A Data-Driven Approach to Player Evaluation and Ranking in League of Legends Esports

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ABSTRACT

The objective of this study is to create a model that can predict the top-performing players in the League of Legends Champions Korea (LCK) through statistical analysis. Our model was trained using data from the Spring and Summer split seasons of the LCK between 2015 and 2022, and its performance was evaluated using data from the LCK's 2023 Spring season. The rankings produced by our model were then compared to the All-Pro Teams selections, which are determined by a panel consisting of industry experts, media representatives, and fans. Our study aims to determine the top three players in each role according to the performance metrics employed in our model, which include factors such as damage dealt, gold earned, and kill participation. While the limitations of our project include its focus on the LCK and the performance metrics we utilized, our model represents a valuable tool for coaches, teams, and fans to evaluate player performance, despite its inability to account for intangible factors such as player experience, mentality, or team chemistry. The accuracy of our model in predicting top performers suggests that it can be a useful resource for the aforementioned parties.

Keywords: Player metrics, prediction model, machine learning algorithm, League of Legends, ranking system

1. INTRODUCTION

The world of esports has exploded in recent years, with millions of fans tuning in to watch their favourite teams compete on the global stage. One of the most popular games in the esports world is League of Legends (LoL), a multiplayer online battle arena game developed and published by Riot Games. In LoL, players control a champion with unique abilities and battle against a team of other players to destroy the opposing team's nexus, a structure located in the enemy base. The game is played at a high level of competition, with professional players from around the world competing in organized leagues and tournaments for lucrative prizes and recognition.

Player performance evaluation and ranking are of utmost importance in LoL esports as they can provide valuable insights into a player's strengths and weaknesses, and can help teams make informed decisions when selecting players for their rosters. The LoL community uses a variety of methods to evaluate and rank players, including statistics-based rankings, expert evaluations, and fan voting. These rankings are used to identify the top-performing players in the game, as well as to inform team management decisions, such as player trades and roster changes. Despite the importance of player ranking and evaluation, there is still much debate over the best methods to use and which factors should be considered in the evaluation process. This research paper aims to explore the current methods of player evaluation and ranking in LoL esports and to propose new and innovative approaches that can improve the accuracy and usefulness of these rankings.

Our objective is to develop and demonstrate a new statistical framework for player evaluation and ranking in LoL esports. The methodology used for developing this model will involve the use of various data sources and the consideration of relevant variables, and will not focus intensely on hyperparameter tuning. To obtain the necessary data for our model, we utilized various sources, including the Riot-API and private API data from Oracle's Elixir, as the Riot-API does not support pro games. We also incorporated Group Stage MVP rankings from reputable sites such as liquipedia to enhance our data. To ensure accuracy, we adjusted for factors such as team names and player role swaps.

The statistical techniques employed for this project are geared towards accurately evaluating and ranking players based on their performance. This includes the use of regression analysis, neural networks, and other statistical techniques. The ultimate goal is to develop a model that can accurately predict a player's performance and provide an accurate ranking of players in the LoL esports scene. The developed model is compared with other existing methods of player evaluation and ranking in LoL esports. This comparison is important in demonstrating the efficacy of the model in accurately ranking players based on their performance.

2. MOTIVATION

Currently, player evaluation and ranking in esports like League of Legends often rely on expert evaluations and subjective opinions, leading to a lack of standardization and inconsistency in rankings. For instance, in the League of Legends Champions Korea (LCK), the All-Pro Team selections are determined by a panel of industry experts, media representatives, and fans, leading to an amalgamation of subjective opinions and not accounting for objective performance metrics. Although some works have aimed to use a statistical approach for ranking players in esports, there still exists a significant gap in the application of statistical models to evaluate player performance in League of Legends. Our research aims to bridge this gap by utilizing advanced statistical techniques to provide a data-driven approach to evaluate player performance, and rank them objectively based on their in-game statistics. By adopting a more rigorous methodology, our work has the potential to provide a more objective and accurate player ranking that can complement existing methods and offer valuable insights to esports teams, fans, and enthusiasts.

Subjective ratings have been the norm in sports for a long time due to the inherent subjectivity of evaluating a player's performance. Factors such as player chemistry, experience, and mentality cannot be captured by objective statistics, leading to a heavy reliance on expert opinions and subjective evaluations. However, incorporating objective performance metrics in player evaluation can enhance the accuracy and usefulness of rankings, as it provides a more data-driven approach to evaluating player performance. By utilizing a statistical model to analyze player performance, we can supplement existing subjective evaluations with objective performance metrics, leading to a more comprehensive and accurate evaluation of players.

3. RELATED WORKS

The paper by Bahrololloomi et al. (2019)[1] presents a machine learning-based analysis of player performances in League of Legends (LoL) e-sports for winning prediction based on player roles and performances. The authors propose two novel performance metrics based on individual player variables of past LoL matches. The first metric is derived from a machine learning approach while the second metric is based on heuristics derived from the machine learning approach. The authors evaluate the second metric for winning prediction purposes and find that it can predict match outcomes with 86% accuracy. Additionally, the authors evaluate the importance of different roles in LoL teams to the outcome of a match and find that the influence of a particular role on the match's outcome is negligible. The paper highlights the growing demand for in-depth analysis approaches in the e-sports domain, particularly in the MOBA genre with LoL as one of its most successful games. The proposed metrics and evaluation provide insights into the potential use of player and match analyses for our training purposes, as we similarly use individual player data but in the interest of ranking them compared to predicting the winner of a match.

Similar to the above, this paper by ALC Silva et al. (2018)[2] also explores predicting the match outcome but makes use of minute-by-minute analysis instead of overall statistics. By analyzing information about what happens in specific minutes of the game, such as gold advantage and towers destroyed, the authors aim to identify possible win conditions for teams. Such stats also directly correlate to features which we select for rankings players, like the difference in gold versus their lane opponent. The authors compare different types of RNNs and find that a simple RNN is the most effective. Using data from minutes 0 to 5, the accuracy of the RNN model is 63.91%, and using data from minutes 20 to 25, the accuracy increases to 83.54%. The authors use a dataset of 7621 regional and international competitive matches of League of

Legends, which includes information about champions picked, teams in the match, and players' names. This study is the first to use in-game data to predict the outcome of LoL matches and could be useful for teams to identify possible win conditions.

J. McCorey's (2021)[3] thesis and Romero et al.'s (2021)[4] research article both align with our interests in predicting the most valuable player (MVP) in sports using statistical analysis and machine learning techniques. J. McCorey's thesis proposes a framework for accurately forecasting the MVP of the NBA using various machine learning models. Although the study does not account for external factors that may impact MVP rankings, it provides a useful framework for predicting the MVP based on statistical analysis. On the other hand, Romero et al.'s research article focuses on addressing the problem of modelling expert judgment using a data-driven approach, which is subjective and challenging. The authors' approach uses statistical indicators and meta-heuristics to weigh the attributes and choose the MVPs optimally. The study also recognizes the importance of accounting for out-of-field factors that may impact MVP rankings, such as team atmosphere and leadership. Overall, both studies contribute to a new framework for predicting MVPs using statistical analysis and machine learning techniques, with Romero et al. specifically recognizing the importance of accounting for out-of-field factors that may impact MVP rankings.

According to Mora-Cantallops and Sicilia (2019)[5], team efficiency in the League of Legends professional scene is positively affected by the intensity of their interaction while centralization of resources is detrimental. Networks with high intensity and low inner centralization are related to higher team performance not only in traditional sports but also in computer-mediated contexts. The authors note the lack of research on computer-mediated team interactions and efficiency in online competitive environments. They use network analysis as a novel approach to understand the computer-mediated behaviour and social interactions of professional players and link it to their team performance.

S. Donaldson (2017)[6] explores the significance of two types of expertise, mechanics and metagame in LoL. While previous research has explored various expertise models, some focusing solely on mastery of controls and others taking the game's overall context into account, Donaldson's model highlights the importance of both in-game and out-of-game practices in pursuing competitive success in League of Legends. The article further supports the need for out-of-game or 'metagame' expertise to measure competitive success, which we feel is one of the key lacking points of our model.

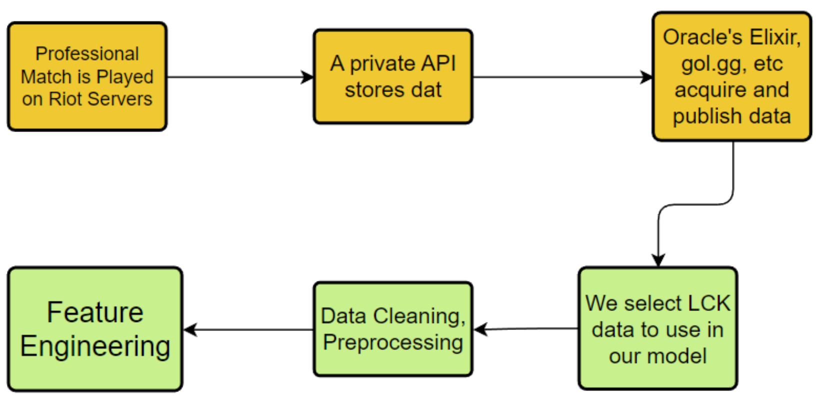
4. PROPOSED WORK

4.1 Data Acquisition and Preprocessing

To evaluate player performance, we first establish a baseline using POG (Player of the Game) points, also called MVP points, and then consider role-specific statistics. Choosing which role-specific stats to use is not straightforward, but we use a combination of human judgment and available data to select the most representative few. Availability of stats is a consideration, as game changes and updates can render old features irrelevant and introduce new ones. For example, the stat STL (Number of neutral objectives like Dragons, Heralds, and Barons stolen by a particular player) was unavailable until recently, despite the feature being present in the game. We choose to use LCK data due to its consistent availability of POG points and BO3 (Best Of 3) format, which ensures we also have a general feeling of a player's reliability. Identifying consistently high-performing players in the LEC and LCS regions is more challenging due to the Best of 1 format, which inherently involves more unpredictability. However, LEC and LCS data can also be used similarly.

We used websites such as Oracle's Elixir [7] to acquire data from pro matches, as the Riot-API does not support pro games[8]. Additionally, we incorporated MVP rankings from reputable sites like Liquidpedia[9] to train our models using MVP Points values as a predictor. Accuracy was ensured by adjusting for factors such as team names and player role swaps.

Image 1*: Data acquisition process*



To account for the impact of game patches on player performance and playstyle, we scaled the data by split. This allowed us to compare performance across different periods while accounting for the impact of game updates. To further explore the differences in player performance across different roles, we attempted to cluster players by role using KNN clustering. Clusters of sizes 2, 3, 4, and 5 were considered and the best silhouette score was taken. However, the obtained silhouette scores of approximately 0.3 with unscaled data and 0.2 with scaled data. This suggests that distinct clustering of different playstyles within a given role was not possible.

Table 1*: Silhouette scores after KNN Clustering within roles*

Role	Scaled Data	Unscaled Data
Top	0.213	0.378
Jungle	0.167	0.326
Middle	0.210	0.323
Bottom	0.226	0.321
Support	0.179	0.267

Note: All roles formed the cluster set with best silhouette score at 2 clusters.

It is worth noting that the availability of data on professional games played on the League of Legends platform is limited, with private API data being one of the only sources for such data. As such, we needed to use a combination of sources to gather the data needed for our analysis.

4.2 DATASETS

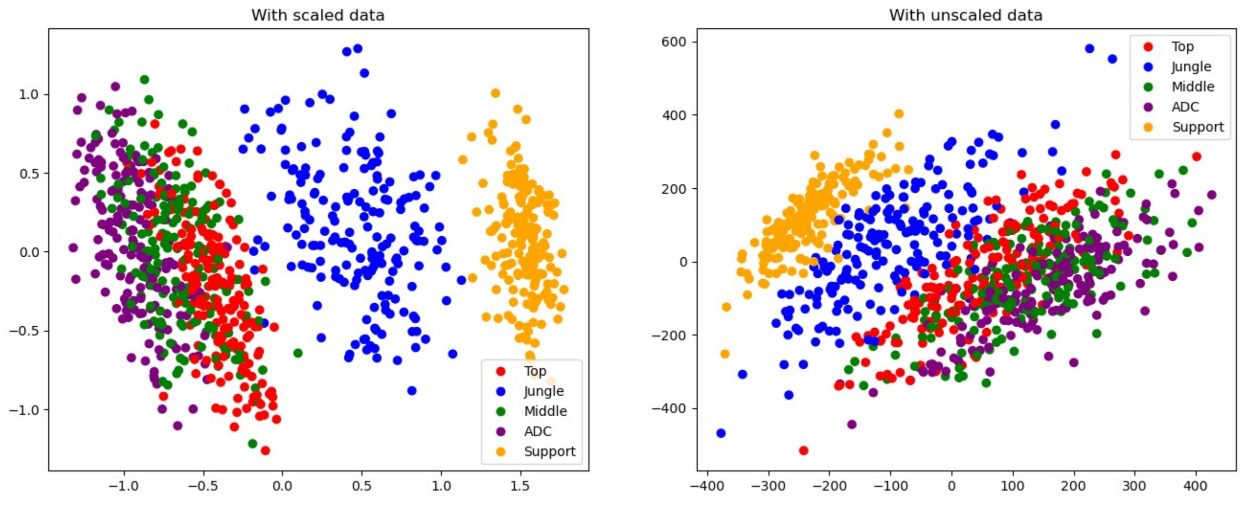
To develop different models and rank players based on their roles, we first conducted a series of tests to verify whether there were significant enough differences between roles to justify using separate models. To visually analyze these differences, we utilized scatterplots based on PCAs 1 and 2. Our results indicated that while Support and Jungle were distinguishable from other roles, Top, Middle, and ADC had some overlap but were also considerably offset from each other.

To assign roles to players based on their data points, we utilized two different models: an XGBClassifier and an LSTM model. These models achieved an accuracy of ~80% and ~75%, respectively.

Table 2*: Accuracy of LSTM and XGBClassifier on categorizing players into their role*

Data	Accuracy	
	XGBClassifer	LSTM
PCA	73..48%	76.79%
Scaled	89.50%	76.79%
Unscaled	88.40%	77.90%

Image 2*: Scatter plot of players along PCA 1 and 2 lines, colour coded by role*



These results further affirmed the significant differences between player roles and supported our decision to use separate models for each role.

Finally, we used a correlation plot and ran Recursive Feature Elimination (RFE) for each role to minimize the noise in the dataset and obtain a list of representative columns for each of our roles. This pre-processing and feature selection process allowed us to create a robust dataset for our model training and evaluation, ultimately contributing to the accuracy and validity of our results.

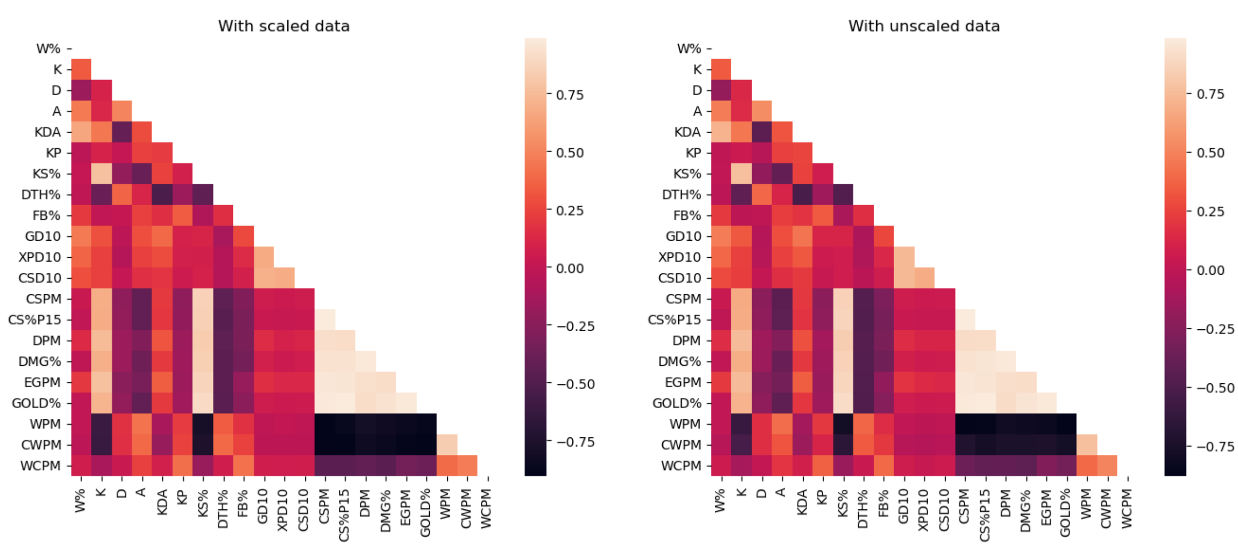
4.3 Model Architecture and Methodology

We first start by mentioning that one of the objectives is developing a new framework, and as such we do not focus extensively on hyperparameter tuning or exact results in predicting the MVP Points values, but rather the rankings obtained.

We do not use black-box models and focus on more transparent, interpretable models through the application of feature selection. This decision is supported by research such as Gilpin et al.(2018)[10], which highlights the importance of being able to provide insights into the behaviour and thought processes of complex machines and algorithms. The interpretable nature of our model enables us to point to a stat and explain why we (our model) rank a player lower than another. We first run a correlation plot to find features with significantly high correlation, dealing with multicollinearity.

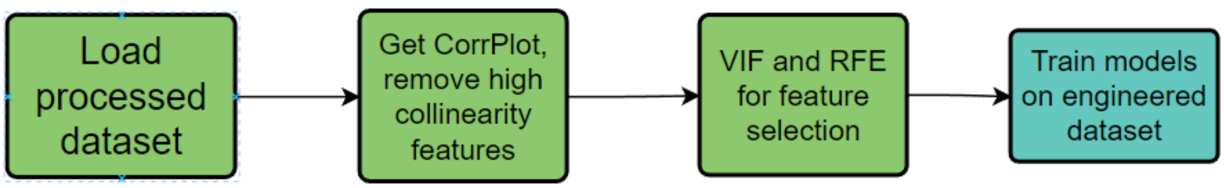
In our modelling approach, we have addressed the issue of high multicollinearity among certain features by removing those that exhibit a very high correlation. It is worth noting that this method of handling high multicollinearity has been the subject of some debate in the literature, as alternative approaches may exist[11]. However, we argue that the features we have removed are essentially redundant and provide overlapping information.

***Image 2**: Correlation Plot of features for both scaled and unscaled datasets*



Specifically, the features we have removed are CS%P15 (Average share of the team's total Creep Score post the 15-minute mark), EGPM (Earned Gold Per Minute), DPM (Damage dealt to enemy champions per minute), and W% (Win percentage). GOLD% is a player's gold as a percentage of the team's total gold. Players with higher Earned Gold Per Minute will also have higher GOLD%, while a higher Creep Score Per Minute is also associated with earning more GOLD. A higher GOLD% typically results in more items and thus, more damage dealt. This relationship between GOLD% and damage dealt suggests a strong correlation between DPM and DMG%. Furthermore, having a higher Creep Share percentage after 15 minutes is also a highly correlated factor, as creeps will typically be 'funnelled' into the team's carry players, who are the ones with high DMG%. The decision to exclude win percentage as a predictor variable is motivated by a desire to mitigate the influence of team performance on individual recognition and as an attempt to isolate player skill and contribution.

Image 3*: Feature Selection process*



It should be acknowledged that the selection of these specific features for removal is somewhat arbitrary, and future work may explore alternative methods for dealing with high multicollinearity in our special case. Nonetheless, our approach has allowed us to effectively address the issue and enhance the interpretability of our model.

We next use a combination of Variance Inflation Factor (VIF) and Recursive Feature Elimination (RFE) to find the ten features most representative of MVP points for each role. RFE recursively removes the least important features, leaving us a set of features for each role. We find the features of Kills (K), WPM (Wards per Minute), and Assists (A) to be amongst the RFE-selected features for each role. Kill participation (KP) is further shared between all roles but Support, and GOLD% is shared between the three roles of Top, Mid, and Bottom.

In this study, we utilized a variety of Neural Networks and Traditional ML models to predict the ranking of players within their respective roles. We trained a total of five Neural Network models, including a basic LSTM with a linear activation function (LL), a basic LSTM with a sigmoid activation function (LS), a stacked LSTM with a Dropout layer (LD), a Convolution (Cnv), and a simple RNN. Our models were decently able to identify relative rankings for Top, Middle, and Jungle roles, but were surprisingly poor performers for the Bottom and Support roles.

Table 3*: Loss, MAPE, and R2 Score for Neural Networks on scaled data, by role*

Role	Loss					MAPE					R2 Score				
	LL	LS	LD	Cnv	RNN	LL	LS	LD	Cnv	RNN	LL	LS	LD	Cnv	RNN
Top	0.04	0.03	0.03	0.03	0.03	0.36	0.37	0.37	0.37	0.42	0.16	0.21	0.19	0.17	0.21
Jgl	0.01	0.01	0.01	0.01	0.01	0.41	0.44	0.42	0.42	0.42	0.40	0.34	0.37	0.34	0.34
Mid	0.03	0.03	0.03	0.03	0.03	0.39	0.45	0.43	0.42	0.47	0.31	0.35	0.42	0.41	0.40
Bot	0.06	0.05	0.06	0.05	0.05	0.26	0.28	0.26	0.28	0.29	-0.49	-0.10	-0.30	-0.12	-0.05
Supp	0.02	0.03	0.02	0.02	0.03	0.31	0.30	0.31	0.32	0.30	0.08	-0.02	0.04	0.07	-0.11

Note: results for unscaled data are significantly worse

Each neural model was trained on data from each role separately, resulting in 25 such models, i.e; a basic LSTM model with linear activation function would have a separate output model for the Top, Jungle, Mid, Bottom, and Support roles.

The basic LSTM model consisted of a single LSTM layer with 32 units and a linear activation function. The second basic LSTM model had a sigmoid activation function. The stacked LSTM model consisted of two LSTM layers with 32 and 16 units, respectively, and a Dropout layer with a dropout rate of 0.2. The Convolution model had one Conv1D layer with 64 filters and a kernel size of 3, followed by a MaxPooling1D layer with a pool size of 2 and a Flatten layer. The simple RNN model consisted of a single SimpleRNN layer with 32 units. These models were compiled using the 'mean_squared_error' loss function and the 'adam' optimizer.

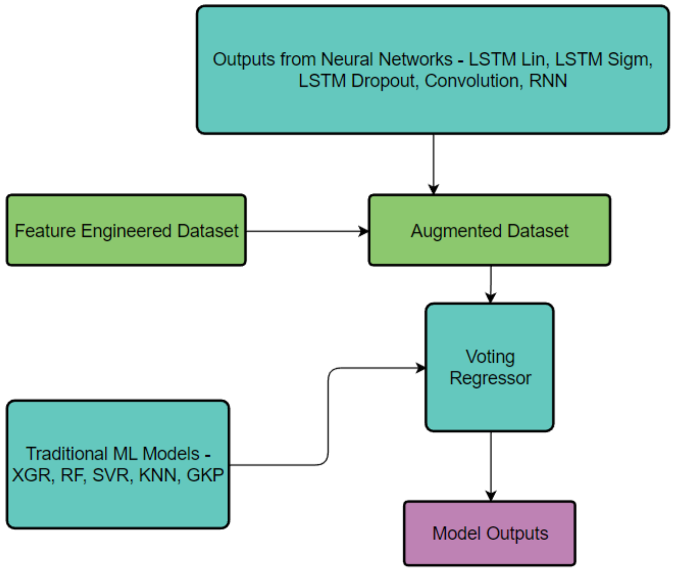
In addition to the Neural Networks, we employed Traditional ML Models, including XGRegressor, Random Forest (RF), Support Vector Regression (SVR), K-Nearest Neighbors (KNN), and Gaussian Process Regression (GPK). We similarly executed these models to the neural networks and found that they typically performed similarly overall. These models had lower Mean Absolute Percentage Error (MAPE), slightly higher Mean Squared Error (MSE), and similar or better R2 scores. Interestingly, our ML models seem to perform significantly better in ranking Top and Support roles compared to our neural networks.

Table 4*: Loss, MAPE, and R2 Score for ML Models on scaled data, by role*

Role	Loss					MAPE					R2 Score				
	XG	RF	SV	KNN	GPK	XG	RF	SV	KNN	GPK	XG	RF	SV	KNN	GPK
Top	0.03	0.03	0.05	0.03	0.08	0.35	0.33	0.35	0.31	0.45	0.24	0.28	-0.24	0.21	-0.89
Jgl	0.02	0.01	0.03	0.02	0.04	0.31	0.26	0.35	0.37	0.46	-0.04	0.35	-0.41	-0.27	-0.90
Mid	0.01	0.02	0.03	0.03	0.06	0.22	0.23	0.30	0.27	0.33	0.62	0.56	0.18	0.34	-0.36
Bot	0.04	0.04	0.06	0.04	0.06	0.28	0.30	0.37	0.34	0.41	0.02	0.00	-0.51	-0.10	-0.46
Supp	0.03	0.01	0.02	0.02	0.07	0.36	0.28	0.35	0.25	0.49	-0.36	0.28	-0.08	0.16	-1.87

The XGRegressor model had 100 estimators and a learning rate of 0.1. The RF model also had 100 estimators and a maximum depth of 7. The SVR model used the 'rbf' kernel with a regularization parameter C of 1e3 and a gamma value of 0.1. The KNN model had 5 neighbours.

Image 4: *Full Model working*



Our main objective is to accurately rank players within their respective roles, rather than solely predicting MVP points. Combined with our threefold ranking methodology, the numerical output generated by our models is not of primary concern as long as the final rankings are reliable and valid. We are confident in the effectiveness of our models and will elaborate on their accuracy in the following discussion.

Finally, we created an Ensemble Model using a VotingRegressor to combine our Traditional ML models. To incorporate our Keras Neural Networks, we passed the outputs from the networks as a feature along with the other selected features. By augmenting the dataset in this manner, we can send the combined features to the Voting Regressor to obtain a final output. Using this method, we can ensure that our model is interpretable and also accounts for hidden patterns and combinations that a neural network may find.

Table 5: *Loss, MAPE, and R2 Score for ensemble model on scaled data, by role*

Role	Loss	MAPE	R2 Score
Top	0.03	0.30	0.15
Jungle	0.02	0.31	0.07
Middle	0.03	0.27	0.37
Bottom	0.04	0.32	-0.14
Support	0.02	0.27	0.15

We utilized a threefold ranking method to create our final rankings. We first use expert opinions in the form of MVP ratings of each player to assign them a rank. Players with higher MVP ratings in the same role are ranked higher than players with lower MVP ratings. We follow this up by using a percentile-based approach, where the RFE-selected features for each role are used to find the rank of the players within each feature. We account for variables where a high value should equate to lower rankings like the Number of Deaths (D), following which we take the average of these ranks to sort and assign our second rank.

We finally use our model to generate the player rankings within their respective roles. The model outputs are sorted and rankings are thus assigned. To combine our three ranking schemes, we take the average and convert the results to a final ranking of our players.

5. NOVELTY

The novelty in this work is the development of a predictive model that uses a combination of machine learning algorithms and statistical analysis techniques to rank professional League of Legends players in the Korean league (LCK) based on their in-game statistics, while also taking into account expert opinions and percentile rankings based on the performance of other players in each role. The study also explores the differences between player roles and uses various models, including Neural Networks and Traditional ML Models, to predict player rankings within their respective roles. The use of an Ensemble Model to combine the predictions from the various models is also a unique aspect of this work.

6. RECOGNIZED ISSUES

1. Stat Availability: While our model uses various performance metrics to rank players, it relies on the availability of those metrics in the training dataset. However, certain stats may not be available for different regions or leagues. For example, datasets from the LPL may lack certain stats like FB% or CSD10, which could impact the accuracy of our predictions.
2. Feature Selection: In the process of feature selection for our model, the ability of features to accurately predict MVP points is given primacy, potentially resulting in the selection of features that are not conventionally used for evaluating specific roles. For instance, evaluating the Bottom role using WPM, CWPM, or WCPM may seem counter-intuitive and can lead to unexplainable choices, complicating the justifications for player rankings. Additionally, the impact of removing high collinearity features warrants further exploration.
3. Limited Model Adaptation: Our model ensemble may not account for the differences in performance between different regions or leagues. In the interest of simply proposing a new framework, we do not weight the outputs based on any loss function and use arbitrary weightings based on visual analysis to compare different models. This limited model adaptation can lead to suboptimal results when evaluating players from different

regions, which may have different criteria, playstyles[12] or cultures around choosing the MVP players.

4. No Accounting for Picks: In professional League of Legends, teams often prioritize certain champions based on their strength in the current meta and their team composition. This can result in certain players being consistently put on champions that are considered "priority picks" or "power picks", while others may be put on champions that are considered weaker or less impactful in the current meta. Consequently, players in other positions may be relegated to utilizing champions with a lower performance ceiling or may find themselves struggling against counter matchups, both of which can adversely affect their statistical performance [13]. Furthermore, some champions may have high win rates in certain positions, but may not necessarily be considered "carry champions" in the traditional sense. For example, a tanky support champion that provides a lot of crowd control and protection for their team may not have high damage or kill participation stats, but can be crucial in team fights and in helping their team secure objectives. Our model may not fully capture the value of these types of champions and the players who excel at playing them.

7. RESULTS

The data utilized for testing our model is the Spring 2023 LCK data. To evaluate the efficacy of our model, we compared our rankings with the All-Pro Teams from the same split. The All-Pro Team is a prestigious annual recognition awarded to the top-performing professional League of Legends players in the Korean league (LCK). The selection process involves voting by a panel of industry experts, media representatives, and fans to identify the most outstanding players in various positions throughout the Spring Split season. The All-Pro Team represents the pinnacle of individual achievement in the LCK and serves as a benchmark for evaluating player performance. There are three such teams each split, namely the First, Second, and Third All-Pro Teams.

To compare our results with the All-Pro Teams, we consider the first-ranked individual in each role to be a part of the First All-Pro Teams, and the same for the second and third-ranked players.

The top 3 players according to the All-Pro Teams are the following [14]

***Table 6**: LCK Spring 2023 All-Pro Teams*

All-Pro Team	Top	Jungle	Middle	Bottom	Support
First Team	Zeus	Oner	Faker	Gumayusi	Keria
Second Team	Kiin	Peanut	Chovy	Deft	Kellin
Third Team	Doran	Canyon	Bdd	Peyz	Lehends

Our model gives the following results

***Table** 7: Model-generated All-Pro Teams*

All-Pro Team	Top	Jungle	Middle	Bottom	Support
First Team	Kiin	Oner	Chovy	Viper	Keria
Second Team	Doran	Peanut	ShowMaker	Deft	Kael
Third Team	DuDu	Canyon	Faker	Peyz	Kellin

Note: Red indicates player not in expert-ranking, Yellow indicates player is in expert ranking but has a different rank, Green indicates player with the same rank as expert ranking

Our rankings contrast with the All-Pro Teams as follows.

- Top: Kiin and Doran were ranked first and second, respectively, with Zeus as a close fourth.
- Jungle: Oner, Peanut, and Canyon were ranked in the same order as the All-Pro Teams.
- Middle: Chovy and Faker were identified as the top performers, with ShowMaker replacing Bdd in the top three.
- Bottom: Our rankings identified Viper as the top performer, with Deft and Peyz ranked second and third, respectively. Gumayusi was ranked sixth in our rankings.
- Support: Keria and Kellin were ranked as the top performers, with Lehends ranked fifth and Kael replacing him in the top three.

It is worth noting that all players from team 'T1' were included in the First All-Pro Team selected by experts, which is an unprecedented feat. The differences between our rankings and the All-Pro Teams may be due to nuances or other factors that our model does not account for, which we discuss below.

7.1 Possible Explanations for Model Deficits

While our model has shown high efficacy in predicting top-performing players, it is necessary to recognize its inherent limitations.

One of the major challenges is the overlapping of statistics with an inherently limited nature across different roles. For instance, a player's kills or GOLD% may be low simply because they have another player on their team who gets 'funnelled' the kills. This may lead to an unwarranted loss in rankings for the first player.

Another limitation of our model is the inability to account for intangible factors that can significantly impact a player's performance, such as team chemistry and mental state. While we take into account various performance metrics, our model cannot consider other important factors such as player experience or degree of comfort while playing certain champions.

It is also important to note that our model does not consider factors such as a player's effect on a team's atmosphere, strategizing skills, and leadership qualities, which can greatly influence their ranking. For example, ex-pro player Huni mentioned how Faker's ability to call plays minutes in advance and set up the team for success had a significant impact on their performance[15]. While our model can provide valuable insights into a player's performance based on in-game statistics, it cannot fully capture the nuances of a player's impact on their team.

8. CONCLUSIONS

Our novel framework for evaluating the performance of professional League of Legends players has produced promising results, showcasing a high degree of correlation with expert rankings. By incorporating a wide range of performance metrics, including traditionally neglected ones such as wards placed per minute, we have developed a more comprehensive approach to ranking players which enabled us to correctly generate 11 of the selected top 15 players, with two more being ranked a close fourth by our model. Our ensemble model, which combines the outputs of multiple individual models, provides a robust evaluation of player performance across all positions. The relative ranking is maintained in 4 out of 5 cases when comparing the correctly chosen players, only failing for the case of Midlane where Faker is ranked below Chovy. While acknowledging limitations such as the availability of certain statistics and the model's inability to account for intangible factors, our framework offers a valuable tool for evaluating player performance. Overall, our results demonstrate the potential of our approach to accurately rank players and highlight the importance of considering a broad range of metrics in evaluating player performance in League of Legends.

9. FUTURE WORK

Moving forward, there are several avenues for expanding upon the present research to enhance the accuracy and reliability of our novel framework for evaluating the performance of professional League of Legends players. One potential area of exploration is the development of new metrics that capture previously unmeasured aspects of player performance. For example, future research could investigate the incorporation of new statistical measures that better account for a player's ability to create and exploit opportunities, such as measures of map pressure or strategic decision-making. Additionally, there is potential for more sophisticated machine learning models to be applied to more precisely and flexibly capture the complex relationships between a player's performance and their role within the team.

Another area for future investigation is the refinement of existing metrics to reduce the impact of the limitations discussed above. For example, further research could focus on identifying and accounting for the influence of pick-and-ban strategies on player performance or developing more sophisticated methods for evaluating the impact of different roles and positions. Additionally, more advanced statistical techniques could be used to address the collinearity issues that arise when using certain metrics to evaluate player performance.

It is also possible to consider expanding the scope of our model to include other factors that influence player performance. For example, the research could investigate the impact of factors such as team dynamics, communication, and player mindset on individual player performance, and how they interact with various performance metrics. Finally, given the importance of understanding the nuances of player performance in competitive gaming, further research could focus on developing more comprehensive frameworks for evaluating player performance, incorporating both quantitative and qualitative measures.

Overall, there are many avenues for future research in this area, and continued development of our framework will require an interdisciplinary approach that combines expertise from fields such as statistics, computer science, and psychology. Through continued research and development, we can further enhance our understanding of the complex relationships between player performance and team success in League of Legends, and provide valuable insights into the world of competitive gaming.

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Appendix

Code Repository: https://github.com/AdvaitDeochakke/DataDriven_LCK_Analysis