The graphs are also able to be interpreted by teachers to see what activities engaged their students.

5.0 Conclusion

Student inattention in classes affects academic performance and can impact a student's access to academic and occupational opportunities in the future. By tracking individual student attention levels, students and teachers will have access to data that can help assess environmental factors and teaching methods. A pair of glasses that detects student attention levels based on their blink rates was developed and shown to accurately differentiate high and low engagement scenarios. The attention tracking glasses were utilized during full class sessions with data showing the complexities that arise in a classroom environment, as students engage in both visual and cognitive tasks.

5.1 Future Work

The next prototype of the SAM-EE system would accommodate for various gaze directions in order to minimize the false positive blink counting as discussed in 4.1. Additionally, the attentiveness interpretation process would be made automatic. The student would have to input a log of what they did during each class in order for the software to classify blink rates based on different visual/cognitive tasks. This automated process would allow counselors and teachers to accurately and efficiently identify which classroom activities are causing the student to struggle with inattentiveness. Additional research is needed to determine if each student has a unique attentiveness/blink rate correlation value, which will necessitate an individual user calibration mode. Research on the connection between ADHD, blink rates, and attention levels is also needed to ensure the SAM-EE system works accurately for all students. The next SAM-EE prototype would allow for increased portability by powering the SAM-EE with a portable battery and developing our software to allow the camera to collect data without being attached to a monitor. Additional hardware enhancements could include the ability to detect saccade rate (a rapid eye movement between fixation points) and head movement to make attention detection more robust.

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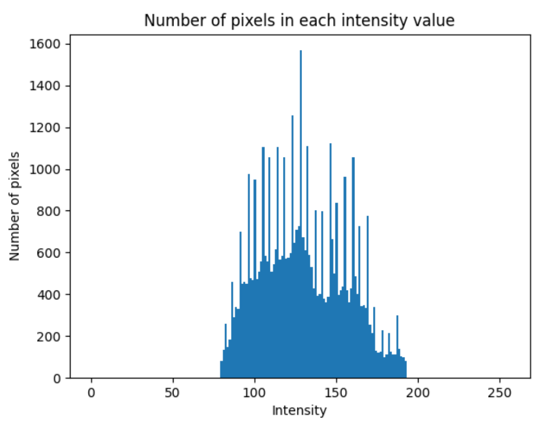
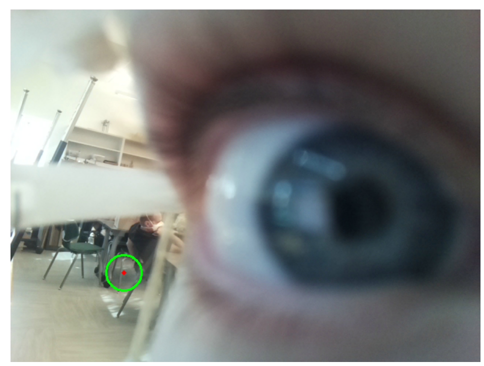
7.0 Appendices

7.1 Blink Detection Background

Several algorithms can be developed to detect eye blinks using video data. Python libraries, or collections of written code grouped for efficiency, such as Numpy and OpenCV can be utilized to write such algorithms. Below is a chart of the blink detection algorithms tried by the group along with the reason it was not ultimately successful.

Method	**Description**	**Difficulties**
Facial Recognition	Haar Cascades were used to detect a student's face. Once the face was detected, the algorithm could also tell if the student's eyes were open or closed.	In order for the program to recognize open or closed eyes, the student's whole face had to be seen by the camera, making it impossible to create a discreet device. 
Black vs. White pixels	Uses OpenCV to count the number of black and white pixels in a black and white image of an eye. By counting these pixels, the algorithm would detect if the eye is opened or closed (more black means a closed eye)	The difference in white and black pixels in the eye picture weren't always what the group expected (sometimes open and closed eyes had the same number of black pixels), largely due to lighting. In order to address the lighting issue, many different types of photo

		normalization techniques were attempted, none of which made a significant difference.
Tensorflow/Machine Learning	Uses a dataset of open versus closed eyes to determine if a new eye picture is opened or closed.	In order to use the tensorflow library, the group would have to move their project from a Raspberry Pi to a Coral board which would be time consuming and difficult.
Histograms (grayscale and RGB)	Images of students' eyes were turned to grayscale then graphed on a histogram to look for trends in pixel frequency. This process was repeated on color images as well. 	No significant correlation in color frequency could be seen in open/closed eyes between different students.
Average color of images (HSV and RGB)	The average color of images of open and closed eyes were taken and compared. The group assumed that the open eye would always have a lighter color due to the white of the eye.	The average colors between open and closed eye images ended up being too similar for the algorithm to make a distinction between them.
Darkest point of an image detection	The darkest point of open and closed eye images were found and compared. If the	The position of the pupil was not consistent enough for this method of

	darkest point was found in the middle of the image, then the algorithm counted the eye as closed. If the darkest point was elsewhere, the algorithm counted the eye as open.	blink detection to be reliable.
Color search	Using OpenCV, the algorithm was instructed to find pure black pixels in an image. If the program detected these pixels, the eye was open due to the pupil. If the eye was closed, no black pixels would be detected, indicating an open eye.	Black pixels were still detected in the closed eye picture due to the student's eyelashes and eyebrow.
Circle detection	In a picture of an open eye, a circle would be detected around the student's pupil or iris. In the closed eye picture, no circle would be detected.	Even in closed eye pictures, the algorithm would still draw circles in unexplainable places, making this method of blink detection too unreliable to use. 

After the methods above were attempted, the group chose to use Canny Edge Detection to detect blinks.

7.2 Figures

Figure 13: Second 75 min trial data

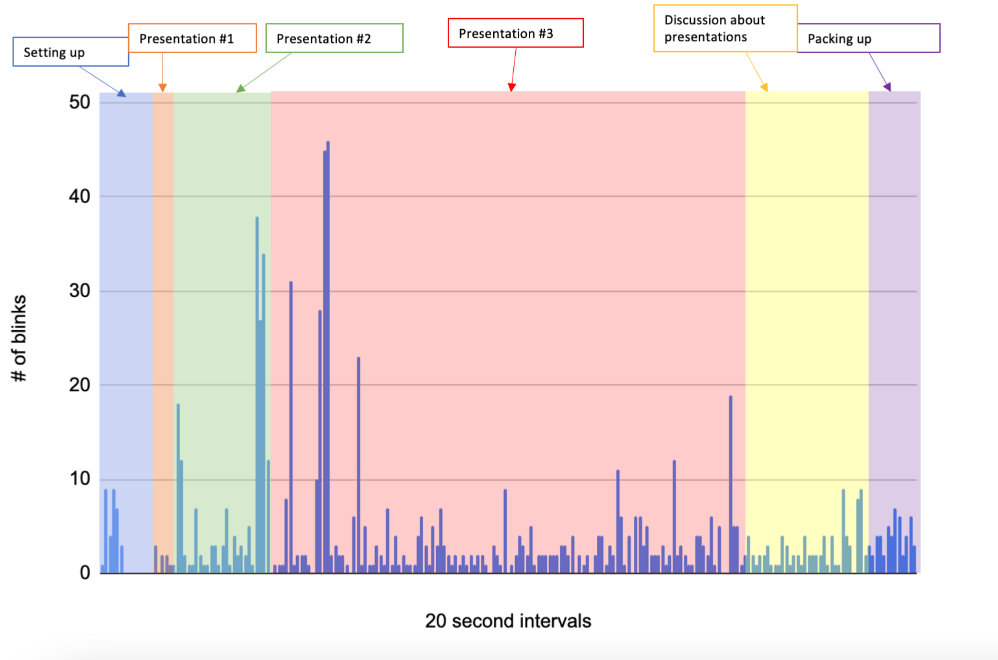


Figure 14: Blink Counter Conditional Statement

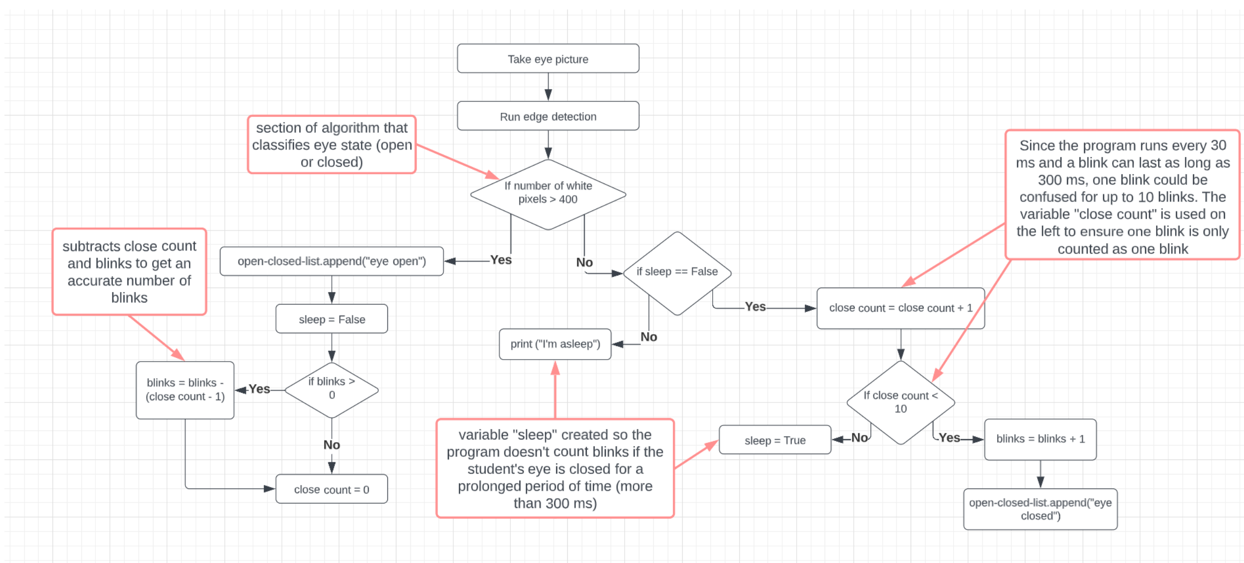
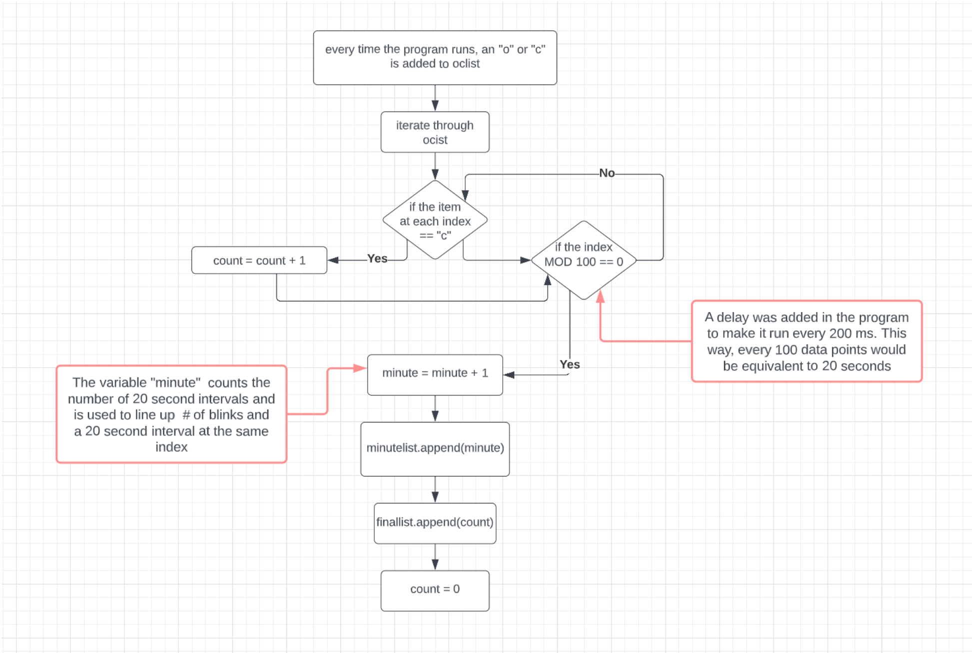


Figure 15: Conversion of eye state to blink rate


every time the program runs, an "o" or "c" is added to oclist
iterate through ocist
if the item at each index == "c"
No
Yes
count = count + 1
if the index MOD 100 == 0
Yes
A delay was added in the program to make it run every 200 ms. This way, every 100 data points would be equivalent to 20 seconds
The variable "minute" counts the number of 20 second intervals and is used to line up # of blinks and a 20 second interval at the same index
minute = minute + 1
minutelist.append(minute)
finallist.append(count)
count = 0