INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

Predict Result of League of Legends Using Machine Learning Approach

[1]CHINTHALAPUDI NARENDRAREDDY, [2]M NARESH

[1]PG Scholar, Dept. of MCA, Newton's Institute of Engineering, Guntur, (A.P)

[2]Associate professor, Dept. of CSE, Newton's Institute of Engineering, Guntur, (A.P)

***Abstract**:* Nowadays, the MOBA game is the game type with the most audiences and players around the world. Recently, the League of Legends has become an official sport as an e-sport among 37 events in the 2022 Asia Games held in Hangzhou. As the development in the e-sport, analytical skills are also involved in this field. The topic of this research is to use the machine learning approach to analyse the data of the League of Legends and make a prediction about the result of the game. In this research, the method of machine learning is applied to the dataset which records the first 10 minutes in diamond-ranked games. Several popular machine learning (AdaBoost, Gradient Boost, Random Forest, Extra Tree, SVM, Naïve Bayes, KNN, Logistic Regression, and Decision Tree) are applied to test the performance by cross-validation. Then several algorithms that outperform others are selected to make a voting classifier to predict the game result. The accuracy of the voting classifier is 72.68%.

***Keywords**:* League of Legends; machine learning; Voting classifier; MOBA

I. INTRODUCTION

There has been a significant shift in how people feel about video games compared to the previous decade. Instead of seeing video games as a gateway to the spirit world, as was formerly widely thought, today's parents approach these activities with an open mind. The video game business is expanding, and with it comes a wider variety of game genres, such as role-playing games, first-person shooters, strategy games, and more. E-sports are competitions in video games that are recognised as legitimate sports. In addition, the 2022 Asia Games in Hangzhou will include e-sport as one of the 37 disciplines on offer. The Multiplayer Online Battle Arena (MOBA) game is the most watched and played of all the e-sports. There are around 205 million players of MOBA games in 2018, as stated in an article by Mora-Cantallops and Sicilia. League of

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE
ISSN: 2057-5688

Legends is the most talked-about multiplayer online battle arena currently being studied. In 2013, 27 million people watched the League of Legends Championship online. In kind, resources and focus have been allocated to improving players' on-field output. One focus of this study is on using machine learning to analyse data. The study focuses on the use of machine learning techniques in competitive games, specifically on the prediction of competition outcomes using game indicators and the identification of the most influential of these variables. The study gives an impartial way to evaluate the game without resorting to personal opinions. The findings of this study may also be used to other e-sports and traditional sports in order to better prepare gamers and athletes for competition. The most up-to-date research on using machine learning in League of Legends is then compared to earlier studies. Xia, Wang, and Zhou's study focuses mostly on another well-liked multiplayer online battle arena (MOBA) game: Defence of the Ancients 2 (DotA 2). Using R, they conduct an in-depth analysis of the data, discovering that tactical awareness has a greater impact than operations on the multiplayer killing indication and the outcome of the game [2]. DOTA 2 data was also researched for a different purpose. They use common machine learning algorithms to provide real-time forecasts of MOBA game outcomes [3]. In the third study, results from the Linear Regression, Neural Network, and LSTM models are compared. In yet another study, the Naive Bayes classifier, Logistic Regression, and Gradient Boost were the primary learning models. Their findings also demonstrate that the forecast varies with the operating abilities of the participants [6]. Researchers in the realm of League of Legends have been increasingly turning to deep neural networks that take into account players' historical performance with certain champions to choose which ones to recommend to them [5]. While yet another study [7] focuses primarily on the impact of pre-game conditions on game outcomes. One study uses recurrent neural networks to analyse League of Legends data. They found that using data from only 0-5 minutes led to a less accurate model than using data collected over 20-25 minutes [8]. This study draws inspiration from Lin's [9] work, in which the author implements a number of well-known machine learning models.

II. LITERATURE SURVEY

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE
ISSN: 2057-5688

The following are examples of software-based profiling systems, hardware-based profiling systems, and hybrid profiling systems. In 2005, Arnold and Groove utilised a stopwatch and utilising a dynamic call graph and an event-based sampling strategy, we can pinpoint frequently-used methods with just a 1-2% performance hit. By using a sampling-based instrumentation approach, Arnold and Ryder (2001), Arnold (2002), and Arnold et al. (2002) have shown that they can reduce overhead during profile gathering. Using a permanent profile repository, Arnold et al. (2005 a) improved selected optimisation for several programme runs rather than a single execution, incurring an average cost of 0.5%. Suganuma et al. (2001) employed a sample profiler that installs and uninstalls instrumentation programmes to gather value profiles for code specialisation. Overhead ranges from 47 to 56%, according to a sampling-based profile analysis of the present call stack conducted by researchers (Binder 2006, Binder and Hulaas 2006). They've made an effort to lessen Java's load by gathering profile data on the go via portable instrumentation. There are a few more examples of works that use the sampling-based profiling technique, including Whaley (2000) and Mousa and Krintz (2005).

Profile data has been utilised to make predictions about actual programme behaviour by Wall (1991). Ball and Larus (1994) have devised a method to decrease the profiling cost by instrumenting edges to monitor vertex profiles in a control-flow graph. Binder et al. (2009) have employed bytecode instrumentation to obtain calling context profiles as part of their work on cross profiling and platform agnostic profiling. Overhead factors ranging from 1.33 to 9.99 have been incorporated in bytecode instrumentation by Binder and Schoeberl (2009) to estimate programme execution times. Moret et al. (2009) have also profiled Java methods with the use of instrumentation.

Combining hardware and software profiling methods is a hybrid approach used by certain academics. Example: Gordon-Ross and Vahid (2003) have created a hardware/software partitioning strategy to dynamically optimise by identifying frequently run codes or "critical regions" and the relative frequency with which they are performed. Kumar (2004) has utilised a relative estimate approach, profiling high-usage algorithms to determine which ones should

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE
ISSN: 2057-5688

be compiled and optimised at runtime. Through their research, Kumar et al. (2005) have decreased the number of instrumentation sites required for profiling, as well as the associated cost of equipment. In order to minimise the overhead by 58%, Nagpurkar et al. (2005) develop a phase-aware profiling that only profiles a representative of each phase of a programme. Smith (2000) elaborated on why knowing how the programmes behave over time is important for effective feedback-directed optimisation.

Since there is also the issue of overhead with profile gathering, Zhao et al. (2006) have made an effort to reduce the profile size. Bond and McKinley (2007) have developed a method for representing the calling context with a probabilistic unique value and an average cost of 3%.

In order to predict whether or not a technique would be popular in the future, Namjoshi and Kulkarni (2010) have established loop iteration limitations before entering the loop. Taking into account just the big bound loops and implementing profile gathering on a separate thread both help to decrease the profiling cost.

III. PROPOSED SYSTEM

A. Game map introduction Figure 1 below is the classical map for the MOBA game including League of Legends. There are three lanes on the map which are the top, middle, bottom lane. Each lane is separated into 2 parts for each team. Each lane has 2 defend towers. At the end of each lane, it is the base of each team and consists of 3 defend towers and a Nexus. Between each lane, it is the Jungle where there are jungle minions in it which can provide experience and gold. There are also some elite monsters in the jungle. They are dragons and heralds which can bring great benefits to the team who kills them.

Fig 1. The general map for the MOBA games

B. Debut of the Dataset The average length of a League of Legends match is between thirty and forty-five minutes. The dataset

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

utilised in this study collects information from the first 10 minutes of various games to guarantee the model's accuracy and make the prediction usable in e-sports games. Each and every one of the diamond-ranked games in the dataset. In addition, there are over 10,000 data in the set to provide sufficient data for training. The first ten minutes of the game are recorded in great detail in the dataset, which has 40 columns. When it comes to section C, "data processing and visualisation," the first order of business is to remove any duplicate or erroneous values. Thankfully, this dataset does not include any duplicate or missing information. Because the dataset has so much information. In this study, it is crucial to choose the right characteristics. Some elements that will be helpful for this project are listed in Table 1.

Different teams have different game paces. Moreover, some champions can dominant the game at the early stage which may affect the accuracy of the model. So, several features are standardized to make it easier to compare their differences. The main standardized function is shown below:

$$\text{Standardized ratio } = \frac{blue\ data - red\ data}{blue\ data + red\ data}$$

In this research, this function is used to standardize the following features: blue Kills, blue Assists, blue Wards Placed, blue Wards Destroyed, blue Total Gold, blue Total Experience, blue Avg Level, blue Total Jungle Minions Killed, blue Total Minions Killed, red Kills, red Assists, red Wards Placed, red Wards Destroyed, red Total Gold, red Total Experience, red Avg Level, red Total Jungle Minions Killed, red Total Minions Killed. Because the features of elite monsters, dragons, heralds and first blood are so close to each other. So, they haven’t been standardized it. Then the processed data is visualized in the following figures.

IV. CONCLUSION

The vote classifier has a test accuracy of 0.72638, leaving room for development. A more comprehensive dataset that meticulously logs data at each game level will be used in future studies. Every step in the process is compared to others to establish which one is crucial. The games in which a champion's performance was recorded against another champion will be analysed in detail by the dataset. Next, we'll use the available game data to train an algorithm that can provide guidance at any point in time.

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

ACKNOWLEDGMENT

First, I want to express my deep appreciation to the university teachers who have provided me with invaluable guidance throughout the algorithm selection phase and who have helped me to overcome some coding challenges. Second, I'd want to express my appreciation to our teaching assistant Kunyu An, who was instrumental in helping me settle on the subject of my study: using machine learning to analyse League of Legends. Finally, I'd want to express my gratitude to my loved ones, who, without their support, I would not have been able to see this project through to fruition.

REFERENCES

[1] Mora-Cantallops, M., & Sicilia, M.-Á. (2018). MOBA games: A literature review. Entertainment Computing, 26, 128–138. https://doi.org/10.1016/j.entcom.2018.02.005

[2] Xia, B., Wang, H., & Zhou, R. (2019). What contributes to success in MOBA games? an empirical study of defence of the ancients 2. Games and Culture, 14(5), 498-522. https://doi.org/10.1177/1555412017710599

[3] Hodge, V. J., Devlin, S., Shepton, N., Block, F., Cowling, P. I., & Drachen, A. (2021). Win prediction in multiplayer esports: Live professional match prediction. IEEE Transactions on Games, 13(4), 368-379. https://doi.org/10.1109/TG.2019.2948469

[4] Akhmedov, K., & Phan, A. H. (2021, June 3). Machine learning models for DOTA 2 outcomes prediction. arXiv.org. Retrieved January 9, 2022, from https://arxiv.org/abs/2106.01782v1

[5] Do, T. D., Wang, S. I., Yu, D. S., McMillian, M. G., & McMahan, R. P. (2021). Using machine learning to predict game outcomes based on player-champion experience in League of Legends. The 16th International Conference on the Foundations of Digital Games (FDG) 2021. https://doi.org/10.1145/3472538.3472579

[6] Semenov, A., Romov, P., Korolev, S., Yashkov, D., & Neklyudov, K. (2017). Performance of machine learning algorithms in predicting game outcome from drafts in Dota 2. Communications in Computer and Information Science, 26–37. https://doi.org/10.1007/978-3-319-52920-2_3

[7] Costa, L. M., Mantovani, R. G., Monteiro Souza, F. C., & Xexeo, G. (2021). Feature analysis to league of legends victory prediction on the picks and bans phase. 2021 IEEE Conference on Games (CoG). https://doi.org/10.1109/cog52621.2021.9619019

[8] Prasadu Peddi (2017) "Design of Simulators for Job Group Resource Allocation Scheduling In Grid and Cloud Computing Environments", ISSN: 2319- 8753 volume 6 issue 8 pp: 17805-17811.

[9] Lin, L. (2016). League of Legends Match Outcome Prediction. Retrieved January 10, 2022, from http://cs229.stanford.edu/proj2016/poster/Lin-LeagueOfLegendsMatchO utcomePrediction-poster.pdf

[10] Michel's fanboi, "League of Legends Diamond Ranked Games (10 min)", Kaggle, April 13, 2020, https://www.kaggle.com/bobbyscience/league-of-legends-diamond-rank ed-games-10-min

INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

[11] Prasadu Peddi (2023), Using a Wide Range of Residuals Densely, a Deep Learning Approach to the Detection of Abnormal Driving Behaviour in Videos, ADVANCED INFORMATION TECHNOLOGY JOURNAL, ISSN 1879-8136, volume XV, issue II, pp 11-18.

[12] Naga Lakshmi Somu, Prasadu Peddi (2021), An Analysis Of Edge-Cloud Computing Networks For Computation Offloading, Webology (ISSN: 1735-188X), Volume 18, Number 6, pp 7983-7994.