Esports Athletes and Players: a Comparative Study

We present a comparative study of the players’ and professional athletes’ performance in Counter Strike: Global Offensive (CS:GO) discipline. Our study is based on ubiquitous sensing and machine learning which involves the analysis of game telemetry and physiological data. The research provides better understanding why the athletes demonstrate superior performance as compared to other players.

Esports is an organized and competitive gaming with a specific goal at the end of game where single players or teams compete against each other. Esports has become popular worldwide and is recognized as a professional sport in many countries. The global esports audience numbered 380.2 million in 2018 and has tended to grow up to 557 million by 2021\(^1\). Apart from the rapid increase in the quantity of professional athletes and teams, the number of players has dramatically gone up: 27 million people play League of Legends every day\(^1\).

In spite of popularity and official recognition of esports (the Olympic Committee has recognized video games as sports\(^2\)), the debates as to the assessment of esports as an actual sport are still going on. Although cyber athletes spend 8-12 hours a

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\(^1\) Newzoo. 2018 Global Esports Market Report. https://asociacionempresarialesports.es/wp-content/uploads/newzoo_2018_global_esports_market_report_excerpt.pdf

\(^2\) Are Video Games Olympic Material? Some Boosters Say Yes. https://www.nytimes.com/2018/08/30/world/asia/esports-violence-asian-games-olympics.html
day for their training, video games are nevertheless considered in the society as a sort of entertainment. At the same time, esports research is in its infancy and we do not know much about the psycho-emotional aspects of the athletes and their audience during tournaments. The aggressive behavior may suddenly occur, which is followed by some grave consequences including human victims. We still do not know how to efficiently conduct trainings of esports athletes and how to compose the teams - the coaches rely on their professional experience rather than on scientific approach.

In fact, a number of online services\(^3\) are able to provide the generic in-game statistics for further analysis. However, there are no tools available for the detailed physiological and in-game analysis to prove the qualification of either Athlete or Player. The recent advances in pervasive sensing and computing that shape the emergence of pervasive data science\(^2\), as well as the involving of professional athletes into the esports research, will help answer hotly debated questions including those of how to detect cheaters and toxic players.

The present research is done in collaboration with the professional esports team Monolith\(^4\), Russia, in the scope of Skoltech Cyberacademy activity. Our collaboration ensures practical feasibility of this work and allows researchers to dig deeper into the details of esports. In this article we demonstrate the outcome and share our experience in applying pervasive data science for investigating and understanding esports athletes.

## RELATED WORK

Existing research efforts in esports lack the experimentation and the involvement of professional athletes. Although the research which is going through its infancy has been conducted so far without taking into account the multidisciplinary approach, we summarize some recent advances in the area.

The lion share of the current research in esports is carried out in the scope of affective computing in games. It is the interdisciplinary field where the community works on modelling and development of systems able to recognize, process and simulate human affect. The authors demonstrate how to classify an emotion of the athlete relying on the physiological data collected during the game and processed using deep neural networks\(^3\). The detailed discussion on the emotions representation and annotation with a special focus on the advantages of ordinal annotation comparing to the state-of-the-art methods is reported recently\(^4\).

Research on prediction of the player skill upgrading within a gaming season and forecasting the player behavioral data is reported in \(^5\) and \(^6\), respectively. In \(^5\) the authors figure out how the player performance depends on skill learning. For this analysis the authors build two multivariate classifiers. At the end of the research the authors come to the conclusion that the final performance in a game under investigation has a strong relationship with early skill learning. In \(^6\) the authors perform an experimental analysis using artificial intelligence methods for daily forecasting of playtime and sales. The research outcome is as follows: deep learning\(^10\) could be used as a general model for forecasting various time series characterized by the different dynamic behaviour.

Another important research direction is associated with the investigation of social structures in player groups \(^7\). This work presents the analysis of correlation with the aim to identify the effect of players' group characteristics on group activity. For conducting the analysis the authors combine the information from the social network with self-report information available at a social matchmaking service across the players of the online first person shooter Destiny. This paper is featured by integrating demographic and preference data apart from considering the information from a player established community only.

However, the gameplay input recorded using a computer mouse and the buttons of keyboard remain the main source of collecting data on and modelling the players behavior and their ability prediction\(^8\). The appearance of wearables and “earables”\(^9\) makes them an excellent candidate for

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\(^{3}\) CS:GO Demos Manager, https://csgo-demos-manager.com

\(^{4}\) Monolith team profile, https://www.hltv.org/team/9182/monolith
upgrading the behaviour models. Indeed, the running machine learning algorithms on the re-
source constrained devices\(^{10}\), e.g. wearables, is a promising research direction for many domains
including esports.

In our comparative study we employ most of the listed approaches and share our research out-
come.

**ESPORTS BACKGROUND**

The situation with gaming has changed dramatically over the last decade. According to recent forecasts 60
percent of Americans play video games daily, 41 percent of players use personal computers and shooters are
the most popular multiplayer games.

Nowadays Counter-Strike: Global Offensive (CS:GO) is one of the most popular shooter and an eSports dis-
cipline for professional gaming. People start playing CS:GO at an early age despite the formal 18+ age re-
striction. Esports athletes train as hard as the athletes in any other professional sport and finally are signed
with a work contract. In most eSports disciplines, an instant assessment of the game situation, the fastest pos-
sible reaction over several game rounds and concentration on game for a long time are essential for profes-
sional cyber athletes.

A CS:GO professional team typically includes 5 players and a coach. The coach objectives are to help the
athletes in analyzing their game, devising the team strategy and tactic, assigning the in-game roles, to cheer
the team, to develop the players’ skills and to scout for new team members. Successful cyber athletes are
characterized by a number of metrics which are not formally defined, but widely used in the gaming commu-
nity. The Monolith team identifies six key metrics for a successful esport athlete:

- **Aim** - the ability to quickly and efficiently work with the reticle.
- **Decision making speed** - the ability to effectively react in the stressful game situations, e.g. the
  ‘clutch’ when a single player competes against multiple opponents.
- **Game sense** - the general gaming intellect, e.g. the efficiency of athlete decisions assessed by the
  coach.
- **Team communication** – the ability to communicate by voice with the team members during the
  game, e.g. to generate ideas, report on the game status and context.
- **Team work (or Professional Behavior)** – the ability to follow recommendations of the coach and
  the daily regimen.
- **Impact** - the athlete’s personal contribution to the team success, e.g. exchange of players in certain
  game situations for getting benefit for the team.

Apart from the metrics used in the teams, there is the CS:GO ranking system for each single
player. There are currently 18 ranks\(^{(5)}\) in CS:GO starting from the lowest “Silver 1” to the high-
est “The Global Elite”. The “1-18” rank scale system was used in this research for the better data
interpretation.

**DATA COLLECTION**

The goal of our experiment is to collect biometric data from professional and non-professional
cyber sportsmen and perform a comparative study of the data obtained. This includes engineer-
ing of relevant features and identifying the feature importance using machine learning models.

In our laboratory we created a testbed which is the complete gaming place with integrated sen-
sors for recording the biometric data. We give the details of the hardware in the Hardware sub-
section and describe the sensors in the Sensing System subsection. The photo of the testbed is
given in Figure 1.

\(^{(5)}\) Ranking system in CS:GO, [https://csgo-stats.com/ranks](https://csgo-stats.com/ranks)
We invited 28 players to participate in our experiment (4 professionals and 24 non-professional players). Every participant came to the game station at the scheduled time and signed a consent form which allowed recording data from the game and physiological data from sensors.

Each participant adjusted the position of the seat, selected mouse sensitivity and we calibrated the eye tracker for the participant’s eyes. After that, the participant played 30 minutes game session in CS:GO server with Deathmatch Modification (the details of the modification are given in the Game Scenario section). During participant’s play we recorded the biometric and in-game data.

Participants

In our experiment, the professional class was represented by 4 players from Skoltech’s team Monolith CS:GO. The Monolith, being a professional team, has established a good reputation and are currently ranked from 65 to 100 in the world ranking according to HLTV resource. All of them are males from 19 to 25 years old. An average athlete from Monolith eSports has spent 7 years playing the CS:GO at least 8 hours per day and achieved the highest in-game rank.

Besides professional eSports athletes, 24 motivated and healthy people (21 males, 3 females) were recruited through the online advertising at Skoltech internal website or posters to take part in the experiment. Most of the participants are Skoltech’s students and employees. They form the non-professional class of players.

The participants were also questioned about their previous gaming experience in CS:GO. Depending on their previous experience in CS:GO we also splitted the non-professional class into 3 subclasses:

1. newbie (less than 10 gaming hours) - 6 players
2. low-skill amateur (from 10 to 700 hours) - 7 players
3. high-skill amateur (more than 700 hours) - 11 players.

This class sub labeling is only required for visualization purposes in Data Analysis Section.

(6) HLTV resource, https://www.hltv.org.
Hardware

Our team aimed to provide every participant with the best gaming experience with high frame rate, high speed internet and comfortable input devices, etc. The specially equipped place at Skolkovo Institute of Science and Technology had:

1) System block:
   a) Processor Intel(R) Core(TM) i7-5820K CPU @ 3.30GHz, 3301 Mhz, 6 Core(s), 12 Logical Processor(s);
   b) Motherboard MSI(TM) MS-7885;
   c) NVIDIA(TM) GeForce GT 1030;
   d) RAM (KINGSTON(TM) KCP424NS8/8 x4) 32 GB;
   e) SSD SanDisk(TM) SD7SB6S256G1122 256 GB;

2) Input block:
   a) Razer(TM) DEATHADDER mouse;
   b) Razer(TM) BLACKWIDOW keyboard;

3) Output block:
   a) Razer(TM) TIAMAT headset;
   b) BENQ Zowie XL2546 25” monitor - 1920x1080 resolution at 100Hz;

Besides that, participants seated on the professional cybersport chairs DXRacer Formula OH and used the gaming Razer(TM) Chroma mouse pad.

The data acquisition system includes several sensors: the eye-tracker Tobii, the in-game data logger, the mouse and the keyboard loggers. The scheme of the data acquisition system is given below in Figure 2. All the sources of data record the time of reading so that all the data is synchronized during the analysis.

![Figure 2. Data collection system.](image)

The eye-tracker relies on the built-in library which performs the analysis of the position of each eye and calculates the average coordinates relative to the edge of the screen. We developed a script which takes this data and streams it to a file. The Tobii eye tracker provided the eye position, the gaze point data and time stamps. It has 30 Hz sampling rate, 50-75 ms system latency. It was calibrated before every game session for each player for high measurement accuracy.

The keyboard and mouse devices were recorded during every game session (with the 10 ms period) by our custom software to prevent any conflicting situations with running game and to avoid the system overload. The mouse coordinates, as well as the pressed mouse and keyboard buttons, were recorded.

Statistics from the game was collected from the game demo file and further parsing was carried out for understanding and defining the game key events. A special script based on the open-source code of Valve ([https://github.com/ValveSoftware/csgo-demoinfo](https://github.com/ValveSoftware/csgo-demoinfo)) was written to analyze the in-game data. A log file containing in-game events e.g. deaths, shoots, jumps, movement etc. was extracted from the CS:GO *.demo file which was recorded by GOTV script. Each of those events had a start and an end time timestamp to synchronize with all the other data.
Game Scenario

There are several popular official and unofficial game modifications of CS:GO: deathmatch, re-take, surfing, zombie mod among others. They provide the players with many tactical and strategic decisions to make during each game: location to go, weapon to buy, role to play, e.t.c.

For our study we chose the **Deathmatch** (DM) modification. In DM, the goal of the player is to achieve as many kills of other players as possible keeping the number of own deaths as low as possible. If a player is killed he immediately spawns again according to DM rules. The set of possible weapons to use is usually defined by the game server and remains the same for each player on the server.

There are several reasons why we chose DM modification. First of all, this modification is used by professional cyber athletes on the regular basis as part of their training process. It helps players to improve reaction and aiming skill. The amateur players often play DM too. Secondly, while playing DM, the player is placed in the same situation many times: he either sees the enemy and kills him or vice versa the enemy kills the player. This removes the necessity of taking into account the impact of tons of in-game factors, such as teamplay [there are no teams in DM], radar controlling [the radar is disabled], game economics [the equipment is given automatically], etc.

DATA ANALYSIS

In this section we describe the features and models we use to classify players into two skill groups (professional vs. non-professional players) using their biometric data.

In the **Feature Extraction** subsection we list the features that we compute to characterize each player’s session. In the **Machine Learning** subsection we describe machine learning models we train (on the basis of the computed features) to classify players into skill groups. We also show the importance levels of the used features, i.e. explain which features are most relevant.

It should be noted that to perform the advanced data analysis we preprocessed the raw dataset. The player gaze coordinates and heart rate we resampled to the rate of 128 Hz (it is equal to the tickrate of game log) and then linearly interpolated. Also, using the recorded game data (demo files), we extracted for analysis only those moments when the players were alive.

Feature Extraction

For each player’s preprocessed game session we compute the list of features that characterize his session. Most of the features are based on single sensors (e.g. the eye-tracking based features), some features are cross-sensor (e.g. the mouse and the keyboard).

**Eye-tricking based features.** To characterize each player’s gaze during his game session we compute features that estimate the mean deviation of player’s gaze from the screen center:

Mean gaze Euclidean distance to screen center;
Mean gaze distance to screen center per axis ($Ox$);
Mean gaze distance to screen center per axis ($Oy$);

The choice of the features is motivated by the following fact. Since CS:GO is a first person shooter, players mainly look at the center of the game screen where the aiming crosshair is located. Nevertheless, there are some other screen areas of interest, such as User Interface (UI) elements: the health & armor bar, the weapon & ammo panel, the radar, the kill & death log, the game timer & the player list.

One of the reasons why we chose the Deathmatch game mode for our experiment is that it minimizes the necessity of looking at the UI elements. Indeed, the radar in the deathmatch mode is completely disabled, health, armor and ammo automatically get restored after each players’ kill
or death. Thus, players’ gaze is mainly concentrated on the game environment (objects, enemies, shooting, walking) rather than on the UI elements.

Our experiment shows that there are significant differences in player’s gaze between the skill groups. It turns out that the higher skill the player has, the more his gaze is concentrated in the screen center (where the aiming crosshair is located). To illustrate this, we build the gaze heat maps for players of different skills (see Figure 3). The heatmaps are obtained using the Gaussian kernel density estimation.

Figure 3. Gaze heat maps for players of different skill. Different colors represent the percentage of time that the player spent looking into the area. The darker the area, the more time player spent looking into it.

There are two main reasons why players with high skill spend more time looking into the screen center. First of all, they have better knowledge of the game map and always know how to position themselves and where to aim. This fact significantly makes it unnecessary to look around the screen. Secondly, in the situation when an enemy appears (not in the expected screen center position), the skilled players much more quickly moves the in-game aiming crosshair at the enemy and then again looks at the screen center (where an enemy and the aiming crosshair is located).

**Keyboard and Mouse Based Features.** We describe the keyboard and mouse buttons data streams by different features of two types:

- The average number of time ticks per second when some combination of keys and mouse buttons were pressed (either together or any of them), i.e. the usage of specific control elements;
- The average length of continuous time interval (in ticks) when the specific keys and/or mouse buttons were used, i.e. the duration of them being pushed.

The main controls in game are the keys: W (forward), S (back), A (left), D (right), Ctrl (“duck”, i.e. squat pose) and the **Left Mouse Button** (weapon fire).
Some distributions of player’s class over feature values are shown below. Figure 4a shows the average usage of a single key (the average number of time ticks per second when only one key is pushed) and Figure 4b shows the usage of the left mouse button. As one can see, professional athletes demonstrate the higher usage of these controls as compared to players of other classes, which is quite expected.

Figure 4. (a) the usage of any single key on the keyboard. Professional players use the keyboard more actively than players of other classes. (b) The usage of the left mouse button for players of different levels. Professional players use the left mouse button more actively, although their usage has significant spread.

Here are some more interesting insights into behavior of different players when using control keys. Quite unexpectedly, professional players make forward and backward motions like newbies in the case of usage of W or S keys (see Figure 5a). Moreover, among all classes of players professionals have the minimum time of keeping W or S keys pushed, which means that they press these keys in the more discrete manner (see Figure 5b).

Along with the fact that professional athletes have the low usage of forward and backward motions, they move left and right more often than players of other classes (see Figure 5c). Moreover, the usage of A and D keys can be considered as one of the characteristic of player’s skills: the higher this usage, the higher the skills. Also, the class of professionals appears quite compact in Figures 5b and Figure 5c, which means that these two features can distinguish the class of professionals from other classes of players.

Also, the usage and duration of more exclusive combinations peculiar to professional athletes, such as A, Ctrl and the left mouse button, are considered (see Figure 5d). Although the variance of using this combination among athletes is large enough, the high value of this feature indicates a highly skilled player.
Figure 5. (a) The usage of W or S keys. Professional players have the low usage of forward and backward motions. (b) The duration of pushing W or S key. Professional athletes press these keys more intermittently than other players. (c) The usage of A or D keys. The left and right motion usage as a characteristic of player’s skills. (d) The usage of A, Ctrl and the left mouse button pressed together. The combination peculiar to professional athletes.
Machine Learning

In this section we construct a classification model to predict the player skill group on the basis of the features of his game session (see the previous section). The final dataset consists of 28 players and each player is characterized by 36 features.

**Classification model.** We use Extremely Randomized Trees\(^2\) as the classification model. This type of classifier builds an ensemble of totally randomized decision trees the structures of which are low-dependent of the output values of the training sample. Thus, the resulting classifier is quite robust and highly protected from overfitting. This is of high importance in our case since the training sample is small and the number of features is bigger than the size of the training sample. On the other hand, this classifier has a small amount of configurable parameters, which also decreases overfitting to data and simplifies the optimal parameter selection procedure.

In order to identify the optimal parameters of the classifier, we performed a grid search over the classifier hyperparameters (number of trees [10 to 1000], maximal depth [1 to 7], usage/non-usage of bootstrap). Overfitting was controlled through the leave-one-out cross-validation procedure.

The optimal selected hyperparameters are to use an ensemble of ~70 trees of maximal depth 4 without using the bootstrap. The optimal classifier accuracy is 96.5%. The next step would be to apply imbalanced classification approaches\(^3\) to leverage under-representative class of professional players and robustness of the classifier.

**Feature importances.** We determine the relevance of all the used features to the problem of identifying players skill. The Extremely Randomized Trees classification model, as well as any decision-tree-based model, has the natural feature importance score. The importance score of each particular feature is based on how much the splits in the tree nodes by this feature improve the model quality. The importance score is shown in Figure 6.

![Figure 6. Feature importance (Top 20) for 2-class classification problem (pros vs. non-pros).](image_url)

Different colors correspond to different data streams. The key and mouse features are either usage or duration of their combination. Features with sign “&” mean that the keys are pressed together with or without any other controls pressed, whereas features with “or” mean that any of the two specified keys is pressed without any other controls pressed. “1 key”, “2 keys” mean that the given number of the keys is pressed, “MOUSE1” means the left mouse button. The values of “1 key (usage)”, and “MOUSE 1 (usage)” are shown in Figure 4. The values of features “W or S (usage)”, “W or S (duration)”, “A or D (usage)”, “A & Ctrl & MOUSE1 (usage)” are shown in Figure 5.

It turns out that the gaze features are extremely relevant to classifying players into professionals and non-professionals based on their biometric data. At the same time, the usage of special in-game movement & fire combinations are also of high significance. For example, the A & Ctrl &
Mouse1 (Top-3) combination corresponds to the special weapon recoil cancellation trick which allows the player to attain the better shooting accuracy. This trick is widely used by the professional players, whereas non-professionals may not even know about it. Another example is the usage of W and S buttons (forward-backward movement, Top-4): professional players are more cautious in their movement and, therefore, use these keys less frequently.

CONCLUSIONS

Data science and machine learning have dramatically progressed over the last decade and provide great support in instrumenting our physical environment. They help with problem solving in numerous computing applications, in particular the cutting-edge applications such as cybersport.

In this work we have demonstrated how to apply machine learning techniques to cybersport for evaluation of players and athletes followed by their classification. For conducting this comparative study we collected heterogeneous data including physiological and in-game data while non-professionals and professional athletes from the Monolith team were playing CS:GO. The outcome of this research is to help professional cyber teams to identify and analyze the specific game features - without this analysis the team members had to rely on their experience rather than on science.

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