Development of a Low-Cost REM Tracking Device Using Closed Eye Motion During Sleep

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Abstract

Rapid Eye Movement (REM) sleep is responsible for the long-term memory restorative process and enhances the prefrontal cortex's ability to filter unwanted thoughts, making abnormalities in REM sleep strong indicators of developing unhealthy habits, and even sleep disorders. Current sleep tracking devices, such as polysomnography (PSG), are expensive, ranging from $500 to more than $10,000. Products such as Oura Ring are cheaper, but less accurate. To provide a more affordable, accurate, and comfortable alternative, a low-cost preliminary screening REM sleep mask was developed based on eye movement detection. This device produces a personalized sleep report that includes the number of REM groups, start/end time, REM duration, etc. Validation in a simulated environment demonstrates the device's ability to differentiate between motion and non-motion. Furthermore, preliminary results from overnight sleep tests show promising results.

1.0 Introduction

Although many think REM is only valuable for the dreams it provides us, t (News, 2025). Furthermore, during REM sleep, the brain improves neuron connections by pruning unneeded synapses, further contributing to cognitive function (Li et al., 2017). A lack of REM sleep leads to a weakened prefrontal cortex and impaired memory control. Therefore, good sleep habits must be developed to avoid poor general health and even the onset of sleep disorders. Products designed to improve sleep habits must accurately and affordably detect REM. This paper will describe the details of sleep stages, review current REM measurement techniques, and provide a rationale for creating a cheap, at-home REM detection device that will help improve adults' sleep habits through personalized printed sleep reports and encouraging messages. It will also discuss how the detection device was created, validated, and its successes and shortcomings.

1.1 Sleep Stages

A typical night of sleep in healthy individuals consists of 4-6 sleep cycles (approximately 7 hours) that increase as the night goes on. Each cycle is made up of 4 stages: N1, N2, N3, and REM (Stages of Sleep: What Happens in a Sleep Cycle, 2021). During light sleep (N1 and N2), the heart rate slows down, but muscle contractions in the body still occur. In terms of brain waves, N1 is characterized by low frequency, high amplitude Alpha waves, and N2 is characterized by even lower frequency and higher amplitude Theta waves (See *Figure 1*). However, during N2, bursts of brain activity occur, making N2 critical for memory development. During deep sleep (N3), muscle contractions and heart rate both decrease, and low-frequency, high-amplitude Delta waves dominate (OpenStax & Lumen Learning, 2019).

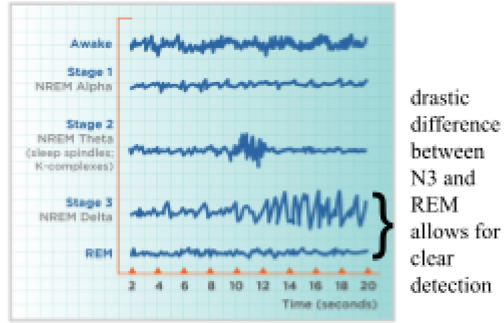

Figure 1 Correlation between sleep stage and type of brain waves; displayed on EEG

After 60-90 minutes of sleep (N1, N2, and N3), REM occurs for approximately 10-60 minutes. REM, the fourth and final stage of the sleep cycle, is characterized by high-frequency, low-amplitude waves. REM is physically distinguished by small, rapid eye scrunches ranging from 1 movement/ 30 seconds to 8 eye movements/ 30 seconds. Note that the eyes do dart left to right, however, scrunches are more noticeable. The frequency and amplitude of eye motion are highly individualized and change throughout the night. (Z. Elmaghraby, personal communication, January 16, 2025).

1.2 Sleep Stage Detection Methods

Both brain waves and physiological measurements (muscle contractions, heart rate, and eye motion) differentiate the stages of sleep, but brain waves follow a predictable pattern in each stage of sleep; this makes them the most helpful measurement for mapping sleep stages and detecting abnormalities. Most physiological measurements are less accurate than brain waves as they are influenced by outside factors. When detecting REM, eye motion is the only reliable physiological measurement because it directly reflects brain wave activity and is not influenced by outside factors (Pagel, 2024). Thus, both brain waves and physiological measurements are monitored to track sleep in the form of in-lab tests, at-home systems, and iPhone apps.

I.2.1 The Gold Standard: In Lab Testing

The most common method to identify disrupted sleep patterns and diagnose sleep disorders is a polysomnography (PSG) test, also known as a sleep study. During a PSG, electrodes are placed on the scalp, the outer edge of the eyelids, and the chin to record the patient's brain activity, eye movements, and muscle activity (See *Figure 2*). An Electroencephalogram (EEG) records and displays the patient's brain activity on a monitor, visualizing N1, N2, N3, and REM typical wave formations. However, distinguishing wave patterns, locating transitions from one sleep stage to the next, and detecting sleep abnormalities requires both the ability to recognize artifacts and a deep understanding of "normal benign variants" that may be misinterpreted as abnormal activity, but are normal. This makes EEGs extremely difficult to interpret (Emmady & Anilkumar, 2023). In addition to requiring expert interpretation, sleep studies are also uncomfortable. Sleep disturbances/disorders are heavily linked with skin irritation (Misery et al., 2021). Thus, for the 50-70 million people in the US who suffer from sleep disorders/disturbances, skin irritation from PSG electrodes and sleeping in an unnatural setting, a sleep clinic, make PSGs an outstandingly uncomfortable experience (*Polysomnography (Sleep Study) - Mayo Clinic*, 2025).

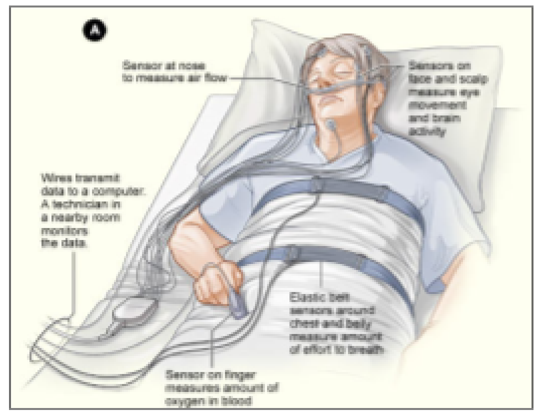

Figure 2: PSG set up (Medicom MTD Ltd, 2024)

PSGs also use Electrooculograms (EOG) to detect REM start, stop, duration, and density. EOGs detect left and right eye movement in the form of electrical signals from the cornea and retina (front and back of the eye). During REM, EOGs display "sharply contoured waves" that stand out amongst the long waves during NREM (Forrester et al., 2015). As seen in *Figure 3*, eye motion is not constantly happening during REM. However, consecutive eye movements within 30 seconds of each other are considered a single REM session. EOGs are the gold standard for REM detection because they take direct measurements of eye movement. (Z. Elmaghraby, personal communication, January 16, 2025).

Overall, PSGs are a strong tool for analyzing N1, N2, N3, and REM, but are expensive, uncomfortable, and extremely difficult to interpret.

1.2.2 At Home Products

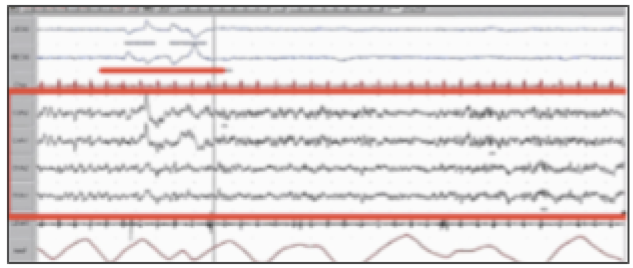

Figure 3: Period of rapid eye movement is underlined in red. A period of brain waves, associated with REM sleep are outlined by the red box.

Although PSGs use EEGs and physiological factors to track sleep and detect abnormalities, many at-home products like Oura Rings and Health Apps on iPhones solely rely on related factors like body motion detection and heart rate to differentiate sleep stages (Ong et al., 2024). Because of this, these products are cheaper and do not require expert interpretation, but they provide less accurate evaluations of sleep. Specifically, at-home products tend to overestimate how many times customers wake up throughout the night, resulting in exaggerated sleep reports (Kilpatrick, 2023). At the same time, at-home products are more effective in terms of making changes in customers' sleep habits because they are accessible, easy to use, and can take advantage of behavior change techniques (BCT) like a graphical display of sleep patterns.

Unlike PSGs, current products utilize online feedback systems to help customers improve their quality of sleep. Many studies have proven BCTs such as self monitoring, focus on past success, graphical display of sleep, and visual indicators of success/ goals are the most effective to improve sleep habits while BCTs like leader boards, and the use of challenges are detrimental since they only cause worry and increase anxiety in the customer (Duncan et al., 2017). Therefore, it is in the best interest of companies to use encouraging and self-improvement-focused BCTs to make a change in sleep habits for customers with or without sleep issues.

1.4 Lit Review

To fully understand the intricacies of high quality direct detection and indirect measurements, Dr. Ju Lynn Ong and colleagues (2023) from the Sleep and Cognition Laboratory compared six different wearable trackers across 4 tiers of quality: EEG-based headbands, research-grade noninvasive activity trackers, enhanced consumer products (Oura Ring, Fitbit), and low-cost consumer products. Each product was compared with PSG results to assess how often PSG data and wearable tracker data matched in identifying sleep stage and abnormalities. A comparison of these devices is shown in *Figure 4*. Notice the correlation between direct vs. indirect tracking and concurrence with PSG.

Figure 4: REM Detection Wearable Comparison

Devices	Class	REM tracking method	REM tracking ability (concurrence with PSG)
Dreem	Clinical EEG- based headband	Direct: EEG	Almost perfect (93% match)
Oura Ring	Improved consumer tracker	Indirect: Heart Rate, Accelerometer	Moderate-Substantial (82% match)
Fitbit	Improved consumer tracker	Indirect: Heart Rate, Accelerometer	Moderate (69% match)
Actigraph	Research-grade	Indirect: Accelerometer	No acceptable REM classification

This product comparison demonstrates that devices that infer REM based on indirect physiological measurements are worse at detecting REM compared to devices that measure REM directly (Ong et al., 2024). For example, despite the Actigraph being research-grade, it did not successfully classify REM because it only used an accelerometer, an indirect measurement.

1.5 Project Statement

Many suffer from sleep disorders, and other options for REM detection are too expensive. In light of sections 1.2 and 1.3, detecting REM based on direct eye motion measurements, identifying abnormalities, and using the most common BCTs to present findings will improve customers' general health monitoring experience. People need an affordable, comfortable, and easy-to-use mechanism to directly track REM periods through user-friendly monthly preliminary screenings so as to monitor general health and thus improve the quality of sleep. Combining high-quality detection methods with appropriate feedback, BCTs enabled the development of a low-cost REM tracking device using a Raspberry Pi 5 camera and eye motion detection.

2.0 Methods

The hardware and software were built and validated with three goals in mind: functionality, safety, and comfort.

2.1 Hardware

2.1.1 Hardware Requirements

The chart below details the hardware necessities and how each condition was met.

Figure 5: Hardware Requirements Chart

Requirements	**Build**
1. The head strap was secure and adjustable for every customer	3D printed buckle loop allowed the user to feed the strap through and adjust the tightness
2. The mask did not leave indentations on the face	Built a foam mask with rounded sides and a stretchy band
3. Consistent 8-hour eye illumination	One IR sensor was draped in front of the nose and powered by its 3V battery; adjustable with velcro
4. Consistent 8-hour video	Raspberry Pi Camera was sewn into place on the right eye (note: during sleep, eyes move in the same direction at the same time) Strips of grippy fabric were attached along the headband to prevent sliding off; currently inconsistent
5. Set up the REM mask solo	Sewed a peephole on the left eye; attached with velcro that allows the customer to view the preview screen while the mask is on
6. The mask must not get tangled throughout the night	Sticky tabs connected the LED wire and the camera strip at 3 points
7. Raspberry Pi Camera must continue to take an 8-hour video even when Live Feed and Processing are happening simultaneously	Separate 3V battery pack for the IR Sensor, so that it has a separate source of power, and Raspberry Pi 5 is not overworked

2.1.2 Safety

When determining methods for detecting REM, safety is a main concern. Note, prolonged or intense exposure to IR radiation can pose significant health risks like intense burns, damaged retinas, or cataract formation. Furthermore, skin exposure to IR can also be dangerous because skin to IR contact can raise skin temperature ≤ 10°C and indirect exposure ≤ 5 °C. In its current testing format, the IR sensor was positioned approximately 1 cm away from the eye, satisfying the safety standard of > 0.85 cm away. Furthermore, the sensor was angled at 80° adjacent to the eye, strategically preventing direct radiation into the retina. By maintaining this orientation, this project eliminated the possible risks of IR radiation when the eye was open or closed.

2.2 Software

2.2.1 Software Requirements

To accurately detect REM periods, the software had to detect individual eye motion events, group events based on inter-saccadic intervals (time elapsed between eye motion events), record time intervals between consecutive motion events and non-motion events, and produce a live sleep report that included REM start, stop, duration, a graph of sleep with REM groups labeled, and analysis for any abnormalities. To accomplish this, the software calculates the Mean Absolute Difference (MAD) by directly summing up the pixel values of photos and finding the mean absolute difference between the pixel intensities (Ref *Appendix 3* in the appendix). The code captures two photos, one second apart from each other, and then uses the equation MAD = $\frac{1}{n}\sum_{i=1}^{n}|a_i - b_i|$. If the two images were similar and there was no movement, the MAD was low, and vice versa. A threshold number, found through calibration trials, determined how much movement qualified as “motion.” A MAD of 0.6 was chosen since at that threshold, movement deemed “motion” was verified as motion 97% of the time. Another integral part of the software was developing the inter-saccadic interval, or the threshold of time between detected eye motion events that either separated two events into separate REM groups or grouped them into a single REM group. The inter-saccadic interval was set to 5 minutes since eye movements in the same REM group shouldn't be more than 5 minutes apart (Z. Elmaghraby, personal communication, January 16, 2025). If the next set of tests showed too many REM groups, the inter-saccadic interval would be increased.

2.2.2 Sleep Report Requirements

Considering the BCTs described in section 1.3, the sleep report must provide a visual representation of the night of sleep, indicating REM start, stop, and duration. Additionally, it must communicate abnormalities in a non-stressful way and continue to encourage the user to improve their sleep through sleep habit suggestions.

2.3 Validation

2.3.1 Simulated Validation

To validate that the software detects simulated REM eye scrunches and groups them as separate REM groups, a 5-minute test was conducted. A participant wore the mask and was instructed to simulate REM by scrunching their eyes for specified intervals for 5 minutes and 30 seconds. Software recorded video solely for validation and detected REM/NREM intervals based on eye motion.

2.3.2 Real World Validation

To test the whole system, the sleep mask was worn in several overnight trials and evaluated for comfort and stability. Pictures of the participant's face (front, left side, and right side) were taken before sleeping with the mask, so that the participant could use these photos in the morning to pinpoint any signs of discomfort, like sleep-mask indentations or redness. By stabilizing the camera and making the IR sensor adjustable, the sleep mask produced clear, well-lit images, usable for REM analysis. The current prototype meets the specifications described in the table (see Figure 5).

3.0 Results

3.1 Hardware Results

During all tests, the sleep mask demonstrated overall comfort and basic functionality. The user experienced no irritation around sensitive areas such as the eyes and ears, and there were minimal skin indentations. The device was well within designated safety margins for IR exposure (10° angle). However, a key limitation was the mask's inability to maintain position throughout the night. The mask was worn for a full night's sleep 10 times for an average of six hours each night. During these trials, evaluation of the video showed 2 instances of the mask slipping off the user's face and 3 instances of IR darkness, which both prevented analysis of REM. Note that the camera and IR sensor stayed in place when the mask shifted, demonstrating these components were adjustable and secure, but the mask itself was unstable. See *Figure 6* for the final hardware design and *Appendix 4* through *7* for more details.

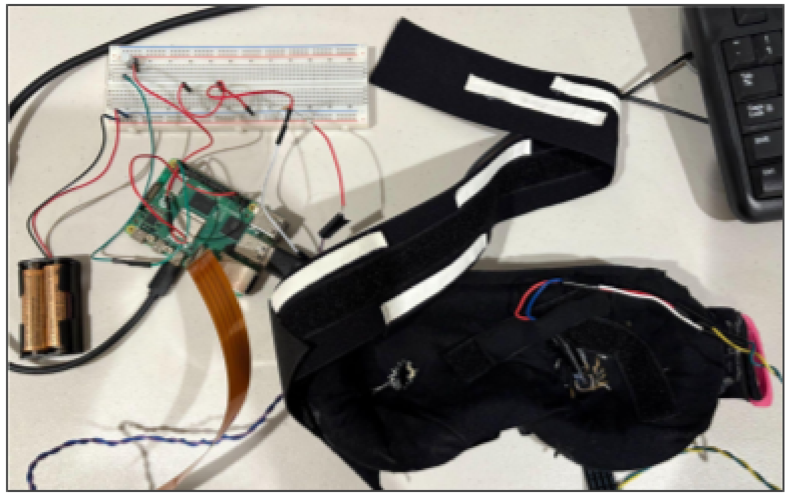

Figure 6: Final Hardware: Foam Mask, Raspberry Pi 5, Camera, IR Sensor, Breadboard, and 3V Battery

3.2 Software Validation Results

Data from the in-lab simulation is shown in *Figure 7* below. A variable representing the maximum time difference between REM groups, the inter-saccadic interval, was set to 15 seconds to accommodate the test setup. There were three separate simulated REM groups, each separated by 45 seconds of non-REM. The software successfully identified the REM groups, which were then verified by manual observation. Since the intent of sleep reports is to find out when REM was in minutes, any accuracy at the sub-minute level is sufficient.

Validation Method	non	REM	non	REM	non	REM	non
Actual	60 sec	61 sec	45 sec	44 sec	46 sec	44 sec	30 sec
Software	60 sec	61 sec	44 sec	44 sec	45 sec	46 sec	30 sec

Figure 7: In-Lab Simulation Timing

3.3 Preliminary System Results

The two charts below, *Figure 8* and *Figure 9*, show data from two separate overnight tests. Every point indicates a motion event that the software detected. The software's sleep report was graphed based on the annotated time stamps. For both tests, the MAD was 0.6, and the inter-saccadic interval was 1 minute for 3/12/25 and 5 minutes for 3/16/25. In reality, the inter-saccadic is known to be 30 seconds; however, because the software could take more than 30 seconds to process 2 consecutive motion events, using that interval would risk missing REM data.

Figure 8: 3/12/25 Sleep Report Graph

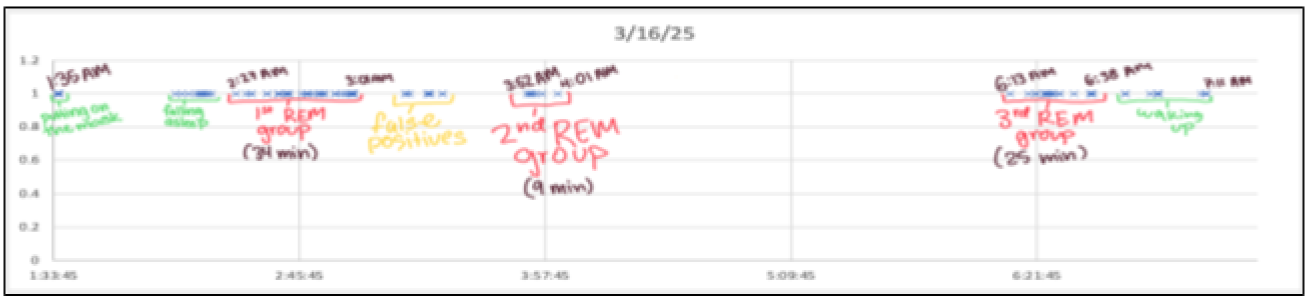

Figure 9: 3/16/25 Sleep Report Graph

The goal is to detect eye motion events that occur during REM, so eye motion that occurs when falling asleep or waking up can be disregarded. If REM was correctly detected by the software in the 3/12/25 and 3/16/25 reports, eye motion events should be seen in dense clumps ranging from 10 minutes to 60 minutes in length. Any other motion detected is considered a false positive, and any motion expected but not detected is considered a false negative.

Furthermore, for each test, the software produced a list of motion-detected events. Then, REM groups were calculated based on the inter-saccadic interval.

As seen in *Figure 8*, during the 3/12/25 test, the software detected many false positives, indicating the MAD threshold was too low and the

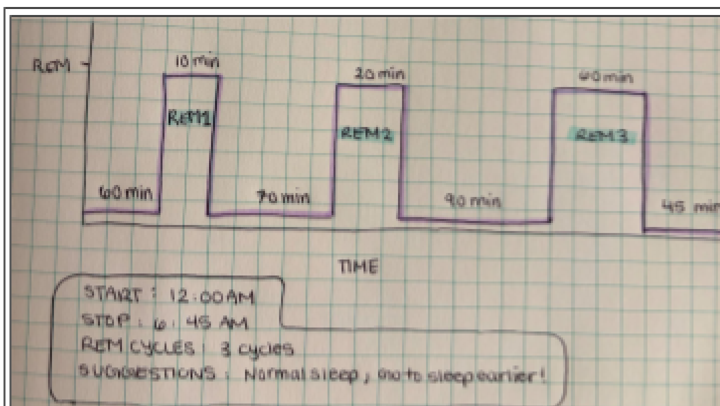

Figure 10: Mockup Simulated Data Sleep Report

software was hypersensitive. However, the density of the events was generally constricted to specific areas, indicating the device's semi-functionality. *Figure 9* (3/16/25) shows improvement over the early *Figure 8* (3/12/25), as fewer false positives were detected. The user will receive a sleep report similar to *Figure 10*, which uses simulated data for example purposes. A graph will represent the data from their night's sleep. It will also display essential information that the user should know. The alert section will highlight abnormalities that prompt the user to visit a healthcare provider to get tested.

4.0 Discussion

To address people's need for an affordable, comfortable, direct REM tracking device, an easy-to-use mask was developed using a Raspberry Pi 5 camera. This device can detect eye motion, differentiate between REM and NREM using MAD calculations, and distinguish REM groups based on 5-minute inter-saccadic intervals.

4.1 Success

The In-Lab Simulation Timing test demonstrates the accuracy of the REM tracking device when eye motion is exaggerated. To determine the success rate of the REM tracking device in a real environment, accuracy was calculated using the formula: accuracy = (inferred true REM events/total amount of motion events detected). For the 3/12/25 test, 35% of motion detected meets the parameters described in section 1.1 to be considered accurate REM. Note that there were 79 false positives. For the 3/16/25 test, 90% of motion detected could potentially qualify as REM. However, there was a significant number of false negatives that may have excluded another REM group, limiting the device's accuracy.

4.2 Limitations

All eye motion events were determined using standard inter-saccadic intervals. The process was as objective as possible however, REM eye motion is highly individualized and has minimal mathematical parameters, creating room for some subjectivity. Therefore, full validation requires simultaneous video footage of the eye for a manual cross-referencing of the software's sleep report. As well as a more concrete validation of the report was not possible; therefore, Future hardware and software work is needed to fully validate the device.

5.0 Conclusion

As people need an affordable, comfortable, and easy-to-use mechanism to monitor general health by directly tracking REM periods through monthly preliminary screenings, this device successfully detects simulated and inferred REM start, end, and duration. In-lab validation proves the mechanism can clearly distinguish eye movement from non-movement, and *Figures 8* and *9* show that the software can detect motion when worn to sleep.

Future Work

To mitigate false positives/negatives, an adaptive threshold that adjusts depending on the user's eye motion should be developed. Additionally, a suggestion system should be programmed to notify the user if any abnormalities are detected during sleep, so they can consult their healthcare provider. Abnormalities may include not having enough REM groups or having a delayed onset of REM. In terms of hardware, a case should be developed for the main breadboard, battery pack, and Raspberry Pi 5. This way, transportation and setup will be easier. Furthermore, creating a wireless system where the mask is not physically connected to the main hardware will allow the user to sleep without getting tangled in/pulling on wires comfortably. Dual-Processing by running the software and taking video footage overloaded the Raspberry Pi, so using a separate Pi with a camera on the other eye might mitigate this issue. Post-processing was also not an option due to the complexity of real-time analysis

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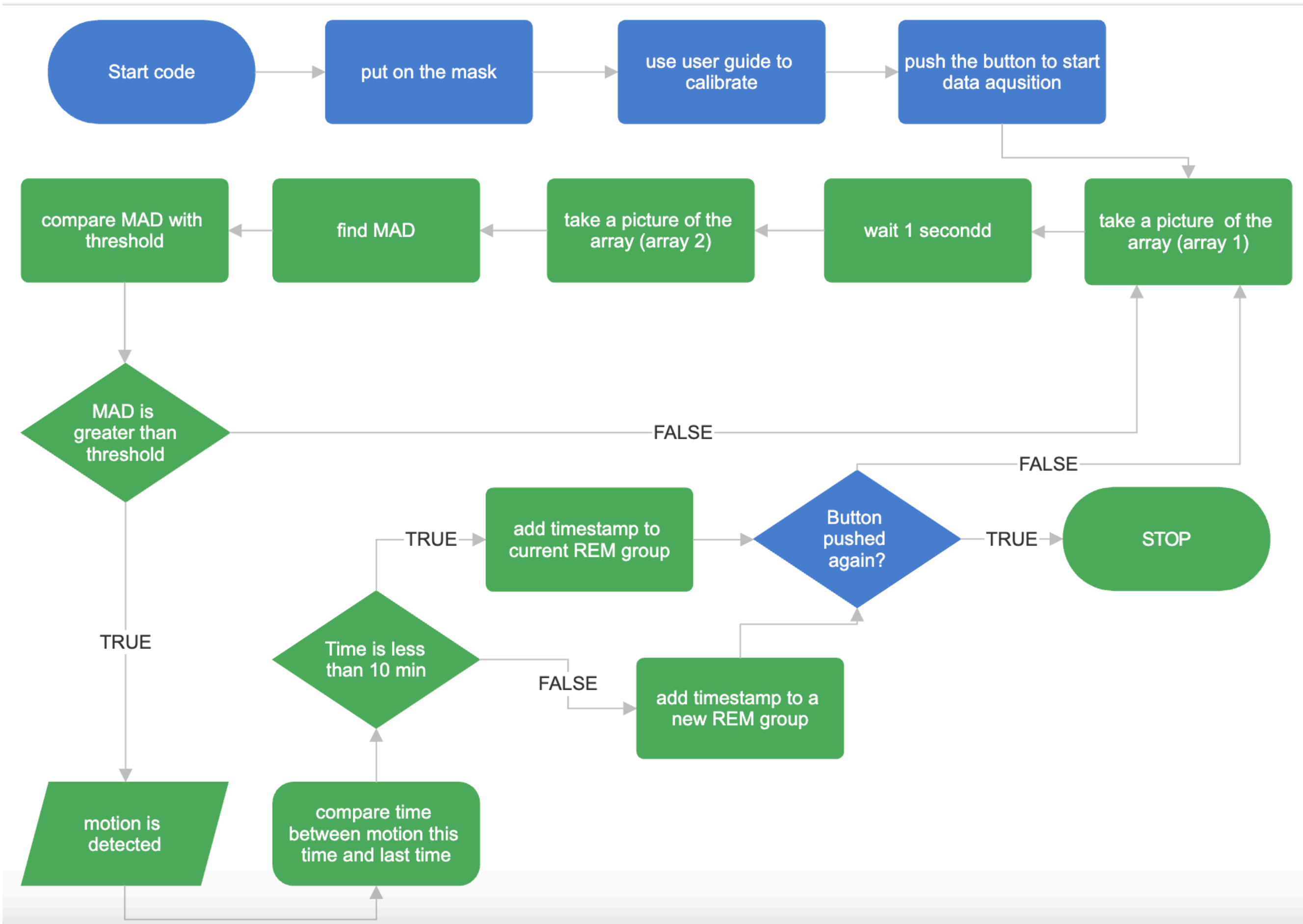
7.0 Appendices

Appendix 1: 5:30 min Validation Report CDR

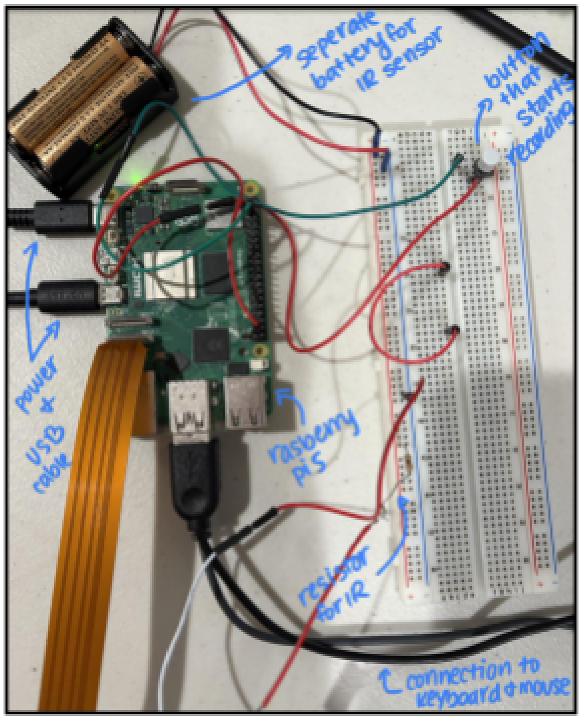
Appendix 2: Software Folder- REM Software

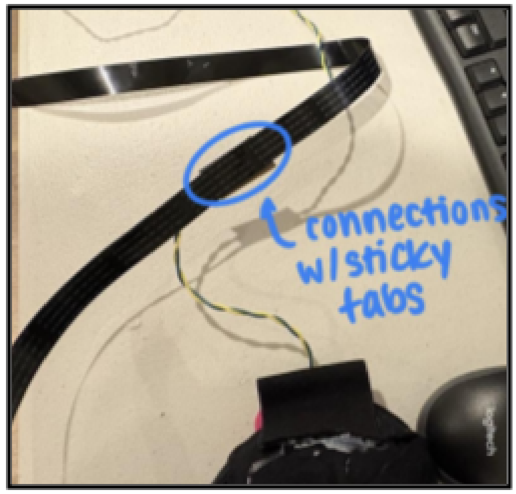
Appendix 3: Software Flowchart



Appendix 4-7: Hardware Details

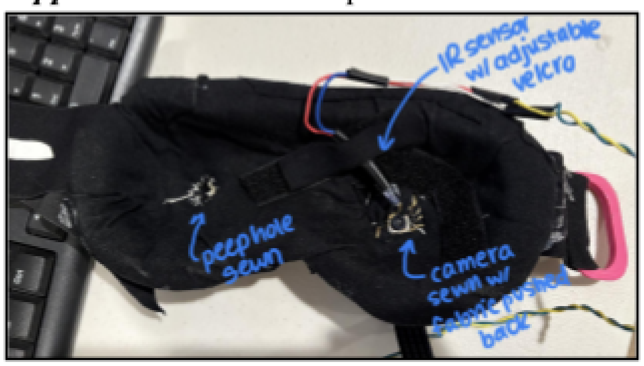
Appendix 4: Hardware Setup





Appendix 5: Cabling w/ connections

Appendix 6: Mask Setup Back



Appendix 7: Mask Setup Front