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# Feature Analysis to League of Legends Victory Prediction on the Picks and Bans Phase

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***Abstract*—Victory prediction in online video games has become an important application for machine learning due to the large amount of data generated by these games and their growing popularity. The creation of professional leagues also drives these applications, as teams want to know their chances of victory and know what are the determining factors to achieve it. Thus, in this research, we analyze whether pre-game information can be explored for victory prediction of professional matches of League of Legends (LoL), one of the main MOBA games. In experiments, we benchmarked different feature sets and algorithms to assess the victory predictions in LoL. The results show that historical performance information is the most accurate features for performing this task. The induced models, especially Random Forest and Logistic Regression, achieved AUC values of** $0.97$**.**

***Index Terms*—League of Legends, Feature Analysis, Esports, Victory Prediction**

## I. Introduction

Esports match prediction is usually treated with one of two approaches. First, as a classification problem in which there are two classes (win or lose, for example) to be predicted. Second, it can be treated as a regression problem, i.e., the task is to predict a continuous value based on the input variables. Win prediction can be done by using the historical performance of the teams, characters data, match features, among many other characteristics. Nonetheless, to obtain an effective prediction model, one must know the set of features that is more adequate to the problem. Features in Machine Learning (ML) algorithms are quite important since the quality of them in a dataset has a significant impact on the value of the insights that will be gain from the model. However, depending on the different prediction problems in several domains, one of the most critical tasks is to understand the goal of the application as a match prediction in esports.

Although some articles document different algorithms for the prediction activity in Multiplayer Online Battle Arena (MOBA) games [1] [2] [3], little attention has been given to analyze the set of features and its importance in the game context [4]. Thus, the main purpose of this research is to analyze whether information obtained during the Picks and Bans Phase are valuable ML features for victory prediction of League of Legends professional matches.

League of Legends[1] (LoL) is a MOBA game developed and published by Riot Games. Each match has two teams (red and blue) of five players fighting across three lanes. The main objective of the game is to destroy the enemy nexus, a structure localized on the base of each team, while simultaneously defending theirs. Before the match begins, players must select a character (also known as champion) before the match begins in a step called Picks and Bans Phase.

Due to the growing popularity of LoL, several championships have emerged, for instance, the League of Legends World Championship, which is the biggest in the world. Furthermore, to the millionaire award to the winning teams, the broadcast of the matches attracts fans from all over the world. This scenario also provided different types of studies, including the development of tools[2] and the will to predict results before a match, which is the focus of this research, as well.

This study also aims to obtain an effective prediction model and employ it as a part of a tool that is being developed from our previous research [5] for team recommendation using genetic algorithms. The aim of Costa [5] is to recommend teams based on some players and character attributes. In the future, we wish to provide a tool for League of Legends team recommendation, including the prediction of victory for the suggested team.

This paper is organized as follows: Section II details the related work. Section III presents the experimental methodology. Section IV analyzes the results obtained and discusses the benefits, relevance, and limitations. Finally, Section V makes the concluding remarks and future directions are discussed.

## II. Related Work

Many publications have appeared in recent years studying different ML features for victory prediction on MOBA professional games. Among these studies, most of them analyze the game DOTA 2 [6] or use real-time match information to make predictions [7] [3]. According to our findings, only Ani [4] conducted experiments combining both pre-game information and League of Legends. Despite the general similarity between DOTA and League of Legends, each game has particularities

[1] leagueoflegends.com/
[2] blitz.gg and shadow.gg

(such as roles positions) that make a generalization between both difficult.

Victoria Hodge et al. [6] focus on the audience experience while watching DOTA 2 games and aims to explain professional esports matches to the spectators as the matches progress by accurately predicting the winner throughout the game. The authors used Random Forest and Logistic Regression algorithms in a dataset with more than 5.8K matches for model training. The evaluation occurred in a professional DOTA 2 championship, where an accuracy of 85% was achieved after 5 minutes of gameplay.

Victory prediction throughout the game in League of Legends was also analyzed by Silva, Pappa, and Chaimowicz [3]. It was used a simple Recurrent Neural Network and five different match intervals: from 0 to 5 minutes, 5 to 10, 10 to 15, 15 to 20, 20 to 25. The highest accuracy was obtained in the interval of 20 to 25 minutes, reaching 83.5%. Given that many games are not much longer than this, predicting the result when the game is finishing is a much easier task.

Kim, Lee, and Chung [7] proposed a confidence-calibration method for predicting the winner of League of Legends matches. The authors claim that focusing on achieving accuracy may not be adequate for the esports winner prediction; instead, the predictor should be able to calculate the actual winning probability. Their proposed method achieved the best calibration capability in terms of expected calibration error and maximum calibration error compared to commonly used Platt scaling methods.

Overall, based on the studies found in the literature, we can note that no study has easily replicable results in the context of League of Legends win prediction using pre-game information. Thus, our research stands out by having public datasets with features analyzed and ranked according to their Gini importance, in addition to the benchmark test performed with different algorithms.

## III. Methodology

### A. Datasets Description

We generated a total of five different datasets for the experiments. All of them contain statistics of 2.840 League of Legends professional matches that occurred from 2021/01/01 to 2021/03/23. The difference between them is the set of features used to describe the collected matches. All data was obtained from Oracle's Elixir[3], a portal that has been providing information about professional matches since 2015. The generated datasets are available on Kaggle[4]. A general explanation of them is presented below:

- **Banned Champions dataset:** a total of 11 features that describes details about the champions banned from both teams in each match and the match result. This feature set was obtained from Ani [4] and will be our literature baseline;
- **Picked Champions dataset:** a set with 11 features detailing the champions picked from both teams in each match and the game result;
- **Players Statistics dataset:** it contains pre-game statistics from each player with the picked champion, i.e., win rate percentage (WR), games played (GP), and the ratio of number of kills plus assist over deaths (KDA) with that champion in previous matches. In total, the dataset has 31 features;
- **Picked Champions and Players Statistics dataset:** it merges data from Picked Champions and Players Statistics datasets, totaling 41 features;
- **Complete dataset:** it contains information from all previous datasets. In total, the dataset has 51 features.

All these datasets are binary classification tasks: the last column is the target feature indicating the game result **according to the blue side team**: (1) for a win or (0) for loss. The target feature is the same for all datasets, with a class distribution of 46.37% won by the blue team and 53.63% games won by the red team (0).

As mentioned before, data were obtained from Oracle's Elixir portal. The platform's maintainers provide a CSV file that is updated daily and contains all the professional matches of the year. From this file, we used Python 3 to develop a crawler that aims to obtain information from the performance history of the 10 players involved in each match with the champions they selected for the game in question.

### B. Supervised Classification Algorithms

We conducted a benchmark comparison process using several ML algorithms. The choice was based on their extensive application in multiple predictive tasks and also presenting different learning biases. In this way, the following algorithms were performed in experiments: Logistic Regression (LR), a linear classifier; Decision Trees (DTs), through the CART implementation; Naïve Bayes (NB); k-Nearest Neighbors (kNN) with K = 7 using Minkowski distance measures; Random Forest (RF) with 500 trees and Support Vector Machines (SVMs) with Gaussian kernel. We used the `R` language[5] and the `mlr` [6] [8] along with their default hyperparameter values to implement experiments.

### C. Experiment Design

Each algorithm was performed using a 10-fold cross-validation (CV) resampling with 5 repetitions using different seeds [9]. In addition, the data was stratified to ensure the same distribution of classes on each partition. Since we have a binary classification problem, the Area Under the ROC curve (AUC) [10] performance measure was used to handle different class distributions. The experiments were performed through a laptop with Intel Core i5-9300H 2.4GHz CPU, 16GB memory in the Windows operating system.

## IV. Results

This section presents and discusses the main experimental results regarding victory prediction exploring different algorithms and feature sets.

[3]oracleselixir.com/about

[4]kaggle.com/tekpixo/leagueoflegendsprematch2021

[5]r-project.org

[6]mlr.mlr-org.com

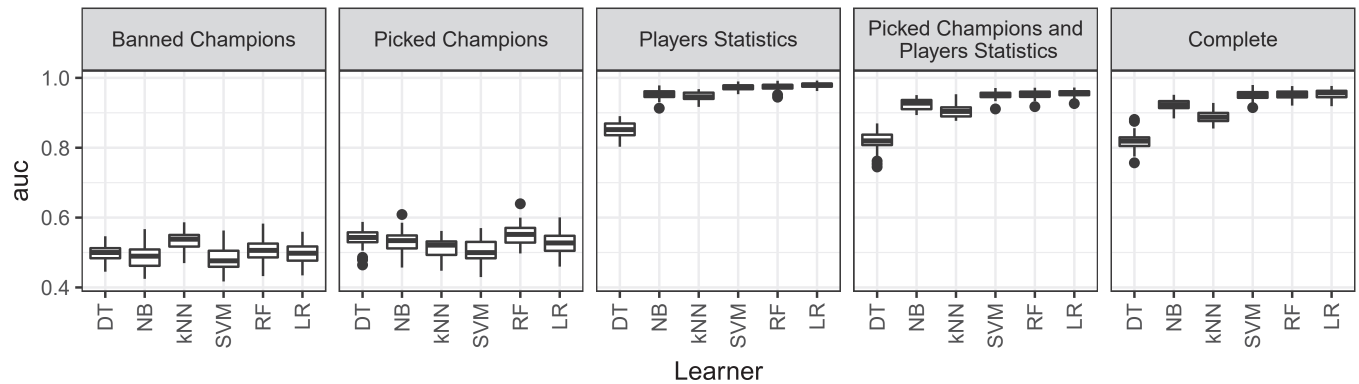


Fig. 1: Benchmarking the selected algorithms with different feature sets. Results are presented in terms of AUC values.

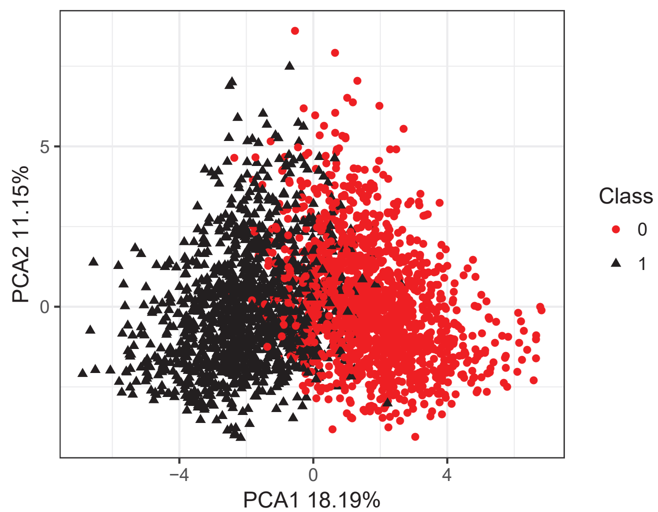


Fig. 2: Data separability projected by the first PCA two components.

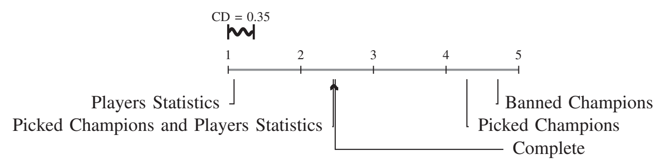


Fig. 3: Comparison of the AUC values of the different feature sets according to the Friedman-Nemenyi test ($\alpha = 0.05$).

## A. Overall results

Figure 1 depicts the average performance values obtained by the induced models in terms of the AUC. Overall, the obtained values in `Banned Champions` and `Picked Champions` datasets were lower than 0.6. Despite the good results presented by other authors [4] using banned champions-based features, the same was not observed here. These features are not descriptive enough to provide useful information of the matches' results, with results close to random guesses (0.5). The LR, RF and SVM algorithms achieved the highest AUC values when performing in the `Complete`, `Picked Champions and Players Statistics`, and `Players Statistics` datasets. In addition, the `Players Statistics` dataset is the smallest one, i.e., and it provides better results reaching an AUC value higher than 0.9 with a lower number of features.

The good results obtained by the Logistic Regression algorithm suggest that the problem is linearly separable. To analyze this possibility, the 11 features of the dataset were condensed through a Principal Component Analysis (PCA). Figure 2 depicts datasets' targets projected into the two most important components. Together, they describe almost 40% of the data variance, indicating that more components are necessary to solve the problem. However, these two first components suggest nearly linear decision boundaries to the problem. It is possible to identify two different dense point cloud representing the different classes, red dots and black triangles. Thus, a hyperplane separating them would classify most of the examples correctly.

The Friedman test [11] was applied to assess the statistical significance of the different feature sets considering a significance level of $\alpha = 0.05$. The null hypothesis states that all the feature sets have equivalent predictive performance. When the null hypothesis is rejected, the Nemenyi post-hoc test is also used to indicate which strategies are significantly different. Figure 3 presents the resultant Critical Difference (CD) diagram. Strategies are connected when there are *no* significant differences between them.

The `Banned Champions` and `Picked Champions` datasets were the worst-ranked ones. Their results are also statistically worse than the other feature sets. On the other hand, the `Player Statistics` features were the best-ranked set, being statistically better than any other feature set. Finally, the `Picked Champions and Player Statistics` and `Complete` feature sets were equivalent, which indicated that adding banned champions features to the other sets does not improve models' performance.

## B. Feature importance

From the induced RF models, the Gini impurity index is used to calculate the node splits [12]. It can be used to measure the relative importance of the features. Figure 4 shows the average relative importance of each feature when using the

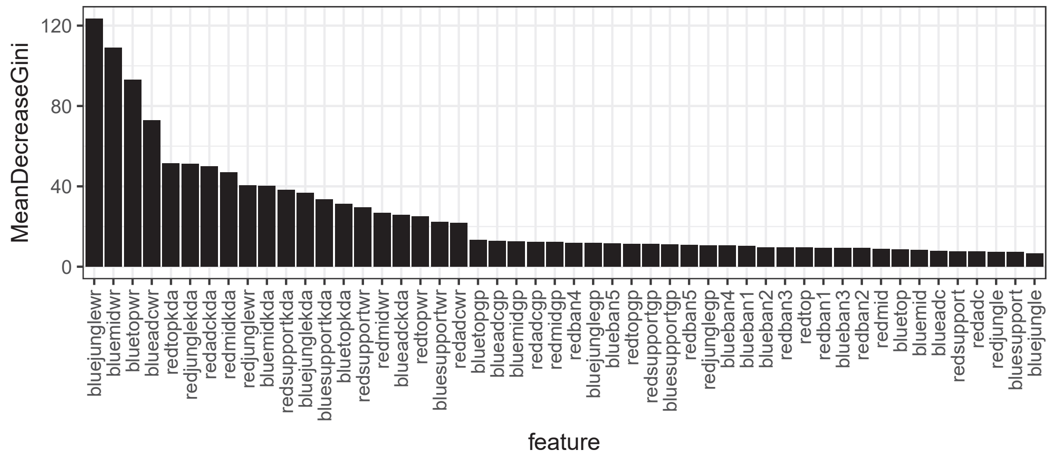


Fig. 4: Average features' relative importance obtained from RF models.

`Complete` dataset. Features are presented on the x-axis in decreasing order according to their values.

The most important features are those related to players' performance in previous games with the selected champion, i.e., their win rate (WR) percentage. The number of games played with the selected champion is also in the performance category. However, his relative importance is smaller, such as champions banned or selected. These results strengthen our hypothesis that information obtained from Picks and Bans Phase are important to victory prediction in LoL. It also shows the importance of the history of the players involved in the game and indicates that only details about banned and picked champions are not relevant in this context.

### C. Final Remarks

Overall, our results are interesting and valuable for players and coaches of professional esports teams since the findings related to feature analysis outperform state of the art and highlight the importance of the performance history of the players involved in the match, as presented by AUC values reached with `Players Statistics` dataset. In addition, the benchmark experiment performed with different supervised classification algorithms corroborates other authors, establishing RF, SVM and LR as the best algorithms for this purpose (victory prediction) comparing with DT, NB, and kNN.

## V. Conclusions and Future Work

Predicting the results of League of Legends professional matches from Picks & Bans phase is a valuable and interesting problem. Our models achieved $0.97$ of AUC using RF and LR algorithms using a dataset with pre-game player statistics. It indicates that reliable prediction of match results is possible in professional League of Legends matches using only pre-game data. Although the performance of this dataset seems obvious, as far as we know these characteristics that consider the performance of players with a certain champion had not been analyzed in previous research.

More research into feature engineering of victory prediction in MOBA games is still necessary before obtaining a definitive answer to each feature relevance. Nevertheless, our research presents results that show that the most important features are players' win rate and KDA (as demonstrated by Ani et al. [4]) with the selected champion, while the least important are the picked champions and the banned ones, different from what was also presented by Ani. Besides that, our results corroborate what was presented by other authors [4] [2] and demonstrate that RF, SVM, and LR are the best algorithms for performance in the League of Legends win prediction scenario.

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