BACHELOR'S THESIS

Using in-game data to give insights in the performance of eSporters

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Abstract

eSports is becoming an increasingly important sector within sports and gaming. With tournament prizes over the millions and millions of fans watching it, it is more popular now than ever. However, where there is a lot of research about traditional sports, there is less to no research investigating the factors that influence the performance of eSporters. Due to this literature gap, eSporters are unable to make educated decisions about their performance management. As eSports' performance is improving constantly for success and high stakes, performance management research is crucial.

In this research, a machine learning methodology for obtaining data and understanding the game EA SPORTS™ FIFA 20, an upcoming game within the eSports, has been developed using controller input and a Convolutional Neural Network (CNN). This has been done to answer the main research question of this report: "Which FIFA in-game data has a relation to the in-game performance of eSporters?".

A combination of the Convolutional Neural Network and the controller input, together with the end screen data concluded to give a proper indication of the eSporter's performance. These three levels of data obtained in this research give insights in the eSporters' performance, as they have been visualised to guide the eSporters in evaluating their missteps within their gameplay in order to improve their performance. This project is the basis for new research opportunities in domains like Data Science, Data Visualisation, in-game strategy and tactics extraction, and how to deliver the feedback to the eSporters.

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1. Introduction

Technology has a major impact in people's lives nowadays. In 2020, the current number of mobile phone users is almost 4.8 billion, which makes more than 60% of people in the world a cell phone owner. According to Statista, the current number of smartphone users in the world today is 3.5 billion, and this means around 45% of the world population owns a smartphone [1]. These incredible numbers give an indication of the dependency that people have with mobile phones.

Besides mobile phones, other technology industries rise up as well. The game industry is one of them. It has gained an enormous amount of popularity over the past decades. Due to the technological advances, there is an increased access to gaming platforms. From all over the world, it is now possible to play online and it thus becomes more competitive within the gaming community [2]. With this popularity came new profitable opportunities.

At the start, the game industry earned its money by selling games. There has been a transition from earning money by selling games, to in-game purchases. In-game purchases, like buying weapons, cars, characters and character outfits, has become the main source of income. However, not only the game industry makes profit out of their games anymore. Gamers themselves can earn money by streaming their gameplay. Although this might sound strange, not only professional sportsmen earn huge amounts of money, professional gamers as well. High level gamers can sometimes earn up to a million dollars per year [3]. They broadcast their gameplay to platforms like Twitch and YouTube. This way people at home, mostly children, can watch them at home playing the games. The global eSports audience in 2021 is expected to almost double compared to 2018, up to 557 million. So eSports is becoming a topic of the future, as it gains popularity and in some cases already surpasses the viewership of traditional sports.

The remainder of this chapter will provide brief descriptions of eSports and some determinants of eSporters' performance will be discussed. Subsequently, the research questions will be addressed, followed by the outline of the report.

1.1 eSports

How does an individual become a professional gamer? With this interesting question one key answer comes to mind, namely practice a lot. Yet, this alone would not make that individual a professional gamer. To give an illustration, playing football and practising a lot does not necessarily make someone a professional football player. There are other factors that play a role. Similarly, this is also the case for professional gamers. However, where there is a lot of research on which factors determine and improve the performance of professional athletes, there is barely any research on eSports. With eSports becoming increasingly popular, improving the performance of eSporters needs to be as well. This project will focus on improving the performance of eSporters. More specifically, the project will focus on eSporters playing the game EA SPORTS™ FIFA 20.

For this project, it is necessary to understand which factors improve the performance of eSporters. The project stands at the very beginning of research on this topic. In order to find the factors that improve eSporters' performance, methods must be explored to understand the factors that determine the performance of eSporters. Therefore, the main objective of section 1.1.1 is to provide an overview of the determinants of eSporter's performance of the researched methods thus far. With regard to performance, differences between eSports and traditional sports are visible. Furthermore, differences between eSports themselves are noticeable. These differences need to be taken into account when focussing on understanding the determinants of eSports. The differences will be described in section 1.1.2.

1.1.1 Determinants of eSport performance

There are a number of factors that determine the performance of eSporters. First of all, Paravizo and Souza [2] stated that pressure is an important determinant. This pressure can come from the community, their organisation or they bring themselves under a lot of pressure. Coping with stress positively affects a player's performance when he is under pressure. In the same way, not being able to cope with stress under pressure affects their performance negatively. Laborde et al. [4] add that people make better decisions in low-pressure conditions compared to high-pressure conditions. Likewise, confidence is assumed to be an important factor as well. Kent et al. [5] point out that increased confidence enhances the ability to cope better under pressure. In addition, research [6][7] shows that individuals reporting lower levels of confidence performed less than individuals reporting higher levels of confidence. If a player consistently wins matches, this will boost his confidence and will affect the performance positively. However if a player loses a lot of matches, or loses a match badly, this will affect his morale and might cause negative effects on his performance.

Besides pressure and confidence as factors, Aung et al. [8] have shown that there is a strong relationship between early skill learning and performance in eSports. There is a relation between learning rates and performance. Furthermore, Bonnar et al. [9] added that the performance of eSporters may be vulnerable to the harmful effects of sleep restriction. Within eSports this is more likely to happen than within traditional sports. To give an example, the game EA SPORTS™ FIFA 20 has a game mode called FUT Weekend League (WL). eSporters and other gamers can play up to thirty matches every weekend. eSporters are expected to play these thirty matches every weekend. This can cause them to play matches during the night, due to unique situations or conditions that might happen per weekend. So eSporters are likely at risk of sleep disturbances. Sleep pattern disturbance, pressure and confidence are all factors that affect the eSporter's performance. These need to be taken into account when looking for ways to improve the performance of eSporters playing the game EA SPORTS™ FIFA 20.

1.1.2 Differences

Within eSports itself, differences are noticeable. Numerous different kinds of games are played in eSports. In tactic games like League of Legends, research [8] has shown that a correlation exists between player performance and IQ. League of Legends is a very complex game, demanding a lot of focus and strategy of the player. Players with a high IQ showed to perform better than players with a lower IQ. Furthermore, League of Legends is a team game. There are games played in teams and there are games played individually within eSports. In teams, the communication between each other is an essential aspect [2]. During the matches, each player has a specific role to play. It is important for the team performance that the internal organisation within a team is top notch. During the competitive multiplayer, it is necessary to be completely focused. So in order to achieve victory the players' communication is non-verbal. There is no distraction, yet they still communicate with each other in a way.

eSport games like EA SPORTS™ FIFA 20 are played individually. The communication is completely different. To illustrate this, examples of different game modes will be explained. EA SPORTS™ FIFA 20 has multiple qualifying tournaments as will be further discussed in chapter 2.1. One of these tournaments is the weekly returning FUT Champions Weekend League (WL). Within this game mode eSporters and other gamers are allowed to play up to thirty matches. This is a game mode which is mostly played from home. There is barely to no communication and the setting is completely different compared to other competitions like the eDivisie, where the eSporter has to play one or two matches, accompanied by their teammate(s), coach, commentators and hosts. To give an example, every club in the Eredivisie has eSporters that play for their club in the eDivisie. The eDivisie competition takes half a year. This means that the eDivisie finals happen twice a year and twice a year there are eDivisie winners who receive the price money. During the matches in the eDivisie, the coach can instruct the eSporter. Their communication needs to be top notch because they only play one or two games each week against another eDivisie club.

eSports has major differences compared to traditional sports. Whereas traditional athletes' performance is determined by the combination of cognitive and physical abilities, eSporters' performance is constituted heavily by cognitive abilities [9]. Traditional athletes train their power, strength and endurance together with cognitive abilities like attention and visual processing. Only those cognitive abilities are necessary within eSports. Bonnar et al. [9] added that games with more than two players could require the eSporter to make quick motor movements to react to the rapidly changing information from multiple other eSporters combined with other in-game elements. Additionally, Tartar et al. [10] observes that eSports increases cognitive flexibility, which improves the brain's ability to transition from thinking about one concept to another [11]. To give an illustration, eSporters need to process visual information and they have to subsequently enact with their on-screen avatar movement via keyboard and mouse on a PC or via a controller on a console.

Notwithstanding the limitations of the methodology used, it was a necessary literature study in the development on how to improve the performance of EA SPORTS™ FIFA 20 eSporters. In the next sections, the research questions and the outline will be mentioned. In the upcoming chapter, the state-of-the-art will be described.

1.2 Problem Statement

Where there is a lot of research about traditional sports, there is less to no research investigating the factors that influence the performance of eSporters. Due to this literature gap, eSporters are unable to make educated decisions about their performance management. eSports' performance improves constantly for success and high stakes, so this performance management research is crucial. This is also the case for the game EA SPORTS™ FIFA 20. During the corona crisis happening in 2020, brands, companies, and news platforms are increasingly attracted to eSports.

Currently, barely any research investigates the data within the game. EA SPORTS is an uncommunicative company, when it comes to data, because they have no API (Application Programming Interface). The information about what happens within the game and its data is missing. To what extent does the in-game data correlate with each other? As eSports becomes an important sector in the future, with prizes going into the millions and millions of fans watching [12], it is also necessary to find ways to optimize the performance of eSporters. Mapping the data from the game and obtaining an understanding of the controller usage are examples which have not been done yet and thus will be focussed on throughout this project.

1.3 Research Questions

The research question for this report is as follows:

"Which FIFA in-game data has a relation to the in-game performance of eSporters?"

In order to develop insights in the EA SPORTS™ FIFA in-game and which data improves the eSporters' performance a number of sub-questions will help to understand this relation better. There is lots of data to obtain from eSporters and the game EA SPORTS™ FIFA 20, so it is important to understand which game data is relevant. The next two sub-questions will help:

"Which game data is relevant and how to get the relevant game data?"

"To what extent does the in-game data correlate with each other?"

Obtaining data from a controller can be done by coding. With the use of Python we hope to collect relevant data. This might also be done with the use of hardware. So, the sub-question for retrieving data from the controller follows:

"How to obtain data from a controller?"

1.4 Outline

The structure of this report is based on the Creative Technology Design Process [13]. In the second chapter the state-of-the-art review will be described. This chapter consists of two parts, where the first part of this review will be a literature review of background research. The third chapter describes the methodology and requirements of this project. It briefly explains what to expect in the next chapters iteration, specification, realisation, and evaluation.

2. State of the art

As this project is focused around the game EA SPORTS™ FIFA 20, it is important to understand the ways the current eSports works within this game. The first section of this chapter focuses on the game scenarios of eSports within the game EA SPORTS™ FIFA 20. The consecutive section describes the current technologies used already within this area of sports.

2.1 Game scenario

This project is narrowed down to the game EA SPORTS™ FIFA 20. It is a football game with multiple different game modes. eSports has been centred around the game mode called Fifa Ultimate Team (FUT). Within this game mode, the gamer is allowed to build his own team using any football players from all the leagues. He can win coins by playing matches online or offline. Within this online FUT game mode there is a competition called the FUT Champions Weekend League. FUT Champions Weekend League, often called Weekend League (WL) or FUT Champions (Figure 1.a), is a competitive game mode in Ultimate Team that allows qualified players to play 30 matches each weekend and rewards players with different prizes based on the number of victories and ranking [14].

Furthermore, if a player wins more than 26 matches in a single Weekend League, they can achieve the FUT Verified status. However, they first need to be registered. Twice a year, there is the possibility to register, by indicating that the player wants to compete for prices within the game. Once a player achieves this Verified status, they are able to earn Global Series Points and play online qualifiers for the rest of the season. Qualifiers are Online Qualification Tournaments which are held throughout the season within different FUT Champions Live Events. Verified players may be invited to these Online Qualification Tournaments in their region for these FUT Champions Cups. This way, and by playing in the Weekend League, they can earn Global Series Points. These points rank a player in the Global Series Ranking [15]. The PlayStation 4 and Xbox One have a separate leaderboard, and earned Points will not be shared between those leaderboards. Similarly to traditional football, players can try to qualify themselves for the highest possible price in the EA SPORTS™ FIFA 20 eSports; the FIFA eWorld Cup.

In order to qualify for the FIFA eWorld Cup, FUT Champions Verified Players will need a great deal of Global Series Points. As players earn points, they will move up the Global Series Rankings. Live events will provide the majority of Global Series Points, while a smaller, but not insignificant, number can be earned by achieving 20 to 27 or more wins in Weekend Leagues from November through April.

Apart from the Weekend League, there are six FUT Champions Cups throughout the year (Figure 1.b). In these large open tournaments, 32 players per platform are competing for Global Series Points and a prize pool of around €185.000,- ($200,000).

Like last year, the eNations Cup and the eClub World Cup will be part of the competitive 'Road to the FIFA eWorld Cup 2020'. These are called the FIFA Majors (Figure 1.c). The FIFA eNations Cup is EA SPORTS™ FIFA official inter nations competition. The world's best players in EA SPORTS™ FIFA 20 will represent their country in two versus two matchups in their 'eNational' team. All eligible nations can construct an official national team. Again, Global Series Points and money can be earned.

The second FIFA Major is the FIFA eClub World Cup. Similar to the eNations Cup, the world's best players will represent their club instead of their nation. The clubs start in the group stage and can earn a place in the finals via a knock-out stage. There are a total of 24 teams; 16 teams from Europe, 2 teams from North America, 2 teams from South America, 2 teams from Middle East & Africa and 2 teams from Asia & Oceania.

Figure 1: The different tournaments on EA SPORTS™ FIFA 20

In addition to the FUT Champions Cups and the FIFA Majors, smaller in scale Licenced Qualifying Events may be offered to Verified FIFA players (Figure 1.d). These events are in collaboration with key partners of EA SPORTS™ FIFA 20.

Moreover, League Qualifying Tournaments are held (Figure 1.e). EA SPORTS™ FIFA 20 and twenty or more football leagues partner up to offer even more players a chance to represent their favourite football clubs in their domestic leagues. To give some examples, the Premier League, La Liga, the Bundesliga, Ligue 1, the Eredivisie, and the Champions League are partnered with EA SPORTS™ FIFA 20. This project has a deeper focus on partnering with the Eredivisie (the eDivisie), as mentioned earlier in chapter 1.2. Like the traditional footbal, EA SPORTS™ FIFA 20 has their own eChampions League, a joint venture between UEFA and EA Sports (Figure 1.g). It is exclusive to PlayStation 4.

Another event that is exclusive to PlayStation 4 are the PlayStation 4 Country Tournaments (Figure 1.h). PlayStation will run tournaments in countries around the world. The restriction of these events are country or region restrictions.

The final event to earn Global Series Points will be at the Global Series Playoffs (Figure 1.f), where the top 64 players on the Global Series Rankings on each platform will make one last push to secure a spot in the FIFA eWorld Cup [16]. The FIFA eWorld Cup Grand Final would have taken place in July 2020, if not for the corona crisis.

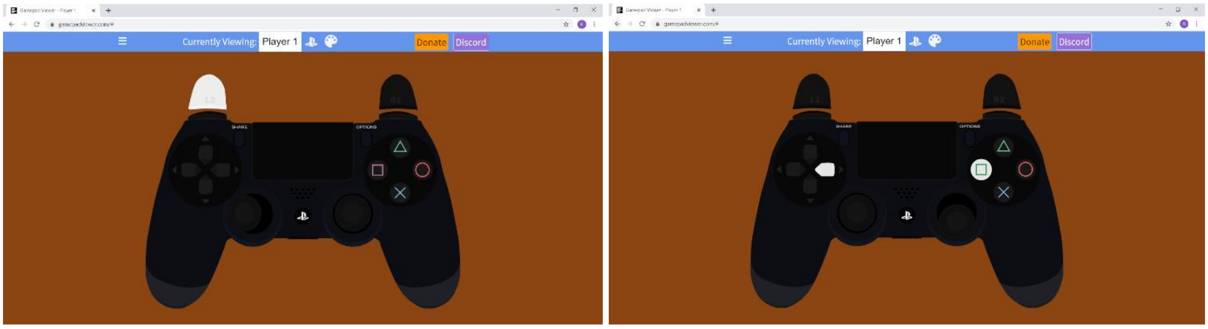
2.2 State of the art

In order to find new solutions, it is necessary to look for the technologies that are already here. This chapter describes the level of development reached, as a result of the modern methods, meaning devices, procedures, process so far, techniques and/or science.

2.2.1 Gamepad viewer

This project focuses on eSporters who play on a console. The two most common consoles for the game EA SPORTS™ FIFA 20 are the PlayStation 4 and the Xbox One. The game is played with a controller. Xbox One has its own Xbox One controller. DualShock is the line of gamepads developed by Sony Interactive Entertainment for the PlayStation systems. The one currently used for the PlayStation 4 is the DualShock 4.

There are already numerous sites that are able to track user input from the controller. One example is the website 'https://gamepadviewer.com/' (Figure 2) [17]. This web-based tool represents gamepad input visually. The website uses HTML and CSS code to let the user see their gamepad usage on screen. In Figures 2.1 and 2.2, a PlayStation 4 controller is connected to a laptop. Figure 2.1 shows a DualShock 4 controller where the left trigger, also known as the L2 button, is pressed and that the left joystick is pushed to the right. Figure 2.2 shows the controller with the directional right button pressed, the action square button pressed and the right joystick pushed downwards.



Figures 2.1 and 2.2: Web-based gamepad viewer showing the DualShock 4 controller with different buttons pressed

2.2.2 Convolution Neural Network and Long Short Term Memory Networks

Convolution Neural Networks (from now on referred to as CNNs) are used in image recognition, object detection and speech recognition. CNNs are designed to handle two dimensional input data. They can directly take pixel values as inputs without software to translate the input information [18]. This multi-layered artificial neural network has a number of benefits compared to the traditional machine learning methods. For example, it can effectively reduce the learning complexity of the network model [19]. Creating more hidden layers will result in a more complex network structure. CNNs are trained by deep learning algorithms to achieve many large-scale identification tasks within computer vision, which task is analysing collections of images or videos, to make judgements or decisions. To give an illustration, a simple CNN will be described, shown in Figure 3.

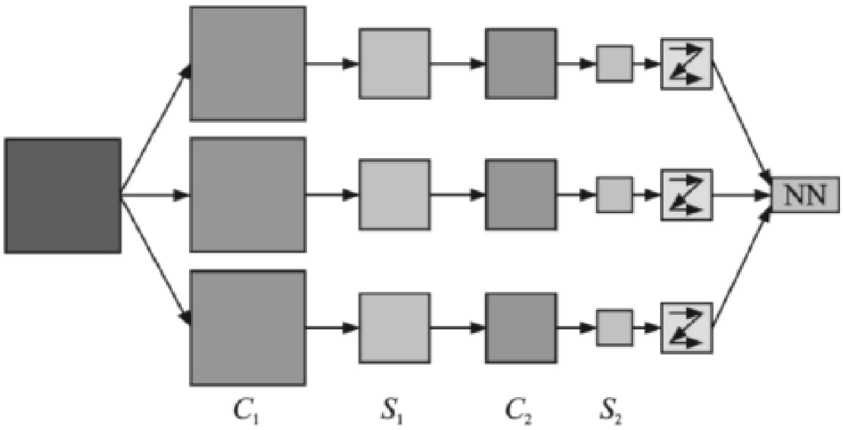


Fig. 1. Simplified convolution neural network structure.

Figure 3: A simplified CNN structure

First, three convolution kernels, which are trained filters, convolute the original input image. Then through the C1, S1, C2, and S2 layers, feature maps are created before being weighted and averaged. After being twice convoluted, the output of the S2 layer is vectorised and will be used as input for training for the traditional neural network. So, to put this in other words, each CNN layer learns filters of increasing complexity. The first layers learn the basic feature detection filters, like edges, corners, etc. The middle layers learn filters that detect parts of objects.

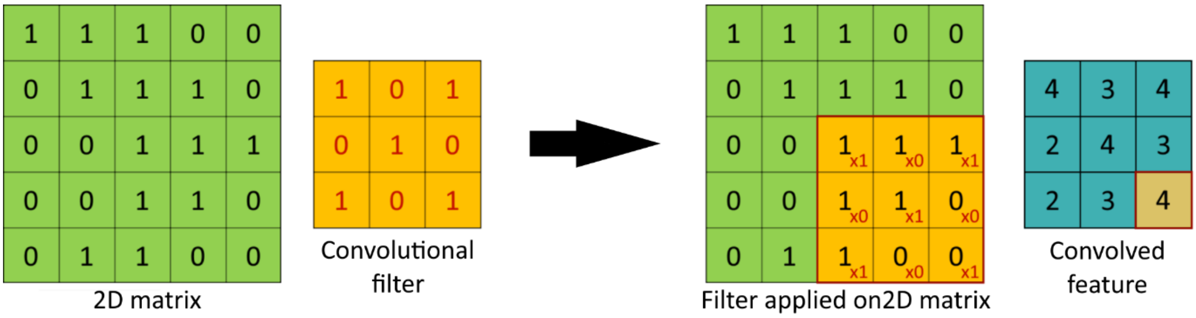


Figure 4: Example of one filter used to create a convolved feature

As an example, in Figure 4 on the left has an image grid and a certain convolutional filter. Each matrix element in the convolutional filter is the weights that are being trained. These weights will impact the extracted 2D matrix to create a new convolved feature, shown in Figure 4 on the right. These convolved feature will give predicted outputs, so that backpropagation can be used to train the weights in the convolution filter [20].

For the game FIFA, the first layers might learn to respond to scoreboards, the minimap, player names, the ball, etc. The last layers have higher representations, as they learn to recognize full objects, in different shapes and positions [21].

This way, CNNs can very accurately detect objects in an image. Dealing with the fact that EA SPORTS™ FIFA 20 has no API, this can be very useful. CNNs can recognise where the players and other objects of interest are located on the screen, due to the high level understanding of images obtained from the feature maps. The only thing needed is a simple screenshot of the game window.

'Building a Deep Neural Network to play FIFA 18' is an applicable project that uses CNNs with the game EA SPORTS™ FIFA [22]. The feature map retrieved from gameplay images of the game is used to detect the players on the pitch along with the ball and the goals (Figure 5). The Single-Shot Multibox detector creates Bounding boxes that represent the players, the ball, and the goals.

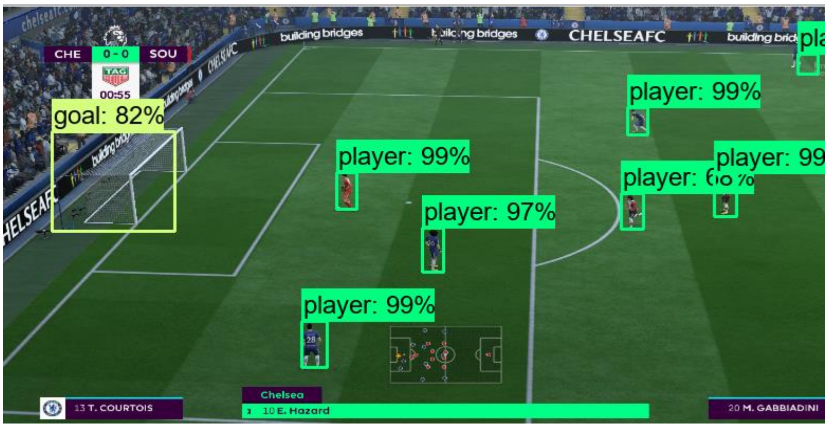


Figure 5: Output CNN together with Single-Shot Multibox detector

Long Short Term Memory networks (LSTM) are designed to model and label temporal data into sequences. They feature a sequence of memory blocks. Three gate units, an input gate, a forget gate and an output gate, inside one or more memory cells are included in each memory block. (Figure 6)

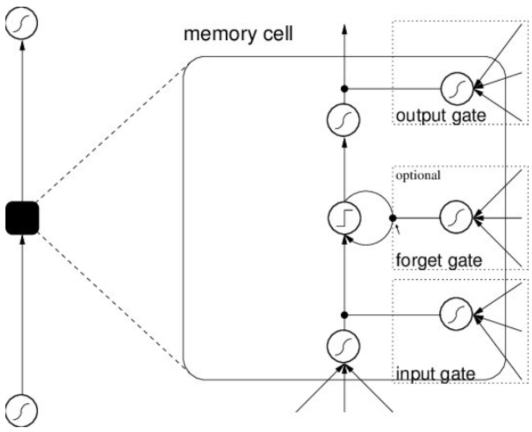


Figure 6: An example of a simple LSTM network

In the project of C. Trivedi, the consecutive feature maps retrieved from the CNN model are fed into two LSTM networks at the same time (Figure 7). The first LSTM is about the movement of the player. The second LSTM receives the same input and decides what action the player needs to take. In this project, the outputs are converted to key presses. This way, an AI bot is created to play the game EA SPORTS™ FIFA. According to Trivedi [22], the AI bot picked up on the basic rules of the game, with limited training. This includes moving towards the goal and putting the ball in the back of the net.

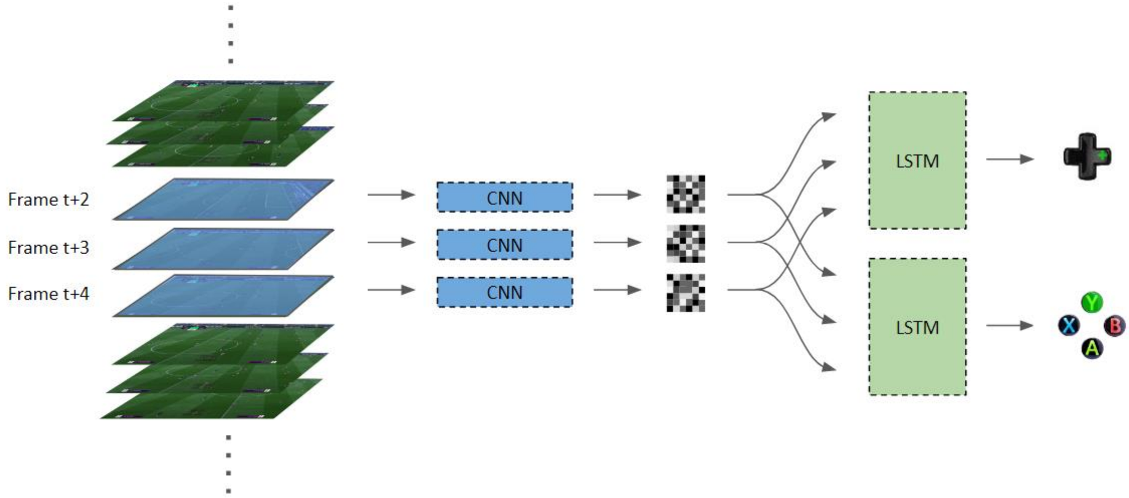


Figure 7: Screenshots are first put through a CNN before the feature maps are fed into two LSTMs

2.2.3 Team Gullit

Team Gullit [23] is the world's first independent EA SPORTS™ FIFA eSports academy. They are a branch within the company Triple. It is named after the Dutch ex-professional football player Ruud Gullit, who has his share in the company. As they mention themselves: "Talented FIFA-players had a difficult time breaking through internationally without being part of a professional football club." Their goal is to make the FIFA eSports talents better. The team consists of talented eSporters, trainers and coaches. Their main focus is to provide the best training options, create a suitable atmosphere and create the best tools to help their talents improve their skills. Team Gullit offers professional guidance and training to help the talents become the stars of the future. They started with three Dutch eSporters and from that point on they have doubled to six eSporters, including a Brazilian and a Swede. They have a competitive advantage towards the rest of the EA SPORTS™ FIFA eSports scene, with excellent coaches and training methods. They have proven this by winning the FUT Cups twice in a row with talents from their Team Gullit academy.

Team Gullit developed its own hardware and software tools to analyse and improve the gameplay of their eSporters on both tactical and strategic level. Additionally, they guide the eSporters in dealing with social media and creating their personal brand. However, they stopped further developing these tools a year ago, because it just was not necessary at that time. There was no market for it yet and they were already at the top of the rank.

The focus of those tools was on gameplay analysis via image recognition and focus on the input and statistics. The basis that they scrape the statistics of the in-game pause screens and end screens. To give an illustration, use image recognition to know the score, so know when a goal was scored. This is also used to make automatic summaries of matches. Furthermore, Team Gullit followed the ball via image recognition to trace back patterns. Finally, they worked with the minimap which is shown during the matches at the bottom of the screen to read the teams' line-ups. Team Gullit extracted data from the obtained data points. They captured the whole gameplay, 60 frames per second, together with the data obtained from controller input which was even more data points per second.

The main challenge for Team Gullit was the physical setup that was necessary to extract the data. Team Gullit stood for the difficult task to design a suitable setup for the eSporters and other gamers, which was functional, good, and easy to use at home. Hardware was necessary to extract controller input. They mention that hardware was at that time the only way to have no lag or controller delay for the eSporters. The usage of software to extract data from the controller caused too much delay. Furthermore, for that setup, a capture card connected to the PC was necessary. Moreover, Team Gullit was dependent on third party hardware. The challenges all together made Team Gullit decide to end further development in the setup.

2.2.4 Beyond Sports

Beyond Sports [24] is a subsidiary of Triple. It is an Artificial Intelligence (AI) based visualisation company that offers a new way of experiencing, training, and analysing sports. The company uses software which, on the basis of video image, builds its own Virtual Reality world. An example is shown in Figure 8 below. The software provides the option to track every moment at every place in the field. This is made possible by a mixture of AI specialists and Unity developers who can envision and execute the new way of sports analysis and entertainment. AI is used to input data sets of orientations that they know are right and match these to new player data. Beyond Sports have built a way to integrate, evaluate and correct the best available tracking data into their systems. The system is very agile, which means that certain things learned from one sport can be easily translated to another, causing them to rapidly expand into different sports and new markets.

Initially, the software was made to serve trainers with football analysis. Beyond Sports offers Virtual Reality Match Analysis and Virtual Reality training. It is possible to look back at certain specific match moments in Virtual Reality from the player's point of view, to a tactical top-view, and even from the opponent's point of view. In a plug and play design, the virtual simulation is combined with event tagging and real video. This is the next generation of video analysis. Using a controller, players and trainers can play, pause, fast-forward and rewind and easily switch between perspectives. Interactive training scenarios are used to educate the first team as well as youth players according to the tactical ideas of the club or coach.

Beyond Sports is nowadays also used by leagues and media platforms as an entertainment tool to make the sport more attractive. For example, they played back the Superbowl with Minecraft figures. Beyond Sports made this possible by extracting data points live from video images and translating this to a Virtual Reality world. The company turns real matches into live virtual experiences. It converts traditionally passive sports viewing into an interactive, captivating experience. With player positioning tracking data, it is possible for a user to see every perspective of any moment the user can image to any platform. Beyond Sports is hundred percent virtual, it can be locally rendered directly on the user's device, and based on real data to allow the user to interact with the broadcast.

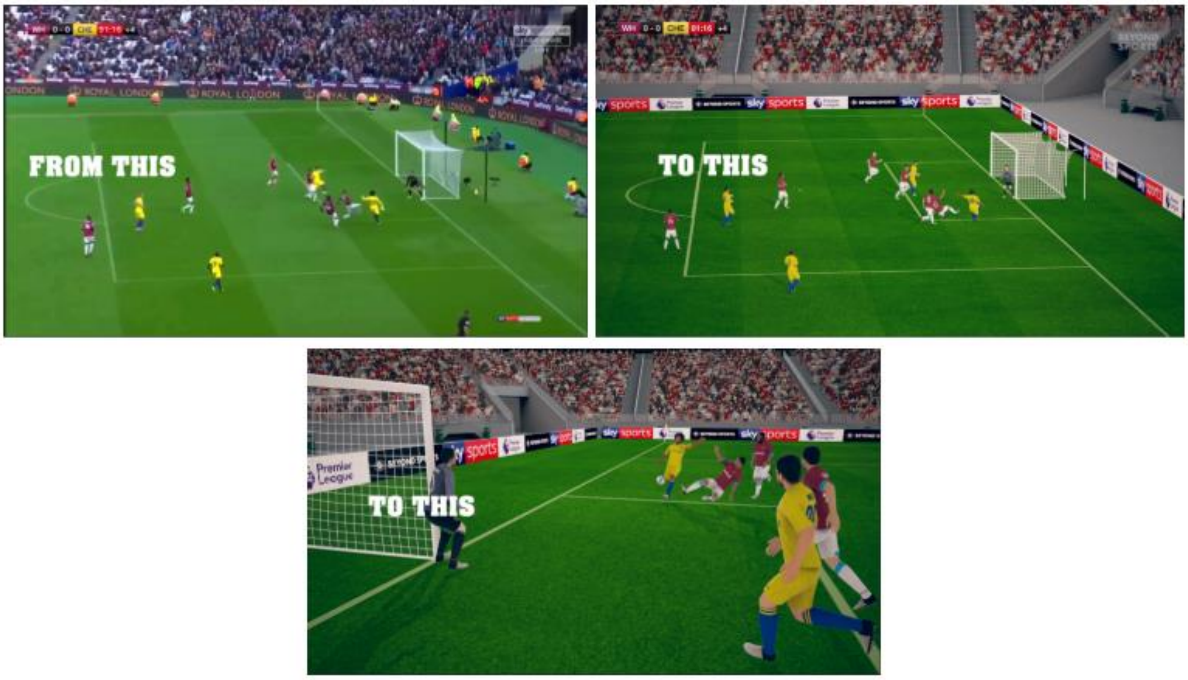


Figure 8: From real life video images of a match to two of Beyond Sports' virtual world camera perspectives

Through virtualisation, Beyond Sports enables the interactivity of different sports content directly to the user's device and the possibility to select different virtual camera perspectives. Their goal is to make Beyond Sports be a part of the everyday world, like Instagram is for image sharing today.

2.2.5 SciSports

SciSports [25] is a company that provides football data intelligence for professional football organisations, football players, media and entertainment. The company has a number of services. One of these services is that SciSports offers a state-of-the-art data delivery. Data analysis will be a major part in the search and selection process of a player transfer in the future. SciSports' data delivery gives direct access to the best football analytical models out there including SciSkill Index, which can be used for statistical support, player flagging or player comparison. It helps identify talents, find players with the player profile that the club wants, and it can help with the analysis of the opponent. It also quantifies the influence of a player on its team and is available in an API service. The SciSkill Index includes which roles a certain player has, his contribution ratings and how many expected goals the player could make. The data from SciSkill Index can be used to analyse or predict matches. Its algorithm applies artificial intelligence to assess the quality and potential of every professional player in the world. The SciSkill proved its accuracy and even managed to outperform the bookmakers. The input variables of the SciSkill information are the line-up, including position, the substitutions, the type of match, the competition strength, the goals scored and the red cards. SciSports [26] explains that the algorithm behind the SciSkill Index is an expectation-maximization model, which is an iterative machine learning algorithm that determines the quality of a player based on historical information. The current quality of a player is assessed by training the algorithm on historical data. In 2019, the SciSports platform offers actionable insights into more than 90,000 active players, 244 competitions and 3,698 clubs. [27] The partnership with data provider WyScout enables SciSports to perform in depth player analysis, with up to 230 enriched statistics per player. In total, SciSports collects data of over 200,000 football players around the world.

BallJames is a separate branch within SciSports with the ambition to generate 3D football data of all 22 players and the ball. The goal of BallJames is to convert a football match in real time into 3D pixels. Football stadiums have their own camera system where they record the football matches. A set of 14 cameras will be installed in the stadium, where each camera captures every movement in the 14 zones in which the field is divided. It can be compared with goal line technology that spans the entire field. The Polman Stadion, the home ground of the Dutch Eredivisie club Heracles, was the first stadium equipped with the BallJames system. Along the road, they became the first company in the world to generate 3D data in the Premier League.

SciSports is the first in the world that developed an accurate real-time data tracking machine that automatically generates 3D data from video images of the football matches. It digitally follows the ball very accurately. To give an illustration, BallJames is like an MRI scan that spans the entire football pitch. It can convert a match in real-time and can provide accurate statistical data. SciSports mentions that this video-analysing system can determine what the heading power and shot velocity of a player is, what the movement of a team without the ball is and the quality of a player's touch, based on 3D data [28]. BallJames generates its own data, such as passing data, like correctness, direction and velocity. Furthermore, it generates jumping, sprinting, strength, running lines and how close the ball stays at the foot during a first touch. The system detects everything that happens, even players without the ball. SciSports is the first system that generates this data three dimensional. The challenge is to build a system that can accurately distinguish small objects from its background, considering that the ball is only a few pixels, which makes it difficult to track. Automatic camera calibration is thus extremely important. BallJames has a lot of potential influences with all this new data. For example, it could potentially improve the way of refereeing a game. Furthermore, it might potentially help in the battle against match fixing, by recognizing aberrant and suspicious patterns. After installing pilot tracking systems in individual stadiums, the fully automated 3D tracking system is ready to release in a full league and will provide new, real-time and tailormade insights to improve the level on the pitch and enrich the engagement of supporters.

BallJames is based on the principles of deep learning and artificial intelligence and operates together with machine learning, the programming language C++, computer vision and advanced analytics technologies. Large amounts of data can be analysed and give insights as a result of machine learning. It then uses the data to improve and continuously develop the system itself. The solution for achieving more accurate data was found in radiology. BallJames tracks how so-called voxel-clouds move through their virtual stadium. BallJames gets accurate data without any human operators, as they obtain over 50.000 voxels per frame. Their machine learning algorithms teach the system what the players and the rules of the game are. With these algorithms and patterns recognition, SciSports can predict player value very accurately.

Other state-of-the-art tools used within the company to develop football analytics metrics include Jupyter Notebook, Python, pandas, scikit-learn, seaborn, XGBoost and CatBoost.

2.2.6 Conclusion State of the art

All these examples hint for possible directions to go, yet none of them analyse or observe EA SPORTS™ FIFA 20 in-game data. This is becoming increasingly important as the FIFA eSports is rising and more importantly, eSporters desire to improve their performance. This project will look into the possibilities of reading controller input by using Python code and use this data to make assumptions about the way the game has been played. Furthermore, the project will go into depth in how to extract data efficiently from the game EA SPORTS™ FIFA 20 and analyse this data. Lastly, there will be looked into the possibility of analysing possession and ball location while the match is played in real-time with the help of the minimap.

3. Methods and Techniques

This chapter will elaborate on the techniques and methods that will be used to get to the final project prototype. In order to structure this process, the project is divided into multiple phases according to the method of the Creative Design Process [13] shown in Figure 9.

The four phases used within this project are ideation, specification, realisation, and evaluation. During the ideation phase the focus is on generating ideas. So to say, to come up with multiple ideas as a starting point for the project. A number of techniques are used during this phase. The phase starts off with a stakeholder analysis to understand the key elements which make the project. Moreover, a number of brainstorms were used to narrow down the options and to understand the possibilities within the time period of the project. Finally, after iterating towards a more concrete concept for the project, an PACT analysis will be conducted to get better knowledge when to use the concept created during this phase. The specification phase has a more technical focus. The MoSCoW method will help in this phase, creating a more detailed picture of the prototype program and its functions. After finalizing the concept of the program and its functions, a prototype program will be built in the realization phase. The last phase will focus on the evaluation that has happened throughout the project and will evaluate on the final prototype with the eSporters using situational interviews [29].

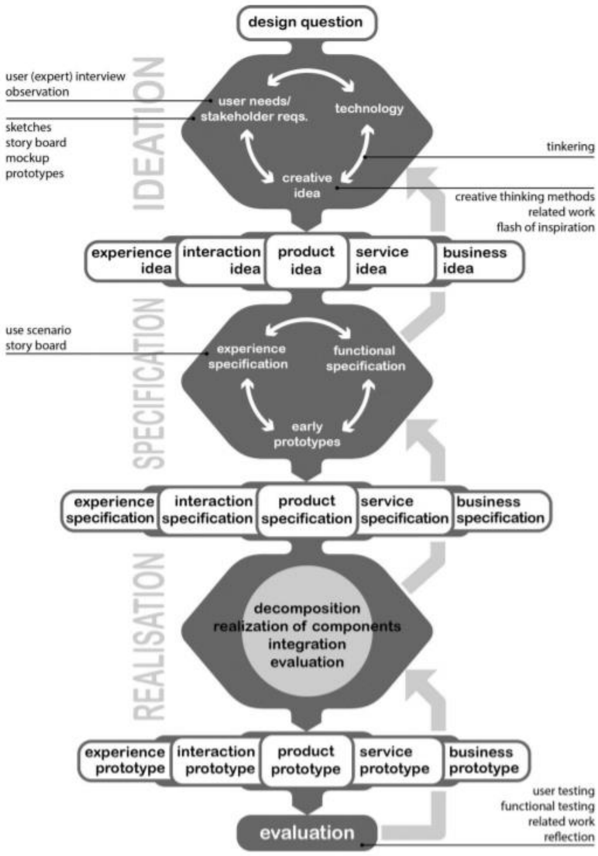


Figure 9: Creative Design Process [13]

3.1 Stakeholder analysis

Explaining why each stakeholder might be interested in this project, and what their role is within this project is significant. Research [30], [31], [32] mentions this can be done through the Power/Interest matrix (Figure 10), creating four groups (A,B,C,D). Group A are the stakeholders with little interest in the project and have little power to influence the project. The stakeholders in group B are the ones with a high level of interest in the project, yet have little power to influence the project. Good communication between this group is essential, so it is important to keep them fully informed of the major decisions throughout the project. The stakeholders in group C are the most difficult to manage, due to their low level of interest and high level of power to influence the project. It is best to keep them satisfied. Finally, Group D is the most important group when formulating a project strategy. These are the key stakeholders and acceptance of the decisions made throughout the project is needed for a proper outcome of the project.

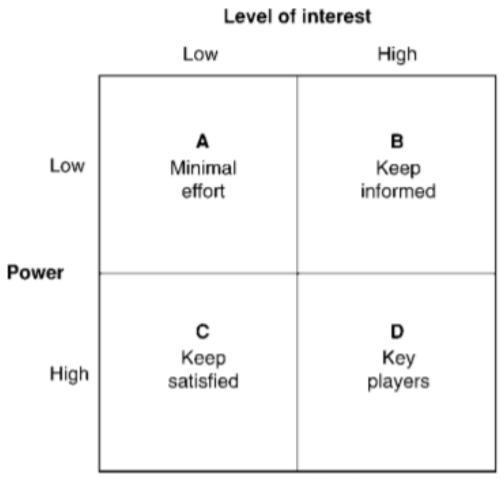


Figure 10: The Power/Interest Matrix [30]

3.2 Brainstorm sessions

During the ideation and specification a number of time constrained brainstorm sessions were performed with the help of rapid ideation [33]. This is done to collect a large amount of ideas about current problems within the project's topic. Ideas and suggestions were written down and discussed to get a sense of the possibilities for this project. In the brainstorm together with the stakeholders the current state of where the project stands and what the stakeholders expect to receive were constantly discussed and kept up-to-date.

3.3 Requirements

In order to define criteria that can be built upon during the specification and realization phase, a list of considerations and requirements was constructed. The main aspects and functionalities are depicted that focus on data. The requirements are further adjusted and specified in the specification phase.

These are divided into the functional requirements and non-functional requirements, which are explained in *Table 1*. Non-functional requirements specify constraints that can be used to judge the operation of a system, rather than specific behaviours, whereas functional requirements specify the things the system should be able to do [34]. To give an illustration, a functional requirement could be that the program must work on all devices, and a non-functional requirement could be that it must be easy to use.

Functional Requirements	Non-Functional Requirements
Product features	Product properties
Describe the actions of the user	Describe the experience of the user
Functions that can be captured in use cases	Global constraints that result in development an operational cost
Can be traced as individual module of a program	Is a basement of a program module

Table 1: Functional Requirements vs. Non-Functional Requirements [34]

3.3.1 MoSCoW

Due to the many possible ways to go about with this project, the MoSCoW (Must have, Should have, Could have, Won't have) method is used to prioritize the greatest and most immediate benefits early [35]. The tasks are categorised into four states of requirements. The 'Must have' provides the minimum of tasks which the project guarantees to deliver. From there the project will expand into the 'Should have' and 'Could have' tasks, however these will be first to be removed if the delivery timescale looks threatened. The 'Won't have' tasks came up during the brainstorm sessions, however will not be created for this project. These tasks will be described in further detail in the chapter Ideation.

3.4 PACT analysis

PACT is short for People, Activities, Context, and Technology. This analysis will give a better understanding of the context in which the device will be used as well as understanding who the users are. First, there will be looked at the relevant users, their characteristics and skills (People). This can be done best with the help of personas. Secondly, getting an idea of how the activities currently are carried out. Why they are carried out that way and what can be improved (Activities). The next part of this analysis will look at the environment of the activity (Context) and lastly, look at what tool are used now, and how might new developments be used (Technology) [36].

3.5 Interviews

During the evaluation phase, interviews with the eSporters of FC Twente were held to evaluate on the final prototype program. The type for these interviews was a situational interview were the researcher puts before hypothetical situations where the eSporters explain what aspects they expect they will use and which aspects for further research can be useful [29].

4. Ideation

The first section will be about the stakeholder analysis that is performed. This is done to get a good understanding of the people who will be involved in this project. The second section will be about the brainstorm sessions. The rapid ideation technique [33] is performed, because operating within a time limitation can often produce higher quality work. The third technique that is used is the PACT-analysis to .

At the start of the project there was a number of brainstorm sessions, in order to generate ideas. These sessions were together with some of the stakeholders of the project. However, before going into further details on the ideas, it is necessary to clarify and analyse whom the stakeholders of this project are and what requirements they expect to be useful for this program. It is the key part of any project strategy analysis. This will be done through a stakeholder analysis in the upcoming section. Furthermore, the whole process of creating ideas for the program that will obtain in-game data is discussed with the help of techniques like brainstorm sessions, PACT analysis. This will eventually lead to three final ideas at the end of this chapter.

4.1 Stakeholder analysis

There is a number of different stakeholders of this project (Figure 11). All of them will be analysed throughout this section. The eSporters and coaches are two of the key stakeholders (Group D) (group definitions can be found in chapter 3.1). The end result of the project can be used by the eSporters and coaches to analyse the eSporters' performance and detect points of interest where they can improve. They will be primary users. Their main concerns were that the program should not create a delay in the gameplay. This will irritate the eSporters and will have a negative effect on their performance, the opposite of what this project is trying to create. Furthermore, they want the program to be easy and quick to use. It should not distract the eSporters so the program should run on the background, without the eSporters having to check every once in a while if the program still works properly.

Guido Bruinsma is the supervisor of the project, the third key stakeholder (Group D). He, together with the University of Twente, represented by critical observer Erik Faber, created the project proposal and set the time frame for this project. They will help throughout the project as decision makers and they support with resources and advice. Guido is involved in the development of the product and has the power to make decisive actions regarding the future of the project. Guido will build on this project alongside other projects to improve the eSports' scene, so a solid basis of a program to build upon is preferred, with enough data to build a picture of an eSporter and his performance.

Team Gullit [23] and SciSports [25] are the two stakeholders in group C. As SciSports focusses on real football, and Team Gullit is already at the current top of the EA SPORTS™ FIFA eSports scene, they are less interested in the project. However, they boost the project with valuable tips and advice. It will be favourable to keep them satisfied as they might help further along the way and become more interested in the project. The prototype program will become interesting for Team Gullit, if it also helps the eSporters who are already at the top. So the data collected should be meaningful and give added values to the evaluation of the matches. SciSports is a multimillion dollar company that uses these types of technologies within the real life football. For them the project will become interesting if the program adds value and provides an extra service to SciSports' current partner football clubs.

The University of Twente and the eDivisie club are group B as they are interested in the project, however the University itself has little power to influence the project and the eDivisie clubs as well, because both stand further away from the project. It is still necessary to keep them informed about the major decision made throughout the project. During the project, the University acquired more influence as the corona measures took place. These measures limited the Face-to-Face contact and made user testing more difficult. This was forcibly necessary in order to keep the corona outbreak causing minimal effects in this country. The University of Twente is represented by Erik Faber, the critical observer of the project and Guido Bruinsma, the supervisor of the project. The University expects correct and reliable conducted research throughout the project.

Lastly, the fans of the game might be considered as the stakeholders in group A. They have little to no power to influence the project, and might not be as interested as the professional eSporters. For them, it should be easy to use, as well as informative in the way they play. It should have the possibility for their data to remain private, in order to reduce the chance of cyber bullying with that data.

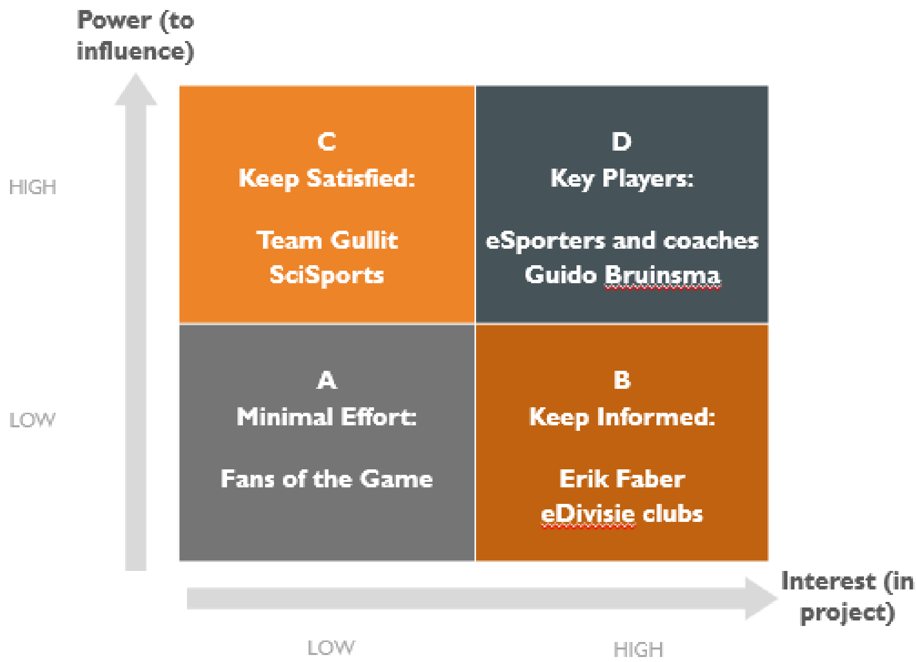


Figure 11: The Power/Interest Matrix of this project

4.2 Brainstorm ideas

During the ideation and specification a number of time constrained brainstorm sessions were performed. This is done to collect a large amount of ideas about current problems within the project's topic. The first brainstorm session was together with Thijs Lieverse, who's the head and founder of Blueshell [37], Guido Bruinsma, the supervisor of the project, Johan Kroeze, who's the head of the Kidsclub and YoungReds from FC Twente [38] [39], the three eSporters of FC Twente and their trainer. The current obstacles mentioned by the eSporters are consistency, focus loss after a couple of matches, and they want to improve their self-evaluation as well as recognising patterns. With the help of the three professional EA SPORTS™ FIFA 20 FUT eSporters of FC Twente, data will be collected in order to better understand the current performances, which will help improve their self-evaluation.

The sub-question *"Which game data is relevant and how to get the relevant game data?"* is discussed during these brainstorm sessions as well. The first idea is to collect the end screen data, to know the end result and some statistics of the match already. It is important to know the end result in order to further analyse the game. They identified that the data from the end screen after a match, alone was not enough to actually understand the course of the match. This helped to further improve the design goals really early in the ideation process.

After talking with the founder of Blueshell, Thijs Lieverse, the concept of an automated end screen screenshot program was brought to mind. The idea that came up from this meeting was that whenever the eSporters start playing the game FIFA 20, they stream their matches. A software program must be created that analyses the streams, for example in steps of 5 seconds, and detect when the end screen is shown. The scraping program ended up having to look something like:

1. Start program
2. Go forward 5 seconds
3. If screen is recognised as end screen (for example by recognising certain pixel or colour combinations around the edges), take a screenshot
4. Go forward a number of minutes (so that the same end screen is not recorded twice)
5. While not end of stream: Loop back to step 2
6. Otherwise, shut down program

This way, the screenshots will be collected automatically and will thus be easier, instead of having the eSporters take a picture of the end screen every time the match ends and send these images. However, this was not of upmost importance for this project, so in the end it ended up as a 'Won't have' for this project.

In the meeting with founder and ex-CEO of SciSports [25] Giels Brouwer, currently Chief Innovation Officer at SciSports, a number of other, more in depth options to collect data from the game EA SPORTS™ FIFA 20 were discussed. After explaining how the data was currently collected, he mentioned this can be done even more automatically. Instead of writing the data of the screenshots manually, use computer vision to arrange the data from the screenshots into a file. Recognising patterns requires data that is harder to obtain. Giels mentioned that the minimap within the game could help to retrieve this data.

During the meeting with Corné Dubelaar of Team Gullit, the topic sleep was mentioned. Corné was interested in the data around the sleep of eSporters and which effects do their sleep patterns have on their performance. This data might be collected as well.

4.3 PACT-analysis

In order to get a better understanding of the potential users and the way they will going to use it, an PACT-analysis is conducted [36].

4.3.1 People

Personas will be used to get an insight in the potential users. The first potential user is Cody. Cody is 21 years old and an experienced FIFA player. He is recently asked to play for one of the Eredivisie clubs as an eSporter and he has agreed to sign. He frequently competes in the Weekend League (WL). He has on average one or two losses. However, it was not possible for him to finish every week very high in the Weekend League, due to the fact that he also plays traditional football every Saturday, so he is not always playing all the 30 matches. When he does, his average is 28-2. With the signing for one of the Eredivisie clubs, he gets very busy weekends, because he is expected to play at least 25 matches and finish high. Before his signing, he did not train or evaluated his matches, because he played just for fun and happened to be good at it. Only with a little bit more training, he might become even better. He has no idea about the way he plays FIFA, and thus suggested the Eredivisie club he should use the project's prototype. This way he get a better insight when he uses skill moves, where in the field he performs certain actions and which are not effective. This is shown by him by his game data that is visualised for him. The fact that program is easy to understand and to use makes him decide to use it every week from now on, to build a picture of what kind of FIFA eSporter he is and helps him improve his performance, because the data will tell him his general statistics of his matches, the patterns and button combinations he uses and shows where he performed actions that have led to loss of possession of the ball.

Willem is 25 years old and an experienced eSports trainer. Three years in a row his team, consisting of two eSporters, ended up in to top 4 of the eDivisie. One of his eSporters managed to be in the Top 100 of FIFA six times, where the other managed it four times this year. He uses the project's program now for a year and it happens to be a really effective way of giving feedback to his eSporters. Unfortunately, his team did not become champions of the eDivisie, because they lost in the final, yet this was his highest performance with the team so far, after becoming fourth twice before. He knew the one mistake which caused his team almost all their counter goals, rushing the keeper to early out of the goal. However, in the final it was not enough, the opponents were just slightly better. He will keep on using the project's program because it really helps him focus on improving his team's performance and it has really worked out for them so far.

4.3.2 Activities

The program will be used while the eSporters are gaming. Before they start they can turn the program on together with the console. Once the controller is connected to the computer and the program is set up to record, they can play. It can happen that the eSporter stays in the home menu for a very long time or that he takes a break, so the program must understand not to record this data, as this is useless data.

4.3.3 Context

The usual set-up is depicted in Figure 12 below. Figure 12.a is the setting in which eDivisie matches are played between clubs. Both eSporters of each club sit on a gaming chair opposite of each other with both a screen in front of them. Their teammates and coaches sit behind them on a couch. Figure 12.b is an example of a more relaxed environment inside the eSporters house, most of the time their bedroom or game room, where they play their Weekend League matches

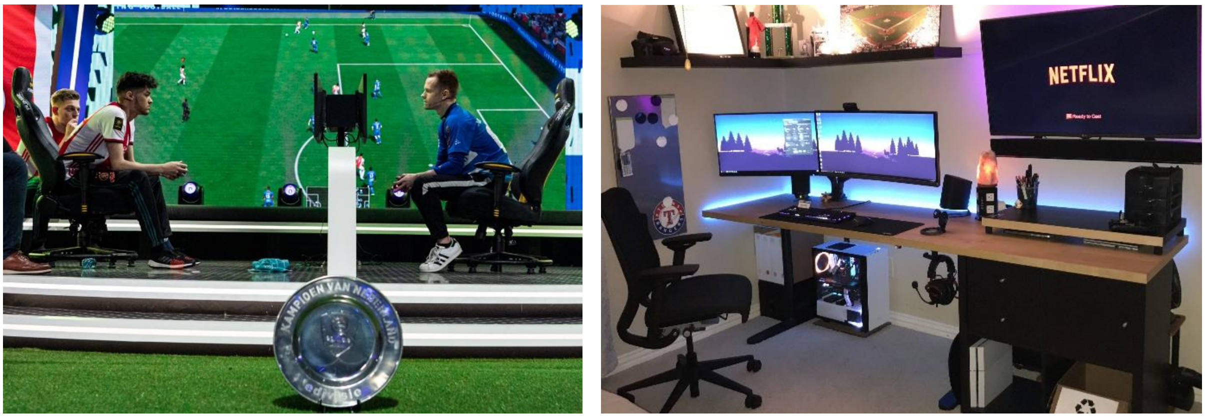


Figure 12: Two different environments; 12.a: an eDivisie match (left). 12.b: an example setup at the eSporters home (right)

4.3.4 Technologies

- Python code
- CNN
- A PC to run and train the CNN
- A Capture Card or Remote Play
- Software (python)
- Data of the eSporters from the Weekend League
- Recorded footage of eSport matches
- Raspberry Pi (optionable)

Standard eSporter's setup. This list consists of:

- A PlayStation and/or a Xbox One console
- A PS4 and/or Xbox One controller
- The game EA SPORTS™ FIFA 20
- A headset

4.4 Requirements

As mentioned in the Stakeholder Analysis, the eSporters are the main users. The requirements are split up in Functional (F) and Non-Functional (NF)

The program must:

F Not create delay for the eSporters when playing

F Autonomously run in the background, not distracting the eSporters

F Output the data all in the same format to quickly get results out of the data

F Collect controller input

F Be a solid working basis to build upon in future projects

F Have enough data to paint a picture of the eSporter and his performance

F Know which player has the ball

F Know where in the field the possession is

F Have the option for the data to remain private

F Understand that when the game is in the home menu, it should not record data (because that is useless data)

NF Display the data in an understandable way

NF Be easy and quick to use

NF Be informative about the performance of the eSporter

NF Be reliable and truthful

4.5 Final ideas

At the end of the ideation, the general idea was to obtain data from three different levels, the game level; which will be obtained using the end screen, the controller level; which will be obtained from the controller input, and the in-game data level; which will be obtained using a Convolutional Neural Network [18].

4.5.1 Game level

The end screen data will give a first impression of how the game went, as it depicts the general characteristics of the match. Together with the subjective opinion of the eSporter about the match, a global picture is created about how the eSporter played. However, the statistics alone are not at all a good representation of the way the match went. More in-game data is necessary.

4.5.2 Controller level

With controller input, it is possible to get an insight in the way the eSporters play and which skills and tricks they use. The python module where the code of this project is based upon is the module inputs.py [40].his module is a collection of code for keyboard, mouse or gamepad input. In order to actually obtain data from the controller, code had to be written. This code can be found in Appendix L. This code will be further explained in the Realisation phase. The code will output the data in a CSV file. This data will include:

- Which type of input is used, i.e. a key, a joystick, or a trigger.
- The exact input that is used, i.e. left trigger, right joystick, circle-button (PlayStation) or B-button (Xbox), etc.
- Pressed or released along with the action or direction performed
- The exact time the type of input is used, i.e. hours, minutes, seconds, milliseconds (14:08:01.771439). This way, when linking the data to the in-game object detection it can be easily synced.

There are two possible setups to obtain the controller data. The first possibility is to connect the PlayStation with Remote Play (Figure 13). Remote Play is a program which runs on the PC where the PlayStation can be connected to via Wi-Fi. This way the projects prototype program can run its analysis on the PC screen, while the eSporter can play on the monitor connected to the PlayStation itself. The controller is connected to the PC using Remote Play as source to obtain in-game data. However, in order for Remote Play to work properly, a good internet connection is required. If not, the gameplay shown on the PC monitor results in a pixel blurred screen, which makes it impossible to analyse properly.

Figure 13: Setup PlayStation connected with Remote Play on a laptop

The other possibility is by using a capture card to split the input to the monitor and the PC monitor. This way the game can still be played on high quality and a USB connection will output a slightly less quality (1080p), yet still of enough to properly analyse the gameplay.

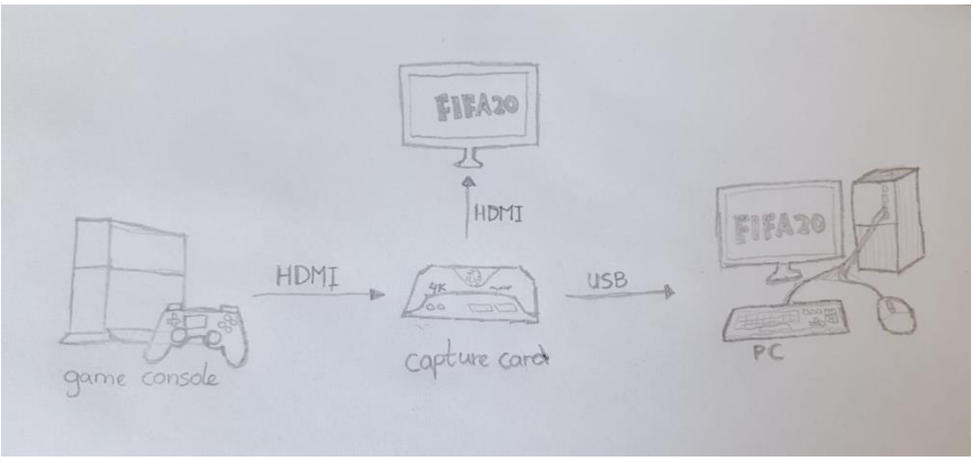


Figure 14: Setup with the capture card

For the final idea, the Remote Play option was used, because a capture card not available for this project (Figure 14).

4.5.3 In-game data level

The more tricky part of the project was to obtain the in-game data. The option to go for in this project is decided to be a program called YOLOv3. YOLOv3 is a convolutional Neural Network, however it works slightly differently than other CNNs. YOLO in this case is short for You Only Look Once. This way of detecting objects is a new and different approach than other CNNs. Instead of multiple evaluations, which other CNNs use, YOLO predicts the bounding boxes and class probabilities in one evaluation [41]. This prediction can directly be done from full images to optimize the detection performance, predicting the objects that are present and their location.

The reasoning behind YOLO came from our humans. We detect object with one look of the eye very quickly and accurately. Together with our hand-eye coordination it allows us to play difficult games, like FIFA 20, and perform complex tasks within these games. YOLO wants to recreate the human way of playing with fast, accurate algorithms for object detections, to collect data from the games this way. With the help of pre-learned data, YOLO can learn how the game works. Due to the fact that it is a single Neural Network, it is faster than the current CNNs.

The third and current version has made the biggest improvement compared to the prior versions. The new features include multi-scale detection, stronger feature extractor network, and improvements in the loss function. To get the complete picture of YOLOv3, Ethan Yanjia Li [42] has a thorough and understandable article which explains YOLOv3 really in depth. Figure 15 represents the general idea of YOLO.

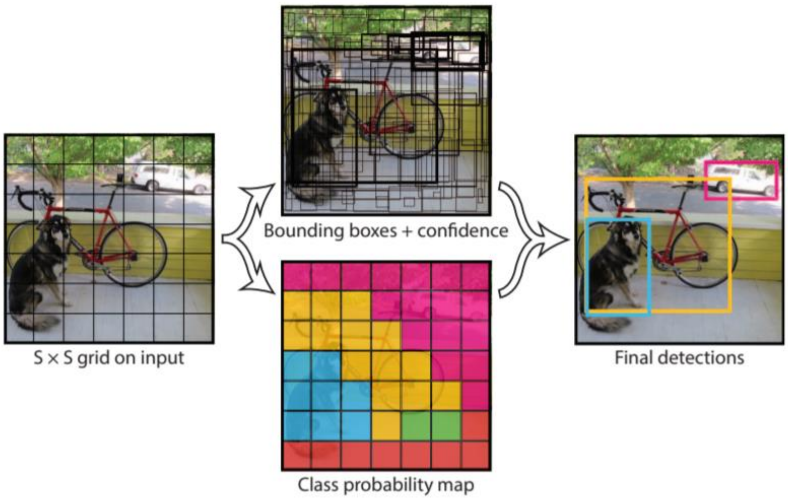


Figure 15: General concept of YOLO [41]

As can be seen in Figure 15, an S x S grid is formed in the input image and each grid cell is responsible for predicting the object centred in that grid cell. Each grid cell predicts a number of bounding boxes and their corresponding confidence scores [43].

The first step was to understand how the code works and what it can do. Using a number of different projects on GitHub based on YOLOv3, it became quite clear which features this code had.

5. Specification

By first creating a activity diagram for the project, both computational and organizational processes are modelled to give an implication of what a potential application could perform, once the data has been collected. This data flows intersecting with the related activities.

Finally, the requirements from the ideation phase are more specified, and the MoSCoW method is used to receive a more clear structure project is defined to understand the important matters. over the less important matters

5.1 Activity Diagram

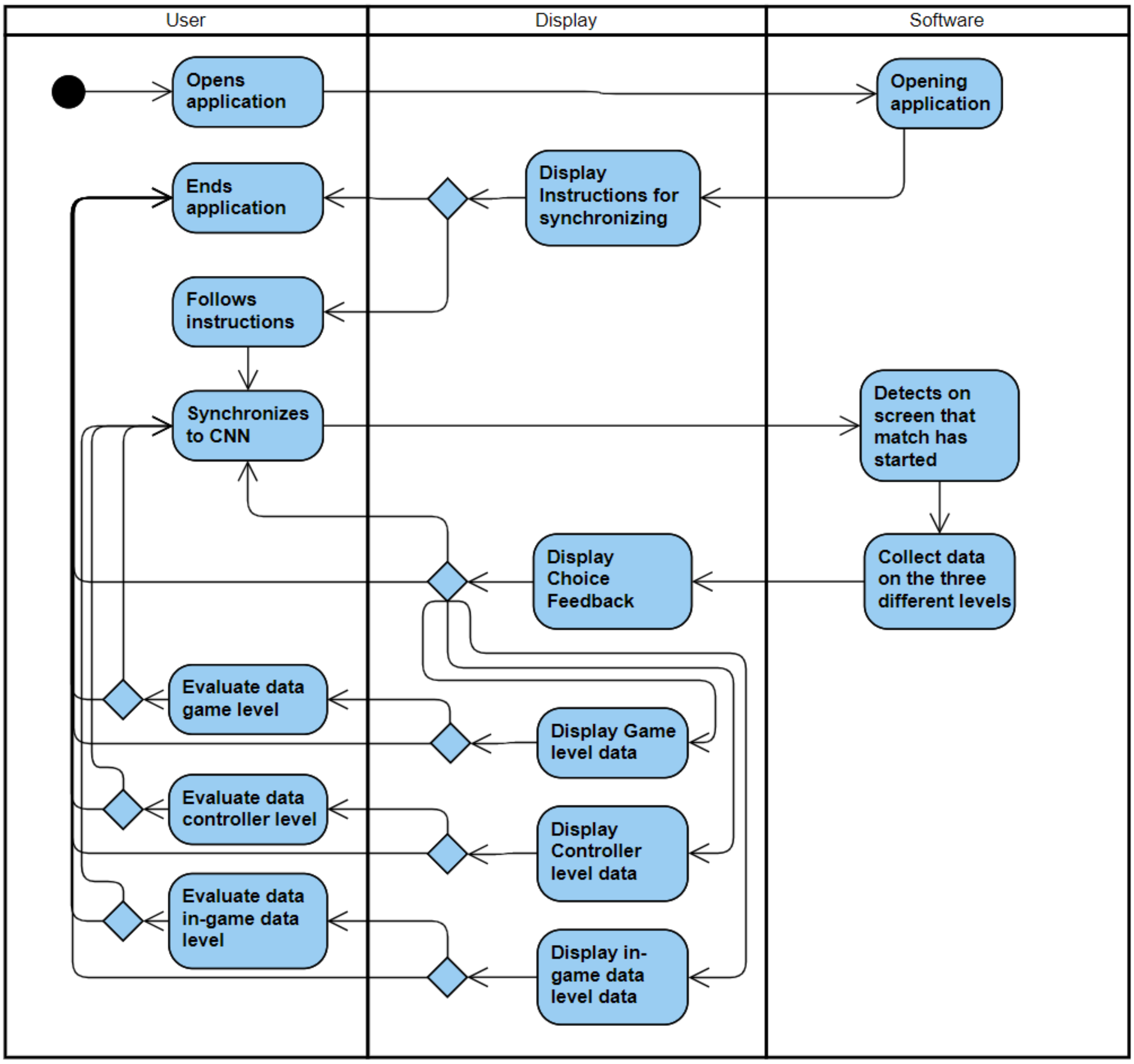


Figure 16: Activity Diagram. Block meaning an action and a diamond meaning a decision or choice

The activity diagram for this project is divided into three parts, the user interaction, the display, and the software of a possible application (Figure 16). The user block represent the actions that could be performed by the users. The display block represents the visuals of the application displayed on the screen. The third block, software, represent the actions performed by the software of the eventual application to make it work.

The user start the application manually. The application need to be synced with the streaming eSporter to be able to detect and obtain the data. So therefore, the application displays the instructions to synchronize with the stream. Once the instructions are followed and the stream is connected to the Convolutional Neural Network, and the controller functions properly, the eSporter can start playing, where the application will detect if matches are played or that they are in the menus. Once a match is started, the data on three different levels is collected and put into CSV files. After a match, the eSporter has the option to directly look at the feedback on one or all the data levels, or just want to play on. If the last option is chosen, the cycle starts again by synchronizing and detecting the match. At any time after a match, the eSporter can decide to stop the application. He can do so with an option directly, or first evaluate one or more matches.

5.2 Requirements

After careful considerations more specific, in depth requirements were formulated based on the requirements from the ideation phase. The findings conclude that the program must:

F Be synced properly with the controller input and gameplay causing no delay

F Work fluently with the game EA SPORTS™ FIFA 20

F Output the data all in the same format, for this project CSV format

F Obtain exact time, in milliseconds, when the buttons are pressed

F Have at least 3.000 data point for the CNN to be able to detect objects itself

F Know if the player is in possession of the ball or not

F Know where in the field the possession is

F Have the option for the data to remain private

F	Understand that when the game is in the home menu, it should not record data (because that is useless data)

NF	Display the data in an understandable way

5.2.1 MoSCoW

The MoSCoW method for this project is shown in Table 2. The three parts connected within this project are the in-game data, controller input and eSport performance, displayed in the columns.

MoSCoW	Game Level	Controller Level	In-game data level
Must have	Data end screen	Inputs when pressed and which way they walk etc.	Recognize if eSporter is in possession of the ball or is not in possession of the ball
Should have	Statistics that show current performance eSporters (player profile)	Button combinations (certain skills used)	Connect the Convolutional Neural Network [18] to the controller input
Could have	Based on obtained data show where eSporters can improve	Link those to certain skills; where in the field used? Etc.	Read tactics and line-ups out of the minimap
Won't have	Program that automatically writes the data from the end screens into a file or a program that automatically takes screenshots of end screen when recognised based on pixel combinations	Based on skill stars in-game player, knowing which skill is used	Dashboard where this data is represented

Table 2: the MoSCow method of this project

6. Realisation

There are three levels of data collection done throughout the project, which will be explained throughout this chapter. These level are 1. The game level; the general aspects of the match, 2. The controller level; the input which an eSporter gives and what can be detected from this input, and 3. The in-game data level; a more deeper level to examine tactics and strategies. Each level will be discussed in this order throughout each section. The three levels will each give different insights in the performance of the eSporters. Section 6.1 will explain the procedure how to get to the results, section 6.2 will present the results, and the final section will conclude the results of this chapter.

6.1 Procedure of the results

6.1.1 Game level

In order to get a better picture of the match that has been played, general characteristics of the match have to be obtained. This first impression of the match can be found at the end of the match on the end screen (Figure 17). So, the first data which could be obtained was the end screen data.

The three eSporters of FC Twente were asked to take a screenshot of every match of two consecutive Weekend Leagues (the online competition where eSporters have to compete in 30 matches each weekend to advance in an international ranking), along with filling in extra data shown in Appendix A. One Weekend League consists of 30 matches, so a maximum of 180 screenshots of end screens could be collected. A sample of 79% of the matches was obtained, due to the fact that the eSporters not always play 30 matches and the fact that some matches were not reported, so a total of 142 screenshots of end screen match data was collected. An example data set is made for the project and put in an Excel sheet (Appendices K, L, M). This data includes:

- The end screen statistics:
    - Shots

    - Shots on Target
    - Ball possession %
    - Tackles
    - Fouls
    - Corners
    - Shot Accuracy %
    - Pass Accuracy %
- Day match played
- Start time match played
- Time of the goals, both eSporter and opponent
- Win or Loss
- The end of Game (Rage Quit or not, or Match Extension, or even Penalties)
- Comment of the eSporter on the match
- Number of the corresponding screenshot of the end screen
- Total number of goals scored per player throughout one Weekend League (30 matches)

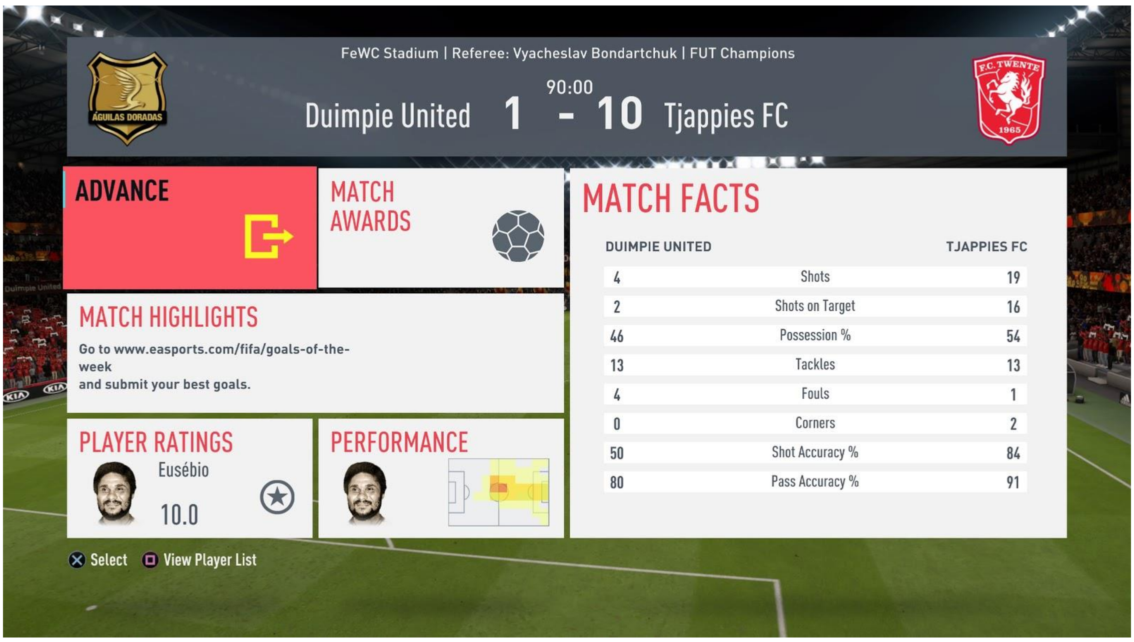


Figure 17: Example of an end screen of a match played on EA SPORTS™ FIFA 20 FUT Champions Weekend League

6.1.2 Controller level

Looking only at the end screen statistics will give a global idea of the match, but does not tell the whole story of the match. One solution to get more in-game specific data is the controller input data. This data will help to understand eSporters' patterns and button combinations. It is obtained using python code. The python code outputs the results in a CSV file. The code for the controller input is connected to the Python module inputs.py. This is a module which aims to provide easy to use, cross-platform, user input device support for Python. What this means, it supports keyboards, mice, gamepads, etc. The platforms which it supports are the Raspberry Pi, Linux, Windows, and Mac OS X.

For this project, only the gamepad support is necessary, as both consoles, Xbox and PlayStation, use controllers. The inputs for an Xbox One controller and a PlayStation 4 controller are displayed in the Table 3 below.

PlayStation 4 (DualShock)	Xbox One
6 axis motion sensing (3 axis accelerometer, 3 axis gyroscope)	-
2 point capacitive touchpad with click mechanism (see buttons)	-
2 Analog sticks	2 Analog sticks
2 Pressure-sensitive buttons (L1, R1)	(see buttons)
2 Analog triggers (L2, R2)	2 Analog triggers (LT, RT)
10 Digital buttons (Triangle, Circle, Cross, Square, L3, R3, "PS", SHARE, OPTIONS, touchpad click)	13 Digital buttons (Y, B, A, X, LB, RB, left stick click, right stick click, Menu, View, "Xbox", Wireless pairing, Share)
4 Digital directional buttons	a Digital D-Pad [44]

Table 3: Inputs of both console controllers

The game FIFA 20 has a number of actions which can be performed. Some controller inputs have more than one functionality. Within a match, the different functionalities occur at two states: the player is in possession of the ball or the player is not in possession of ball. This can be detected using the Convolutional Neural Network (CNN). Within the code for the controller input, the detection of the CNN is displayed as the boolean in_possession. When in possession, the player performs different actions than when the player is not in possession. These actions are displayed in Appendix B [42].

Once the code is executed, it creates a new CSV file where the data will be collected. The file is written as: "Match_2020-06-23_201043.csv", with the date the file is created, so that it is easy to track when the eSporters used the program. It performs all the actions while a controller is connected. As soon as the controller disconnects or is not connected at all, the program will stop and shows the error inputs.UnpluggedError: No gamepad found. During the while loop, the code is constantly looking for events to happen. All these events (the inputs) have a code and once that code is detected, it will be printed in the CSV file (Table 4). As stated earlier, four elements will be printed, namely:

- the type (Absolute or Key),
- the specified button/joystick/trigger,
- pressed (1 or 0) and the action, or, i.e. fake shot, tackle, etc., in case of the keys, or HALF or FULL in case of the triggers, or the direction in case of the joysticks, i.e. UP-LEFT, RIGHT, etc.
- and the exact time it is performed (hh:mm:ss.ms)

Type	SpecifiedButton	Pressed	TimePressed
Absolute	ABS_X	NEUTRAL	16:01:15.262447
Absolute	ABS_X	LEFT	16:01:20.448365
Absolute	ABS_X	NEUTRAL	16:01:20.526084
Key	BTN_EAST	1	16:01:28.388530
Key	BTN_EAST	0	16:01:28.488794
Key	BTN_SOUTH	1	16:01:30.640327
Key	BTN_SOUTH	0	16:01:30.753732

Table 4: Example of the output from the controller input

Connected to these events are the actions from the game FIFA 20. With the help of the if-statement: if in_possession, these different actions can be executed and written in the CSV file. This way the exact performance of the eSporters is pinned down.

The absolute values of the joystick output are first compressed to values between 0 and 1, where the state values of the joystick event are divided by . Then with the use of the unit circle the joystick rotation is organized into 9 directions; neutral, up, up right, right, down right, down, down left, left, and up left.

Now that the data is collected, it can be visualised to make the data more comprehensible. The program that is used in this project to visualise the data obtained from the controller is

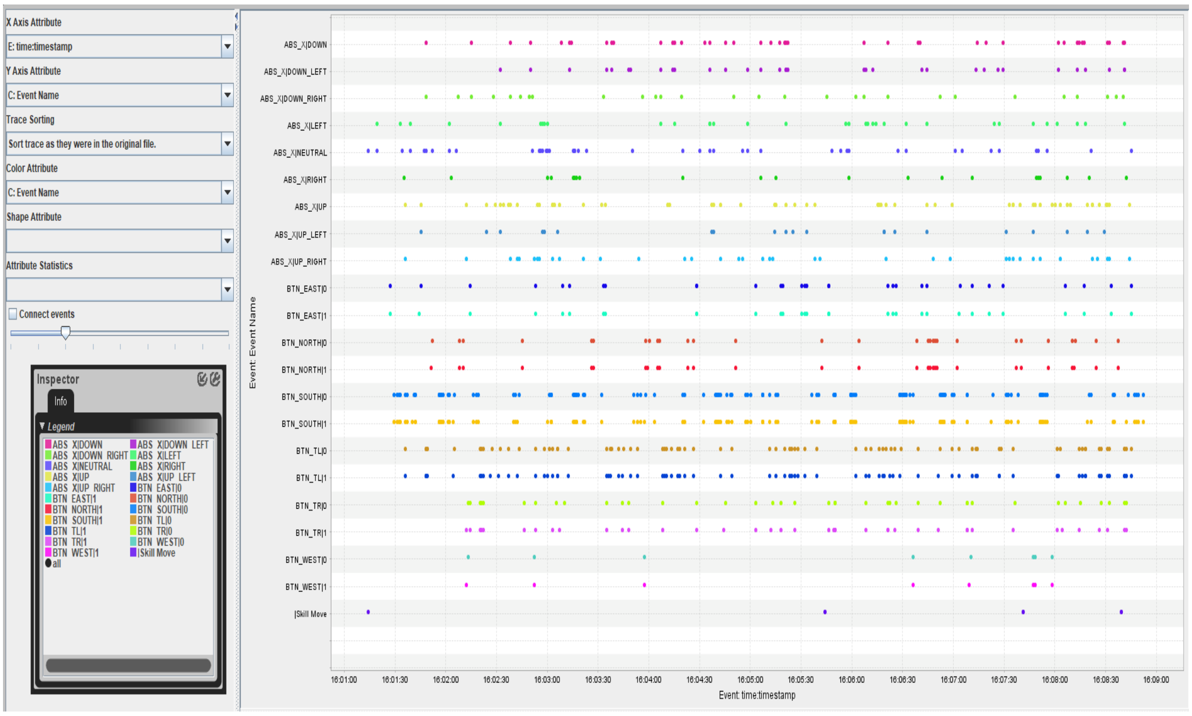


Figure 18: Match DNA of buttons pressed using ProM Lite 1.2 (Appendix C) [45]

ProM Lite 1.2 [43]. ProM is an open-source, extensible process mining framework [44], which helps to gain insight in performance and data by providing advanced visualization and verification capabilities [45]. These techniques allow for extracting information from event logs. The ingredients for an event log are a case identifier, description, and attributes. CSV files are transformed into XES (Extensive Event Stream) files which records traces of sequences of events. These XES files have at least a trace, activity and timestamp. The traces usually always have one attribute, the Case, named “concept:name”. In the case of the controller data, this was the type. Furthermore, the activity “event:name, in this case the Specified button, combined with the Pressed are the activity of this project. Lastly, the time “time:timestamp” is used. By filtering some double values and putting the timestamp on the x-axis and the event name on the y-axis a dotted chart can be created of the controller output. All the calculation were done in the Naïve mode, which is the fastest. Figure 18 is an example of a visualization a first half of a match between the researcher of this project (Ruben Nijland) and the computer AI at world class level using ProM Lite 1.2, creating a match DNA. From this visualization can be observed the amount of time each button is pressed, the direction the joystick went, when certain actions were executed and which actions were performed at the same time (Appendix C). However, this chart was still unclear. So, there have been played three more matches with the controller input code by the researcher (Ruben Nijland). This time, all three matches were played in the online competition Division Rivals. Appendices D, F, and H provide a more clearer representation of the buttons pressed during one match in dotted charts. Appendices E, G, I are screenshots of the end screens of the matches, belonging to these dotted charts. Figure 19 is the dotted chart of the first match of Division Rivals played by the researcher.

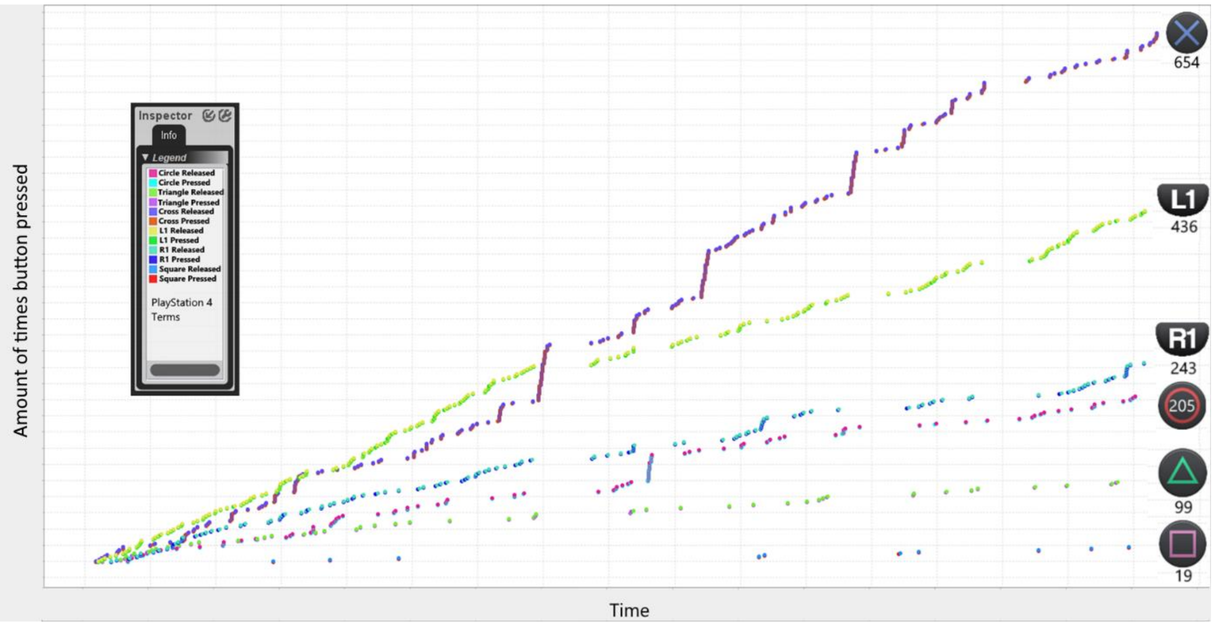


Figure 19: Amount of times button pressed over time of the first match Division Rivals using Prom Lite 1.2 [45]

This already gives a good indication of the gameplay of a player once combining this to the CNN program. Furthermore, certain breaks or when goals have been scored can be observed. Once connected, instead of representing the buttons, the actions can be depicted in this visualization (Appendix B).

6.1.3 In-game data level

The next level is deeper in the game and harder to obtain. As the other two levels can be analysed immediately after obtaining the data manually or using code, this program needs to be trained in order to collect the data eventually. The code had a number of prescribed classes at its disposal. However these prescribed classes were not useful when it came to detecting objects within the game EA SPORTS™ FIFA 20. So it had to learn to detect new objects. First, it was necessary to have an initial set of data of which it can learn to detect these new objects. The python module run.py [46] as used along with screenshots from recorded games between eSporters. The initial list of 44 classes was too ambitious for the period of time for this project. Figure 20 represents one screenshot of a match where these classes were put in bounding boxes.

Figure 20: Screenshot of a match with 44 classes and all the bounding boxes

The first reduction step was to still use the 44 classes, however only put bounding boxes around players that were close to the ball, depicted in Figure 21. However, this meant that an enormous amount of pretrained data had to be made in order to retrieve a proper, accurate picture of the game and the gameplay.

Figure 21: Screenshot of a match with 44 classes and the bounding boxes closest to the ball

Soon followed that the initial 1 sec period between screenshots became too much of a hassle. This meant that within a total of 875 screenshots bounding boxes had to be placed around the different aspects.

Due to the time restraint of the project, a reduction in the amount of classes was suggested, along with a bigger interval time between screenshots. During the weekly meeting, Guido proposed to reduce the amount of bounding boxes to 7 classes, namely:

- The Menu
- The In-game Menu
- The player is in possession of the ball
- The opponent is in possession of the ball
- The Ball
- The minimap
- The location of the ball within the minimap, to track where the player is in possession of the ball.

This will give enough information to get a basic idea of where the player uses the ball in what situation, as this data will be linked to the controller input.

To train the program with data from FIFA 20, eventually three recorded matches between the eSporters from two Dutch professional clubs were used. With the help of the Python module run.py [40] bounding boxes were set around the 7 classes: 1. Menu, 2. Ingame_Menu, 3. In_Possession, 4. Not_in_Possession, 5. Ball, 6. Minimap, and 7. M_Ball (the Ball icon in the minimap). Menu and Ingame_Menu are necessary for the program to detect when there is no match playing at that moment, so that the controller input is not related to the certain actions which happen during the match. Ball is necessary for the program to detect which of the 22 players in the field is in possession and the In_Possession and Not_in_Possession are connected to if the gamer has the ball in possession or not. The bounding boxes were put around the total of 7 classes every frame. Within the bbox.txt folder, the corresponding bounding boxes of the image were located. Every bounding box has 5 attributes in one line. First there is the class number, so between 0 or 6 (the 7 classes). However, not every class has to be within the image. To give an example, the Ingame_Menu cannot be shown at the same time as the Ball or Minimap. After the class number the percentage of the width and the height are given in numbers between 0 and 1, followed by the percentage of the width and the height of the bounding box itself, also in numbers between 0 and 1.

3	0.5932291666666667	0.47129629629629627	0.03333333333333333	0.1111111111111111

Table 5: Output of the object labelling as bounding boxes

So in Table 5 above, it is class number 3, which means the fourth class: 'Not_in_Possession' out of the 7 classes. Measuring with the full screen as 100% width and 100% height, this bounding box is placed 59,32% from the left, and placed 47,13% from the top. The bounding box itself has a width of 3.33% and a height of 11,11%. The two different states, In_Possession and Not_in_Possession, are shown in both Figures 22 and 23. When the gamer is in possession of the ball, the indicator above the in-game player is red (for player 1). When the opposition is in possession of the ball, the indicator is grey white.

Figure 22: Screenshot 1 with the labels of the bounding boxes. Opponent is in possession of the ball

Figure 23: Screenshot 2 with the labels of the bounding boxes. Player is in possession of the ball

6.2 Results

The results of this project show a number of features of the matches played in the game EA SPORTS™ FIFA 20. Using the end screen data, general characteristics of the match can be derived, like if a match is won or lost. To get a better understanding of the match itself, the controller input can be obtained to look for patterns and button combinations the eSporter uses. This can be eventually synced to the CNN to get a really strong indication of the eSporters performance, because knowing if the eSporter is in possession of the ball or not will give the opportunity to connect the input to the actions performed (Appendix B), and will thus create the image of the eSporter with the actions he performs in the game.

6.2.1 Game level

There are so many possibilities to analyse the performance of the eSporters, now that it shown that this data can be obtained (Appendices K, L, M). From the end screen data general characteristics of the match can be derived. As an example a data set was made from 3 eSporters from 2 consecutive weekends.

The win/loss percentage over a weekend is an example of one of the features which can be analysed. Figure 24 shows the percentage of wins and losses of the three eSporters, which is derived from all the screenshots of the matches the eSporters played. This will give a first indication of how they performed during the weekends. From this graph can be concluded that all the three eSporters performed better in the first weekend. This is information that can help to evaluate about what have happened, why all of them performed worse in the second weekend.

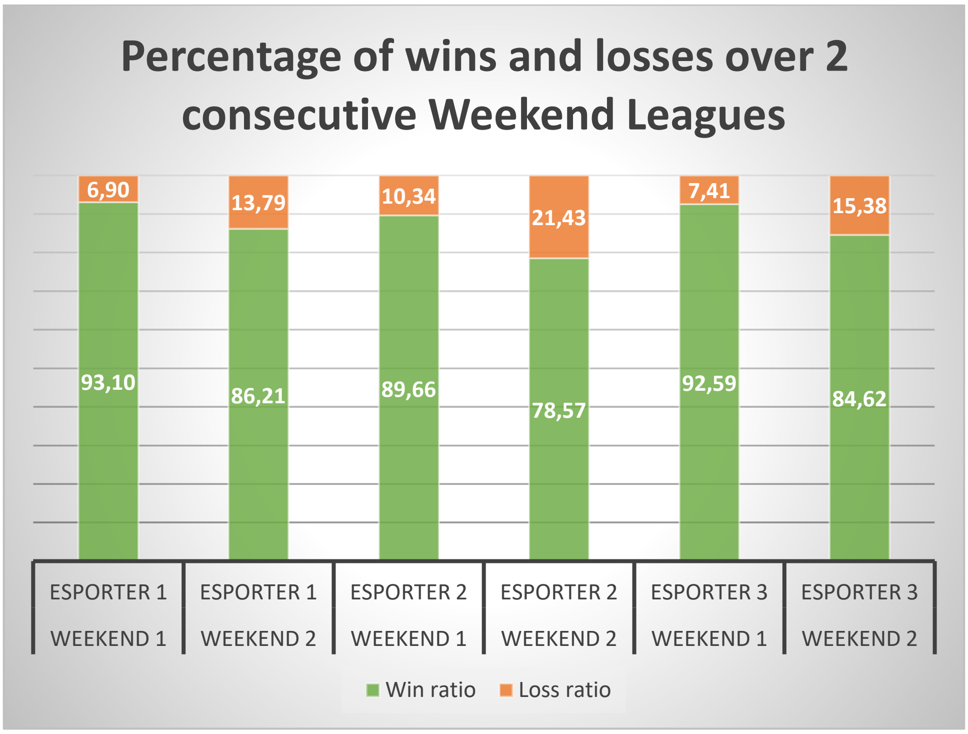


Figure 24: Percentage of win and loss of the three eSporters of FC Twente over 2 consecutive WLs

During a match within the Weekend League, if a player scores in the early minutes of the game or the difference in goals between the opponent becomes more than 2, the opponent tends to leave the game early. This is called a rage quit. So if you are a really good player, like the eSporters, you tend to receive a lot of rage quits, as can be observed from Figure 25. This is also another indicator of how the weekend went, because if you receive a lot of rage quits, you performed really well early in the games. And if the player get a lot of match extensions or penalties, this can mean two things. The player is up against a very tough opponent of similar quality as the player or the player is just not focussed enough to win within 90 minutes to an opponent that is less than the player.

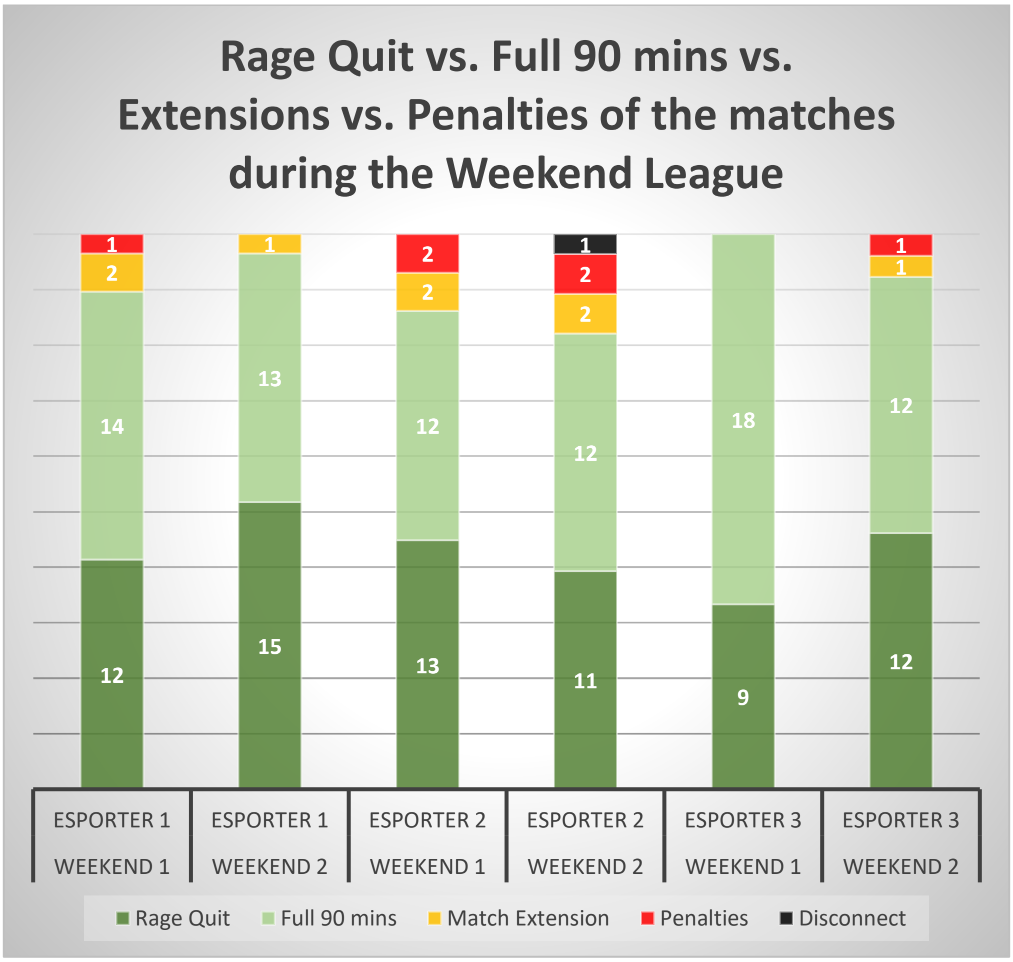


Figure 25: Rage Quit vs. Full 90 mins vs. the extensions of the matches during the Weekend League

As mentioned, these are only two of the possibilities to analyse eSporters' performance with the end screen data. More possibilities for analysing this data are listed in Table 6 below.

Possibilities for end screen data	
Perform a prediction analysis on:	Which day he can play best
	The time during the day when he played best
	If amount of matches played per day has an impact on the performance
	What determines scoring goals
	When receiving more counter goals (does it depend on possession? Pass accuracy? Other game stats?)
	The comments the eSporters make on the match. Is there a difference between the objective measurements and what the eSporters themselves of the match?
Perform a regression analysis on:	When he scored the most goals (full 90 mins matches), which stats (possession, shot accuracy, etc.) have most impact
	When he receives the most rage quits (during the weekend/ on the days itself, link between stats?)
	What determines the shot accuracy
	Which opponent's stats have the most impact on a negative performance of the eSporter
Think of ways to:	Best visualise these statistics

Table 6: Possibilities for end screen data

Receiving feedback on these data statistics might help to improve the eSporters performance. For example, from future research analysing the end screen data, it came forward that if eSporter 'X' wants to score more goals, he needs to focus on his pass accuracy, because this proved to be effective. So the outcomes of analysing the end screen statistics will help to improve the eSporters performance.

6.2.2 Controller level

Now that the controller input data is obtained and visualised, a number of things can be observed. There have been played three matches with the controller input code by the researcher (Ruben Nijland). Appendices D till I show the three different online Division Rivals matches, with one explicit thing in common. All matches were lost by the researcher due to the lag with Remote Play. When looking at the dotted charts, it can be observed that the x-button (PS4) is pressed most, which is used for passing and to skip replays, followed by the left pressure sensitive button, which is mostly used to switch between players (Figure 26). The second and third match the researcher played better than the opponent, more shots on target, the better play, however the shots could not be performed accurate and it was hard to keep possession of the ball with the lag. So most of the time during all three matches, the researcher was defending. This is why the L1 button is pressed in all three games a lot, due to the switching between players while defending. The incredible cross button mash visible in the second match (Figure 26) was caused by, in the researcher opinion, a totally undeserved second goal of the opponent, while the opponent did not skip the replays.

Figure 26: Amount of times buttons pressed over time. Second match Division Rivals (Appendix F)

The data from the controller input give insights in the button combinations, button mashing, reaction speed, and the actions performed by the eSporter. Being able to collect this data opens up a whole lot other opportunities for analysing performance. For instance, next steps for future research could be to:

- Analyse different combination used and which combination are used most.
- Analyse the reaction speed. Can this be improved?
- Ask: "What do these combinations mean as actions performed within the game?

- Analyse patterns of the eSporters, are these effective or not?

6.2.3 In-game data level

The in-game data level will be most effectively used in combination with the controller level. The in-game data level opens up the possibilities to analyse lots of new research areas. Questions like:

- Is there a connection between the position on the field and controller input?
- Where the player is in possession of the ball and where in the field he loses the ball most often?
- Which combinations were used at those moments?
- Which choices does the player make and which ones are effective?
- Which is the most effective tactic for the player?
- Which line-up counters the opponent's line-up best?
- What is the best strategy for the player? Go all offensive or play around in the back and wait for a gap? Or something else?

All these questions can be studied now that the basis for receiving this data is set and that it is concluded that it is possible to collect this data.

6.3 Conclusion

- The project is the basis for a lot of new research opportunities.
    - Data Science
    - Artificial intelligence
    - Data Visualisation
    - Football analytics
    - Ways to deliver feedback to the eSporter
- The ambitions for the project were set high, as one of the starting goals of the project was to try to create a picture the eSporters performance and which data correlates to their performance. This is still one step ahead of this project.

- This project has come up with a systematic to collect data and designed a procedure that could be used in future work.
    - Three data levels:
        - Game level → obtain general characteristics of the match
        - Controller level → look for patterns and button combinations
        - In-game data level → understand if the ball is in possession or not, by the use of a Convolutional Neural Network (YOLOv3)

We eventually did three levels of data extraction. From the game and controller level, it shows that collecting this data is already possible. The sample data from the end screens of the eSporters of FC Twente of two consecutive Weekend Leagues were manually put in an Excel sheet. A next step would be to make this procedure automatically, as it takes a lot of time to fill it in manually. With this data, it is now possible to perform regression analyses to understand which of the statistics have a correlation with each other.

The controller input can be obtained using python code and is collected in a CSV format. And although the project hit some difficulties with the in-game data level, the procedure used in the project has set the basis for future work into the domains of data science, data visualisation, football analytics (like SciSports [25]), and how to deliver the feedback to the eSporters.

All the questions and new analysis directions that have come up within the three levels can be evaluated, now that the basis for receiving this data is set and that it is concluded that it is possible to collect this data shown within this project.

7. Evaluation

In the evaluation phase a functionality check was done based on the requirements set in the specification phase. Furthermore, interviews were held with the eSporters. The outcomes of this project are built upon input from the stakeholders. The end goal of this project was to get an understanding of the eSporters' performance with the help of the in-game data collected from the game EA SPORTS™ FIFA 20. During this evaluation phase the results will be showed to the stakeholders to evaluate whether the final product is what is to be expected.

7.1 Requirements

The requirements put down in the specification phase are stated below. These will be checked and explained why they were achieved or not in the remainder of this section.

F Be synced properly with the controller input and gameplay causing no delay

F Work fluently with the game EA SPORTS™ FIFA 20

F Output the data all in the same format, for this project CSV format

F Obtain exact time, in milliseconds, when the buttons are pressed

F Have at least 3.000 data points for the CNN to be able to detect objects itself

F Know if the player is in possession of the ball or not

F Know where in the field the possession is

F Have the option for the data to remain private

F Understand that when the game is in the home menu, it should not record data (because that is useless data)

Some of the requirements appeared to be too ambitious for the timespan of this project. For example the set-up for the CNN has been put into place, however there was no time left to obtain at least 3.000 data points for the CNN to be able to detect objects itself. Therefore the functional requirements like syncing it with the controller input and having enough data points to paint a picture of the eSporter and his performance was not yet possible.

Furthermore, because it was not yet a complete application, there was not yet the focus on the privacy part of the project, so the functional requirement to have the option for the data to remain private is still one step ahead of this project.

The three data levels worked fluently with the game EA SPORTS™ FIFA 20 as the data from the end screen could be collected, the controller input could be obtained while playing, and it was possible to label the object within FIFA 20 from screenshot of multiple matches.

As shown in the Figures 22 and 23 it is possible to make the CNN understand the basics of the game EA SPORTS™ FIFA 20 by making it recognize if the eSporter is in possession of the ball or the opponent. The 7 different classes make it possible to understand the differences between menus and in-game menus and the real gameplay. Furthermore, it is possible to extract out of the minimap what the location of the ball in the field is by tracking the yellow cross icon which corresponds to the location of the ball in the field. This will give an indication where the eSporter does certain skills or where in the field he loses the ball the most. The classes 1. Menu and 2. Ingame_Menu will show if the eSporter is in the menus so that that data will not be obtained.

It was also possible to obtain the exact time in milliseconds when buttons were pressed, as was shown in Table 4 of section 6.1.2 Controller level. Appendix L shows the code for the controller input, which detects the exact time the buttons are pressed. Furthermore, by outputting it as a CSV file, the data can be retrieved quickly and the results can be obtained in an easy way out of the CSV file and this was possible for the game level and controller level. This project used the program ProM Lite 1.2 to visualise the results, because stakeholder Guido and the researcher managed to get understandable visualisations out of it fast. For future work could be looked into other visualisation programs which might even output the results in an easier and more explanatory way.

Creating an image of the performance of an eSporter in the FIFA 20 has been done by linking the end screen data, together with the controller input. A basic representation of the performance of the eSporter could be visualised, as shown in Appendices C, D, F, H, J.

7.2 Interviews

For evaluation of the project, the eSporters were once again asked to give feedback, this time to give feedback on the final results. This is done by performing an interview. During the interviews the results of the three data levels have been shown to them and with the help of a situational interview [29], they gave feedback and suggestions on the project. Their perspectives on the future work are shown in Table 7 and further explained below.

	eSporter 1	eSporter 2	eSporter 3
Analysis game level	Correlation of data of: Amount of shots – Percentage of possession – End result	Only first match lost and matches against pro players	Which day and time to play best
Analysis own gameplay	Location in the field of his possession Effectiveness; which choices are best in certain situations	Way to defend: make the right decisions switching between players around the own target area	Way to defend: best ways to close the running lines Passing accuracy of normal passes and through balls
Analyse alone or with a coach	Analyse together	Coach only analyses his gameplay	First alone, then with coach adds points for improvement

Table 7: Overview of feedback eSporters during evaluation interviews

eSporter 1 would like to see an analysis on the correlation of the amount of shots, the percentage of possession, and the end result. Going more in-depth, he would like to analyse where he has the most possession of the ball in the field. As he mentioned, he might have a lot of possession when he passes the ball over in the back, however in the statistics, it might show that he performs better when he focusses more on the counter-attacks, so let the opponent control the play, where he waits for the best moment.

Furthermore, he would like to analyse the effectiveness of different options in certain situations. For example, if he shoots from the 5 meter line always in the nearest corner of the goal and scores 10 goals out of 20 shots, however if he brings himself in the position further from the goal and scores 5 goal out of 5 shots, it is best for him to switch to that tactic and build on there, because it is more effective.

According to eSporter 2, it is not necessary to analyse all his Weekend League games, as he stated that eSporters often know what went well when they performed well, yet it can be difficult to discover things that went wrong when they lost a match. The best analyses for him would be the first loss of the weekend, because eSporters always strive to win all 30 matches every weekend. So during the first loss, he was still very focussed. It is best to look at those matches for what went wrong, because he might unnecessary lose more matches, because he is less focussed after his first loss. Other good matches to analyse are the matches played against pro players which he won, to analyse what went well.

eSporter 1 has a different mindset. He stated that when you lose early in the weekend, there is still enough time to take a break. This indicates that he is still very focussed after his first loss.

eSporter 2 and 3 would like to analyse the ways they defend for future work. Good opponents pass the ball around with their midfielders on the attacking side of the field, looking for the gap. So when the eSporters are defending, they constantly need to switch between players at the right time. They want to analyse if they make the right decisions, closing down the running lines.

eSporter 3 would like to analyse the best times could play together with the best days. He mentioned that gamers have mixed opinions on when it is best to play the Weekend League. Some say it is best to play during the night, while others say it is best to play during the day.

Furthermore, eSporter 3 would like to analyse the passing accuracy of normal passes and through balls, because he mentioned that in some situations these passes succeed, where in other situations they do not. He want to analyse why this is the case.

All eSporters mentioned a coach could be really beneficial when analysing their gameplay. It is not possible to analyse everything by themselves as they might not see everything. eSporter 2 argued that he wants a coach that really understand and can perform the analyses, and explain those to him, so that he does not have to analyse it, whereas eSporters 1 and 3 stated that for them, it would help best if they first analysed it alone. They first want to analyse by themselves where they can improve. Then afterwards evaluate with a coach, because a coach might add different points to improve their performance.

8. Conclusions and Recommendations

The final chapter of this research project will state all the conclusions obtained during this project. The last section will give recommendations for future work building on this research project.

8.1 Conclusions

The question throughout the project was: "Which FIFA in-game data has a relation to the in-game performance of eSporters?" We eventually did three levels of data extraction. From the game and controller level, it shows that collecting this data is already possible. The sample data from the end screens of the eSporters of FC Twente of two consecutive Weekend Leagues were manually put in an Excel sheet. A next step would be to make this procedure automatically, as it takes a lot of time to fill it in manually. With this data, it is now possible to perform regression and prediction analyses to understand which of the statistics have a correlation with each other.

The controller input can be obtained using python code and is collected in a CSV format. From this data it is now possible to look for pattern and button combinations that eSporters use. And although the project hit some difficulties with the in-game data level, the procedure used in the project has set the basis for future work into the domains of data science, data visualisation, football analytics (like SciSports [25]), and how to deliver the feedback to the eSporters.

With some difficulty it is possible to answer the research question, because having the game level gives the possibility to collect the general characteristics of the match. Furthermore, combining the controller level together with the in-game data level will give a solid understanding of the performance of the eSporter. His actions performed in the game, the buttons he presses tell the way he plays, which means that the data of those two levels combined have a relation to the in-game performance of the eSporter.

8.2 Recommendations for future work

The results from the project are promising. It captures a first indication of the data which can all be obtained out of the game EA SPORTS™ FIFA 20. This project has set the basis for new opportunities to improve performance with in-game data. The data is the trigger to make future work possible.

This project was done in the early stages of research within eSports. In multiple other domain future work is imaginable. These domains include data science, artificial intelligence, football analytics, data visualisation, and how to deliver feedback to the eSporters. Examples of future work are shown in Table 8.

<table>
<tr><td rowspan="9">Data Science</td><td rowspan="2">Regression analysis →</td><td>- causes shot accuracy</td><td></td></tr>
<tr><td>- when receive more Rage Quits?</td><td></td></tr>
<tr><td rowspan="7">Prediction analysis →</td><td>Which day of the weekend played best?</td><td></td></tr>
<tr><td>Which time of the day played best?</td><td></td></tr>
<tr><td rowspan="5">Goals/counter goals scored →</td><td>- Caused by possession?</td></tr>
<tr><td>- Caused by pass accuracy?</td></tr>
<tr><td>- Caused by opponent's pass accuracy?</td></tr>
<tr><td>- Amount of matches played after each other?</td></tr>
<tr><td>- Time of the day</td></tr>
</table>

Artificial Intelligence	in-game strategy and tactics extraction →	Detect the line-ups both teams and predict best line-up to counter	
Ways to deliver feedback to eSporter	Which data do the eSporters and coaches prefer →	Create a dashboard for feedback to the eSporters	
Data Visualisation	Visualise game level, controller level, and in-game data level →	Analysis to look for the best ways to visualise the different data [47]→	Arc Diagram Area Graph Box & Whisker Plot Bubble Chart Bubble Map Bullet Graph Calendar Connection Map Density Plot Donut Chart Dot Map Dot Matrix Chart Flow Map Gantt Chart Heatmap Histogram Illustration Diagram Line Graph (Multi-set) Bar Chart Network Diagram Nightingale Rose Chart Parallel Coordinates Plot Parallel Sets Pictogram Chart Pie Chart Radar Chart Radial Bar Chart Scatterplot Span Chart Stacked Bar Graph Stream Graph Timetable Tree Diagram Venn Diagram

Table 8: Future work possibilities in different domains

The game FIFA 20 itself uses some of the data visualisation options shown in Table 8. For example, they use heatmaps to analyse possession and use radar chart to create a player profile of football players within the game. These visualisation options might as well be useful for future work into visualizing the data of the three different levels or to create a player profile for the eSporter. Future research could look for suitable visualisation options which will depict the data in an understandable way to evaluate and retrieve feedback from, which will help the eSporters and coaches.

Building upon this project, it can be possible to link the end screen data, together with the controller input and the data obtained from the self-trained CNN YOLOv3 which collects if the ball is in possession or not and where in the field the ball is. For the game level, an automation step could come in handy to collect the end screen data. Once the CNN has sufficient data points to learn itself the game EA SPORTS™ FIFA 20, together with the controller input, the project prototype program will be able to detect, when certain combinations are used, i.e. skills, passing, etc., and where these events happened in the field, because the data from the project prototype program will be synced with the controller input data by the use of labelling the events with the exact timestamp.

The detection of the ball within the grid in the minimap is definitely possible for future work as this will help to detect where the player performs certain actions within the field. Due to the limited time for the project, this could not yet been done. With more time, the grid could have been made the same way as the location of the ball, by labelling the grid within the minimap.

Once the CNN works properly, there can be looked into the options of understanding the teams line-ups, by using the minimap. When this data is collected, there can be looked into which line-ups are more effective in certain situations. Furthermore, a player profile can be created with the then connected controller actions. This can all be displayed in a dashboard eventually.

For this project, the option of using YOLOv3 is picked. For future work, there might be looked into the possibility of using Tensorflow Object Detection API instead of YOLOv3 and compare the differences. During this project there were some problems around working with Tensorflow which made the researcher decide to use YOLOv3 instead.

The evaluated data was obtained using PlayStation Remote Play. The mediocre Wi-Fi which was used to connect Remote Play caused lag during the online match. When discussing this with the key stakeholders, the eSporters of FC Twente, they mentioned that this is one thing they do not want to experience during a match, so an alternative, like the capture card, discussed in chapter 4.4 might be an alternative option for future work.

After evaluating with a coach from the eDivisie, he concluded that match facts, like the end screen data and knowing the skill moves can be very useful, and brought some other interesting data points which he wants to look at in the future. For him, he would like to know the ranking of the opponent his eSporters play against, if they are Verified or not. And then learn if his eSporter play better or worse against Verified players. One option to look at this, is to make the CNN understand the gamertag from the opponent's in the game, and the look through the database of the FIFA rankings [15] to see if the opponent is Verified or not and look for his ranking. He wants to look for the tactics the opponent uses and the response time of his eSporters as well. Furthermore, on the more technical note, he wishes to look at the network connection speed and the connection of the opponent and its effects on the game, as well as look at the delay of wireless controllers versus wired controllers.

For follow-up research, questions like:

"Which factors improve the performance of eSporters and why?"

and

"What are the differences between the objective measurements and what the eSporters themselves think have improved? "

are interesting questions to analyse, as the eSporters might not examine or experience the same results as the objective measurements suggest.

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Appendix A: Data Collection Preparation

Day	Start time (e.g. 20:09)	Time of your Goal(s) in Mins	Time of opponent's Goal(s)) in Mins	Comment eSporter	# of Screenshot
					e.g. W1.png or W1

Total # of Goals per player in your squad (GK excluded)

Player	# of Goals
Subs:	-------
Total:	0

Appendix B: The controls for FIFA 20 [48]

MOVEMENT

ACTION	PLAYSTATION CONTROLS	XBOX CONTROLS
Move Player	L	L
Sprint	R2 Hold Down + Direction	RT Hold Down + Direction
Shield/Jockey	L2 Hold Down + Direction	LT Hold Down + Direction
First Touch/Knock-On	R2 + R + Direction	RT + R + Direction
Stop and Face Goal	L + no direction + L1	L + no direction + LB
Face Up Dribbling	L2 + R2	LT + RT
Strafe Dribble	L1+ L	LB+ L
Strafe Dribble (Lock Face Angle)	L1 + R1 + L	LB + RB + L
Stop Ball	R2 + no direction	RT + no direction
Jostle (Ball In Air)	L2	LT
Skill Moves	R	R

GOALKEEPER (In Possession)

ACTION	PLAYSTATION CONTROLS	XBOX CONTROLS
Drop Kick	◯ or ▢	B or X
Throw/Pass	X	A
Drop Ball	▵	Y
Pick Up Ball	R1	RB
Driven Throw	R1 + X	RB + A
Driven Kick	R1 + ▢	RB + X
Move Goalkeeper	R3 Press and Hold + R	R3 Press and Hold + R
GK Cover Far Post	R3 Press and Hold	R3 Press and Hold
Switch to GK	Press Touchpad	Press Touchpad

DEFENDING (Not in Possession)

ACTION	PLAYSTATION CONTROLS	XBOX CONTROLS
Change Player	L1	LB
Switch Player (Manual)	R + Direction	R + Direction
Tackle/Push or Pull (when chasing)	◯	B
Hard Tackle	◯ Press and Hold	B Press and Hold
Sliding Tackle	▢	X
Sliding Tackle (VOLTA FOOTBALL only)	▢	X
Clearance	◯	B
Jockey/Grab & hold	L2 Hold Down	LT Hold Down
Contain	X Press and Hold	A Press and Hold
Teammate Contain	R1 Press and Hold	RB Press and Hold
Running Jockey	L2 + R2 Hold Down	LT + RT Hold Down
Pull and Hold (when chasing)	◯ Press and Hold	B Press and Hold
Quick Get Up (after slide tackle)	▢	X
Engage Shielding Opponent	L2 + L Towards Shielding Dribbler	LT + L Towards Shielding Dribbler
Rush Goalkeeper Out	▵ Press and Hold	Y Press and Hold
Goalkeeper Cross Intercept	▵ + ▵ Press and Hold	Y + Y Press and Hold

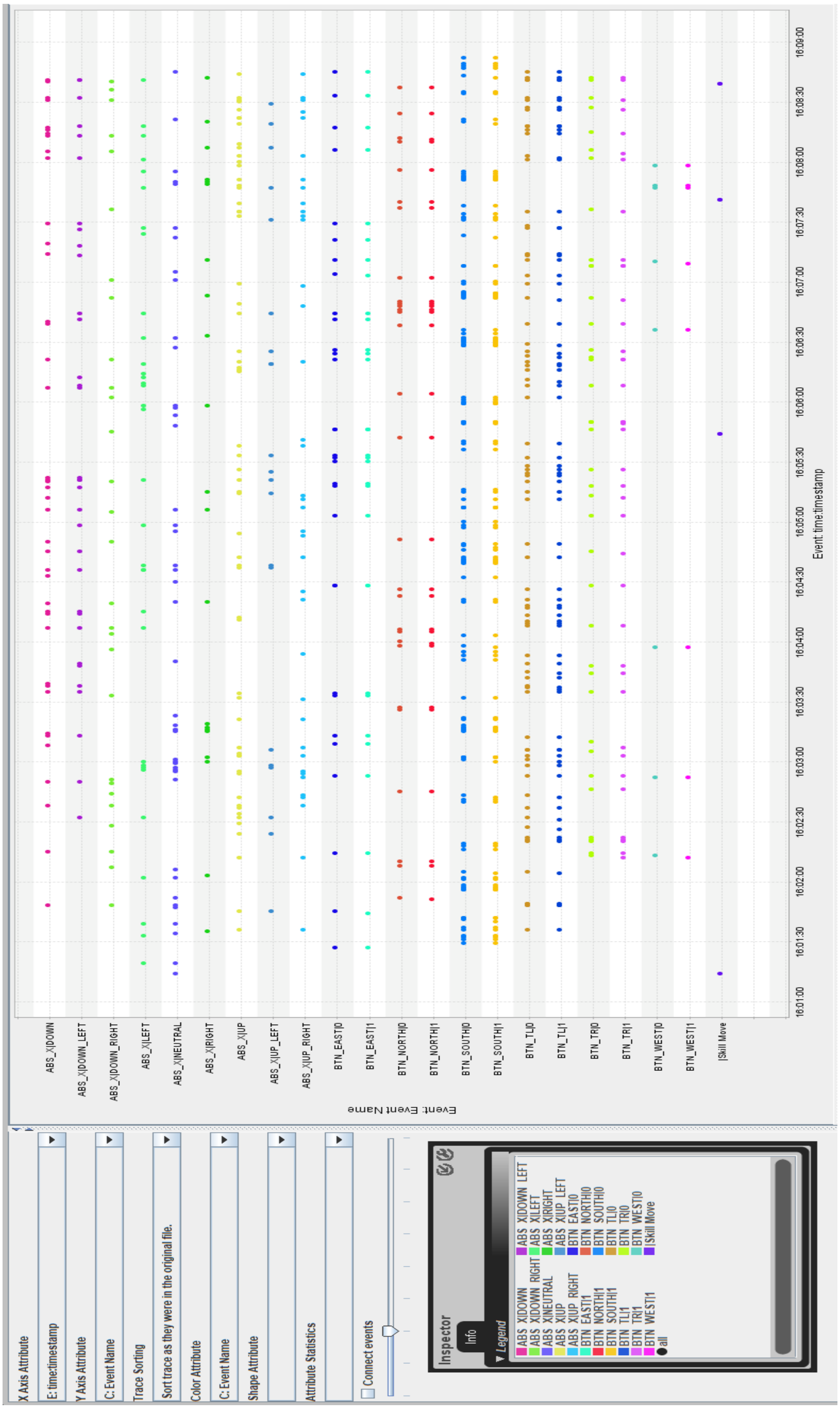
ATTACKING – SIMPLE (In Possession)

ACTION	PLAYSTATION CONTROLS	XBOX CONTROLS
Ground Pass/Header	X	A
Lob Pass/Cross/Header	▢	X
Through Ball	▵	Y
Shoot/Volley/Header	◯	B
Time Your Shot	◯ + ◯ (Timed)	B + B (Timed)
Chip Shot	L1 + ◯	LB + B
Finesse Shot	R1 + ◯	RB + B
Low Shot/Downward Header Shot	L1 + R1 + ◯	LB + RB + B
Fake Shot	◯ then X + Direction	B then A + Direction
Fake Pass	▢ then X + Direction	X then A + Direction
Threaded Through Pass	R1 + ▵	RB + Y

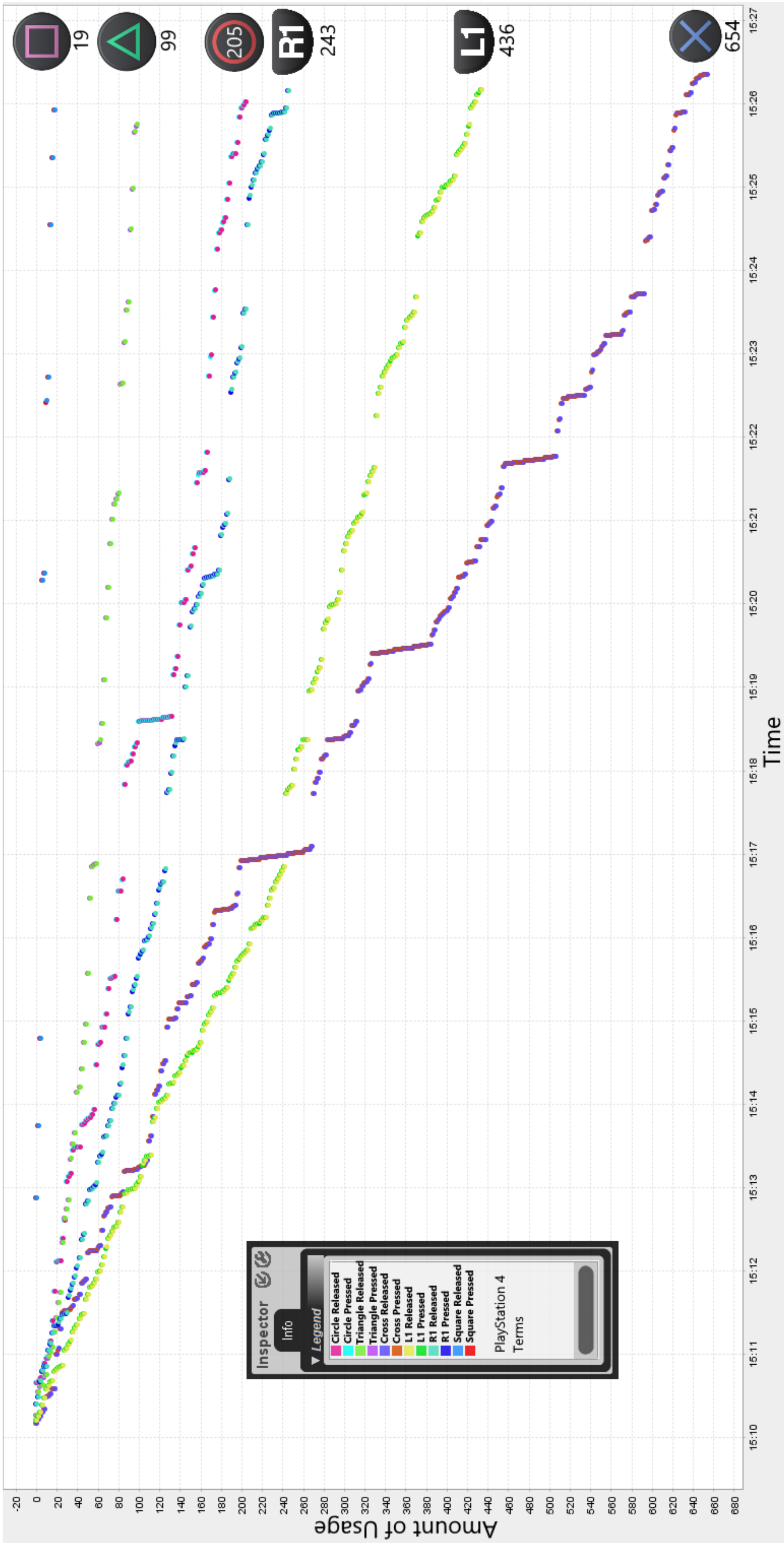
ATTACKING – ADVANCED (In Possession)

ACTION	PLAYSTATION CONTROLS	XBOX CONTROLS
Protect Ball	L2	LT
Driven Ground Pass	R1 + X	RB + A
Lofted Ground Pass	X + X	A + A
Lofted Through Pass	△ + △	Y + Y
Lobbed Through Ball	L1 + △	LB + Y
Driven Lobbed Through Pass	L1 + R1 + △	LB + RB + Y
Driven Lob Pass/Cross	R1 + ▢	RB + X
High Lob / Cross	L1 + ▢	LB + X
Low Cross	▢ + ▢	X + X
Trigger Run	L1	LB
Call for Support	R1	RB
Dummy a Pass	L + no direction + R1 Press and Hold	L + no direction + RB Press and Hold
Cancel	L2 + R2	LT + RT
Flair Pass	L2 + X	LT + A
Flair Shot	L2 + ◯	LT + B
Flair Lob	L2 + ▢	LT + X
Let Ball Run	R1 Press and Hold + L (Away From Ball)	RB Press and Hold + L (Away From Ball)
Flick Up For Volley	R3	R3
Disguised First Touch	R1 Press and Hold + L (Towards Ball)	RB Press and Hold + L (Towards Ball)
Set Up Touch	R1 + R + Direction (Hold)	RB + R + Direction (Hold)

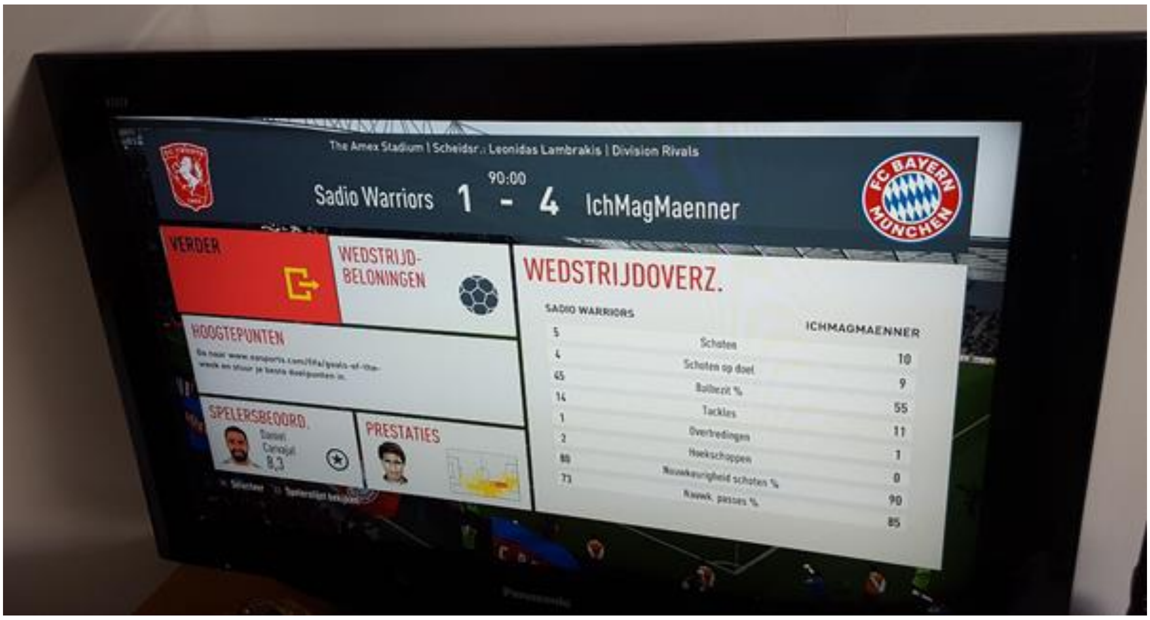
Appendix C: Match DNA - researcher vs computer AI at world class level



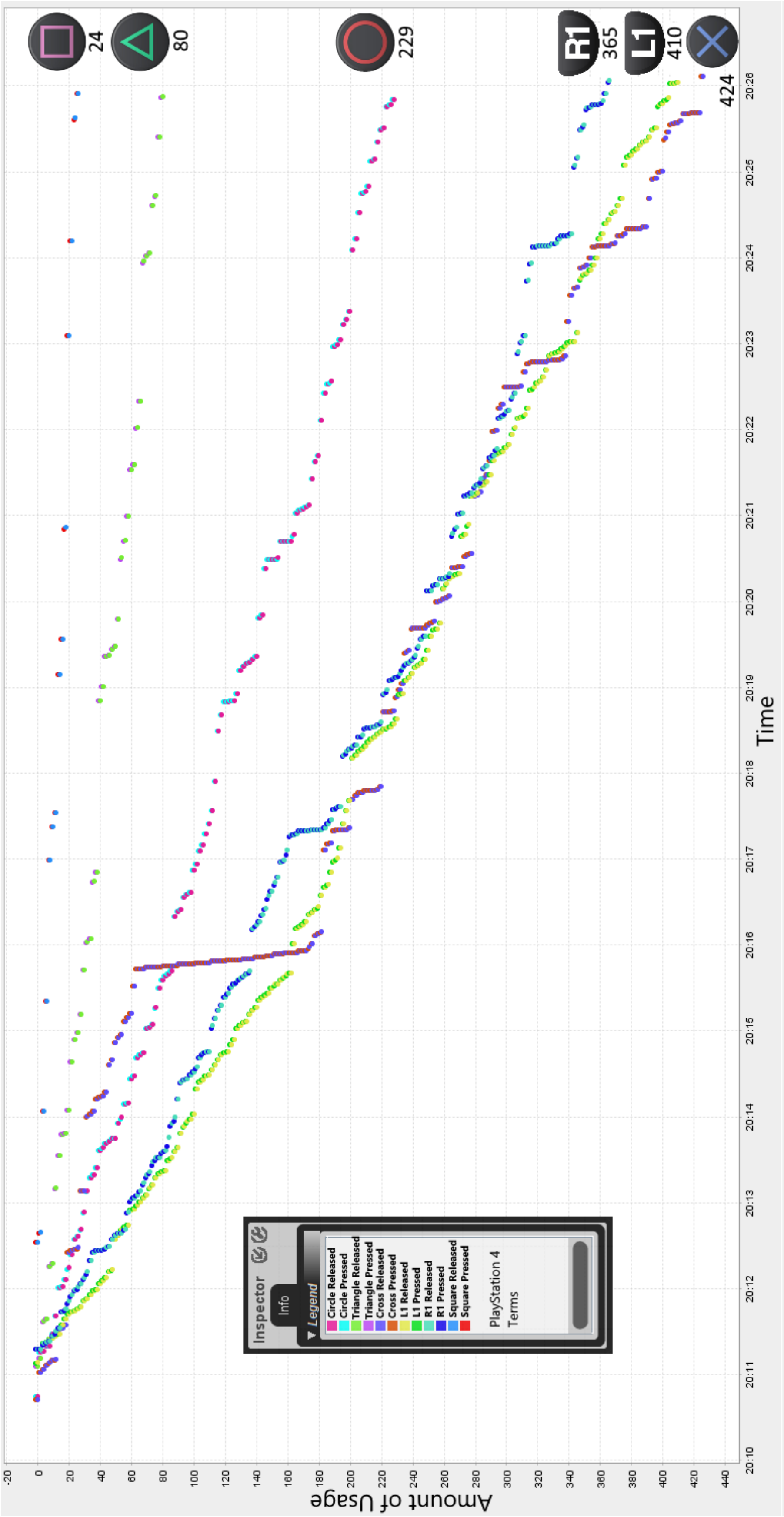
Appendix D: Output buttons used match 1 Division Rivals



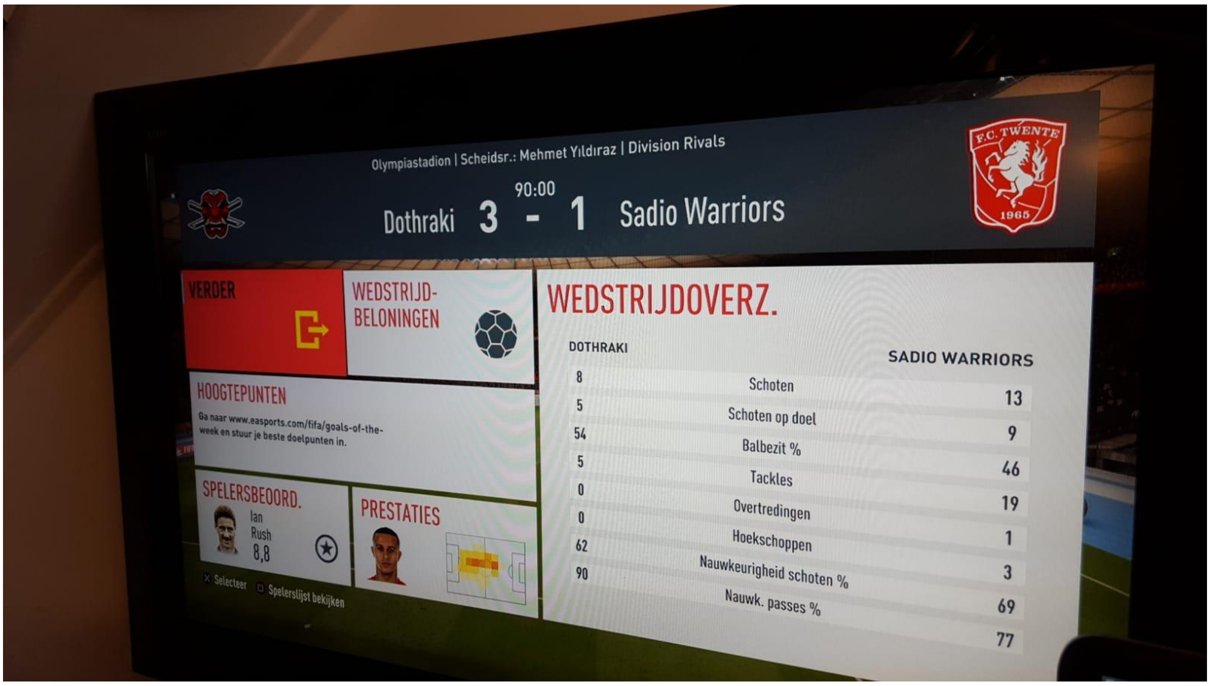
Appendix E: Match 1 Division Rivals end screen



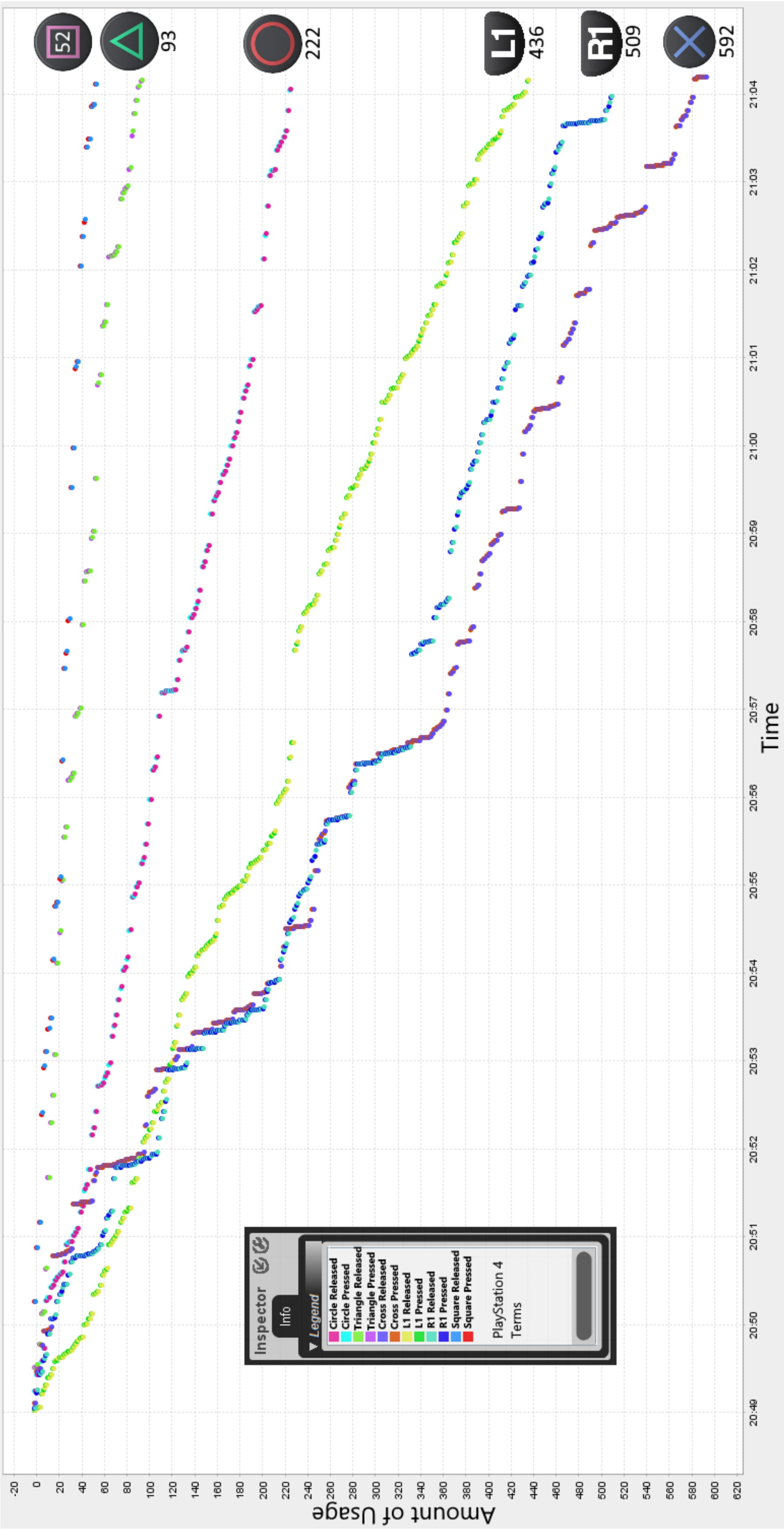
Appendix F: Output buttons used match 2 Division Rivals



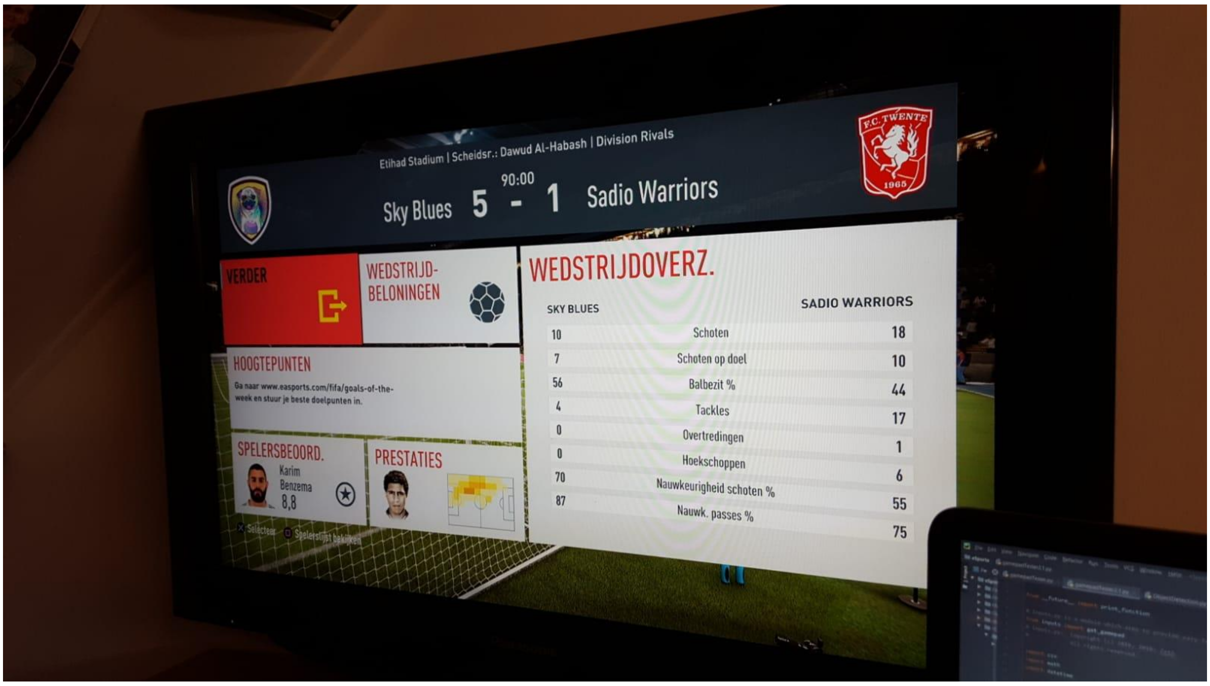
Appendix G: Match 2 Division Rivals end screen



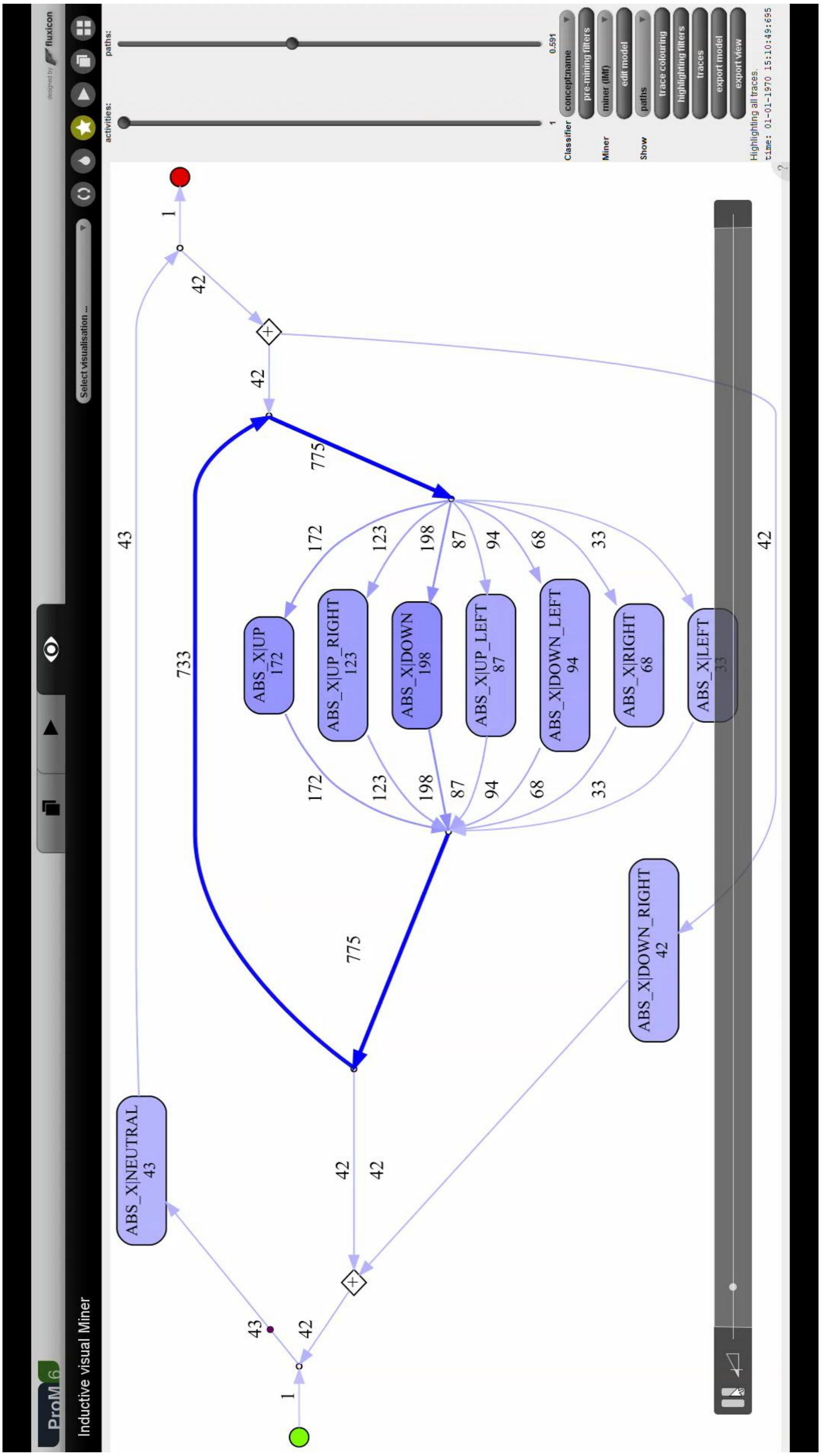
Appendix H: Output buttons used match 3 Division Rivals



Appendix I: Match 3 Division Rivals end screen



Appendix J: Inductive Visual Miner of the left joystick



Appendix K: Data obtained from two consecutive Weekend Leagues: eSporter 1

Date	Day	Start time	MT (Match	Goals (+)	ToG (Time of	Goals (-)	ToG (Time	Result	W/D/L (	EoG	Rage Quit	Shots	SoT	Pos	Tackles	Fouls	Corners	SA %	PA %	Team name Opponent	SO	OSoT	Pos O	Tackles (	Fouls (	Corners (	OSA %	OPA %	Comment eSporter
24-04-'20	Friday	15:38	WL	3	4, 8, 10	0	-	3 - 0	WIN	10	YES	4	4	62	3	0	0	100,0	94	zedFC	0	0	38	0	0	0	0	100	Rage Quit
24-04-'20	Friday	15:59	WL	2	6, 9	0	-	2 - 0	WIN	9	YES	3	2	49	1	0	0	66,7	100	Nantes US	0	0	51	0	0	0	0	88	Rage Quit
24-04-'20	Friday	16:03	WL	2	40, 54	0	-	2 - 0	WIN	62	YES	5	4	51	11	0	0	80,0	91	Son Gotleu FC	0	0	49	10	4	0	0	91	Rage Quit
24-04-'20	Friday	16:32	WL	3	7, 20, 31	0	-	3 - 0	WIN	31	YES	3	3	56	7	0	0	100,0	92	PERICOS BLANCOS	1	0	44	6	0	0	0	80	Rage Quit
24-04-'20	Friday	16:39	WL	1	74	3	16, 84, 88	1 - 3	LOSS	90	NO	5	4	54	14	2	1	80,0	87	Inazuma eleven	8	5	46	17	1	1	62,5	83	Slecht gespeeld, tegenstander was niet zo goed, zelf verloren
24-04-'20	Friday	23:35	WL	3	10, 28, 35	0	-	3 - 0	WIN	35	YES	5	4	60	6	2	0	80,0	86	tmMiLK CF	2	2	40	2	0	0	100,0	86	Rage Quit
25-04-'20	Saturday	00:20	WL	4	23, 82, 85, 88	0	-	4 - 0	WIN	90	NO	8	6	56	13	0	1	75,0	88	FC MOSB	3	2	44	9	0	1	66,7	88	Goed gespeeld, goede tegenstander, lang spannend maar uiteindelijk verdiend
25-04-'20	Saturday	00:38	WL	3	7, 22, 37	1	20	3 - 1	WIN	37	YES	8	6	41	2	0	1	75,0	97	Bah Ouai LOGIK	3	2	59	1	0	0	66,7	90	Rage Quit
25-04-'20	Saturday	00:46	WL	6	32, 45, 56, 74,	1	59	6 - 1	WIN	90	NO	11	7	59	7	0	4	63,6	93	Bilbao eSports	2	1	41	8	5	0	50,0	86	Erg goed gespeeld, beste wedstrijd in tijden, zeer goede tegenstander met een
25-04-'20	Saturday	13:40	WL	3	6, 44, 45	0	-	3 - 0	WIN	58	YES	8	7	55	10	0	3	87,5	95	KNOPHOOFD	1	0	45	9	1	0	0	87	Rage Quit
25-04-'20	Saturday	13:50	WL	3	39, 85, 90	0	-	3 - 0	WIN	90	NO	9	6	47	5	0	1	66,7	95	POPOYE	0	0	53	10	0	0	0	88	Redelijk gespeeld, tegenstander speelde erg op balbezit, dus ook wat meer op I
25-04-'20	Saturday	14:18	WL	4	14, 20, 49, 54	0	-	4 - 0	WIN	54	YES	7	4	61	6	0	2	57,1	85	AS RAJIONEVOLI	1	1	39	7	2	1	100,0	81	Rage Quit
25-04-'20	Saturday	14:34	WL	3	27, 43, 49	2	33, 58	3 - 2	WIN	90	NO	8	7	56	7	1	1	87,5	89	OleGunnerGetYa	6	6	44	9	1	2	100,0	86	Redelijk gespeeld, tegenstander was redelijk goed, verdiend gewonnen
25-04-'20	Saturday	15:11	WL	4	48, 73, 77, 88	1	7	4 - 1	WIN	90	NO	7	6	54	14	0	1	85,7	90	XXXPAC	6	4	46	10	0	0	66,7	89	Redelijk gespeeld, tegenstander had erg veel geluk, alle 50/50s voor hem, goed
25-04-'20	Saturday	15:36	WL	1	32	0	-	1 - 0	WIN	90	NO	5	3	57	5	3	1	60,0	93	PAY TO SKILL	4	3	43	9	1	1	75,0	88	Redelijk gespeeld, goede tegenstander, goed uitgespeeld op het einde
25-04-'20	Saturday	23:54	WL	4	8, 99, 114, 120	2	4, 101	4 - 2	WIN	120	Match Extension	9	5	56	9	0	2	55,6	95	cHoPtHuNdEr	4	3	44	9	1	1	75,0	92	Goed gespeeld, goede tegenstander, zelf veel kansen, tegenstander weinig kar
26-04-'20	Sunday	15:02	WL	2	30, 48	0	-	2 - 0	WIN	90	NO	3	2	56	12	0	1	66,7	84	Komt u maar	7	4	44	17	1	2	57,1	81	Slecht gespeeld, tegenstander was matig, had een grote uitslag moeten zijn
26-04-'20	Sunday	15:21	WL	1	90	2	8, 78	1 - 2	LOSS	90	NO	5	3	54	3	1	1	60,0	92	Balotellitubies	5	5	46	7	1	1	100,0	89	Matig gespeeld, tegenstander erg verdedigend, was moeilijk door heen te kome
26-04-'20	Sunday	16:19	WL	2	45, 105	2	90, 102	2 - 2	P-WIN	120	Penalties	7	6	51	9	2	0	85,7	89	KAMEHAMEHA	9	6	49	15	3	3	66,7	87	Redelijk gespeeld, tegenstander heel erg verdedigend, tegenstander 2 gelukkig
26-04-'20	Sunday	16:55	WL	4	51, 76, 78, 86	3	7, 32, 45	4 - 3	WIN	90	NO	7	6	56	14	0	1	85,7	86	Schnabelinho FC	6	6	44	18	3	3	100,0	85	Redelijk gespeeld, erg veel pech, goed rustig gebleven en de wedstrijd omgedra
26-04-'20	Sunday	17:11	WL	2	3, 6	0	-	2 - 0	WIN	12	YES	2	2	54	0	0	0	100,0	100	Team PF2	0	0	46	1	0	0	0	90	Rage Quit
26-04-'20	Sunday	17:14	WL	1	80	0	-	1 - 0	WIN	90	NO	4	3	48	11	1	0	75,0	89	TheMau13	7	4	52	15	1	3	57,1	94	Redelijk gespeeld, tegenstander erg verdedigend, goed rustig gebleven en de k
26-04-'20	Sunday	17:40	WL	7	6, 16, 33, 62, 7	0	-	7 - 0	WIN	90	NO	12	11	47	14	1	1	91,7	90	TUS 1860 STERRE	2	1	53	12	1	1	50,0	84	Goed gespeeld, makkelijke overwinning, niks speciaals
26-04-'20	Sunday	19:57	WL	3	39, 45, 49	1	28	3 - 1	WIN	49	YES	6	5	56	4	0	2	83,3	90	si senor	3	3	44	9	1	2	100,0	88	Rage Quit
26-04-'20	Sunday	20:18	WL	3	16, 24, 31	0	-	3 - 0	WIN	31	YES	4	4	54	0	0	2	100,0	87	FRAN TEAM	5	1	46	6	0	3	20,0	83	Rage Quit
26-04-'20	Sunday	20:24	WL	2	28, 68	0	-	2 - 0	WIN	73	YES	5	4	50	3	0	1	80,0	88	Berlin Fortuna	1	1	50	8	0	0	100,0	85	Rage Quit
26-04-'20	Sunday	20:37	WL	4	4, 14, 53, 74	1	31	4 - 1	WIN	90	NO	9	5	56	8	1	1	55,6	94	Casemiro FC	2	1	44	8	4	0	50,0	90	Goed gespeeld, verdiend gewonnen, niet heel moeilijk
26-04-'20	Sunday	21:57	WL	3	23, 45, 82	2	45, 76	3 - 2	WIN	90	NO	8	6	56	11	0	1	75,0	91	TchokountinhoFC	2	2	44	11	1	0	100,0	88	Goed gespeeld, erg goede tegenstander met een erg goed team, verdiend gew
26-04-'20	Sunday	22:21	WL	5	62, 76, 105, 11	2	82, 85	5 - 2	WIN	120	Match Extension	11	8	60	12	3	1	72,7	92	SG Dynamo 1953	4	4	40	7	0	4	100,0	86	Redelijk goed gespeeld, tegenstander erg gelukkig, uiteindelijk vrij makkelijk in c
								0 0																					
								0 0																					

Date	Day	Start time	MT (Match	Goals (+)	ToG (Time of	Goals (-)	ToG (Time	Result	W/D/L (	EoG	Rage Quit	Shots	SoT	Pos	Tackles	Fouls	Corners	SA %	PA %	Team name Opponent	SO	OSoT	Pos O	Tackles (	Fouls (	Corners (	OSA %	OPA %	Comment eSporter
01-05-'20	Friday	15:51	WL	3	11, 21, 33	0	-	3 - 0	WIN	33	YES	4	3	53	4	1	0	75,0	89	Brayan12	3	2	47	7	0	0	66,7	84	Rage Quit
01-05-'20	Friday	15:59	WL	3	5, 12, 16	0	-	3 - 0	WIN	30	YES	3	3	55	1	0	1	100,0	93	Charcu09	0	0	45	1	0	0	0	96	Rage Quit
01-05-'20	Friday	17:01	WL	4	3, 13, 16, 24	0	-	4 - 0	WIN	24	YES	4	4	58	2	0	0	100,0	92	Max0108	0	0	42	2	1	0	0	85	Rage Quit
01-05-'20	Friday	17:06	WL	4	26, 38, 41, 45	0	-	4 - 0	WIN	45	YES	5	5	59	9	1	0	100,0	90	FC Niepokonani	1	1	41	10	0	0	100,0	79	Rage Quit
02-05-'20	Saturday	14:53	WL	5	29, 41, 51, 57,	1	45	5 - 1	WIN	90	NO	9	7	49	13	2	0	77,8	88	Iri FC	5	2	51	11	0	2	40,0	86	Makkelijke overwinning, niks speciaals
02-05-'20	Saturday	15:11	WL	1	8	0	-	1 - 0	WIN	8	YES	2	2	73	1	0	1	100,0	87	Turkey5061	0	0	27	1	0	0	0	75	Rage Quit
02-05-'20	Saturday	15:14	WL	4	8, 14, 39, 52	1	74	4 - 1	WIN	90	NO	9	7	58	20	1	0	77,8	92	SjuulMonster	1	1	42	20	0	0	100,0	87	Makkelijke overwinning, niks speciaals
02-05-'20	Saturday	15:42	WL	2	69, 79	1	18	2 - 1	WIN	90	NO	8	6	51	10	2	1	75,0	89	Beast XI	5	4	49	9	0	0	80,0	86	Slecht gespeeld, wel goed rustig gebleven en de overwinning nog weten te pakk
02-05-'20	Saturday	16:26	WL	1	80	3	4, 11, 90	1 - 3	LOSS	90	NO	7	5	53	14	1	3	71,4	90	OpaJasonGunnsen	3	3	47	21	2	0	100,0	81	Slecht gespeeld, tegenstander erg veel geluk, 3 keer in de buurt van mijn 16 ge
02-05-'20	Saturday	16:43	WL	4	8, 14, 29, 80	0	-	4 - 0	WIN	90	NO	12	10	41	15	1	5	83,3	85	TEAM VARGAS	0	0	59	8	1	0	0	91	Makkelijke overwinning, niks speciaals
02-05-'20	Saturday	17:01	WL	1	3	0	-	1 - 0	WIN	3	YES	1	1	53	1	0	0	100,0	100	Hombres De Paco	0	0	47	0	0	0	0	100	Rage Quit
02-05-'20	Saturday	17:07	WL	2	34, 56	0	-	2 - 0	WIN	56	YES	5	5	42	3	0	0	100,0	91	Sevilla fc	0	0	58	4	0	0	0	89	Rage Quit
02-05-'20	Saturday	17:18	WL	2	3, 16	3	9, 32, 120	2 - 3	LOSS	120	Match Extension	5	5	51	10	0	2	100,0	91	US Requista	9	5	49	16	1	1	55,6	89	Slecht gespeeld, tegenstander was niet heel goed, zelf verloren
02-05-'20	Saturday	21:58	WL	3	21, 24, 33	1	7	3 - 1	WIN	33	YES	4	4	53	1	0	1	100,0	88	Hamburg	2	1	47	6	0	0	50,0	79	Rage Quit
02-05-'20	Saturday	22:06	WL	3	10, 48, 67	2	26, 45	3 - 2	WIN	90	NO	6	3	49	11	0	0	50,0	90	AndyBigBucket	5	5	51	12	1	3	100,0	87	Redelijk slecht gespeeld, hele matige gameplay, wel dik verdiend gewonnen
02-05-'20	Saturday	22:26	WL	3	19, 28, 32	1	12	3 - 1	WIN	33	YES	3	3	64	0	0	0	100,0	98	LOLAFC	1	1	36	2	0	0	100,0	87	Rage Quit
02-05-'20	Saturday	22:37	WL	2	7, 19	1	30	2 - 1	WIN	90	NO	7	5	53	13	0	0	71,4	86	doreedeplatine	3	0	47	16	0	0	0	79	Redelijk gespeeld, ruimtes erg slecht uitgespeeld elke keer, meer dan verdiend
02-05-'20	Saturday	22:53	WL	2	9, 14	0	-	2 - 0	WIN	14	YES	2	2	61	0	0	0	100,0	90	idrissa	0	0	39	3	0	0	0	66	Rage Quit
02-05-'20	Saturday	22:57	WL	3	41, 50, 62	0	-	3 - 0	WIN	62	YES	6	4	53	7	0	0	66,7	87	Juventus	2	1	47	7	1	0	50,0	83	Rage Quit
02-05-'20	Saturday	23:11	WL	2	21, 27	1	11	2 - 1	WIN	90	NO	6	4	47	13	0	2	66,7	84	twitchkevin62	2	1	53	10	0	0	50,0	87	Redelijk gespeeld, kansen slecht uitgespeeld, verder weinig speciaals
03-05-'20	Sunday	16:26	WL	5	12, 34, 45, 45,	2	15, 39	5 - 2	WIN	54	YES	5	5	52	4	0	0	100,0	91	AJAX AFC	5	2	48	5	0	1	40,0	89	Rage Quit
03-05-'20	Sunday	16:38	WL	2	20, 27	0	-	2 - 0	WIN	27	YES	4	3	51	2	0	0	75,0	94	You Dig	4	2	49	3	2	1	50,0	92	Rage Quit
03-05-'20	Sunday	16:44	WL	1	21	0	-	1 - 0	WIN	90	NO	5	3	53	7	0	3	60,0	92	Drecksspiel	1	1	47	7	0	0	100,0	92	Erg goed gespeeld, hele pittige pot, erg goed verdedigd, aanvallend had er wat
03-05-'20	Sunday	17:18	WL	2	17, 90	3	32, 81, 85	2 - 3	LOSS	90	NO	3	3	46	1	1	0	100,0	91	FC Royboy	7	5	54	13	0	3	71,4	92	Redelijk gespeeld, pittige pot, erg ongelukkig, onterecht verloren
03-05-'20	Sunday	17:39	WL	7	10, 30, 41, 51,	1	35	7 - 1	WIN	90	NO	11	9	52	13	0	2	81,8	88	UC Diamoli	3	2	48	14	0	1	66,7	86	Makkelijke overwinning, niks speciaals
03-05-'20	Sunday	19:49	WL	1	28	0	-	1 - 0	WIN	28	YES	4	1	53	4	0	1	25,0	95	FALKUM	0	0	47	5	1	0	0	90	Rage Quit
03-05-'20	Sunday	19:55	WL	4	4, 22, 39, 43	1	16	4 - 1	WIN	43	YES	5	5	60	3	1	0	100,0	93	dsds1	1	0	40	4	0	0	0	85	Rage Quit
03-05-'20	Sunday	20:03	WL	1	29	2	33, 90	1 - 2	LOSS	90	NO	5	3	44	9	0	4	60,0	93	Fc DiDi	5	3	56	12	0	0	60,0	92	Redelijk gespeeld, ontzettend veel pech, zwaar onterecht verloren
03-05-'20	Sunday	20:25	WL	3	72, 78, 83	2	44, 57	3 - 2	WIN	90	NO	10	8	50	7	0	2	80,0	91	NeverGiveUp	3	2	50	10	1	1	66,7	86	Matig gespeeld, tegenstander speelde erg irritant, goed rustig gebleven

Appendix L: Data obtained from two consecutive Weekend Leagues: eSporter 2

Date	Day	Start time	MT (Match	Goals (+)	ToG (Time of	Goals (-)	ToG (Time	Result	W/D/L (W	EoG	Rage Quit	Shots	SoT (	Pos	Tackles	Fouls	Corners	SA %	PA %	Team name Opponent	SO	OSoT (	Pos O	Tackles	Fouls (	Corners	curacy)	OPA %	Comment eSporter
24-04-'20	Friday	23:18	WL	5	3,21,24,26,28	0	-	5 - 0	WIN	28	YES	5	4	61	5	0	0	80,0	95	Besiktas	1	1	39	8	0	1	100,0	72	Rage Quit
24-04-'20	Friday	23:28	WL	7	3,22,26,31,36,4	1	5	7 - 1	WIN	45	YES	12	10	56	7	0	3	83,3	88	FCG SAVY	1	1	44	6	2	0	100,0	85	Rage Quit
25-04-'20	Saturday	00:38	WL	5	25,27,33,64,90	0	-	5 - 0	WIN	90	NO	10	7	65	9	1	0	70,0	88	Akinfenwa FC	4	1	35	12	1	1	25,0	80	Matige tegenstander, daarom niet heel gefocu
25-04-'20	Saturday	00:56	WL	3	4,10,33	0	-	3 - 0	WIN	33	YES	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Rage Quit
25-04-'20	Saturday	01:15	WL	3	4,23,29	0	-	3 - 0	WIN	29	YES	5	4	42	3	1	0	80,0	93	jijijiji	0	0	58	0	1	0	0	95	Rage Quit
25-04-'20	Saturday	01:23	WL	1	8	0	-	1 - 0	WIN	8	YES	3	3	63	1	0	0	100,0	91	abcdefghijklmno	0	0	37	1	0	0	0	80	Rage Quit
25-04-'20	Saturday	01:37	WL	3	32,40,62	0	-	3 - 0	WIN	62	YES	8	4	56	7	0	1	50,0	91	Lasagna Fk	1	0	44	5	0	0	0	88	Rage Quit
25-04-'20	Saturday	01:41	WL	3	17,20,31	0	-	3 - 0	WIN	33	YES	3	3	46	4	0	1	100,0	81	FLOWERSFC	2	1	54	2	0	1	50,0	90	Rage Quit
25-04-'20	Saturday	01:50	WL	3	7,26,45	0	-	3 - 0	WIN	45	YES	6	5	65	5	0	1	83,3	88	whoatealldepaii	0	0	35	4	1	0	0	83	Rage Quit
25-04-'20	Saturday	02:00	WL	4	23,65,86,115	4	76,84,90,11	4 - 4	P-WIN	120	Penalties	10	7	63	18	0	1	70,0	90	FC Bal	8	6	37	14	2	1	75,0	85	Goede tegenstander vooral aanvallend heel ste
25-04-'20	Saturday	14:40	WL	3	37,40,52	0	-	3 - 0	WIN	52	YES	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Rage Quit
25-04-'20	Saturday	14:52	WL	1	67	0	-	1 - 0	WIN	90	NO	6	2	56	14	2	0	33,3	87	N/A	1	1	44	11	0	1	100,0	77	Matige gameplay daardoor kon ik niet meer sc
25-04-'20	Saturday	15:10	WL	4	4,29,69,97	4	9,26,56,102	4 - 4	P-WIN	120	Penalties	10	6	56	12	1	4	60,0	93	bermigk	6	4	44	17	0	1	66,7	91	Hele sterke aanvaller, verdedigend was die iet
25-04-'20	Saturday	15:45	WL	4	6,29,51,90	2	58,63	4 - 2	WIN	90	NO	12	7	59	10	0	1	58,3	90	Helle	7	5	41	8	0	2	71,4	87	Redelijke tegenstander met een ziek goed tea
25-04-'20	Saturday	16:03	WL	3	16,51,68	1	19	3 - 1	WIN	90	NO	9	4	56	10	2	1	44,4	84	lolll	6	2	44	12	1	2	33,3	79	Hele slordige wedstrijd van beide kanten, kwal
25-04-'20	Saturday	21:45	WL	2	32,76	3	39,45,57	2 - 3	LOSS	90	NO	9	7	47	9	1	2	77,8	82	TryHardFC	4	4	53	10	1	3	100,0	82	Een typische potje die ik gewoon niet mocht w
25-04-'20	Saturday	22:00	WL	6	9,23,30,38,44,4	2	15,26	6 - 2	WIN	45	YES	6	6	60	5	0	0	100,0	92	Joels XI	5	4	40	9	3	1	80,0	78	Slechte tegenstander, ging eroverheen
25-04-'20	Saturday	22:15	WL	3	5,22,63	1	79	3 - 1	WIN	90	NO	8	5	57	14	1	1	62,5	90	FC Alex	6	4	43	7	2	0	66,7	87	Decent tegenstander, kon mijn aanvallen niet s
25-04-'20	Saturday	22:35	WL	1	50	2	7,41	1 - 2	LOSS	90	NO	6	3	49	9	1	1	50,0	86	Vipxz XI	4	3	51	9	0	0	75,0	87	Gelijkwaardige wedstrijd, alle 50/50- duels wor
26-04-'20	Sunday	11:45	WL	4	12,24,43,88	0	-	4 - 0	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Slechte tegenstander, was al snel beslist
26-04-'20	Sunday	12:00	WL	2	42,78	0	-	2 - 0	WIN	78	YES	7	6	54	18	2	2	85,7	95	HAMBURG49DIGGI	3	1	46	11	2	2	33,3	88	Verified speler, verdedigde erg goed, uiteinde
26-04-'20	Sunday	12:20	WL	2	30,34	0	-	2 - 0	WIN	34	YES	5	3	60	9	0	1	60,0	90	Fc SpielSpass	0	0	40	5	0	0	0	86	Rage Quit
26-04-'20	Sunday	12:32	WL	4	10,44,55,59	0	-	4 - 0	WIN	59	YES	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Hij had niks in te brengen, makkelijke pot
26-04-'20	Sunday	12:58	WL	5	17,44,73,98,12	3	19,41,90	5 - 3	WIN	120	Match Extension	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Onvoorstelbaar dat het tot verlening is gekome
26-04-'20	Sunday	13:15	WL	2	13,24	1	81	2 - 1	WIN	90	NO	7	6	56	13	0	2	85,7	84	Usakspor	3	2	44	12	1	0	66,7	83	Slordige pot van mij, niet goed gespeeld geluk
26-04-'20	Sunday	17:53	WL	4	30,65,80,89	1	74	4 - 1	WIN	90	NO	14	11	52	10	0	5	78,6	88	Ultras1894	4	3	48	7	0	1	75,0	84	Niet heel gefocust gespeeld, ondanks dat wel
26-04-'20	Sunday	18:22	WL	0	-	1	83	0 - 1	LOSS	90	NO	1	1	49	7	0	0	100,0	87	OLcsi2005	2	2	51	16	0	1	100,0	87	Hele irritante tegenstander, zat alleen maar ac
26-04-'20	Sunday	18:55	WL	3	10,15,111	2	33,56	3 - 2	WIN	120	Match Extension	11	8	51	14	3	1	72,7	90	DzPower	2	2	49	11	2	2	100,0	85	Slecht gespeeld door mij mocht nooit tot een v
N/A	N/A	N/A	WL	N/A	N/A	N/A	N/A	4 - 2	WIN	90	NO	10	6	59	9	1	1	60,0	90	AJAX AMSTERDAM	5	5	41	13	3	0	100,0	79	N/A
								0 - 0																					

Date	Day	Start time	MT (Match	Goals (+)	ToG (Time of	Goals (-)	ToG (Time	Result	W/D/L (W	EoG	Rage Quit	Shots	SoT (	Pos	Tackles	Fouls	Corners	SA %	PA %	Team name Opponent	SO	OSoT (	Pos O	Tackles	Fouls (	Corners	curacy)	OPA %	Comment eSporter
01-05-'20	Friday	13:30	WL	2	29,34	0	-	2 - 0	WIN	34	YES	7	4	63	8	0	1	57,1	97	Tricky Trees	0	0	37	4	0	0	0	83	Rage Quit
01-05-'20	Friday	13:40	WL	2	2,10	0	-	2 - 0	WIN	11	YES	2	2	72	1	0	0	100,0	94	The Shield	0	0	28	1	0	0	0	87	Rage Quit
01-05-'20	Friday	13:50	WL	3	24,38,50	0	-	3 - 0	WIN	52	YES	7	6	58	6	0	1	85,7	96	LaBestiaNegra	0	0	42	7	1	0	0	84	Rage Quit
01-05-'20	Friday	14:22	WL	2	10,24	0	-	2 - 0	WIN	26	YES	2	2	50	4	1	0	100,0	94	Frappo United	0	0	50	0	0	0	0	89	Rage Quit
01-05-'20	Friday	14:46	WL	10	7,22,28,35,45,4	0	-	10 - 0	WIN	90	NO	19	14	49	15	0	0	73,7	91	MADDAF4KKATEAM	2	1	51	7	1	1	50,0	85	Tegenstander moest allang eruit, helaas ging
01-05-'20	Friday	15:15	WL	2	8,23	0	-	2 - 0	WIN	24	YES	2	2	56	4	0	1	100,0	83	thiago fc	1	0	44	3	0	0	0	100	Rage Quit
01-05-'20	Friday	15:45	WL	4	7,15,19,42	1	25	4 - 1	WIN	45	YES	6	5	50	4	0	0	83,3	92	DXN FC	1	1	50	7	0	0	100,0	92	Rage Quit
01-05-'20	Friday	16:10	WL	3	55,64,90	2	40,52	3 - 2	WIN	90	NO	6	5	39	4	1	2	83,3	90	mbazan	4	4	61	7	0	1	100,0	91	Hele irritante tegenstander, speelde heel erg c
01-05-'20	Friday	16:25	WL	2	12,28	0	-	2 - 0	WIN	28	YES	3	3	57	6	0	0	100,0	91	GBest7 United	0	0	43	4	0	0	0	92	Rage Quit
01-05-'20	Friday	16:45	WL	3	71,103,105	1	61	3 - 1	WIN	120	Match Extension	5	4	45	15	2	0	80,0	90	Huch XI	4	3	55	7	0	1	75,0	92	Redelijk goede tegenstander speelde veel op b
01-05-'20	Friday	17:15	WL	2	54,94	2	81.105	2 - 2	P-WIN	120	Penalties	7	5	55	14	0	4	71,4	87	Chewbaccrie	3	2	45	17	1	1	66,7	87	Slecht gespeeld van mezelf kansen niet afgem
01-05-'20	Friday	17:35	WL	1	3	0	-	1 - 0	WIN	4	YES	1	1	100	0	0	0	100,0	100	Lille US	0	0	0	0	0	0	0	0	Rage Quit
01-05-'20	Friday	20:22	WL	2	3,23	0	-	2 - 0	WIN	23	YES	3	3	65	2	0	1	100,0	93	Taras	0	0	35	4	0	0	0	81	Rage Quit
01-05-'20	Friday	20:50	WL	1	86	2	9,23	1 - 2	LOSS	90	NO	6	3	47	10	0	3	50,0	89	JMR FC	4	4	53	12	0	2	100,0	92	Ik was de betere helaas laat de scheids nog d
01-05-'20	Friday	21:30	WL	2	8,14	0	-	2 - 0	WIN	14	YES	3	2	43	1	0	0	66,7	92	San Juan FC	1	0	57	0	0	0	0	96	Rage Quit
01-05-'20	Friday	21:39	WL	2	15,28	0	-	2 - 0	WIN	28	YES	4	4	59	6	0	2	100,0	96	Trabzonspor	0	0	41	3	0	0	0	93	Rage Quit
01-05-'20	Friday	22:15	WL	1	90	2	50,89	1 - 2	LOSS	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegen een pro player, verdiend verloren
01-05-'20	Friday	22:35	WL	1	49	1	14	2 - 2	P-LOSS	120	Penalties	6	4	42	9	1	4	66,7	89	George CGF YT	6	6	58	15	0	3	100,0	92	Weer een pro player, verloren op penals
02-05-'20	Saturday	14:00	WL	0	-	1	71	0 - 1	LOSS	90	NO	9	3	47	10	1	5	33,3	88	Oregano CF	2	1	53				50,0		Statistieken spreken voorzich, bal wou er gew
02-05-'20	Saturday	14:25	WL	4	8,29,45,82	0	-	4 - 0	WIN	90	NO							#####					100				0		Slechte tegenstander, hij wou er helaas niet u
02-05-'20	Saturday	14:40	WL	4	3,10,37,86	2	56,67	4 - 2	WIN	90	NO							#####					100				0		Aanvallend goede tegenstander, verdedigend
02-05-'20	Saturday	15:00	WL	4	4,10,72,77	4	25,45,61,90	4 - 4	DRAW	120	Match Extension							#####					100				0		Ongelofelijkndat ik dit verloren heb, ook totaal
02-05-'20	Saturday	19:43	WL	2	10,90	0	-	2 - 0	WIN	90	NO							#####					100				0		Saaie potje,gaf niks weg was duidelijk de bete
02-05-'20	Saturday	20:00	WL	2	72,90	0	-	2 - 0	WIN	90	NO							#####					100				0		Tegenstander wou balbezit houden, ging vol d
02-05-'20	Saturday	20:20	WL	0	-	0	-	0 - 0	LOSS	0	Disconnect	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Disconnect
02-05-'20	Saturday	20:30	WL	6	15,24,36,60,75	2	3,49	6 - 2	WIN	90	NO							#####					100				0		Matige tegenstander, zwaar overklast
02-05-'20	Saturday	20:45	WL	3	39,57,67	0	-	3 - 0	WIN	90	NO							#####					100				0		Matige tegenstander, zwaar overklast
02-05-'20	Saturday	21:48	WL	1	12	0	-	1 - 0	WIN	90	NO							#####					100				0		Lastige tegenstander, weinig gecreëerd, uiteir

Appendix M: Data obtained from two consecutive Weekend Leagues: eSporter 3

Date	Day	Start time	MT (Match	Goals (+)	ToG (Time of	Goals (-)	ToG (Time	Result	W/D/L (W	EoG	Rage Quit	Shots	SoT (	Pos	Tackles	Fouls	Corners	SA %	PA %	Team name Opponent	SO	OSoT (	Pos O	Tackles	Fouls (	Corners	OSA %	OPA %	Comment eSporter
24-04-'20	Friday	10:33	WL	4	21,34,65,80	2	1, 5	4 - 2	WIN	90	NO	7	4	55	9	0	2	57,14	85	N/A	5	4	45	14	2	2	80,0	82	Tegenstander was niet al te best, maar ik zat het erg te verkl
24-04-'20	Friday	11:34	WL	2	4,9	0	-	2 - 0	WIN	10	YES	3	2	60	1	0	0	66,67	100	Yes Red	0	0	40	4	1	0	0	75	Tegenstander was niet goed, en ik speelde lekker, en tegens
24-04-'20	Friday	11:38	WL	4	32,51,56,74	3	42,66,90	4 - 3	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was redelijk, maar had alles mee zitten. Ik verd
24-04-'20	Friday	12:01	WL	5	3,16,25,29,45	1	32	5 - 1	WIN	45	YES	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was slecht, en hij had 1 schot op goal. Ik spee
24-04-'20	Friday	12:29	WL	7	22,39,52,65,71	2	45,50	7 - 2	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was slecht, maar ik verdedigde ook weer slecl
24-04-'20	Friday	13:46	WL	6	17,28,62,68,90	1	73	6 - 1	WIN	90	NO	9	8	50	14	0	2	88,89	80	SzaszaFC	8	5	50	15	0	1	62,5	80	Tegenstander was niet goed, ik zat op het eind niet serieus r
24-04-'20	Friday	14:34	WL	3	4,45,72	1	90	3 - 1	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Laatste 25 minuten zat ik veel op mijn telefoon, tegenstander
24-04-'20	Friday	14:57	WL	1	74	0	-	1 - 0	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Het was esporter van Brondby IF, dus hij was zeer goed. Ik
24-04-'20	Friday	16:31	WL	4	3,6,27,30	0	-	4 - 0	WIN	30	YES	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was niet al te best, en hij gaf ook op na de 4-0
24-04-'20	Friday	16:38	WL	4	7,12,35,48	0	-	4 - 0	WIN	48	YES	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was niet goed, en hij gaf ook op na de 4-0
24-04-'20	Friday	23:03	WL	3	22,49,76	0	-	3 - 0	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was niet goed, en ik tikte hem weg. Hij gaf op
24-04-'20	Friday	23:23	WL	4	12,15,39,54	1	31	4 - 1	WIN	54	YES	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was niet al te best, ik creerde ook meer kanse
24-04-'20	Friday	23:41	WL	3	36,73,81	0	-	3 - 0	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander speelde alleen maar op balbezit(60%). Voor d
25-04-'20	Saturday	00:06	WL	3	30,61,76	1	12	3 - 1	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was een goede speler, maar had alles mee. Ik
25-04-'20	Saturday	01:14	WL	4	4,17,66,80	2	64,85	4 - 2	WIN	90	NO	5	4	47	11	0	0	80,00	85	N/A	3	3	53	9	1	1	100,0	88	Tegenstander was aanvallend een goede speler, verdedigend
25-04-'20	Saturday	01:37	WL	6	5,21,33,49,75,8	4	15,24,53,72	6 - 4	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstanders was aanvallend zeer goed, maar verdedigend
25-04-'20	Saturday	19:58	WL	7	8,19,25,52,62,6	3	45,49,66	7 - 3	WIN	74	YES	9	8	59	11	2	0	88,89	92	N/A	8	6	41	14	0	1	75,0	83	Tegenstander was aanvallend goed, maar verdedigend mind
25-04-'20	Saturday	20:19	WL	3	24,36,87	4	41,52,74,81	3 - 4	LOSS	90	NO	5	5	44	9	0	1	100,00	90	Calafell	8	6	56	9	0	2	75,0	93	Tegenstander was slecht, maar gebruikte leenspelers waard
25-04-'20	Saturday	22:13	WL	7	16,44,45,48,54	0	-	7 - 0	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Denk dat de stand wel voor zichzelf spreekt
25-04-'20	Saturday	22:36	WL	4	11,17,43,45	1	41	4 - 1	WIN	45	YES	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was redelijke speler, maar ik speelde goed. Hi
25-04-'20	Saturday	22:46	WL	4	11,22,26,30	1	6	4 - 1	WIN	30	YES	5	4	50	9	0	2	80,00	84	N/A	1	1	50	3	1	0	100,0	87	Tegenstander was redelijke speler, maar ik speelde weer go
25-04-'20	Saturday	23:01	WL	4	15,49,85,89	2	3,64	4 - 2	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was hele goede speler, maar ik speelde zelf o
25-04-'20	Saturday	23:34	WL	2	-	1	-	2 - 1	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Pot vergeten door irritatie :) Eindstand was 2-1
25-04-'20	Saturday	23:38	WL	2	55,68	0	-	2 - 0	WIN	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was goede speler, maar verdedigend was die
25-04-'20	Saturday	00:01	WL	3	6,10,14	0	-	3 - 0	WIN	14	YES	3	3	52	1	0	0	100,00	88	N/A	3	1	48	1	0	2	33,3	88	Tegenstander was niet goed, en gaf op in de 14e minuut
25-04-'20	Saturday	00:06	WL	2	54,88	0	-	2 - 0	WIN	90	NO	5	3	45	12	0	0	60,00	87	N/A	7	3	55	15	1	4	42,9	85	Tegenstander was goede speler, ik had wat geluk nodig om
25-04-'20	Saturday	00:28	WL	2	20,22	3	11,29,88	2 - 3	LOSS	90	NO	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Tegenstander was redelijke speler, maar hij had alles meezit
								0 - 0																					
								0 - 0																					
								0 - 0																					

Date	Day	Start time	MT (Match	Goals (+)	ToG (Time of	Goals (-)	ToG (Time	Result	W/D/L (W	EoG	Rage Quit	Shots	SoT (	Pos	Tackles	Fouls	Corners	SA %	PA %	Team name Opponent	SO	OSoT (	Pos O	Tackles	Fouls (	Corners	OSA %	OPA %	Comment eSporter
01-05-'20	Friday	13:58	WL	7	4,17,52,65,69,8	2	1, 8	7 - 2	WIN		YES							#####					100				0		Tegenstander kon er niks van, maar ik had de eerste 30 min
01-05-'20	Friday	22:14	WL	2	4,7	0	-	2 - 0	WIN		YES							#####					100				0		Tegenstander was slecht, en gaf ook op na 7 minuten
01-05-'20	Friday	22:18	WL	3	3,12,15	0	-	3 - 0	WIN		YES							#####					100				0		Tegenstander was slecht, en gaf ook op na 15 minuten
01-05-'20	Friday	22:23	WL	4	21,45,57,60	0	-	4 - 0	WIN		YES							#####					100				0		Tegenstander kon goed verdedigen, maar slecht aanvallen. I
01-05-'20	Friday	22:33	WL	2	9,24	0	-	2 - 0	WIN		YES							#####					100				0		Tegenstander was aanvallend een redelijke speler, maar verd
01-05-'20	Friday	22:43	WL	3	29,69,80	1	90	3 - 1	WIN		YES							#####					100				0		Tegenstander was een goede speler, alleen hij had een mind
01-05-'20	Friday	23:01	WL	3	6,25,28	0	-	3 - 0	WIN		YES							#####					100				0		Tegenstander was matige speler, die heel veel op balbezit sp
01-05-'20	Friday	23:08	WL	2	12,27	1	16	2 - 1	WIN		YES							#####					100				0		Tegenstander was goede speler, maar met slecht team. Ik sp
01-05-'20	Friday	23:49	WL	2	6,13	0	-	2 - 0	WIN		YES							#####					100				0		Tegenstander was matige speler. Hij gaf op in minuut 13
01-05-'20	Friday	23:55	WL	5	17,32,75,82,85	2	5,7	5 - 2	WIN		YES							#####					100				0		Tegenstander was goede speler. Ik had in het begin moeite
02-05-'20	Saturday	01:33	WL	6	3,8,12,37,45,5	2	15,31	6 - 2	WIN		YES							#####					100				0		Tegenstander was geen goede speler, maar na de 3-0 kreeg
02-05-'20	Saturday	21:58	WL	3	21,37,43	0	-	3 - 0	WIN		YES							#####					100				0		Tegenstander was redelijke speler. In het begin speelde ik sl
02-05-'20	Saturday	22:09	WL	5	7,14,19,24,45	1	5	5 - 1	WIN		YES							#####					100				0		Tegenstander was redelijke speler. Maar ik had hem onder c
02-05-'20	Saturday	22:21	WL	4	22,30,43,57	0	-	4 - 0	WIN		YES							#####					100				0		Tegenstander was goede speler, maar ik had alles meezitten
02-05-'20	Saturday	22:38	WL	1	48	3	18,65,83	1 - 3	LOSS		YES							#####					100				0		Tegenstander was goede speler, maar hij glitchte alleen maa
02-05-'20	Saturday	23:05	WL	5	38,48,52,90,92	5	3,7,41, 68,9	5 - 5	DRAW		YES							#####					100				0		Ik moest tegen proffesionele voetballer(Dabbur) die regelmat
03-05-'20	Sunday	00:28	WL	3	28,41,45	2	60,68	3 - 2	WIN		YES							#####					100				0		Tegenstander was redelijke speler, maar ik speelde op het ei
03-05-'20	Sunday	01:55	WL	5	20,33,55,68,87	1	60	5 - 1	WIN		YES							#####					100				0		Tegenstander was redelijke speler, en ik speelde ook niet op
03-05-'20	Sunday	02:07	WL	1	18	2	38,68	1 - 2	LOSS		YES							#####					100				0		Tegenstander was redelij goede speler, maar ik kreeg de bal
03-05-'20	Sunday	14:13	WL	2	20,44	0	-	2 - 0	WIN		YES							#####					100				0		Tegenstander was redelijk goede speler, en ik speelde goed
03-05-'20	Sunday	14:39	WL	4	3,45,104,114	2	36,43	4 - 2	WIN		YES							#####					100				0		Tegenstander was goede speler, die heel veel op balbezit sp
03-05-'20	Sunday	15:01	WL	2	45,49	3	28,37,90(ei	2 - 3	LOSS		YES							#####					100				0		Tegenstander was goede speler, maar op het einde had hij t
03-05-'20	Sunday	15:32	WL	5	34,39,62,69,74	2	32,72	5 - 2	WIN		YES							#####					100				0		Tegenstander was redelijke speler, en ik had weinig concent
03-05-'20	Sunday	15:46	WL	3	14,64,83	4	16,50,54,60	3 - 4	LOSS		YES							#####					100				0		Tegenstander was goed, maar ik ben er nu klaar mee haha
03-05-'20	Sunday	16:03	WL	3	4,8,15	0	-	3 - 0	WIN		YES							#####					100				0		Tegenstander was slecht, en gaf op na 15 minuten
03-05-'20	Sunday	16:09	WL	3	8,68,88	1	61	3 - 1	WIN		YES							#####					100				0		Tegenstander was redelijk, maar na mijn 1ste verlies, heb ik

Appendix L: Controller input python code

```
from __future__ import print_function

# Inputs.py is a module which aims to provide easy to use, cross-platform, user input device support for Python
from inputs import get_gamepad
# Inputs.py:  Copyright (c) 2016, 2018: Zeth
#             All rights reserved.

import csv
import math
import datetime


# To connect the controller data with the CNN:
# in_possession =
# not_in_possession =
# own_half = False

def main():
    previous_state_tl = 0
    previous_state_tr = 0
    state_tr = 0
    state_tl = 0
    left_joystick_y = 2
    left_joystick_x = 2
    left_joystick_used = False
    left_joystick = "LEFT JOYSTICK"
    right_joystick_y = 2
    right_joystick_x = 2
    right_joystick = "RIGHT JOYSTICK"
```

```
    t_start_cross = 0
    t_start_circle = 0
    t_start_square = 0
    t_start_triangle = 0
    cross_pressed = 0
    square_pressed = 0
    circle_pressed = 0
    TR_pressed = 0
    TL_pressed = 0
    DateUsed = False
    fake_shot_given = False
    chip_shot_given = False
    finesse_shot_given = False
    low_shot_given = False
    start_date = datetime.datetime.now()
    filename = r'C:\Users\Ruben\Mijn Documenten\University\Module 11 en 12
' \
               r'eSports\Python\eSports\Match_Data\TestMatch_' +
datetime.datetime.now().strftime(
        '%Y-%m-%d_%H%M%S') + '.csv'
    print(filename)
    previous_left_joystick_rotation = None
    previous_right_joystick_rotation = None

    with open(filename, 'w', newline='') as csvfile:
        datatitlenames = ['Type', 'SpecifiedButton', 'Pressed',
'TimePressed']
        thewriter = csv.DictWriter(csvfile, fieldnames=datatitlenames)
        thewriter.writeheader()

        while 1:
            events = get_gamepad()
```

```
for event in events:

    time = datetime.datetime.now().time()
    fake_shot = False

    # Time buttons pressed gamepad (Playstation terms in the
    names)
    # Names are made for ps4 controller, but should actually
    also be for Xbox
    if event.state == 1 and event.ev_type != "Sync":

        if event.code == 'BTN_SOUTH':

            t_start_cross = event.timestamp
            cross_pressed = 1
            print(event.ev_type, event.code, event.state)
            thewriter.writerow(
            {'Type': event.ev_type, 'SpecifiedButton':
            event.code, 'Pressed': event.state,
            'TimePressed': time})

            # # if not fake shot:
            #     # if in_possession:
            # print("Ground Pass")
            # thewriter.writerow({'Pressed': "Ground Pass",
            'TimePressed': time})
            #     # if not_in_possession:
            #         # print ("Jockey")
            #         # thewriter.writerow({'Pressed':
            "Jockey", 'TimePressed': time})

        if event.code == 'BTN_WEST':
            t_start_square = event.timestamp
            square_pressed = 1
```

```
        print(event.ev_type, event.code, event.state)

        thewriter.writerow(

        {'Type': event.ev_type,
        'SpecifiedButton':event.code, 'Pressed':
        event.state, 'TimePressed': time})


        # # if not fake shot:

        #     # if in_possession:

        # print("Cross/Lob pass")

        # thewriter.writerow({'Pressed': "Cross/Lob Pass",
        'TimePressed': time})

        #     # if not_in_possession:

        #         # print ("Slide Tackle")

        #         # thewriter.writerow({'Pressed': "Slide
        Tackle", 'TimePressed': time})


    if event.code == 'BTN_NORTH':

        t_start_triangle = event.timestamp

        print(event.ev_type, event.code, event.state)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton':
        event.code, 'Pressed': event.state,

        'TimePressed': time})


        # # if in_possession:

        # print("Through ball")

        # thewriter.writerow({'Pressed': "Through ball",
        'TimePressed': time})

        # # if not_in_possession:

        #     # print ("Rush keeper out")

        #     # thewriter.writerow({'Pressed': "Rush keeper
        out", 'TimePressed': time})


    if event.code == 'BTN_EAST':

        t_start_circle = event.timestamp
```

```
        circle_pressed = 1

        print(event.ev_type, event.code, event.state)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton':
        event.code, 'Pressed': event.state,

             'TimePressed': time})


        # # if in_possession:

        #     # if own_half:

        # print("Clearance")

        # thewriter.writerow({'Pressed': "Clearance",
        'TimePressed': time})

        #     # else:

        #         # print("Shoot/volley")

        #         # thewriter.writerow({'Pressed':
        "Shoot/volley", 'TimePressed': time})

        # # if not_in_possession:

        #     # print ("Tackle/push or pull")

        #     # thewriter.writerow({'Pressed': "Tackle/push
        or pull", 'TimePressed': time})


    if event.code == 'BTN_TR':

        t_start_TR = event.timestamp

        TR_pressed = 1

        print(event.ev_type, event.code, event.state)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton':
        event.code, 'Pressed': event.state,

             'TimePressed': time})


    if event.code == 'BTN_TL':

        t_start_TL = event.timestamp

        TL_pressed = 1

        print(event.ev_type, event.code, event.state)
```

```
        thewriter.writerow(
        {'Type': event.ev_type, 'SpecifiedButton':
        event.code, 'Pressed': event.state,
        'TimePressed': time})

    # All the Possible Actions with the Buttons

    # if square_pressed == 1 and event.code == 'BTN_SOUTH'
    and fake_shot_given == False:
    #     # if in_possession:
    #     print("Fake Shot")
    #     thewriter.writerow({'Pressed': "Fake Shot",
  'TimePressed': time})
    #     fake_shot_given = True
    #
    # if circle_pressed == 1 and event.code == 'BTN_SOUTH'
  and fake_shot_given == False:
    #     # if in_possession:
    #     print("Fake Shot")
    #     thewriter.writerow({'Pressed': "Fake Shot",
  'TimePressed': time})
    #     fake_shot_given = True
    #
    # if (event.code == 'BTN_WEST' or event.code ==
  'BTN_EAST') and fake_shot_given:
    #     fake_shot_given = False
    #
    # # if in_possession
    # if TL_pressed == 1 and event.code == 'BTN_EAST' and
  chip_shot_given == False:
    #     print("Chip Shot")
    #     thewriter.writerow({'Pressed': "Chip Shot",
  'TimePressed': time})
    #     chip_shot_given = True
    #
```

```
        # if event.code == 'BTN_EAST' and chip_shot_given:
        #     chip_shot_given = False
        #
        # if TR_pressed == 1 and event.code == 'BTN_EAST' and finesse_shot_given == False:
        #     print("Finesse Shot")
        #     thewriter.writerow({'Pressed': "Finesse Shot", 'TimePressed': time})
        #     finesse_shot_given = True
        #
        # if event.code == 'BTN_EAST' and finesse_shot_given:
        #     finesse_shot_given = False
        #
        # if TR_pressed == 1 and TL_pressed == 1 and event.code == 'BTN_EAST' and low_shot_given == False:
        #     print("Low Shot")
        #     thewriter.writerow({'Pressed': "Low Shot", 'TimePressed': time})
        #     low_shot_given = True
        #
        # if event.code == 'BTN_EAST' and low_shot_given:
        #     low_shot_given = False
        #
        # Etc. add all the actions once CNN is connected



    # Pressed triggers L2 and R2 (ps4) or LT and RT (xbox)
    # Trigger left
    if event.ev_type != "Sync" and event.code == 'ABS_Z':
        if event.state == 0:
            state_tl = 0

        if 120 < event.state <= 180:
```

```
            state_tl = 1
            tl = "HALF"

        if event.state == 255:
            state_tl = 2
            tl = "FULL"

    if state_tl != previous_state_tl:

        print(event.ev_type, event.code, tl)
        thewriter.writerow({'Type': event.ev_type,
      'SpecifiedButton': event.code, 'Pressed': event.state,
       'TimePressed': time})

    previous_state_tl = state_tl

    # Trigger right
    if event.ev_type != "Sync" and event.code == 'ABS_RZ':
        if event.state == 0:
            state_tr = 0

        if 150 < event.state <= 200:
            state_tr = 1
            tr = "HALF"

        if event.state == 255:
            state_tr = 2
            tr = "FULL"

    if state_tr != previous_state_tr:
        print(event.ev_type, event.code, tr)
        thewriter.writerow({'Type': event.ev_type,
      'SpecifiedButton': event.code, 'Pressed': event.state,
```

```
                       'TimePressed': time})

previous_state_tr = state_tr

# Time buttons released gamepad (Playstation terms in the names)

if event.state == 0 and event.ev_type != "Sync":

    if event.code == 'BTN_SOUTH':

        t_stop_cross = event.timestamp

        time_button_pressed = t_stop_cross - t_start_cross

        cross_pressed = 0

        print(event.ev_type, event.code, event.state, time_button_pressed)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton': event.code, 'Pressed': event.state,

             'TimePressed': time})

    if event.code == 'BTN_WEST':

        t_stop_square = event.timestamp

        time_button_pressed = t_stop_square - t_start_square

        square_pressed = 0

        print(event.ev_type, event.code, event.state, time_button_pressed)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton': event.code, 'Pressed': event.state,

        'TimePressed': time})

    if event.code == 'BTN_NORTH':

        t_stop_triangle = event.timestamp

        time_button_pressed = t_stop_triangle - t_start_triangle
```

```
        print(event.ev_type, event.code, event.state,
        time_button_pressed)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton':
        event.code, 'Pressed': event.state,

        'TimePressed': time})


    if event.code == 'BTN_EAST':

        t_stop_circle = event.timestamp

        circle_pressed = 0

        time_button_pressed = t_stop_circle -
        t_start_circle

        print(event.ev_type, event.code, event.state,
        time_button_pressed)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton':
        event.code, 'Pressed': event.state,

        'TimePressed': time})


    if event.code == 'BTN_TR':

        t_stop_TR = event.timestamp

        TR_pressed = 0

        time_button_pressed = t_stop_TR - t_start_TR

        print(event.ev_type, event.code, event.state,
        time_button_pressed)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton':
        event.code, 'Pressed': event.state,

        'TimePressed': time})


    if event.code == 'BTN_TL':

        t_stop_TL = event.timestamp

        TL_pressed = 0

        time_button_pressed = t_stop_TL - t_start_TL
```

```
        print(event.ev_type, event.code, event.state,
        time_button_pressed)

        thewriter.writerow(

        {'Type': event.ev_type, 'SpecifiedButton':
        event.code, 'Pressed': event.state,

        'TimePressed': time})




# Hardcoding the joysticks rotation

if event.code == 'ABS_Y':

    left_joystick_y = event.state / math.pow(2, 15)


elif event.code == 'ABS_X':

    left_joystick_x = event.state / math.pow(2, 15)


elif event.code == 'ABS_RY':

    right_joystick_y = event.state / math.pow(2, 15)


elif event.code == 'ABS_RX':

    right_joystick_x = event.state / math.pow(2, 15)


# unit circle calculations

if event.ev_type != "Sync":

    left_joystick_rotation = None

    right_joystick_rotation = None

    if -0.4 < left_joystick_y <= 0.4 and -0.4 <
  left_joystick_x <= 0.4:

        left_joystick_rotation = "NEUTRAL"

        left_joystick_used = False


    if 0.866 < left_joystick_y <= 1.2 and -0.5 <
    left_joystick_x <= 0.5:

        left_joystick_rotation = "UP"
```

```
if 0.5 < left_joystick_y <= 0.866 and 0.5 <
left_joystick_x <= 0.866:

    left_joystick_rotation = "UP_RIGHT"


if -0.5 < left_joystick_y <= 0.5 and 0.866 <
left_joystick_x <= 1:

    left_joystick_rotation = "RIGHT"


if -0.866 < left_joystick_y <= -0.5 and 0.5 <
left_joystick_x <= 0.866:

    left_joystick_rotation = "DOWN_RIGHT"


if -1.2 < left_joystick_y <= -0.866 and -0.5 <
left_joystick_x <= 0.5:

    left_joystick_rotation = "DOWN"


if -0.866 < left_joystick_y <= -0.5 and -0.866 <
left_joystick_x <= -0.5:

    left_joystick_rotation = "DOWN_LEFT"


if -0.5 < left_joystick_y <= 0.5 and -1 <
left_joystick_x <= -0.866:

    left_joystick_rotation = "LEFT"


if 0.5 < left_joystick_y <= 0.866 and -0.866 <
left_joystick_x <= -0.5:

    left_joystick_rotation = "UP_LEFT"


if left_joystick_rotation and left_joystick_rotation !=
previous_left_joystick_rotation:

    print(event.ev_type, left_joystick,
    left_joystick_rotation)

    thewriter.writerow(

    {'Type': event.ev_type, 'SpecifiedButton':
    event.code, 'Pressed': left_joystick_rotation,
```

```
                        'TimePressed': time})

                        previous_left_joystick_rotation =
                        left_joystick_rotation


                    if event.ev_type != "Sync":

                        left_joystick_rotation = None

                        if -0.4 < right_joystick_y < 0.4 and -0.4 <
                        right_joystick_x < 0.4:

                            right_joystick_rotation = "NEUTRAL"

                        if ((-0.4 >= right_joystick_y or right_joystick_y
                        >= 0.4) and right_joystick_x) or (

                        (-0.4 >= right_joystick_x or right_joystick_x >=
                        0.4) and right_joystick_y):

                            right_joystick_rotation = "SKILL MOVE"


                    # If right joystick used: write in csv file Skill Move

                  if right_joystick_rotation and right_joystick_rotation !=
                  previous_right_joystick_rotation:

                        print(event.ev_type, right_joystick,
                        right_joystick_rotation)

                        previous_right_joystick_rotation =
                        right_joystick_rotation

                        if right_joystick_rotation == "SKILL MOVE":

                            # if in_possession:


                              thewriter.writerow({'Pressed': "Skill Move",
                              'TimePressed': time})

                            # if not_in_possesion:

                            # thewriter.writerow({'Pressed': "Change
                        Player", 'TimePressed': time})


            csvfile.flush()


if __name__ == "__main__":

    main()
```