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Posture as stress indicator in eSports

Bachelor graduation thesis for Creative Technology

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ABSTRACT

eSports has grown significantly in the past few years. Whilst casual gaming has a global market cap of 200 billion $, professional tournaments can have prize pools of over 34 million $. Because of the very high stakes and drive to win, stress is apparent in both casual and professional players. However, research in eSports is very young, meaning not much is known of the effects of stress and gaming. The premise of this project was to predict stress, by comparing individual stress response to their physical posture. The idea is to use posture to predict stress, as this would keep measurements non-intrusive, such that individual performance can be the best.

From background research, multiple options for stress measurement and pose estimation were found. As priority was given to non-intrusiveness, only a few options remained. On the stress side, the Empatica E4 was chosen for its ease of use and SDK integration. For posture, OpenPose was chosen for its versatility. The resulting prototype used EDA peaks as measure of stress, specifically, the number of peaks in 30s. Posture was classified with LSTM machine learning, as other options had an inherent bias.

During the evaluation, the prototype was tested with 3 college level professional players. Due to unforeseen circumstances and bad preparation, data from these tests were unusable. It was therefore decided to do the test on myself, for a total of three matches. Results showed no significant correlation between stress and posture. Certain moments did show correlation between the two, however, this was only visible during very stressful moments. Furthermore, these results were derived from a casual player, implying that a professional player will most likely show a lesser physical response to stressful situations. Future work should look at different classification of stress and a different configuration of OpenPose.

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1 INTRODUCTION

Esports has been gaining traction in the past few years [1].With titles ranging from FPS such as CS: GO, Rainbow 6 siege and Valorant to card games and everything in between. This broad selection of games to play makes esports easier to watch as there is a game for almost everyone. However, the difference between just playing games and esports is that the latter also involves playing against opponents, local or worldwide, in return for prizes [2]. This type of competition started in 1972, where a contest was held for a year subscription to the Rolling Stones magazine [3]. Today, the prize pool of just a single game is over 34 million dollar US, with a total of 110.6 across 3500+ tournaments [3]. This development has led to certain esports titles to be included in the upcoming Olympic Virtual Games [4]. On the casual side, it is estimated that there are over 2.9 billion players across the globe. This giant player pool resulted a 175.8 billion us market in 2021 alone [5].

With esports becoming as big as it is now, other professions are starting to be implemented into esports [6]. In regular sports, highly competitive athletes have an entire team behind them [7] [8]. These experts are there to optimize every aspect of the athlete's life. In 2016, it was stated that esports deserved such professionalism [6]. Compared to regular sports, esports can access data around the player much easier. However, it is not until recently that teams are trying to take advantage. In 2019, a report was published that stated that jobs in data science are booming [9].This professionalization is further acknowledged from other research in 2019, where esports needs the experts from the medical domain [10]. Esports is becoming more and more like sports from a professional standpoint, however medical experts do not know the solution. An understanding needs to be made in order to be prepared for the moment professional esports calls for medical expertise [10]. This need for professional opinion has led teams to integrate these professions into esports. In 2020, the esports team Fnatic publicly announced that it hired sport scientists to investigate their players [11]. This team is tasked with analysing any aspect that can give an advantage as playing for big prize pools can cause a difference in performance for these players [11].

There are many aspects in which players can optimize their performance [12]. Stress level is an important part of this development. Many downsides have been found when a player has a high stress level [13]. The excessive nature of esports has been proven to cause both physical and psychological problems. Physical problems include eye fatigue, blurry vision, and wrist pain. On the psychological side, effects include depression, uncooperative attitude and aggressive behaviour [13]. If any of these effects were to present itself, performance of the player could be severely impacted. Which is unfortunate, given stress has been researched for quite some time. However, stress should not be mitigated entirely. Stress also improves performance, where the induced adrenaline makes the heartbeat faster and therefore improves reaction speed of the player [14]. In turn, this change can make a person more focused on important tasks.

As stated before, not much is known in stress compared to regular sports. Furthermore, stress coping strategies from the sports domain that do exist may not be applicable to esports. The biggest difference between regular sports and esports is the heavier focus on mental performance in esports. It is argued that in esports, players do not physically outperform their opponents and are therefore competing on a mental level [15]. It is because of this difference that dysfunctional stress is found easier in sports, where most problems often lie in physical errors [15]. In esports, barely any research is available when it comes to bad stress detection [16]. The best moment for big stress management is during halftime, or other rest periods since the coach can only talk to the players during this time [17], [18]. Fortunately, the benefit of esports is that smaller coping techniques can be implemented quicker as players are in direct and constant communication with each other. Furthermore, tournaments in esports have many very short breaks, where coping mechanisms can be implemented earlier [19] [20] [17], however, this is dependent of the game, as other esports do not have such a format [21], [22]. Given that stress analysis is so important, and no method exists that can detect dysfunctional stress in esports, research should be done to do exactly that.

One method to specifically look at is posture. Due to the inherent nature that stress affects almost every part in the human body [23],is it possible that posture is impacted by stress. And research has proven this to be true. In 2021, research has shown that movement can be used to predict stress [24]. Furthermore, posture can be measured easily and non-intrusively. Since the measurement is the actual body, many sensors exist such as tracking suits or complex options using computer vision [25] [26]. Overall, this allows posture to be an indication for stress.

In this project, the aim is to create a tool that can analyse the stress of a player and detect dysfunctional stress as quickly as possible. This system can monitor and provide feedback on stress. The application is aimed at professional gamers playing in eSports competition. By looking at the correlation between posture and stress, an early warning could be given on eventual raging. This system then will be implemented in a posterior manner. Posterior is key here, as feedback is not an option during gaming, but does need to happen whilst the player can still recall their actions. Receiving feedback on a game over a week ago is not effective and can result in lesser performance.

To help tackle this subject, research questions have been set up to guide the process. These are listed below:

How can we create a system that can provide feedback on the current stress level based on player movement in esports?

RQ1: What are the functional requirements of a system that can provide feedback on the current stress level based on player movements in esports?

RQ1.1: How can we predict stress level with the use of player movement?

RQ1.2: When is stress bad and can we measure this difference?

RQ1.3: How accurate is movement for stress prediction?

RQ2: What are the non-functional requirements of a system that can provide feedback on the current stress level based on player movements in esports?

RQ2.1: What non-functional requirements should be included for different roles in esports teams, and how does this affect the design? (i.e., coach, players, for specific games)

RQ3: How would the initial design look like of a system that can provide feedback on the current stress level based on player movements in esports?

RQ3.1: How comparable is the initial design compared to subjective stress perception.

Next is chapter 2, where background research has been given to further elaborate on this topic. Furthermore, a state of the art is presented regarding stress measurements. Chapter 3 will describe methodology to facilitate the design of stress in Esports. Concepts will be handled in chapter 4 and chapter 5 shows how the concept was narrowed down. In chapter 6, the process of creating the prototype is shown, and it is evaluated in chapter 7. Chapter 8 and 9 will conclude this thesis and show further future work.

2 BACKGROUND RESEARCH

Although the problem was identified in the introduction, depth is missing as to find a solution to indicate stress with posture. This first section of chapter 2 goes into more depth as to the specific type of stress that emerges in eSports, how certain aspects from sports can be used and elaboration on the importance of stress. The state of the art will focus on possible methods to measure stress and methods to capture posture.

2.1 CONTEXT

2.1.1 What is stress

Before measuring stress, having a clear definition is vital. Stress is not a concrete subject [27]. Due to the vast research domains where stress is applicable, many definitions exist. Although the concept of stress has been known to humanity since the Greek empire, the definition has changed throughout time [27]. Philosophers such as Aristoteles knew about stress and the human response to it, however, up until 1859, no formal definition was given. Since then, the definition of stress has been iterated by other researchers as stress means something else to different professions. Nowadays it is known that stress affects many systems in the human body [23]. Brain function, immune system, cardiovascular system and digestion are influenced by stress response. However, stress is not necessarily bad. As explained by Hans Seyle, stress is crucial to maintaining life [27].

2.1.2 Stress in sports

Stress in sports as a research topic has been studied for several decades. Studies date back to the 90's where external stress is argued to be included in analysis of athletes [28]. Because stress research has had the time to develop, causes for stress have also been examined [29]. This study showed that athletes perceived stress due to numerous factors. Among other factors, these causes include spectators making noise and a disappointed coach. This is further elaborated by a study from 2005 [30]. This study found other examples that emerged stress. Whilst many causes were given, all forms of stress fell under one of these categories: Performance, Environmental, Personal, Leadership and Team. To counter this, research regarding coping has been done as well. A study from 2010 investigated what effect coping styles have on performance for males and females [31]. Results were gathered using questionnaires. Findings show that a negative relationship was found between approach coping and performance. Causes for this relationship most likely come from the effort needed for this coping style, resulting in less focus on the game itself. The research did find a positive relationship between avoidance coping for male athletes and performance. This difference between genders is explained by the reasoning that males react more significantly to stressors. The higher coefficient between avoidance coping and performance for males suggests that males are more affected behaviourally than females [31]. However, another study showed that females use more avoidance coping [29]. In the discussion of this study, other references were made to other results of coping style. These studies concluded both a difference between genders whilst other studies did not find a difference.

Movement as an indicator of performance has been discussed in many sports. In this study, an overview is given, where each sport and their respective sensor is [32]. In sports, movement is very important. Besides that, it is needed to play the sport, movement is also used to analyse the athlete [32]. By using certain sensors, algorithms can show movement patterns and prevent injury. The company Zepp, for example, makes sensors for varying sports such as baseball and tennis. These sensors focus on the movement specific to the sport such as swinging for tennis, but the soccer sensor measures sprints and power [33].

2.1.3 Stress in esports

The current state of stress in esports is very young in development. As shown in [34]. scientific research has grown since 2016 in all aspects of esports. In an overview of current literature in esports, the most common topics researched did not include stress [35]. Instead, current publications mainly focus on management, behaviour and gaming itself. With stress in mind, this infancy of research has led the few papers that did investigate stress show negative effects on players, including the paper mentioned before, but not the solution to prevent or manage them [23] [13]. A literature study did list results of stress response in Esports [36]. Their conclusion was that although stress response is significantly changed in competitive esports settings, results should be looked at with caution, as little research is available. This is further acknowledged in [37], by their literature review on research gaps on health in esports. This report mentions the gap that managing health risks has not been researched, among many other gaps that are vital for the growth of esports.

In the literature currently available, causes for stress were researched. In [38], multiple causes were found for stress. Players from different games responded to several topics surrounding stress. Physical causes related to daily routine such as sleep, nutrition, and exercise, whilst psychological causes came from mental pressure to perform, burnout and support [38]. Another study also researched causes for stress, both internal and external [16]. Their results showed that internal stressors often come from communication between team members and lack of confidence. External stressors come from bad planning and intimidation from opponents. The study goes further by elaborating on some coping strategies players used to combat these stressors. These coping strategies vary from emotion-focused coping to avoidance coping. Another coping strategy players used was to change their play style in each round. Lack of confidence often resulted in more passive play, as not dying was important [16].

This stress is possible to perceive in games. A study measured heart rate during a game of street fighter and compared heart rate during different scenarios [39]. Their results show that heart rate during rest is lower than playing a match. However, playing against AI and against players resulted in a different heart rate. When playing against players, heart rate was significantly higher [39]. The cause for this comes from the competitive nature of playing against players. “Since the essential motivation of esports athletes is to win against their human opponent [40], esports athletes might not play as seriously when their opponent is a computer and may treat the situation more like practice” [39].

Shown in [23], stress is known to affect almost all bodily functions, including posture. This is validated by research from [24], where movement was found to be a prediction for stress. This was done by putting participants in virtual environments and recording their response to various situations. By emerging stress in the participants, machine learning was able to relate movement to HRV. This was possible due to the unobtrusive nature of movement recording. For the upper body, trackers from the VR headset and controller were used, whilst the lower body was tracked using an Xsens Awinda suit. This possibility is further researched by [41], where trackers were placed inside the fabric of clothes. The reasoning for this development was that other forms of motion capture were either heavy, intrusive, have a short recording or a combination of these three.

2.1.4 Why is stress so important

All in all, what does the known research mean for esports? In short, players and teams are left to their own devices. The lack of research around stress means that quantifiable data is scarce. Stressors can be found; however, the coping step cannot be supported. This is such a shame, as esports is now a big subject. Players are in the dark about long term effects of their career. The increased revenue flow around esports means more and more people are attracted to try professional gaming, without fully knowing all the consequences. Combined with the few physical requirements needed for esports, means that stress has a relatively higher impact compared to physical sports when present. In the short term, coping and feedback solutions with data support are needed, such that the long-term effects are minimized.

Another reason why stress is important for the esports scene, is that cognitive thinking is impacted by stressors [42]. Examples show that stress decreases memory retention and learning. Due to the wide variety of professions where cognition is applied, often studies do not agree on results. A law that does seem to be universal relates to performance and amount of stress. The Yerkes-Dodson law [42], states that performance is best when stress is apparent but not impeding or low. That is why cognitive state is important to know. As this can be an indicator for high stress. Furthermore, the effect of high stress then in turn reduces performance as cognitive load is low. This is like the concept of flow, where focus and challenge in balance allow for optimal performance. The findings in [43] indicate that flow has a similar response on the body across different domains. These results therefore indicate that level of engagement can be measured, where stress can be the underlying cause.

2.1.5 Stress in practice

In order to get a better understanding of research done in practical terms, an interview was done with Esports Team Twente (ETT). ETT currently houses three competitive teams: CS: GO, Valorant and League of Legends. Their goal is to gather as much data from the game as possible, where after analysis is done to improve performance. In the interview, I specifically talked to the Education and research manager. Their job is to coordinate all the research and data analysis projects that happen within ETT. In detail, this person connects the right people to the best research. There already have been numerous research projects with ETT. For example, research was done with the Dutch navy to improve communication. Soldiers got instructions to communicate, after which they played a CS: GO match to test those skills. Although these soldiers do not know how to play the game well, the communication aspect did work. It worked so well, that this test is now part of the actual training of navy soldiers. However, the stress side of research has not been analysed much if at all with ETT. There is one big project around sim racing, where almost all data that can be collected is processed. Stress specifically is not researched, where it could be a potential factor for analysis. ETT has agreed to use their CS: GO team to test stress using posture.

2.2 STATE OF ART

This section lists current methods to measure both stress and posture. This broad overview gives some possibilities to eventually decide a sensor type in the concepting phase.

2.2.1 Methods measure stress

Stress has effects on many physiological metrics. This section lists some types of metrics that measure stress.

2.2.1.1 HR

The first method discussed is heart rate. As elaborated earlier, stress can be measured indirectly with heart rate as the heart is connected to the SVS. To measure this change, an electrocardiogram (ECG) can be used. Other methods such as photoplethysmogram (PPG) can also extract heart rate. In a literature study it was found that heart rate is the most used method to measure stress [44].No elaboration was given as to why ECG is mostly used. My best guess is that this is due to the combination of easily accessible, many accurate sensors and the fact that the heart is also connected to the parasympathetic nervous system (PVS).

2.2.1.2 Stress

This section discusses some papers where Electro Dermal Activity (EDA) was evaluated using classification. Indikawati and Winiarti [45] state that solutions are becoming more prominent due to their non-intrusive nature. The Empatica E4 is the device used. With a classification system, the measurements from the E4 were accurate enough to predict in which state the subject was. Furthermore, Romine et al [46] used the Empatica E4 to measure stress. Indikiwati et al [45] recorded Blood Volume Pulse (BVP), EDA and Skin temperature (TEMP) to predict the stress state of a given subject. Setz et al [47] and Romine et al [46] also used these types of measurements for their respective classification systems.

Interestingly, Indikawati et al [45] state that the classification system had to be trained on a per subject basis, as the physiological response of each subject is different. The other papers have no mention of performing such differentiation. However, the use case of Setz et al [47] and Romine et al [46] is to measure cognition level, instead of stress. Although Romine et al [46] solely focused on cognition classification, Setz et al [47] differentiated stress from cognition as EDA is not a direct indication of cognitive activity.

Conclusively, the devices used to measure EDA are not consistent across the different sources. However, all solutions are using a non-intrusive method.

2.2.1.3 Skin temperature

Another method to measure stress is skin temperature. This method consists of a temperature sensor, usually placed in a wrist device. The advantage of skin temp is that the sensor can be easily integrated in devices that also have other sensors, such as the empatica e4. Furthermore, it has been shown that skin temperature is a valid metric for stress measurement [48] [49].

2.2.1.4 Pupil dilation

Just like the heart, the eyes are connected to both the SVS and the PVS. When stress is induced, changes in pupil size can be measured. To measure this difference, software such as OpenFace can be used. This software provides more features compared to OpenPose regarding facial analysis.

2.2.1.5 Other

Some new developments have been made regarding intrusiveness. Researchers have developed a new easy sensor to measure stress. Besides physiological sensors, there is another method to measure stress: biomarkers. Sensors measure the physical level of certain hormone levels to determine stress levels. The advancement in [50] made is a non-intrusive biopatch that uses microfluidics to measure cortisol level in sweat. The concept showed that more physical measurements can be integrated into the same form factor [50] [51].

2.2.2 Methods measure posture

2.2.2.1 Body tracking

Switching from physiological to physical response, estimating movement activity can be done in a few ways. This section discusses some methods.

The first method is full-body tracking. The goal of Rodrigues et al [24] was to estimate Heart Rate Variability (HRV) based on lower body movement and ECG. The subjects were put in a VR environment and experienced different environments. For movement capture, the xsens awinda was used. This suit is equipped with trackers for every bone used in tracking. The advantage of full-body tracking is high accuracy. The trackers are exactly where the physical part is. Although the xsens awinda is relatively non-intrusive, users are still required to put on a suit. Source xsens

Alternatively, Nathan et al [52] used an Xbox Kinect to record movement. The goal of this study was to estimate mechanical work performed by the body. The Kinect works this effectively due to its depth sensor. The software behind the camera uses this depth information to identify the person and track the entire body around this detection (Kinect software). The Kinect is less intrusive compared to the xsens suit due to the tracking method. However, the Kinect does have a low-resolution camera, resulting in higher error rates for posture estimation.

The third method uses the software OpenPose. This method works by processing images just like the Kinect. The difference between these two is that OpenPose uses deep learning to detect and track the human body. The advantage of OpenPose is that it can take any image input, video, or webcam. Furthermore, the software is open source, meaning improvements are made regularly. However, the biggest advantage over the Kinect is that OpenPose can use any camera. Whilst the Kinect is limited to its built-in camera, OpenPose can use 4k cameras from smartphones or other sources, allowing for lower error rates. The biggest downside is that OpenPose requires some programming to set up.

2.2.2.2 Optimal posture

Many factors influence posture. This section describes some indicators of optimal posture. To illustrate, Marschall et al [53] researched the effect of desk design on posture in young children. They found that ergonomic desk design resulted in significantly less muscle activity. To support this, Straker et al [54] & Asundi et al [55] also investigated desk design and position. Straker [54] found that a curved desk increases muscle activity, implying that a curved desk provides more support to the body. Asundi et al [55] however, researched the difference between desk and laptop-based working. They found that a laptop on the lap resulted in bigger tension of muscles compared to the desktop position. However, in this experiment all positions caused head tilt, wrist extension and deviation.

In contrast, Gutierrez et al [56] researched the effects of chair design on gaming experience and performance. They found that an ergonomic chair improves both comfort and performance. The ergonomic chair provides both back and arm support compared to a regular chair. This implies that a good posture, and therefore less muscle activity, allows the body to focus more attention to gaming performance. However, this experiment had a low number of subjects, which makes the results less significant.

All papers show that good posture should improve both comfort and performance. However, all but one paper discussed have a low sample size, resulting in non-significant conclusions. The results are to be considered, but a bigger sample size like Straker et al [54] allows for better data. Furthermore, Marschall et al [53]tested their results on young children, making these results not comparable to the other papers unless comparison between adults and children is possible.

2.2.3 Methods measure cognition

As stated in the prior paragraph, measuring cognition is also generally done through non-intrusive solutions. The difference lies with the classification of cognitive load. Cognition can be another valid method to indicate stress or find causes for performance. While Setz et al [47] used EDA, breathing, ECG and movement to measure cognitive load, Romine et al [46] used EDA, Heart Rate and Skin temperature. Setz et al [47] chose to measure brain activity and stress level, as these inputs are directly affected by the stress reaction. To induce stress, the Montreal imaging stress task was used. To differentiate stress from cognition, the subjected people were exposed to a cognitively challenging situation in the other session. This allowed them to differentiate the physiological response and train the classification system more accurately.

In contrast, Romine et al [46] used a different method of validating their measurements. In their first experiment, the group was exposed to a set of different levels of cognitive load. In the second experiment, the same set was used, but the subject was asked to give a subjective rating of their cognitive load. The researchers then trained another model with this personal bias for classification. Although both papers used entirely different methods to measure and quantify cognitive load, each classification model was roughly 80% accurate. Based on the extensive measurements needed in Setz et al [47], Romine et al [46] seems an easier method for measuring cognitive load, as the needed measurements are already used for stress measurements.

Measuring cognition has been chosen to explore because cognitive load might have an impact on posture. Ge et al [57] observed that cognitive load can have an impact on posture control. In combination with stress prediction, cognitive load can give better insight on posture improvement.

3 METHOD

With the necessary background information shown in Chapter 2, this section will discuss the process used to create and evaluate the prototype. To facilitate indicating stress with posture, the Design Cycle for Creative Technology is used, described by Mader and Eggink [58]. This method iterates over 4 specific cycles with an explorative approach. In each iteration, an evaluation is made to determine the best solution for each stage.

3.1 IDEATION

This first phase of the design process is to get a grasp on the initial design. Starting from the initial problem statement, the idea is to create several concepts and shape requirements necessary for the prototype. As described by mader and eggink [58], this starts by diverging and converging the different methods listed in the state of the art. From this, the best solution within the context can be found. Afterwards concepts are created which will be evaluated by the target-group to find the best concept to elaborate on.

3.1.1 Interviews

To specifically find the needs of the end-user, interviews are held to shape requirements. These will vary between structured and semi-structured form depending on the context of the interview. For interviews concerning information and feedback, structured style will be preferred. Whilst asking an expert will be semi-structured in form.

3.1.2 Sketching

Sketching is an important technique in the early stages of design. The use for sketching in this phase is to easily create new concepts and communicate design with stakeholders. These will be done with pen and paper.

3.2 SPECIFICATION

This stage is meant to create a clear overview of the final concept. This is done by proposing the concepts to the players and coach, to discuss requirements and finalize a single concept. Specifically, technical aspects are discussed in this stage.

3.2.1 Flowchart/activity diagram

To understand the final concept, a flowchart is useful as it describes the relation between each component. First all software/hardware components are placed on a sheet. Afterwards, what each part needs and send to the other will be displayed.

3.2.2 Interviews

In this part of the design method, interviews are important to gather the needed requirements of the system. These will be done in both structured and semi-structured form depending on the user that is asked.

3.3 Realization

This part of the design cycle allows for prototyping the physical and software design. Python programming was done on Python 3.7 with libraries pandas, matplotlib, scikit-learn, keras, opencv-python and numpy. The cameras were 3 Logitech Brio 4K and 2 Logitech C920 running at a default of 720p. OpenPose 1.7 was run on an intel i7 10700kf with a rtx 3070 with openpose running at a resolution of 240p. The BLED112 firmware was adapted to accept 5 connections with the included 1.6 SDK.

3.4 Evaluation

This part of the design process is crucial to validate the prototype. Testing is done in this phase in order to answer the research question regarding validation and to check whether the requirements have been met.

3.4.1 Interview

To evaluate the design from the user's perspective, a final interview is done in a non-structured format to answer questions on the feedback system

3.5 Covid precautions

Since covid-19 is still a factor during this research and given that human participants are necessary for evaluation, rules and precautions prescribed by the government are followed to limit the chance of infection.

4 IDEATION

Starting the ideation phase, it should first be known what is measured for stress and what is measured for posture. Furthermore, how these aspects are going to be measured. Listed below are the possible options investigated from Chapter 2. Then, options are covered to process the incoming data. Finally, the visualization step of results is discussed.

4.1 SENSORS

4.1.1 ECG

As mentioned in the state of the art, HRV is used in many papers. Due to this popularity, information regarding measuring can be obtained easily. Furthermore, processing the data is also relatively easy, as numerous papers mention how to clean up ECG data.

The downside of this metric is that heart rate is intrusive in most methods. ECG sensors in hospitals use diodes that are placed on the chest. Other sensors such as waste bands exist, however these might still be too noticeable. Furthermore, measurements from common methods have delays, which are not fast enough for esports. Depending on the sensor and software, HRV is an average across time, which is an average of 1 minute [history]. In situations that are quick, HRV won't show a giant difference and is in this instance not a good control for stress. Other studies have shown that 10s average for HRV is possible [59]. HRV is not the ideal solution for this context.

4.1.2 EDA

Just like HRV, EDA is used in many research papers [47] [46]. Because of this popularity, it is not a far fetch to assume it is a valid method to measure stress.

The biggest downside to EDA with respect to classification relates to the accuracy of the system. Research that used this sensor did provide accuracy within the dataset, however, for this use case of real time prediction no mention is made of subjective stress level. A model must be trained for individual response in order to improve individual accuracy. Furthermore, in personal discovery, the EDA data is also influenced by sweat in general. Therefore, a consistent space and temperature must be used to accurately measure EDA.

4.1.3 Skin Temperature

Research has shown that skin temperature is viable as an indication for stress [48] [49].With this in mind, skin temperature will be used if the sensor can be added easily. This is due to the better and preferred methods above.

4.1.4 Pupil

As a sensor, pupil dilation is a very interesting method. However, this method requires a high-resolution camera in order to capture the pupil. Thus, the camera must be placed close to the face. This might not be possible in the setting of eSports.

4.1.5 Cognition

Cognition is an interesting topic to cover stress. However, this method requires a training session on cognitive thinking. As shown in research, it is possible to use EDA to measure cognition using a suitable test. Research around cognition during gaming is out of the scope of this project.

4.1.6 Xsens Awinda

The suit is very accurate for measuring posture. The high polling rate and low latency of the internal sensors entails detailed posture data. However, the Awinda is still a suit, meaning players must either put it on over their clothes, or remove clothing to fit the Awinda. This suit is not ideal for the context of this project, given the requirement of intrusiveness. [25]

4.1.7 Xbox Kinect

As an option, I looked at a Kinect 360 that I have in possession. The downside is that the sdk came out 8 years ago in 2013. The newer Xbox One Kinect is also available, with better cameras and sensors. However, its sdk was released in 2014. This means that the programming used is lacking in current techniques.

4.1.8 OpenPose

Initially, OpenPose is a good option. The program is open source and can accept any image input. The downside is that the output is not directly usable. This means that it requires more programming to adapt the code for classification. Furthermore, the software is very resource intensive, meaning a separate computer must be used alongside the gaming computer. [60]

4.1.9 Conclusion

Table 1: Overview of sensor types

Sensor/Quality	**Intrusiveness**	**Accuracy**	**Speed**	**Ease of use**
ECG	0	+	-	0

EDA	+	0	+	+
Skin temp	+	0	+	0
Pupil dilation	+	-	+	-
Cognition	+	-	+	-
Sensor/quality	**Price**	**Intrusiveness**	**Accuracy**	**Ease of use**
Xsens Awinda	-	-	+	0
Xbox Kinect	+	+	-	0
OpenPose	+	+	0	0

Many products exist with their respective benefits and downsides. Table 1 shows the defined up and downsides of each option. Based on the requirements, only a few sensors will be used. In this context, low intrusive methods are preferred as this reduces variables to the players performance. Accurate heart rate sensors are quite intrusive whilst non-intrusive sensors are less accurate. Because of this separation, current heart rate sensors are not viable for this setting. Therefore, EDA is the method of choice. From research, a common device used to measure EDA is the Empatica e4. Figure 1 shows the E4 device.

Figure 1: Empatica E4 device

It is a non-intrusive wrist sensor which incorporates the EDA and skin temperature sensor. The biggest advantage of the E4 is the easy integration in Android apps. The company Empatica has an SDK available to directly capture the data measured. One point of consideration is cost. The device is very expensive, at 1690$. Here at the university, students can loan these devices, meaning cost is not a factor for consideration.

Switching to the body movement side. Each sensor has its own level of accuracy and intrusiveness. The Xsens Awinda is one of the most accurate systems currently available. Due to the high-quality sensors and low latency, body tracking has been made easy. The biggest downside regarding this project is the intrusiveness. The sensors must be placed on the body, which can be reduced using the suit. However, given the steep price, makes the Xsens Awinda not the best sensor for these requirements.

The Xbox Kinect sensor is on the other side of the spectrum. These sensors can be obtained cheap. An old SDK is available to integrate the data. Although a depth sensor is inside the Kinect, as stated before, the camera on the Kinect is low resolution, giving a relatively high error rate. Given the current requirements, the Xbox Kinect is not going to be used.

The OpenPose software compromises perfectly between price and accuracy. The ability to use high quality cameras in any situation allows for great adaptability. The downside of this software is that it requires some programming to capture and use the data. In figure 2 below, a basic demonstration of OpenPose is shown.

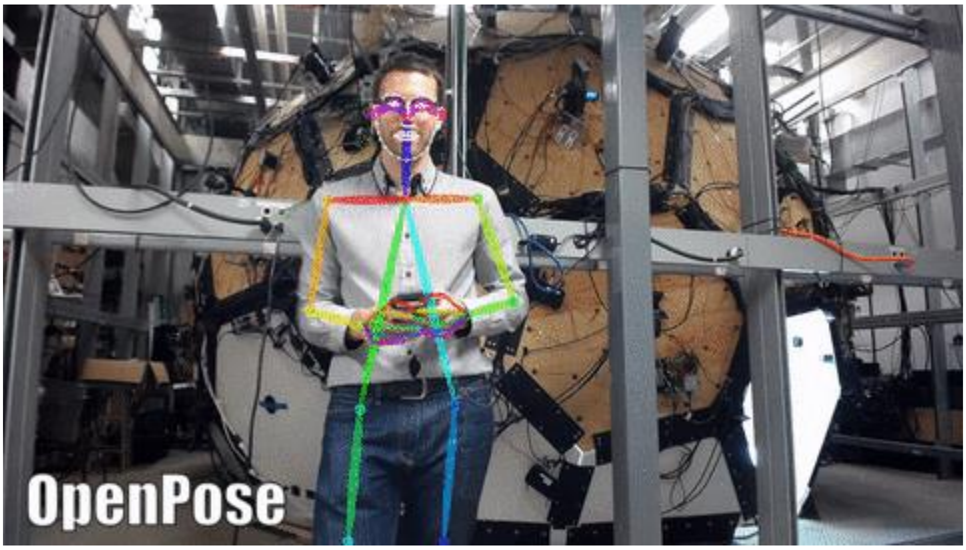

Figure 2: Example of OpenPose

4.2 ANALYSIS

From the known sensors, the next step in the prototype is processing incoming data. In the subsection below, software programs are compared that format the data such that posture is classified.

4.2.1 Stress classification

Coming from the Empatica E4, HRV and GSR can indicate stress. Due to the unreliability of the HR sensor during testing, GSR will be used for classification.

4.2.1.1 Phases

Initially, classifying stress meant knowing the difference between rest and stress. The idea is to record incoming data and classify the respective data depending on the given state. When the section of data came from rest (e.g watching a video) it was classified as rest. However, it was then found that this would indicate whether a person was gaming or not in this context. It was therefore decided to look further.

4.2.1.2 Peak detection

After searching internally in the university, one solution was to use the peak detection script by [61]. Research shows that peaks can be used to identify stress. The software takes the sequence of GSR from the E4 as an input, and outputs a list where it has detected a peak based on the configuration. One thing to consider is the fact that a single peak does not mean a person is stressed. Said in [62], more peaks mean more arousal. This would mean that the software needs to be adapted to output a density of peaks.

4.2.2 Posture classification

Continuing to the posture classification, python has many libraries available with machine learning. Listed below are the most common algorithms.

- kNN
- Decision Tree
- Random Forest
- ADA boost
- GaussianNB
- Linear Discriminant
- Quadratic Discriminant

Optionally, another algorithm can be used: LSTM. Instead of single samples, this algorithm takes a sequence of data, meaning the input is a pattern of posture, instead of a moment in time.

4.3 VISUALIZATION

Finally, these processed results must be displayed in order to gain insight. Different types of visualization are compared to have an understandable overview.

4.3.1 Tilt watch

Tilt watch is a recent software product that uses HRV to measure stress. On the product page it is mentioned that the software uses the root square between heart rate peaks to then determine how stressed a person is. The real-time monitoring aspect allows the user to directly see and intervene their stress levels. Although the base service is free, the paid version offers more insight and control. Furthermore, an HRV device is not included [17]. The visualization aspect works by a circular overview displayed in percentages. When a person is more stressed, the percentage increases and the line in the circle approaches closer to red.

4.3.2 Muse

Another option on the market is the Muse headband. This device includes many stress sensors such as heart rate, brain activity and other smaller sensors such as an accelerometer and gyroscope. The benefit is that the muse headband gives more possibilities to cope with stress. The device has a quite steep price for mass use; however, the device can be used for more than just stress monitoring [18]. In the application, stress is displayed over time categorized between rest, neutral and active. Although the classification is discrete, values are continuous over time.

5 SPECIFICATION

With the options identified, this phase will determine the best configuration to indicate stress with posture. From the broad ideas of the ideation phase, this chapter will narrow it down to a single concept. First, the required specifics are identified through an interview, whereafter the final concept is elaborated on in detail.

5.1 INTERVIEW

In order to gain insight into the needs of an eSports team, an interview was held. The interviewee is the coach of the ETT CS: GO team.

When asked whether stress is predominant in their team, initially the coach argued to not have much stress in games. Tournaments are only at college level, meaning the team will go through most teams without breaking a sweat. Another interesting point is something the coach noticed from observation. He observed that the last player does not experience stress, when they need to clutch the round to win. The team around the player does. The cause for this could lie in the fact that the clutch player is not the cause for the situation, and bad stress will result in a loss. Instead, they play as calmly as can be.

From the interview it was also clear that their college teams are not the best target user. The coach said that stress is not really a subject that they are investigating. Mostly due to the first argument, being college tournaments. Furthermore, the coach does not really know what to do with such a system. Nevertheless, he is interested in experimenting, as does understand that stress can impact performance negatively. He also showed some interest in group stress and correct posture. Where an overview of all stress measurements can be made, optimal posture is out of the scope of this project.

The best moment for a coach to intervene is most likely during timeouts. A coach has 4 timeouts available, each 1 minute long. These moments are the perfect time to intervene. Where the coach would be able to see all the statistics from each player, he can then make an informed decision about the players. The players themselves do not always see this data. Instead, the best moment for them to see their response is when they are dead. This needs to be tested in practice; however, it is a starting point for player feedback.

5.2 SYSTEM DESCRIPTION

From this interview, it is clear that the coach needs a specific tool to make an informed decision. However, requirements are difficult to make, since this iterative process means an explorative approach. This situation means that the requirements made will not mean anything, as these will have to be general. At this point in the process, it is not known when the prototype is successful. Instead, a description of the system can be made, considering point of interest from the interview.

As became clear from the interview, the coach is the target end-user for this prototype. Players cannot afford to check their stress as round strategies are more important in the moment. The coach has an overview for each player and their respective stress response. Overall, the system should allow the coach to gain insight into each players response. To ultimately find point for improvement, both in gameplay and composure. Before the final concept can be made, certain decisions need to be made beforehand. In the section below, the decision is made for the classification algorithm and visualization.

5.2.1 Stress analysis

In the ideation phase, it was mentioned that stress could be classified by EDA peaks. As this is a more scientifically proven method to detect stress, it was decided to use the peak detection script [61]. It was also said that more peaks would indicate higher arousal. However, it is not said, what this timeframe should be. After adapting the code to calculate the number of peaks in each time window, 30s was chosen to be the best. In figure 3 below, it is shown that a 30s window will give a standard deviation of peaks. This would be ideal, as the number of peaks not in the standard deviation would either be rest or stress.

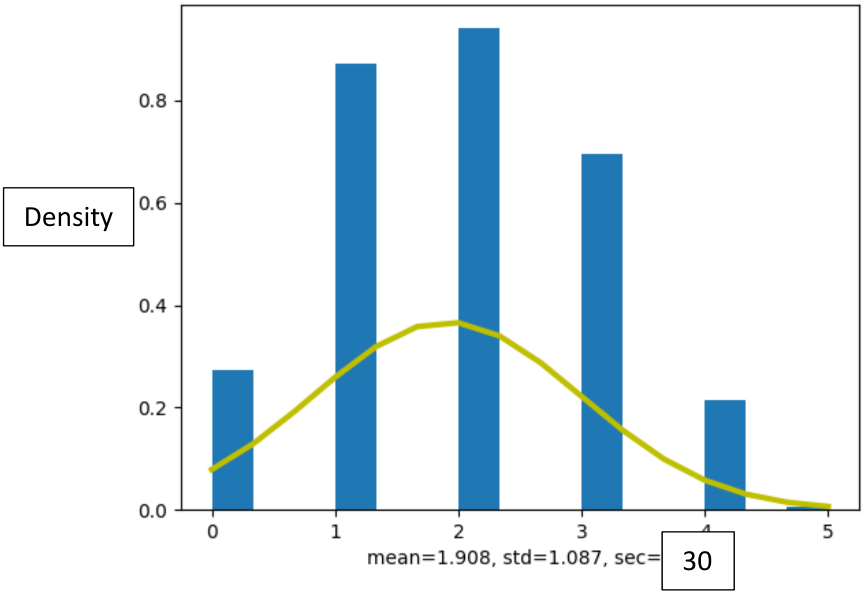

Figure 3: Normal distribution of peaks

Furthermore, the peak detection script also has an artefact detection available. As GSR measurements can vary, this code validates the data to determine whether it is useful. Combining these two metrics, classification can be applied to the posture data.

5.2.2 Classification

In order to compare stress to posture, an algorithm needs to be chosen to classify posture. In figure 4, accuracy results are shown for posture classification between the different algorithms mentioned in Chapter 4: kNN, Decision Tree, Random Forest, ADA boost, GaussianNB, Linear Discriminant and Quadratic Discriminant respectively.

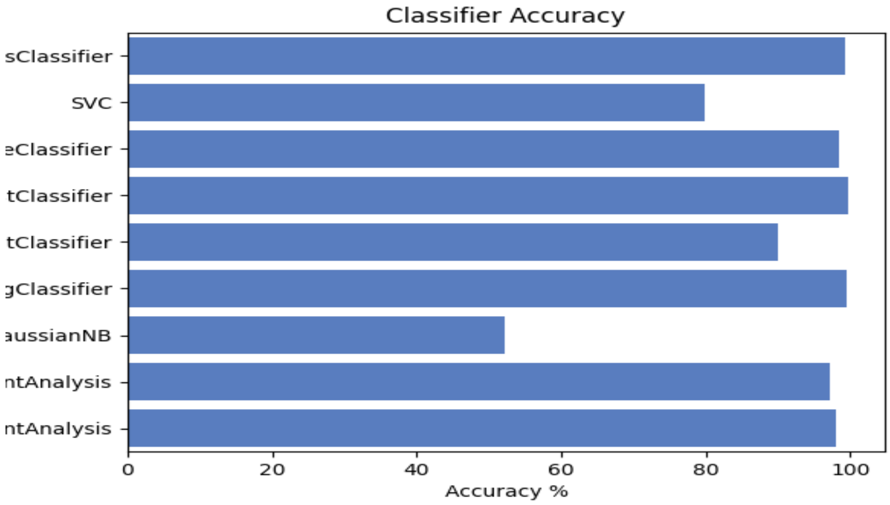

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Figure 4: Classification Accuracy of algorithms

Figure 5 shows the loss results of these algorithms.

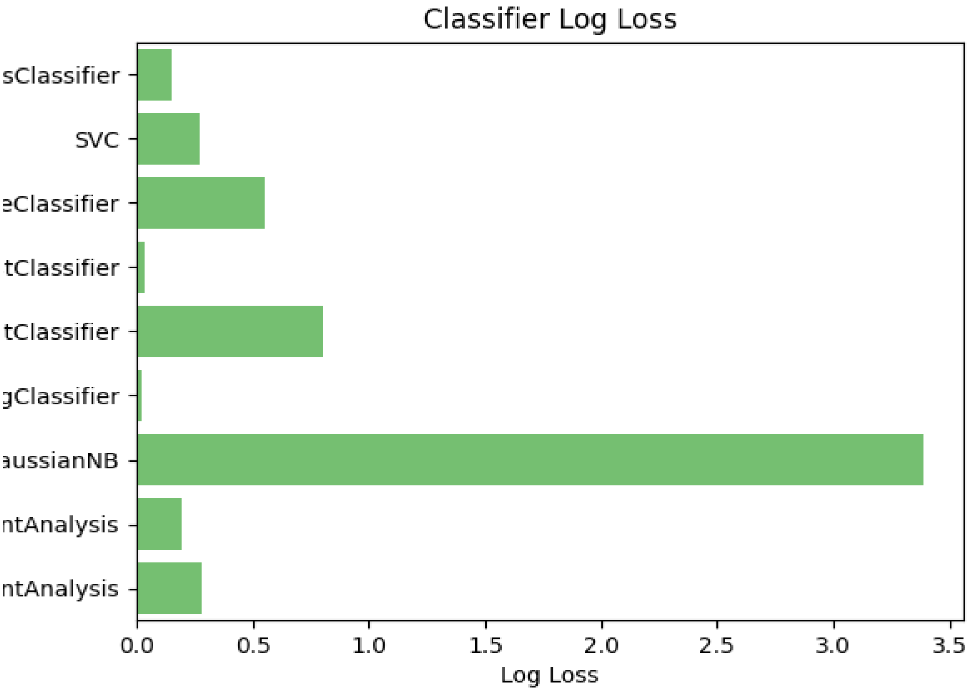

Figure 5: Loss of Classification Algorithms

However, as mentioned in the ideation, another possible classification algorithm was tested: LSTM. instead of entering a single posture sample, a time sequence is used as input. This would mean the algorithm classifies the body movement of the player, instead of the posture. With a sequence of 30s, accuracy reached 98% with a loss of 0.4. From these results, the decision was made to use the LSTM model as the models mentioned above have a bias. By this is meant that testing the models showed that leaning forward would immediately be classified as stress, which is not the case.

5.2.3 Visualization

Finally, the choice must be made for the visualization of the classification. As mentioned earlier in chapter 4.3, some commercially available products already visualize stress. Knowing know that peaks can be normally distributed, choosing a graph over time is more informative to the coach. This comes down to the fact that a coach cannot give attention to each player at each moment in time. A circular overview would not allow the coach to see an individual's response if he was preoccupied with another player. Furthermore, a graph would show a clear and discrete overview of a person's stress. The coach could then possibly see a pattern referring to the situation in game.

5.3 CONCEPT

The Empatica E4 will be used for stress measurement and validation. From this product specifically, data from the GSR and skin temperature will be recorded. The BVP sensor appears to be inconsistent to be used effectively. The device will be worn on the left wrist. In most cases, this arm is used for the keyboard, meaning minimal movement and discomfort.

5.3.1 posture

Physically, a camera will be used to record posture. This device is placed on top of the monitor in order to capture as much of the body as possible. On the computer, OpenPose will be running to identify key joints in the body.

5.3.2 In detail

The basic connection of each E4 device is simple. The devices connect to the computer via the same BLED112 Dongle. On the computer, these devices are then connected to the windows streaming server from Empatica. Code can then connect to this streaming server to receive data. The resulting dataset is then put through the peak detection and artefact detection script.

Incoming video from the camera first goes through the OpenPose code. This part of the software recognizes the joints in the body and exports this data into text. Then, this data is formatted and fed through the LSTM system.

The training code works in these steps. OpenPose data is split into train and test sets in order to produce the accuracy results. Afterwards, a save file is generated with the trained model inside. This is to create an accurate model for each person and to store a model for later use. The corresponding model is then loaded in the second test, in order to predict another dataset. The predictions are then displayed to the coach on a separate monitor. In figure 6 below, a possible overview for all players is shown. In figure 7, a possible visualization is shown that the players will see.

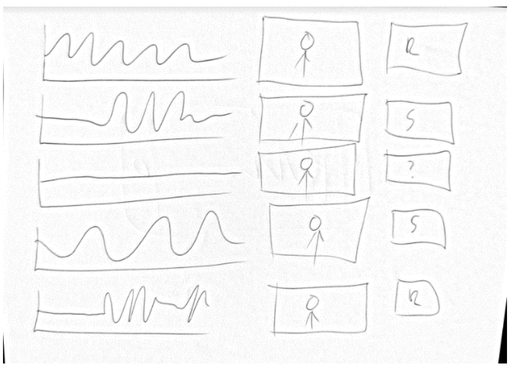

Figure 6: visualization for coach

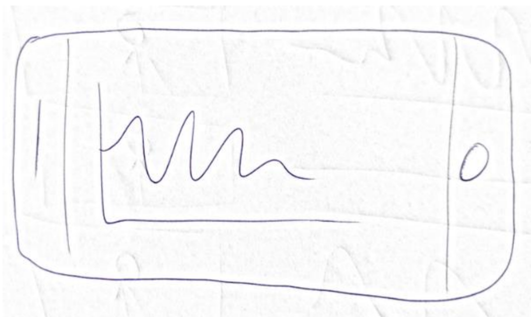

Figure 7: visualization for player

6 REALISATION

The third cycle builds the final concept defined in chapter 5. The correct hardware was placed based on the concept, and programming was done to process the incoming data. Between prototyping, small tests were done to optimize the process.

6.1 HARDWARE

The prototype is split up between two parts: the body capture and stress capture. First the stress capture process is explained.

By design, the e4 device is meant to be placed on the wrist. As the mouse is used excessively during fps games, the e4 is placed on the arm that is set on the keyboard. With that in mind, development started on capturing the stress data. Mentioned in chapter 2, Empatica offers an SDK for quickly connecting to several devices. However, this SDK is only available for Android and iOS platforms. As will be described later, posture capture will be done on the PC itself. It was therefore decided that capturing the e4 data directly to the computer is preferred. Browsing around the Empatica website revealed that Empatica has a windows streaming server. Connection to the computer is done via Bluetooth. Specifically, connection must be done via the BLED112 dongle. Within the BMS department, this dongle is available, meaning the streaming server is a suitable option. Unfortunately, sample code is only available for c#. Given OpenPose runs on python, I asked around the Department to see whether others before me have found a different solution. This resulted in the discovery of the e4 client package available for python. With that in mind, the hardware setup for the stress capture was as follows: For each person, an e4 wristband placed on the left wrist, with each device connected to a single computer with the BLED112 Bluetooth dongle running the python code.

The body capture process started with determining the pose keypoints that needed to be captured. As described by the OpenPose documentation, 18 joints are extracted in the python code. Ideally all joints are processed, as each person could exert their stress response on any body part. However, only the upper body was recorded as using two cameras per person was not an option. Neither was configuring the gaming setup such that the camera could see the entire body as this would compromise on being able to test with multiple people simultaneously. Next was deciding the camera placement. To do this, a Trust Spotlight Pro was used. Placing the camera directly on the monitor as a regular webcam revealed that this would not work as the webcam does not have the field of view to capture the entire upper body from this position. After that, the trust webcam was placed on top of two carton boxes. This provided the needed height, however, did impede on desk space, meaning less space was left for the mouse. Figure 8 shows the setup of prototype 1.

Figure 8: prototype 1

Fortunately, the esportslab has a frame built into the room. Hanging from the ceiling is a system of tubes and clamps to which anything can be attached. With this in mind, these poles were configured such that two of them stand between the desks of the computers, where a third horizontal pole is connected to. On this pole, webcams are then attached and angled properly. Changing from the Trust webcams, better cameras were available. Three Logitech Brio Pro 4K cameras and two Logitech C920 webcams. In figure 9 below, the camera mount is shown, and in figure 10 the output of a camera in the final position is illustrated.

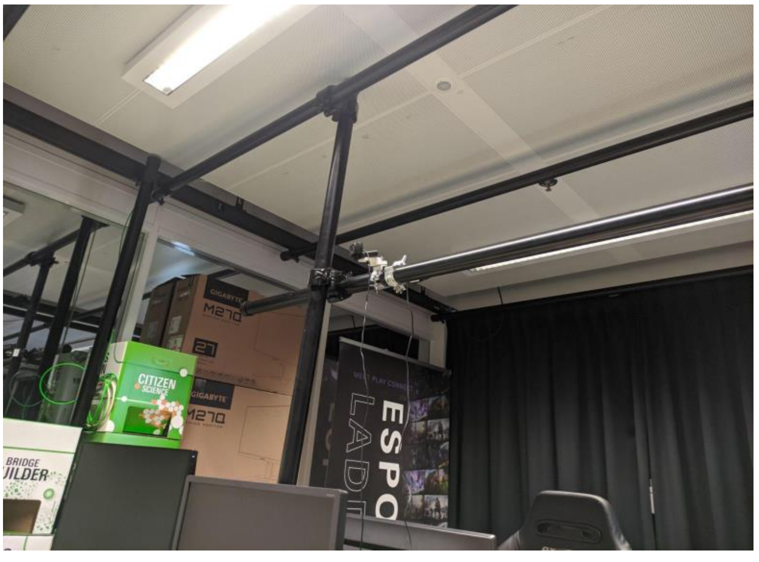

Figure 9: prototype 2 camera mount

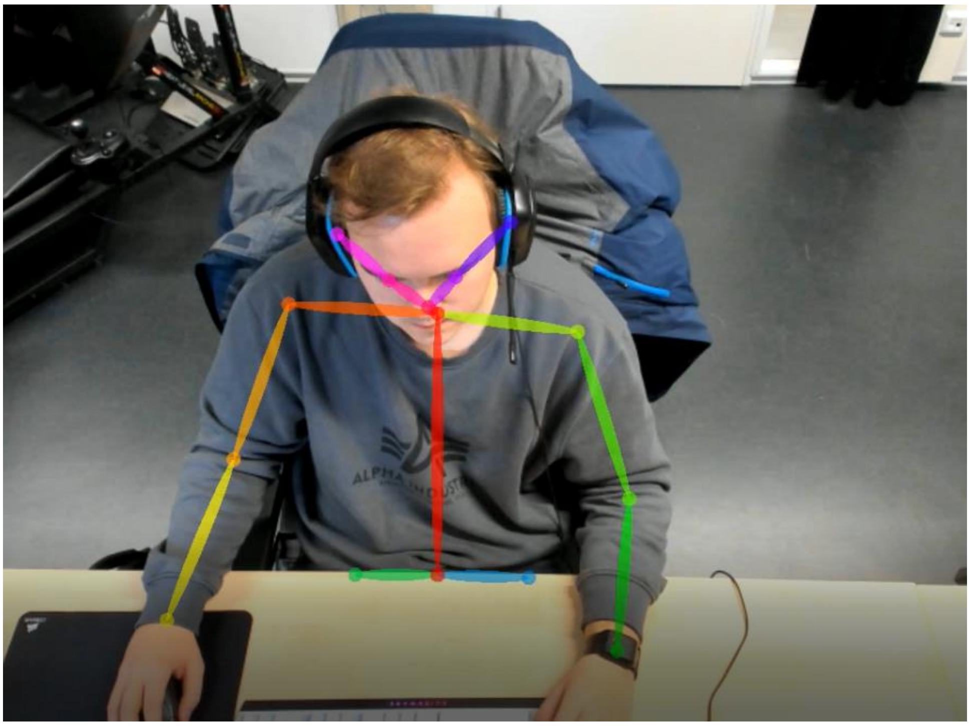

Figure 10: prototype 2 camera view

6.2 SOFTWARE

As stated on the website of Empatica, the default driver for the BLED112 dongle only supports up to 3 simultaneous connections. However, with the included instructions on that same webpage, the driver can be altered to allow up to 7 data streams. The next order of business is to alter the python client to save the incoming data. In this case, the pandas library was used. After the data is stored, classification needs to happen to determine the state of stress at a given moment. At first thought, the idea was to classify the E4 data in three different scenarios: rest, warmup and match. This would give a clear separation between different levels of stress which can be tested upon with new data. However, this was not the best direction as this setup would classify whether a person is in game or not instead of their respective stress level. This is due to the possibility of different stress responses in game than these situations would generate. Instead, classification was done based on stress in the game. As stated in [62], EDA peaks are one of the best indicators of stress due to the abrupt changes in skin response. Using the model provided by [61], peaks from the game are then extracted. From this result, the mean and standard deviation was calculated on the number of peaks in each time window. Depending on the position of a given sample in a normal distribution curve, a corresponding integer was classified to that sample.

According to [63], LSTM models need a 3-dimensional input for processing. Where the width is the number of samples, and the height is the number of inputs. The depth is the number of features. In this project, 13 joints were tracked, each with an x and y component. Following the example, this meant that the depth would have 26 features.

In figure 11 below, the input is shown of a single sample.

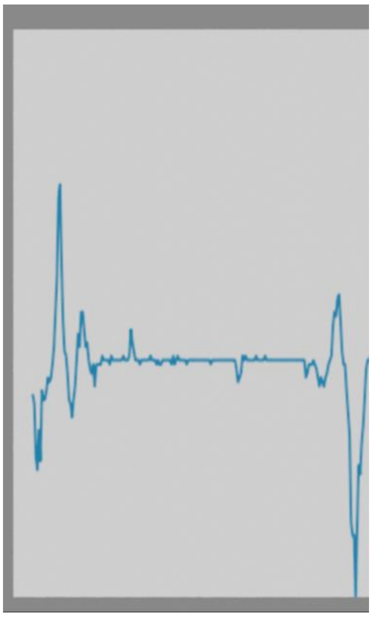

Figure 11: Posture single input

The data points corresponding to the first 30s of the recording is the start. This was done for all 13 joints, with the x and y axis of each joint as a variable, for a total of 26. Figure 12 shows how this was formatted in code.

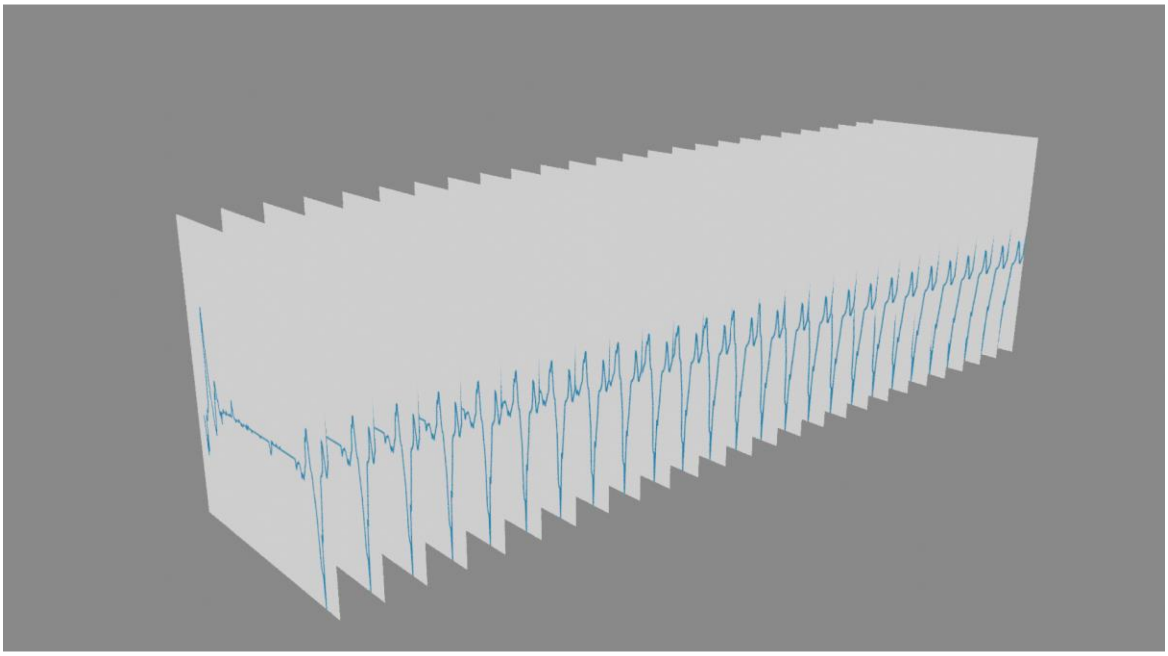

Figure 12: Posture 2-dimensional input

This is then repeated for each datapoint in the recording. For example, row 1 has the datapoints between t0 and t30, whilst row two has the datapoints of t1-t31 and so forth. Each row is then numerically classified. Figure 13 shows this visually. The classification comes from the results of the accompanying stress data. If the stress data has a result of 1, the corresponding posture data has that same class.

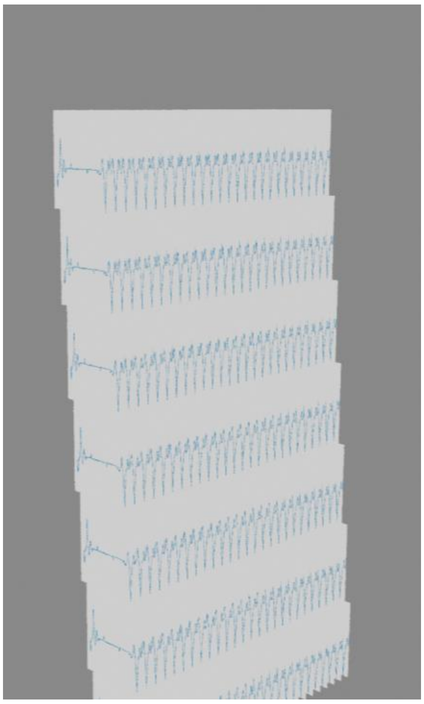

Figure 13: Posture 3-dimensional input

7 EVALUATION

The final cycle in the process is to evaluate the prototype. These results will determine whether posture can indicate stress.

For the stress data, first look at the blue line in figure 14 below. This is the output produced by the peak detection script [61]. Given a person is in rest, skin response starts between 0.5 and 2 uS. As the match progresses, skin response will gradually increase. In the figure, two major dips in skin conductance are visible. At 5 min and 13 min, the person most likely readjusted or touched the device, as this is not physically possible. However, the data does show a gradual increase in each section.

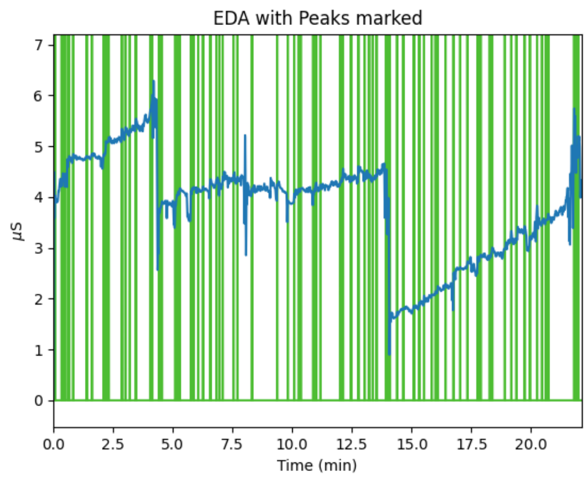

Figure 14: Person 1 EDA peaks

More of this result is shown in the second dataset (figure 15). Here the device was worn too loose as major shifts in skin conductance happened almost all the time. As this data is neither what is expected, nor usable for further analysis, it is difficult to determine whether this person was stressed, and at which point.

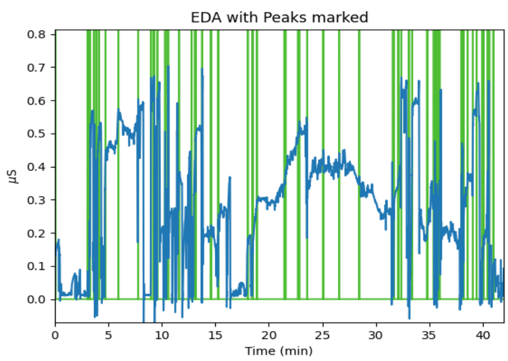

Figure 15: Person 2 EDA peaks

The third dataset had a different problem (figure 16). After the tests were done, it was found that the sensor was defective. This would explain why the skin response on average is very low at 0.05 uS. This means that the data of only one of three people tested is what was expected.

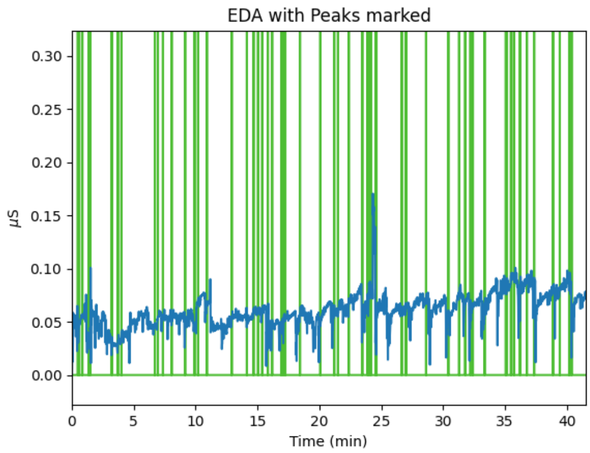

Figure 16: Person 3 EDA peaks

This is confirmed by the second feature, where the EDA data is compared between bad and good (figure 17,18 and 19 respectively). From the website, it is said that two experts looked at 1500 5s windows of data and determined whether it is proper or not. This script takes the same input data but classifies chunks of 5s, either white, grey or red. White means the data is clean, grey means the data is questionable and red means a bad chunk of data. With questionable is meant that the experts in their testing did not know whether the data that is similar was valid or not. Overall, the produced data is relatively clear, only at the moments where we expected something went wrong, the data was classified red.

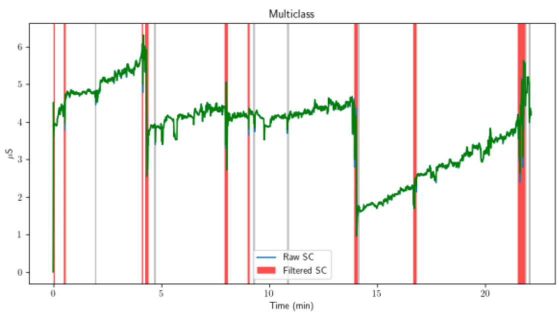

Figure 17: Person 1 Artefact

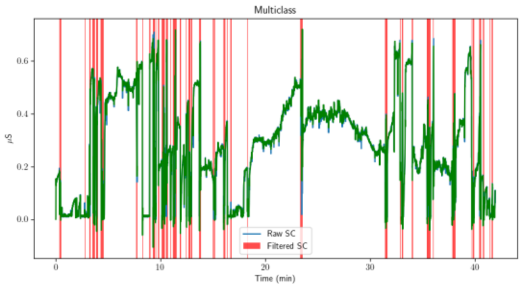

Figure 18: Person 2 Artefact

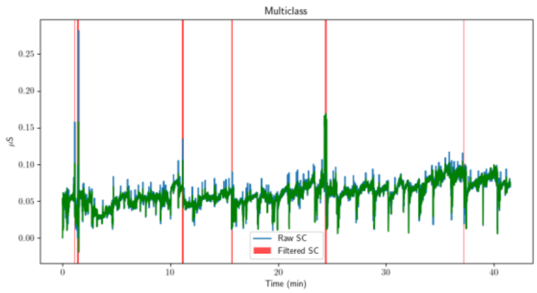

Figure 19: Person 3 Artefact

Even though 2 of the datasets were relatively clean, they are still not feasible for testing. This is because only 1 of the datasets of each person was saved. That means it is possible to train the algorithm, however testing would not be possible, as there is no data of that same person to compare it to.

To still validate the algorithm, three games were recorded of myself. The figures below show the resulting stress data (figure 20, 21 and 22). As you follow the blue line, each figure shows a gradual increase over time with clear changes in conductance corresponding to rounds of a game.

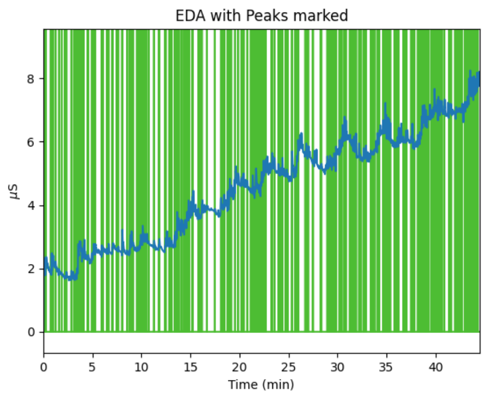

Figure 20: Game 1 EDA peaks

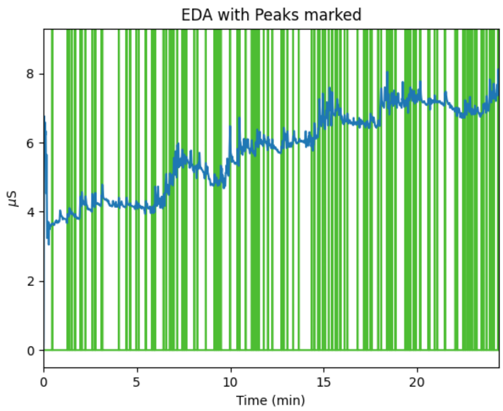

Figure 21: Game 2 EDA peaks

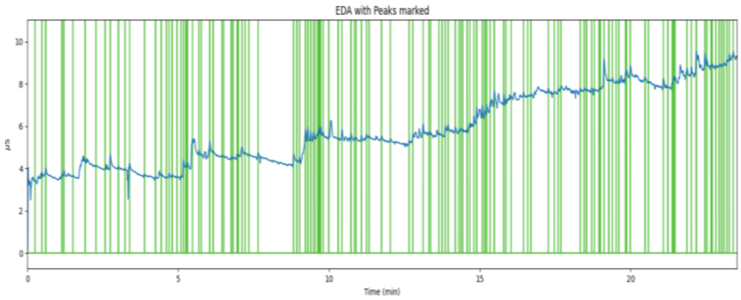

Figure 22: Game 3 EDA peaks

Furthermore, when looking at the artefact graphs, most of the data from the three sets is good (figure 23, 24 and 25).

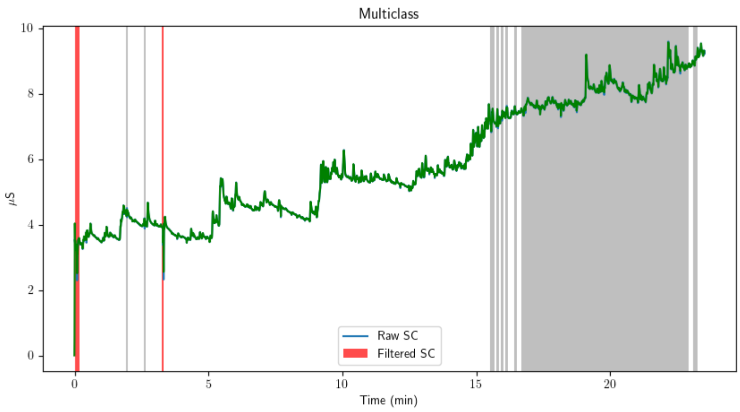

Figure 23: Game 3 Artefact

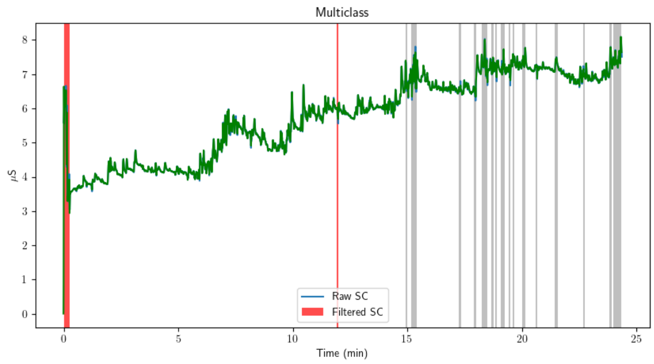

Figure 24: Game 2 artefact

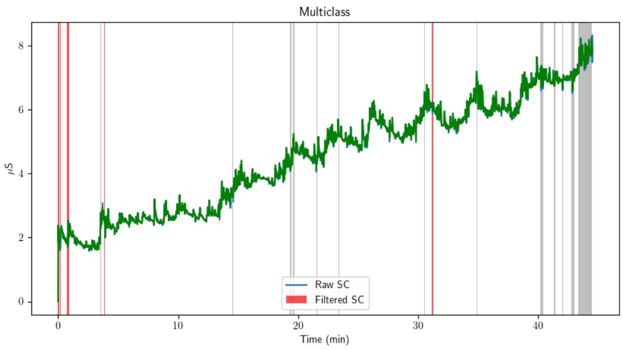

Figure 25: Game 1 Artefact

With these three datasets, classification was trained on one of the sets, where the other two were validated against. Comparison between prediction and baseline was done in two ways. In the first graph, data was sampled with overlap. That means that row 1 had an input of data corresponding to 0-30s, whilst row 2 had data from 1-31s etc. The second test had the data sampled without overlap. Where row 1 had data from 0-30s and row 2 had data from 31-60s etc. Furthermore, the data was classified in terms of standard deviation. If the data from the Empatica E4 was determined to be 1 standard deviation, the corresponding posture data was classified 1. One adaptation is that the negative standard deviation was left out. These were classified as 0. This was done as we are interested in stress response, which means above the average. The lower results, which imply rest, would only worsen the accuracy and results. In the graphs below, these results are shown. Figures 26 and 26 show the configuration where the model was trained on dataset 2. The model was then tested with input data from dataset 1. Figures 28 and 29 were trained on dataset 3 and tested against dataset 2.

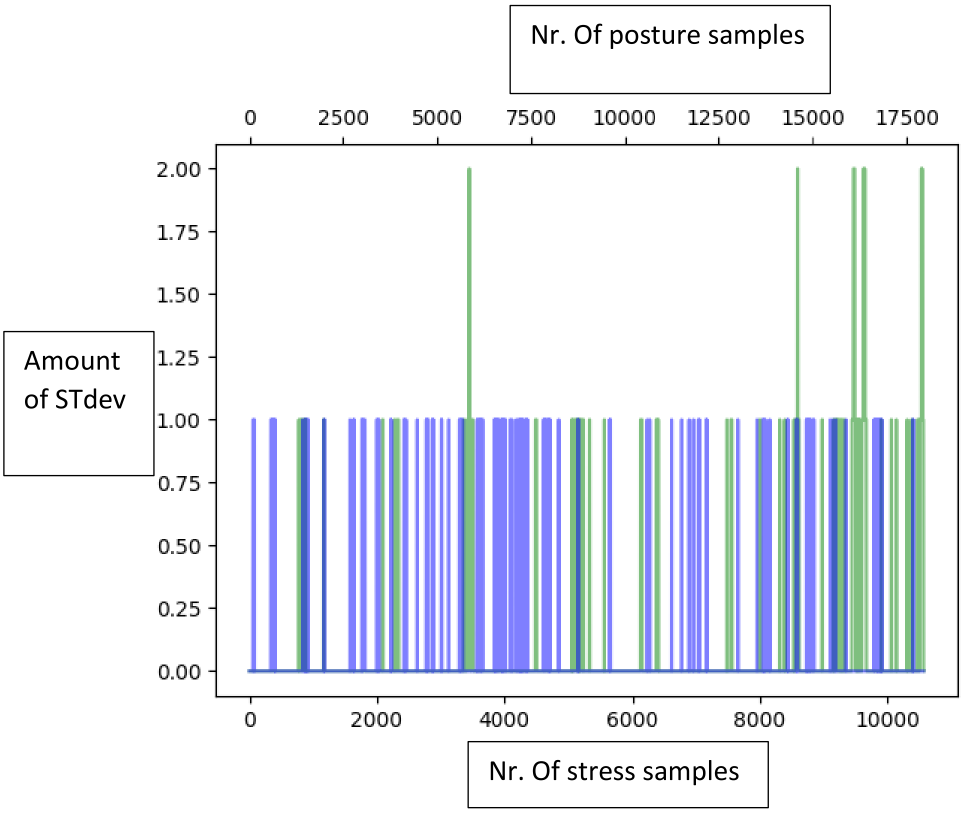

Figure 26: Prediction game 1

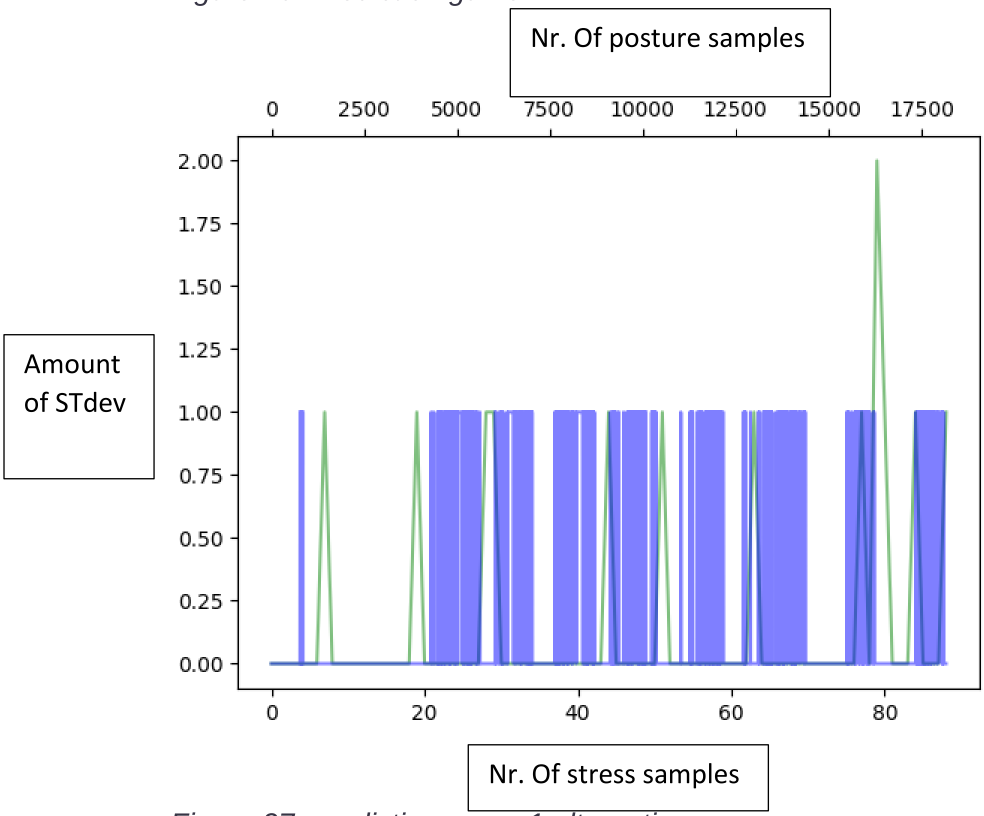

Figure 27: prediction game 1 alternative

In these results it is shown that the prediction of OpenPose has a lot more instances of stress than the ground truth. This is also shown in the second figure where no overlap was used.

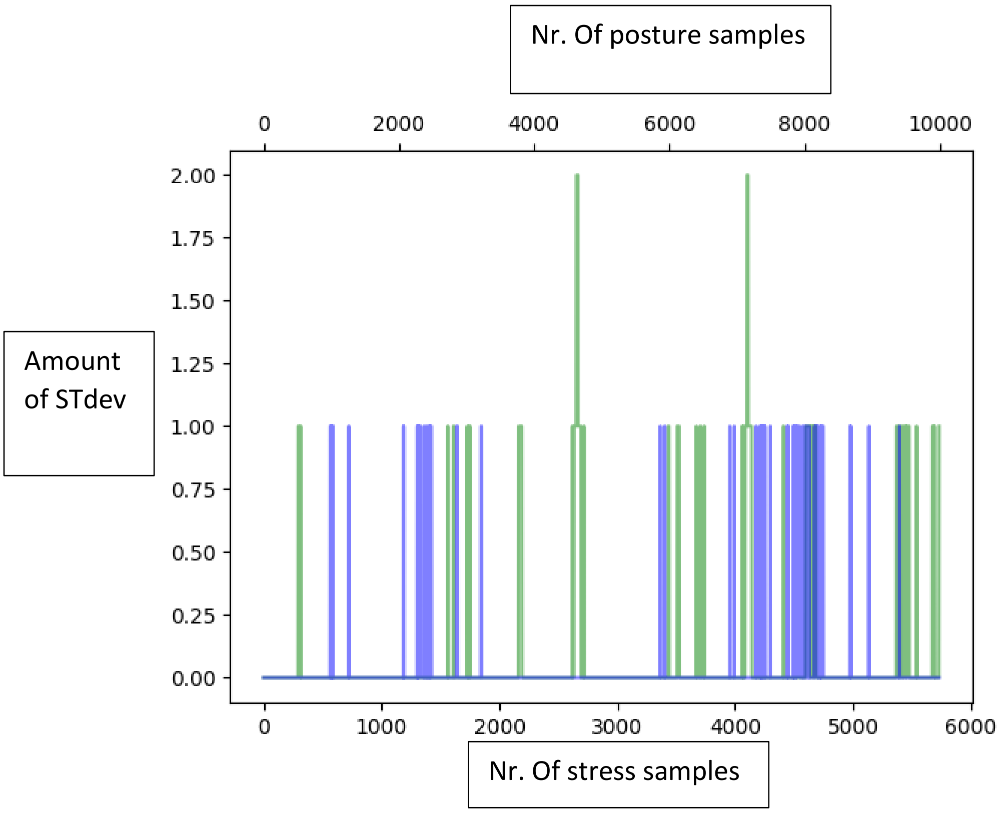

Figure 28: Prediction game 2

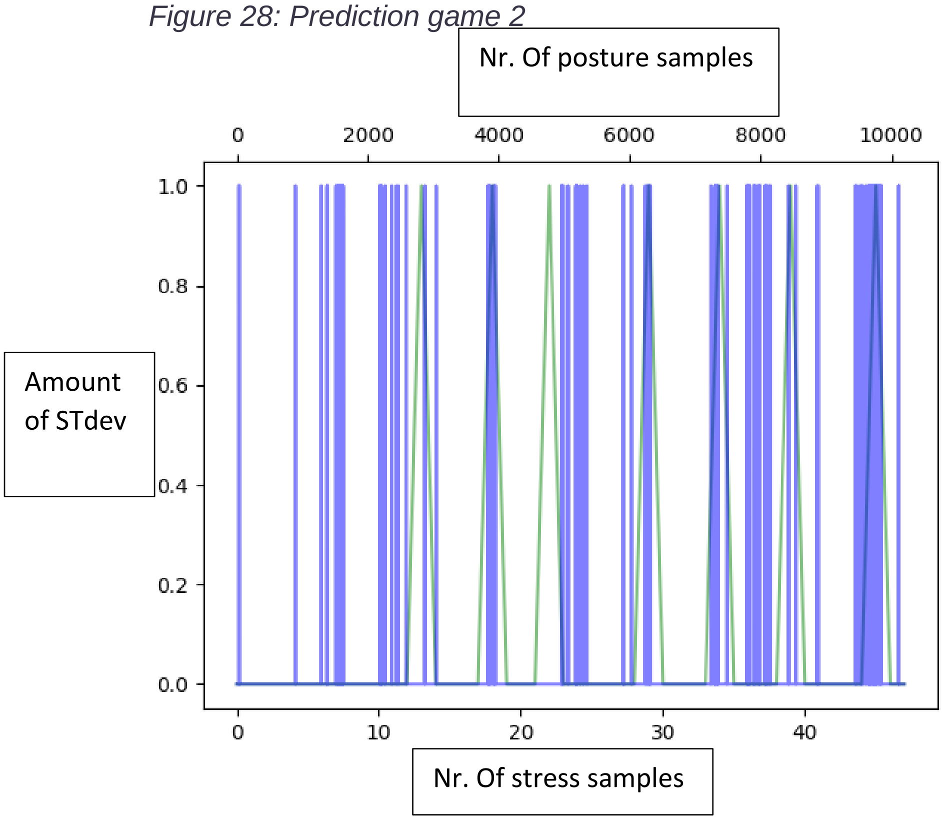

Figure 29: prediction game 2 alternative

In the results of the second classification, peaks from the OpenPose prediction overlap more than the previous results, however, there are still many instances where the prediction was either too high or too low. Another observation in these figures is that the blue peaks never classify as 2, whereas the stress data does have this in some instances. In the results of the first set of figures, figure 27, which was configured without overlap, does not show much overlap of results, whilst the results of the second set in figure 29 above do correlate more.

These results were relayed to the coach as well in a final interview. Although the results do not look promising, he was still enthusiastic about the concept. The coach elaborated on the use case of this prototype. As bad stress cannot be seen in these results, it was clear that these visualizations will be used as a guideline. It is up to the coach to determine whether he should intervene. For example, clutches are moments when stress is necessary. So, no action is taken even when the graph would show high stress. It is only in these other moments where patterns can emerge that the coach will consider a timeout.

7.1 COMPARISON BETWEEN GAME CAPTURE AND VIDEO

To further explain the difference in expectation and result, an analysis was done on the match. Due to time constraints, only one match was recorded on both game capture and posture video. Shown in figure 30 below are points of interest where peaks were found in short succession. These moments were at 05:05, 9:43, 15:02, 22:04 and 23:00 minutes respectively.

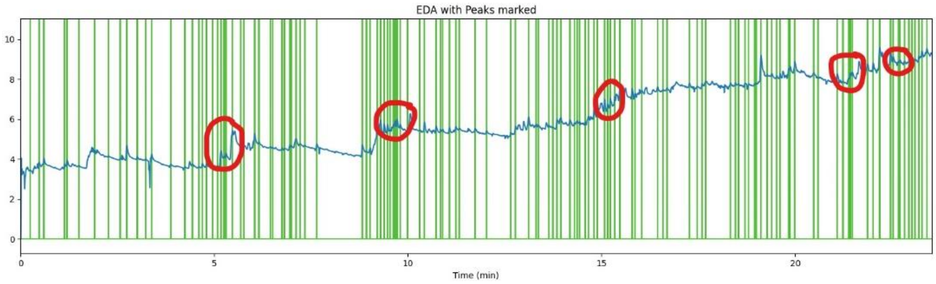

Figure 30: game 3 points of interest

In this competitive match of Rainbow Six Siege, played on Oregon, only 2 moments showed a difference in posture. The first point of interest was during the attacking round where an opponent unexpectedly fired some shots at my character. This resulted in a stressful firefight which does not show clearly on the posture video. During this moment, the video showed me heavily using my mouse as the firefight was happening. I myself leaned forwards a bit as the moment got more intense, after which I returned to a normal state.

The second point of interest at 9:43 was a different firefight where I lost the attrition. In the moment leading up to that point, several quick shots were fired at different opponents that challenged me and my teammates as we tried to gain map control. Eventually, we pushed forwards, where a defender won the firefight. Unfortunately, only my head showed a slight difference in position. This is most likely since this moment happened during the second round, meaning the stakes of winning were not that high.

The third moment however was more interesting. In this situation, I was left in a 1v1 with the defuser down. Ultimately, I won the last firefight and won the round. Comparing that to the posture, I showed a small celebration whilst moving head. The rest of the visible body did not show a difference.

The fourth point of interest was during our defensive side. At this point, the score was 1 to 3, meaning my team loses the match if we lose this round. In this moment, I won a firefight against an opponent, however, I was immediately refragged by another opponent on my flank. With the stakes high, the video shows me leaning back towards a normal state, after which I shook my head due to the situation.

The final moment was during the same round, where I spectated my last teammate fighting for the match. In the 1v1, eventually, this teammate was killed, and we lost the match. As the stakes were high, I most likely was just as invested as the teammate that needed to win. Unfortunately, my bodily response was not visible, most likely since I was not playing.

In conclusion, what does this analysis say? Comparing the highlighted moments between stress and posture response, there are only a few instances where there is a clear humanly visible change in posture. It is only at very stressful moment in game, for example clutches, match point etc., that I show a correlation between stress and posture. It does need to be mentioned that I am a casual player, meaning it is more likely that professional players have a lesser response to stressful situations. As mentioned before in the discussion, it could be possible that the legs or different position of camera can change the results, as these might have a visible response as well. For future work, these pointers and explanation can give an insight into a better method for correlating stress and posture.

8 CONCLUSION

In conclusion, stress in eSports is very new in development. Although research has started investigating the effects of stress in the eSports context, only negative effects are known. The goal of this research project was to quantify stress such that stressful moments in a game could be identified. Specifically, to use posture to indicate stress as a solution for non-intrusive monitoring. A research question was setup to answer this project:

How can we create a system that can provide feedback on the current stress level based on player movement in esports?

From this goal, all possible sensors were compared. This resulted in the Empatica E4 for stress, as the sensors can be used to measure stress, combined with the low intrusiveness of a wristband. On the posture side, OpenPose was deemed to be the suitable fit for the adaptability, low intrusiveness and ease of processing. With the final sensors in place, concepts were made to design the best prototype for indicating stress. From this section, the research questions 1 and 2 can be answered:

RQ1: What are the functional requirements of a system that can provide feedback on the current stress level based on player movements in esports?

RQ2: What are the non-functional requirements of a system that can provide feedback on the current stress level based on player movements in esports?

Unfortunately, these questions cannot be answered in full. Due to the inherit nature of explorative approach, it is difficult to setup requirements that can be evaluated. What can be said is that the prototype works by measuring stress and measuring posture, analysing the interaction between them and finally displays this in a graph.

In the realisation step, the prototype was built. The E4 devices were connected to the computer through the BLED112 dongle. After trial and error, the cameras were placed on a beam that was connected to a suspension system. On the software side, changes were made. Initially, stress was classified by recording the GSR data during rest and during the match. It was then decided that the better approach would be to record a match and, in that data, determine the low and high stress points. This classification was done by utilizing the python code published by Taylor et al [61]. Afterwards, the detected peaks were split into subsections of 30s, where the number of peaks was calculated. These amounts were then used as the input for the OpenPose training.

To evaluate the resulting prototype, testing was done on three (semi) professional eSporters. Due to unforeseen problems, results of the participants were unusable for the evaluation. Therefore, three matches were played by myself and compared against their respective stress responses. Results showed that the trained model produced different results depending on which match the model was trained on and on which match it was tested on. Looking back at the research question 3.1:

How comparable is the initial design in relation to subjective stress perception?

In both tests, results from the posture prediction did not overlap with the respective stress response of that match.

I can therefore conclude that this configuration does not indicate stress. At best there is some correlation between rest and stress, however no correlation is found between standard deviations of stress. In the moments that were investigated, only 2 showed a visible physical difference in posture.

9 DISCUSSION

Now that the project has finished, and the results are not what was expected, it is here that certain aspects are listed that could have been done better in hindsight. I would first like to mention that the start of the project was different than expected. Initially, the project was meant for two people. One focuses on stress, the other on posture. Since this changed to a single person, it seemed like a daunting task to do both things and get results from it. This led to the feedback section being left out, as during the realization phase, unforeseen programming issues and timing only made the deadline even closer. Nevertheless, this project was done to the best of my ability, and, what I thought at the time, to be the best choices.

From the state of the art, priority was given to non-intrusiveness as this would be the best fit for gaming performance whilst measuring the required stress response. This resulted in the Empatica E4 for its ppg and GSR sensor. However, after some testing, only the GSR sensor was left for stress detection. Although the device is worn on the keyboard arm, which has low movement, no HR data came from the device. This is most likely explained by the micro-movements from pressing different keys. These tiny changes in position of the hand led to choosing EDA. This was the case for all devices, meaning it was not a faulty sensor.

The biggest problem that caused the results to be unusable relates to the protocol I used. By that is meant the instructions to save and record the necessary files. Unfortunately, at the time of testing, the protocol was too complicated, which resulted in each person only saving one of the two datasets. It was because of these circumstances that I recorded a few games of myself. With the few results I did gather, no insights can be made whether each player has a different response. After these issues were known, I made the protocol easy, however, that does not matter anymore.

A different factor that could influence the results is the low number of samples. In this case, three samples were not enough to find a connection between stress and posture. Due to the vast differences in prediction, it is unknown whether these results are an outlier or are accurate, depending on which dataset was used.

Another point of interest is the machine learning used to classify posture, and in extent movement. Due to the configuration needed from the chosen algorithm: LSTM, raw data from posture did not provide a high accuracy. Furthermore, posture was not chosen in the other algorithms (kNN, random forest) as these had a bias built in. Whenever a person would lean forward, the classification would immediately think a person was in stress. This is explained by the fact that a focused player tends to lean towards the screen, without being stressed.

In extension, camera placement could have been different. In the prototype of chapter 6, the camera was mounted to a pole suspended above the players. This gave the camera the required distance to capture the upper body. However, this placement does tend to have a bias to certain directions. For example, if the head were to move vertically, this would not show significantly on video. Furthermore, the legs and feet were not captured.

The input of posture came directly from the camera, meaning the values were 834, 830 etc. LSTM gained a high accuracy by subtracting each sample from its previous. E.g., 830-834 = -4. This resulted in a 98% accuracy. This could be explained by the fact that the difference between 830 and 834 is not as significant as the difference between -4 and 1. This normalization could be the reason why the accuracy was high, but the prediction was low.

Another point to mention is the technical limitations of this project. Initially, the idea was to collect and predict the stress in real-time. However, this was left out due to time constraints. In the process however, code was still written to process the webcam video in real-time. Unfortunately, OpenPose does not run on a consistent framerate. This was somewhat controlled by configuring the fps limiter built in. In practice, OpenPose was limited, however never ran at exactly 7 fps. Given LSTM needs equal input sequences, it is possible that certain data was formatted to the wrong row, possibly further lowering the accuracy of the system.

A point of interest regarding the stress standard refers to EDA peaks. From research, it is said that EDA peaks indicate stress, more specifically arousal. However, it is not clearly defined how many peaks mean stress, or in what time frame. It is only known that more peaks mean more arousal. Because of that, I decided to go for a 30s time-window. As this gave a normal distribution of peaks over every time window.

In extent of EDA peaks, this method does not look at stress moments. Although each sample creates a new window, it is stress periods that is used as an input. Each new sample does in fact alter the results; however, it is still an average over 30s, meaning a short, but very stressful moment will not impact the result significantly.

9.1 Future Work

With the discussion points mentioned, this section will elaborate on the options worth considering for anyone trying to do similar research.

The easiest thing to change is the number of examples. A normal distribution of matches, and ideally more than one person, is more likely to see the correlation and detect outliers. Furthermore, this can give insight into individual differences, which can give targeted advice to each player assuming posture does show an indication of stress.

Continuing with posture, normalizing the position of joints between 0 and 1 is a valid option, as this removes resolution bias and returns the data to a posture time series, instead of movement. A different camera position is also worth exploring. In this configuration, a bias would be generated to depth movement, where vertical movement would not be visible. A configuration like [64] could be interesting to see the effects on the entire body.

When it comes to processing the posture data, I would recommend first recording the video and applying OpenPose afterwards. This process would give LSTM a consistent sample input, however this would forgo the real time data processing.

Finally, a change in the standard to which stress was measured is important. As is clear from this research, an untested metric was used as a baseline of stress. A different sensor is worth considering as wrist devices, although convenient, are not ideal for eSports if you want to measure stress through HRV. For example, shown in [41], it is possible to embed sensors into clothing. This way, the control metric of stress can have a tried-and-true method, whilst keeping the device non-intrusive, compared to diodes placed on the body.

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