2022 25th International Conference on Computer and Information Technology (ICCIT)
17-19 December, Cox's Bazar, Bangladesh

Does A Support Role Player really Create Difference towards Triumph? Analyzing Individual Performances of Specific Role Players to Predict Victory in League of Legends

Joyanta Jyoti Mondal
School of Data and Sciences
Brac University
Dhaka, Bangladesh
joyanta.jyoti.mondal@g.bracu.ac.bd

Abrar Zahin
School of Engineering
Brac University
Dhaka, Bangladesh
abrar.zahin@g.bracu.ac.bd

Meem Arafat Manab
School of Data and Sciences
Brac University
Dhaka, Bangladesh
meem.arafat@bracu.ac.bd

Mohammad Zahidul Hasan
School of Data and Sciences
Brac University
Dhaka, Bangladesh
zadid.hasan@bracu.ac.bd

***Abstract*—Players make comments like "Mid Diff", "Top Diff", "JG Diff", etc. in the in-game chat at the end of almost every match of *League of Legends*. It represents the relative difference in in-game abilities of players of the same position that leads to a significant difference between two teams in determining the loss/win of a particular match. However, no player seems to pay enough heed to if there is a difference between players who play the Support role (or "SP Diff" to be specific) which also may have also helped them to win a match. In most places, this role is considered insignificant among players. But do they really not contribute towards the winning of a match? In our research, we investigate the impact of a player who contributes in a Support role toward match victory. Previous researches show collective intelligence (CI) to be a factor in team games that helps to analyze their capacity to work and win collectively. To our knowledge, this is the first work that focuses on the contribution of any single particular role out of the full team of five players toward the victory of a match. We also create a custom dataset based on the match statistics and match-specific performances of different Support role players and evaluate if the outcomes and performance shown by a particular role are crucial enough to the world of teams in competitive online video games, where intensive, self-organized, and time-pressured cooperation takes place entirely online. The results show a stronger correlation between a certain support player's performance and the match result than usually thought of. This points towards more reliable match result prediction in the game. We make the dataset publicly available at https://www.kaggle.com/datasets/joyanta180199/lol-sp**

***Index Terms*—League of Legends, Victory Prediction, E-Sports, Online Gaming, Electronic Games, Monte Carlo Simulation**

I. Introduction

League of Legends (LOL) is a well-known and popular online MOBA PC game developed and published by Riot Games. It also has been reported as one of the largest Electronic sports (E-sports) games in the world, moreover, it has a player base of more than over 100 million monthly players worldwide [1]. Reitman et al. [2] provide a comprehensive explanation of the gameplay of *League of Legends* for people unaware of its unique characteristics. LOL has a worldwide competitive environment. There is significant regional rivalry in different regions such as North America, Europe, China, South Korea, Taiwan/Hong Kong/Macau, and other places. The regional champions have the opportunity to participate in the yearly World Championship. The 2021 World Championship attracted more than 4 million unique viewers and over $2.2 million in total prize money [3]. As the eSports industry develops, it becomes necessary to analyze game techniques. Currently, the majority of professional gaming teams employ analysts to analyze their opponents, determine their plans, and devise counter-strategies. Analysts and shoutcasters provide their insights throughout tournaments and matches. Currently, eSports athletes lodge alongside their team coaches, managers, and strategists. As the level of competition develops rapidly, so does the demand for techniques to improve player performance.

Researchers and business that supports esports are becoming more interested in the concept of victory prediction in video games. Electronic sports, often known as esports, are video games that are played at a highly competitive level in front of millions of spectators. According to a report [4], it is anticipated that more than 31.4 million individuals in the United States would be watching some kind of electronic sports in the year 2023. This is mostly attributable to the expansion of online streaming media, most notably game broadcasts on Twitch and YouTube. In addition to the number of people who watch it, the current value of the global esports industry is 1.08 billion dollars. This represents a rise of more than 10 percent from the period of 2019 to 2021. At the current pace, It's estimated that Esports will be worth about $1.62 billion by 2024 [5].

The primary purpose of making a win prediction is to assess which group of players or individual player will emerge victorious in a certain match. Predicting who will win a match may be researched using three different scenarios: humans vs humans, humans versus artificial intelligence, and artificial intelligence versus artificial intelligence. Predictions can be made based on factors that occur either before the game, during the game, or after the game. In the current research, an analysis of the prediction rate for human vs human matches in *League of Legends* is carried out.

Due to the availability of a massive quantity of data, *League of Legends* serves as a wide testing ground for machine learning algorithms and as a tool for better comprehending human actions. Beserra et al. [6], for instance, examine keystroke and mouse dynamics for user identification in order to determine whether or not the individual using the account is the real account holder. Players in *League of Legends* have the opportunity to compete in a variety of different match types, including player vs player and player versus environment. In addition, the performance metrics in *League of Legends* are comparable to those in other competitive multiplayer online battle arena (MOBA) games like Dota 2 and Smite, and to some extent, they are also comparable to those in First-Person Shooters (FPS) games like Valorant, Fortnite, and Player Unknown's Battlegrounds (PUBG), which makes *League of Legends* a case that is broadly applicable.

Our research focuses on predicting victory based on a single player's impact throughout the match.

Based on our study, we make the following set of contributions to this paper:

- To the best of our knowledge, we are the first one to report the impact of winning a match based on individual performance.
- We publish a novel dataset of matches of a Support role Player which consists of significant features that can be helpful to analyze the performance.

The following is the paper's framework. We begin with describing the game in Section II. Then, we review some related works towards such games in Section III. Afterward, Section IV illustrates the approach we use to check the importance. Then, in Section V, we introduce the dataset we work on. In Section VI, we show and discuss the evaluation of our experiment, and in Section VII, we discuss and demonstrate possible future implications.

II. Game Description

League of Legends (LOL) is a Multiplayer Online Battle Arena (MOBA) game. MOBA games like LOL typically consist of five players per team, with each player controlling a single character. In such games, unlike massively multiplayer online role-playing game (MMORPG) games, neither unit building nor a large number of concurrent players is present on a map. The core of the game's strategy relies instead on cooperative team play and individual character development.

Ten players compete against one another in a game of *League of Legends* on a terrain known as Summoners Rift. There are five players on each of the two teams. Before the fight starts, each member of the team will choose a "Champion" to play. A "Champion" is a character who already exists inside the game and has a distinct appearance as well as a set of powers that are their own. In addition, they have the ability to personalize their champion by choosing two potent abilities (Summoner Spells) and unique stones known

Fig. 1. Simplified Map of A League of Legends Match (Summoner's Rift Mode)

as runes, which confer additional benefits on a champion. Each Champion has a total of five skills, four of which are active and one of which is passive. These powers may be utilized to kill other Champions or monsters. In addition to champions, every member of a team is given a function or position within the team (Jungle, Top Laner, Mid Laner, ADC, or Support) that they are required to complete until the end of the battle. Because *League of Legends* is played as a team competition, each of the five positions plays an important part in the overall outcome.

After making the first purchases for their beginning items with gold, players are required to go to their designated lanes once the match has begun. Gold is the in-game money for a match of *League of Legends*, and Items are physical things that may be used to augment a Champion's abilities while they are being played. The objective of the game is to destroy the Nexus of the opposing team while defending your own. The Nexus of the other team is located on the bottom-left for Blue Team and on the opposite side for Red Team. However, in order for a team to get to the stage where they can destroy an enemy Nexus, they will first need to face a number of challenges. On average, each battle goes on for between 20 and 50 minutes. In the end, the winner of this battle will be determined by whose side is the first to destroy the Nexus.

III. Related Works

Ong et al. [7] employ Logistic Regression, Gaussian Discriminant Analysis, and Support Vector Machines to determine the results of *League of Legends* matches. K-means is used to cluster player behavior. Johansson et al. design a real-time prediction [8] which aims to predict the winning team of Dota

2 (MOBA) matches using limited game-state data. Wang et al. [9] use multi-layer feed-forward neural networks to predict the result of Dota 2 games based on data from hero drafts. Gradient boosted and Random Forest are the two methods that Ravari et al. [10] utilize for win prediction in the game Destiny across a variety of game settings. In addition to this, they investigate the various performance indicators and the impact that each factor has on each mode.

Collective intelligence is used by Kim et al. [11] to make predictions on team performance in LOL. They demonstrate that it is possible for collective intelligence to forecast the team's performance based on the tacit cooperation of the players.

The performance of the teams is split into different categories by Nascimento Jr. et al. [12]. They use machine learning and statistical analysis to analyze the attributes in each group in order to determine how the factors influenced the outcomes in LOL.

Yang et al. [13] create a decision tree that predicts the outcomes of a MOBA game by modeling fighting strategies in graphs and extracting information from the graphs.

Lan et al. [14] provide a player behavior model that enables them to predict the result of a multiplayer online battle arena (MOBA) game after gathering sufficient data on player behavior. They deploy a recurrent neural network to predict the outcome of a game by analyzing the interaction of player behavior variation features.

All of these researches have ignored gameplays or game goals, despite the fact that the major goal of the game is to destroy objectives such as turrets in order to win.

IV. Research Methodology

In our research, we use one of the famous statistical simulation-based approaches, Monte Carlo Simulation.

Monte Carlo Simulation, also known as the Monte Carlo Method or a multiple probability simulation, is a statistical approach is used to predict the potential outcomes of a random or uncertain event. Other names for this simulation include the Monte Carlo Method and a multiple probability simulation. John von Neumann and Stanislaw Ulam come up with the Monte Carlo Method during World War II with the intention of improving decision-making in settings where there was a lot of uncertainty. Because the modeling technique is fundamentally based on the element of chance, much like a game of roulette, it was given a name that is inspired by Monaco, which is a well-known gambling town.

Since its introduction, Monte Carlo Simulations have been used to examine the impact of risk in a wide range of real-world situations, such as artificial intelligence, financial markets, sales forecasting, project management, and pricing, to mention a few. They also provide some advantages over predictive models with constant inputs, such as the ability to do the sensitivity analysis and assess the inputs' correlation. In addition, they provide some benefits over predictive models with predetermined outputs. Using sensitivity analysis, decision-makers are able to examine the impact of each input variable on the final outcome. Correlation enables decision-makers to understand the relationships between all input variables.

In the present day, different industries make extensive use of this method because it is simple to put into practice and there is a large amount of computer power readily accessible [15]–[18].

A. How does Monte Carlo Simulation work?

Monte Carlo simulation forecasts a set of outcomes based on an estimated range of values as opposed to a set of predefined input values. This is in contrast to traditional forecasting models. To put it another way, a Monte Carlo Simulation creates a model of the outcomes that are conceivable by using a probability distribution, such as a normal or uniform distribution, for any variable that has an innate element of unpredictability. The findings are then recalculated an infinite number of times, with each iteration using a new and unique set of random integers that fall between the minimum and maximum values. This activity can be done thousands of times in a standard Monte Carlo experiment to obtain a huge number of possible results.

Because of the high level of accuracy they provide, Monte Carlo simulations are also used to make long-term forecasts. The greater the number of inputs, the greater the number of predictions that can be generated, which in turn enables us to make more accurate projections of outcomes over a longer period of time. When a Monte Carlo simulation is finished, it will provide a number of different potential outcomes along with the likelihood that each one will take place.

Calculating the chance of rolling two regular dice is a straightforward illustration of a Monte Carlo Simulation that can be used as an example. There are 36 possible outcomes depending on how the dice are rolled. We are now able to manually determine the likelihood of a given result based on this information. With the help of a Monte Carlo simulation, we can simulate throwing the dice 10,000 times (or perhaps more), which will allow us to make more precise forecasts.

The Monte Carlo Simulation is based on the idea of taking several random samples from a predetermined collection of probability distributions. This is the simulation's central idea. These may be of any kind, including normal, continuous, triangular, beta, gamma, etc.

In order to implement this strategy, there are primarily four actions that need to be taken:

- Determine all of the process's input components and how they interact with one another, such as whether or not they add or subtract.
- Determine the distributions' defining parameters.
- Take a representative sample from each of the distributions and then integrate the data based on point 1.
- Repeat as per wish.

Even if the source distributions may be quite diverse from one another, the output parameter of this simulation, such as the cost or the risk, will converge toward the Normal Distribution as it runs. This is the impact that the Central Limit

Champion	Kill	Death	Assist	KDA	Match Duration	Win/Lose
Syndra	6	2	10	8	24:06	W
Yuumi	4	2	30	17	37:08	W
Bard	3	11	13	1.454545455	37:08	L
Yuumi	2	2	26	14	31:51	W
Pantheon	5	10	6	1.1	31:51	L
Yuumi	3	10	13	1.6	34:14	L
Pantheon	4	9	23	3	34:14	W
Yuumi	5	7	23	4	39:45	W

Fig. 2. Representation of Proposed Dataset

Theorem has, and it is one of the reasons why this method has been so widely used in a wide variety of business settings.

V. Dataset

We create a custom dataset of 296 matches where we collect the in-game performance of the support role players in 2022.

Here, we take a few parameters which are mainly considered for winning and creating an impact on the positive/negative performance of the match.

We take the parameters of

- Kill
- Death
- Assist
- KDA (Kill-Death-Assist) Ratio
- Time Taken towards The Match
- Win/Lose
- Who Played

In Figure 2, we present how we collect the dataset (we omit the row of names of the players since it is not pertinent to the work at hand).

We take data from different players, playing different champions, and having different levels of mastery of those champions, to create diverse data. Also, we take the data of support role players of both the winning and the losing side of some matches to understand the relation more deeply.

VI. Experimental Evaluation

We test the data using our suggested approach. Our primary objective is to show a positive connection toward the win of a player in support role.

A. Experimental Setup

Monte Carlo Simulation is run and evaluated on one device; having 32GB of Ram and Ryzen 5 2600 Processor with 6 Cores, 12 Threads of performance.

B. Experimental Findings

We compute the p-value that is connected with the Pearson correlation coefficient so that we can determine whether or not this connection is statistically significant. The strength of a link between two variables may be measured by using something called a correlation coefficient. There are a few other varieties

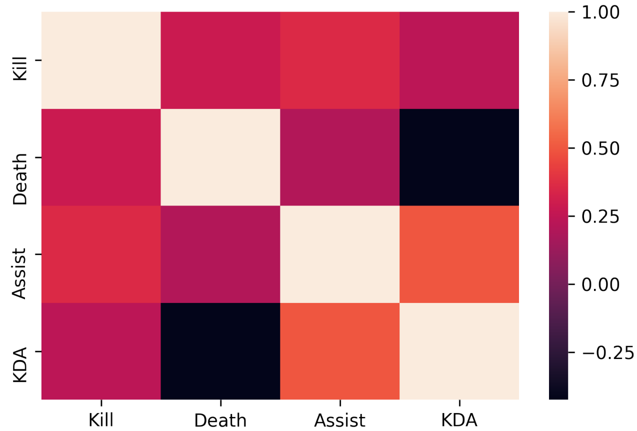

Fig. 3. Data Correlation Heatmap

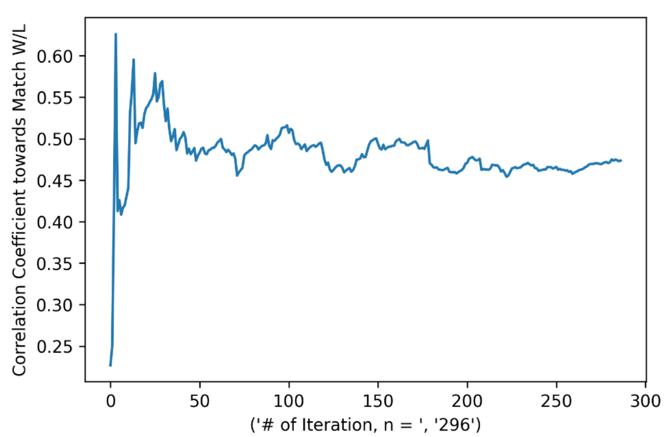

Fig. 4. Correlation Coefficient towards Win/Lose

of correlation coefficients, but Pearson's is by far the most common. The Pearson correlation, often known as Pearson's R, is a correlation coefficient that is frequently used in the practice of linear regression.

The strength of a link between two sets of information can be determined with the use of correlation coefficient formulae. The formulae all produce a result that is between -1 and 1, with the following rules:

- 1 indicates a strong positive relationship.
- -1 indicates a strong negative relationship.
- A result of zero indicates no relationship at all.

  A complete positive association between two or more variables will result in a value of +1 being calculated for the equation. When two variables have a positive correlation, it means that they both move in the same direction. In contrast, a score of -1 denotes a connection that is ideal from a negative point of view. Negative correlations show an inverse relationship between the two variables, which means that while one variable grows, the other one must shrink.

  Pearson's correlation coefficient formula is stated in Equation 1.

$$r = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left[n\sum x^2 - \left(\sum x\right)^2\right]\left[n\sum y^2 - \left(\sum y\right)^2\right]}} \quad (1)$$

After running Monte Carlo Simulation on Correlation Coefficient for 296 iterations, we get that the correlation coefficient is very close to 0.50 which represents a moderate correlation.

From Figure 4, it initially shows an unstable result between around 0.63 and 0.40. After 100 iterations, it starts to be around 0.50 and it ended in 0.473.

C. Discussion

While looking into some matches, we see that even if support performs well in the match, the results turn into a loss which represents only a single player cannot be the only and absolute reason for a win. Also, some matches are ended up earlier than expected where one team surrenders due to a lack of players/lack of understanding. In those cases, even if the support player performs well, it cannot create an impact on the win.

VII. Conclusion

In this research, we investigate the impact of a support role player in a game of *League of Legends*. We present a dataset for our work and according to our dataset, we see a moderate correlation toward the victory. We make our dataset public to facilitate further research on league of legends. Our future work includes adding data of more matches, of four other different roles as well and more parameters to look towards the connection of different parameters on victory in a game; both ranked and unranked matches. Also, the future work may contain building advanced deep learning based model which will be both computationally efficient and fast to detect the percentage of winning based on in-game data which is also an emerging area of research in machine learning community and we already see real-life implementations of such approaches [19], [20].

Acknowledgment

We have our most sincere gratitude to all the random players who assisted in collecting the data for the research work. Especially, Joyanta and Abrar thank their teammates to give them a wonderful experience and time along with helping them enriching the dataset (alphabetically, along with gamertags): Louie Vien M Alcazar (Drifter), Md. Ashik Billah (TheNephilim105), Morsalin Al Rabbi (RawMilk), Motakabbir Hossain (Roronoa Zoro), Mustafa Minhazul Haq (SkinnyJesus), and Naveed Adnan (Hisoka).

References

[1] "League of legends live player count and statistics," https://activeplayer.io/league-of-legends/, 2022, accessed: 2022-9-30.

[2] J. G. Reitman, M. J. Anderson-Coto, M. Wu, J. S. Lee, and C. Steinkuehler, "Esports research: A literature review," *Games and Culture*, vol. 15, no. 1, pp. 32–50, 2020. [Online]. Available: https://doi.org/10.1177/1555412019840892

[3] "2021 world championship - liquipedia league of legends wiki," https://cutt.ly/6VV62sk, accessed: 2022-9-30.

[4] Insider Intelligence, "Esports ecosystem in 2022: Key industry companies, viewership growth trends, and market revenue stats," https://www.insiderintelligence.com/insights/esports-ecosystem-market-report/, Mar. 2022, accessed: 2022-9-30.

[5] J. Wise, "ESports statistics 2022: Market size, revenue & viewership," https://earthweb.com/esports-statistics/, Sep. 2022, accessed: 2022-9-30.

[6] I. da Silva Beserra, L. Camara, and M. Da Costa-Abreu, "Using keystroke and mouse dynamics for user identification in the online collaborative game league of legends," in *7th International Conference on Imaging for Crime Detection and Prevention (ICDP 2016)*. Institution of Engineering and Technology, 2016, pp. 1–6.

[7] H. Y. Ong, S. Deolalikar, and M. Peng, "Player behavior and optimal team composition for online multiplayer games," 2015. [Online]. Available: https://arxiv.org/abs/1503.02230

[8] F. Johansson and J. Wikström, "Result prediction by mining replays in dota 2," 2015.

[9] W. Wang, "Predicting multiplayer online battle arena (MOBA) game outcome based on hero draft data," Master's thesis, National College of Ireland, Ireland, 2016.

[10] Y. Norouzzadeh Ravari, P. Spronck, R. Sifa, and A. Drachen, "Predicting victory in a hybrid online competitive game : The case of destiny," 2017.

[11] Y. J. Kim, D. Engel, A. W. Woolley, J. Y.-T. Lin, N. McArthur, and T. W. Malone, "What makes a strong team?: Using collective intelligence to predict team performance in league of legends," in *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*. New York, NY, USA: ACM, 2017.

[12] F. F. d. Nascimento Junior, A. S. d. C. Melo, I. B. da Costa, and L. B. Marinho, "Profiling successful team behaviors in league of legends," in *Proceedings of the 23rd Brazillian Symposium on Multimedia and the Web*, ser. WebMedia '17. New York, NY, USA: Association for Computing Machinery, 2017, p. 261–268. [Online]. Available: https://doi.org/10.1145/3126858.3126886

[13] P. Yang, B. Harrison, and D. L. Roberts, "Identifying patterns in combat that are predictive of success in MOBA games," 2014.

[14] X. Lan, L. Duan, W. Chen, R. Qin, T. Nummenmaa, and J. Nummenmaa, "A player behavior model for predicting win-loss outcome in MOBA games," in *Advanced Data Mining and Applications*. Cham: Springer International Publishing, 2018, pp. 474–488.

[15] S. Triambak and D. P. Mahapatra, "A random walk monte carlo simulation study of COVID-19-like infection spread," *Physica A*, vol. 574, no. 126014, p. 126014, 2021.

[16] Z. He, "Sensitivity estimation of conditional value at risk using randomized quasi-monte carlo," *Eur. J. Oper. Res.*, vol. 298, no. 1, pp. 229–242, 2022.

[17] S. Franke, F. Franke, and R. Riedel, "Robustness evaluation of production plans using monte carlo simulation," *Procedia Manuf.*, vol. 54, pp. 130–135, 2021.

[18] Z. Syed and Y. Lawryshyn, "Risk analysis of an underground gas storage facility using a physics-based system performance model and monte carlo simulation," *Reliab. Eng. Syst. Saf.*, vol. 199, no. 106792, p. 106792, 2020.

[19] F. C. Liverpool, "From CERN to LFC: The 'weird' journey of william spearman, liverpool's lead data scientist," https://www.liverpoolfc.com/news/cern-lfc-weird-journey-william-spearman-liverpools-lead-data-scientist, Feb. 2022, accessed: 2022-12-9.

[20] J. J. Mondal, M. F. Islam, S. Zabeen, A. B. M. A. A. Islam, and J. Noor, "Note: Plant leaf disease network (PLeaD-net): Identifying plant leaf diseases through leveraging limited-resource deep convolutional neural network," in *ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies (COMPASS)*. New York, NY, USA: ACM, 2022.