



## **Meta Insights: Analyzing Hero Performance in Mobile Legends with K-Nearest Neighbors**

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**Abstract.** This research presents a thorough statistical analysis of hero performance in the latest Mobile Legends meta, employing the K-Nearest Neighbor (KNN) algorithm. Utilizing diverse data sources, the study explores factors influencing hero success, leveraging KNN's ability to identify intricate patterns in complex datasets. Through meticulous data collection, preprocessing, and application of the KNN algorithm, the research classifies and predicts hero performance based on similarities with neighboring heroes. Critical determinants such as win rates, popularity, and hero ban rates emerge, providing profound insights into gameplay strategies. The study emphasizes the importance of understanding meta dynamics, hero attributes, and player expertise for informed decision-making in hero selection within the dynamic landscape of Mobile Legends.

**Keywords:** Mobile Legends; K-Nearest Neighbors; Hero Performance; Latest Meta; Statistical Analysis; Gameplay Strategies

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### **1. Introduction**

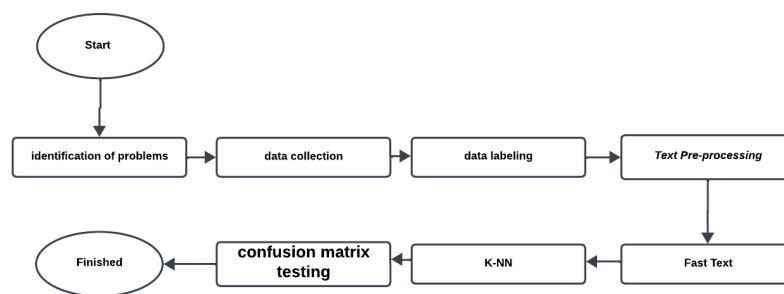
In the ever-changing landscape of online battle arena (MOBA) gaming, Mobile Legends has emerged as a prominent game, demanding players to showcase tactical skills and strategic thinking in hero selection and utilization. Maintaining an edge in the evolving meta is crucial for strategic advantage in Mobile Legends, given the dynamic nature of the game that requires constant adaptation. This research aims to contribute significantly to the field by conducting an in-depth statistical analysis of hero performance in Mobile Legends, with a specific focus on the latest meta. To achieve this objective, the study will leverage the K-Nearest Neighbor (KNN) algorithm due to its ability to classify data based on similarity, making it a potent tool for identifying complex patterns and relationships within the extensive dataset of hero statistics.[1] Aligned with the multidimensional nature of hero performance metrics in Mobile Legends, including win rates, pick rates, and kill-to-death ratios, KNN excels in identifying patterns by considering the proximity of data points in this multidimensional space. This approach promises a nuanced understanding of hero interactions and effectiveness within the current meta, surpassing conventional observations. [2] The research not only aims to uncover trends but also intends to explore the implications of these findings on strategic decision-making in Mobile Legends.

By harnessing the potential of the KNN algorithm, the analysis seeks to offer a profound understanding of the underlying dynamics that influence hero success. [3] The methodology involves the collection and analysis of extensive datasets, capturing the nuances of hero performance in diverse in-game scenarios. Essentially, the combination of advanced statistical analysis and the KNN algorithm promises to illuminate the intricate tapestry of hero performance, providing a valuable resource for players, analysts, and enthusiasts navigating the constantly evolving landscape of Mobile Legends.[17] Additionally, this section will discuss specific techniques used to demonstrate the performance of the KNN algorithm, providing a thorough explanation of why KNN was chosen and offering a more detailed insight into how this algorithm is implemented in the context of this research. This aims to provide a comprehensive and in-depth overview for readers regarding the contribution and utility of KNN in analyzing hero performance in Mobile Legends.

## 2. Methods

### 2.1. Research Stages

The research on hero performance data in Mobile Legends was conducted through a systematic and comprehensive process outlined in Figure 1, illustrating the flowchart of the data analysis process.



**Figure 1.** Flowchart. Data Analysis Process

The initiation of the research involved an exhaustive collection of hero performance data from diverse and reliable sources, including official game repositories, player databases, and esteemed community-driven platforms specializing in sharing in-game statistics. [9] This comprehensive approach aimed to gather a wealth of attributes and relevant statistics for Mobile Legends heroes, forming the basis for subsequent analyses and ensuring a holistic understanding of hero performance.

Following data collection, the collected dataset underwent a rigorous preprocessing phase to validate and ensure its integrity, mitigating potential inconsistencies or errors. This critical step involved meticulous preparation of the data, establishing a robust foundation for meaningful analysis.

### 2.2. Algoritma K-Nearest Neighbors (KNN)

The KNN method was applied to analyze hero performance. This approach allows us to classify and predict performance based on similarity with other heroes in the dataset.[9] K-Nearest Neighbors algorithm, a non-parametric and instance-based learning method, was chosen for its capability to make predictions based on the proximity of instances in a multidimensional feature space. This method operates on the principle that instances with similar features are likely to share similar outcomes.[2]

To implement the KNN algorithm for hero performance analysis, a thorough examination of the dataset was conducted to identify relevant features and establish a meaningful similarity metric. Subsequently, the algorithm was applied to classify and predict the performance of each hero by considering the characteristics and attributes shared with its nearest neighbors.

The selection of an appropriate value for the 'k' parameter, representing the number of neighbors to consider, was a crucial aspect of the implementation. This value was determined through a systematic evaluation process, considering the dataset's characteristics and the desired level of granularity in performance analysis.

The outcomes of the KNN algorithm were then assessed and validated through rigorous testing procedures, ensuring the reliability and accuracy of the performance predictions. The results obtained from this implementation provided valuable insights into the relationships and patterns within the hero dataset, contributing to a more nuanced understanding of hero performance dynamics[19].

$$dis(x_1, x_2) = \sqrt{\sum_{i=0}^n (x_{1i} - x_{2i})^2}$$

**Figure 2.** K-Nearest Neighbors Formula

The distance  $d$  between instances  $X_i$  and  $X_j$  in a feature space is often calculated using the Euclidean distance formula:

$$d(X_i, X_j) = \sqrt{\sum_{l=1}^n (X_{il} - X_{jl})^2}$$

where  $n$  is the number of attributes.

The classification probability for an instance  $I_{ij}$  belonging to class  $C_{cl}$  is computed as follows:

$$P(I=ij|C=cl) = \frac{k}{\sum_{l=1}^k P(I=ij|C=cl)}$$

Explanation:

- $p(I=ij|C=cl)$ : Probability of instance  $ij$  given class  $cl$  based on the k-nearest neighbors.
- $p(C=cl)$ : Prior probability of class  $cl$  in the dataset.

In the context of predicting hero characteristics in MPL Season 12, the KNN algorithm can be applied to features such as Hero Type, Hp Hero, Mana Hero, Defend Hero, and Attack Hero. The algorithm predicts the characteristics of a hero based on the attributes of its k-nearest neighbors in the dataset, considering factors like weapon utilization, health power, mana usage, defense, and attack statistics. The choice of  $k$  influences the granularity of the predictions, with smaller  $k$  values providing more local predictions and larger  $k$  values offering a broader perspective.

### 3. Results and Discussion

Embarking on a thorough examination of our study's methodologies, we delve deep into the nuanced analysis of hero performance within the dynamic Mobile Legends meta. At the heart of our investigative approach lies the strategic utilization of the K-Nearest Neighbors (KNN) algorithm, renowned for its adeptness in deciphering intricate patterns within multidimensional datasets.

The primary objective of our study is to conduct a comprehensive statistical analysis of hero performance in Mobile Legends, with a keen focus on unraveling the subtleties of the latest meta. The deliberate choice of the KNN algorithm is grounded in its non-parametric and instance-based learning capabilities, making it particularly well-suited for predicting outcomes based on the proximity of instances within a multidimensional feature space. The rationale behind opting for KNN lies in its efficacy in analyzing the multifaceted nature of hero performance metrics in the dynamic Mobile Legends landscape. The algorithm operates on the principle that instances with similar features are likely to exhibit comparable outcomes, proving invaluable in a context where hero performance is intricately influenced by factors such as win rates, pick rates, and kill-to-death ratios. Thus, the KNN algorithm becomes instrumental in unraveling complex patterns, providing nuanced insights into hero interactions

and effectiveness within the current meta. [12]. The core formula guiding the KNN algorithm for predicting outcomes is succinctly expressed as:

$$Y = \text{mode}(Y_i)$$

where:

- $Y$  signifies the predicted outcome for a given hero.
- $Y_i$  represents the outcomes of the  $k$  nearest neighbors.

The essence of the KNN algorithm lies in predicting outcomes based on the majority class of nearest neighbors. Our research journey begins with the meticulous collection of hero performance data from diverse and reliable sources, including community data-sharing platforms. This dataset, comprising various attributes like win rates, popularity, HP, attack speed, and magical power, forms the foundation for our analysis. Before applying the KNN algorithm, we undergo a critical preprocessing phase to ensure dataset integrity, eliminating inconsistencies or anomalies. With the dataset curated, we employ the KNN algorithm to unveil hero performance intricacies in Mobile Legends, considering factors like win rates and specific hero characteristics. The algorithm's effectiveness is evident in uncovering complex patterns, providing nuanced insights into hero interactions within the dynamic meta. Our study contributes to mobile gaming's evolving landscape by enhancing understanding of hero attributes and in-game performance dynamics. This empowers players, aids analysts in strategy formulation, and offers valuable insights to game developers for refining the gaming experience. In essence, our research enriches the dialogue on mobile gaming dynamics, augmenting collective knowledge within the gaming community.

HERO	WIN	POPULARITY	BANNED	HP	Physical Attack	Physical Defense	Attack Speed
Rafaela	56.94%	1.33%	15.38%	2571	124	18	1
Ixia	55.14%	1.10%	5.83%	2620	113	17	1.3
Mathilda	54.97%	0.47%	66.24%	2651	120	22	1
Lolita	54.80%	0.57%	31.75%	3051	115	30	0.98
Terizla	54.70%	1.51%	2.08%	2728	159	25	1
Irithel	54.59%	1.96%	1.25%	2540	132	17	1.23
Yi Sun-shin	54.49%	0.25%	0.06%	2570	114	22	1.03
Baxia	54.15%	0.43%	0.62%	3369	125	39	1
Edith	54.05%	1.57%	3.44%	3149	110	27	1.04
Argus	54.03%	0.23%	0.17%	2628	118	21	1.19
Minotaur	53.60%	0.52%	0.46%	3459	123	34	0.91
Belerick	53.42%	0.64%	0.63%	3641	110	25	1.01
Benedetta	53.40%	0.53%	0.26%	2569	131	18	1.11
Hylos	53.40%	0.28%	0.09%	3309	105	33	1.03

**Table 1.** Dataset Hero

Critical Chance	Mana	Magic Power	Magical Defenses	Cooldown Reduction	Movement SPD	MYTHIC+
0%	680	8	17	10%	330	HIGH
0%	440	0	15	0%	300	LOW
0%	430	38	15	5%	325	HIGH
0%	480	0	25	0%	335	HIGH
0%	430	0	21	0%	318	HIGH
0%	0	0	15	0%	325	HIGH

5%	438	0	15	0%	320	LOW
0%	422	0	31	0%	300	HIGH
0%	0	0	25	0%	318	HIGH
0%	0	0	15	0%	332	LOW
0%	0	0	26	0%	325	HIGH
0%	450	0	25	0%	312	LOW
0%	460	0	15	0%	326	HIGH
0%	430	0	31	0%	325	LOW
0%	550	52	15	2%	320	LOW

**Table 2.** Dataset Hero

The effectiveness of any predictive model, such as KNN, relies on its capacity to deliver precise and dependable outcomes. Through rigorous validation and refinement against actual results, the algorithm ensures close alignment with real-world scenarios. This iterative process not only enhances prediction accuracy but also strengthens the credibility of analytical insights derived from the KNN algorithm. The emphasis is placed on uncovering complex patterns and attaining nuanced insights into the multifaceted dynamics of hero interactions within the latest meta.[14]

HP	Physical Attack	Physical Def	Attack Speed	Critical Chance	Mana	Magic Power	Magical Def	Cooldown Reduce	Movement Speed
2571	124	18	1	0	680	8	17	0.1	330
2628	118	21	1.19	0	0	0	15	0	332
2778	139	29	1.05	0	0	0	21	0	312
2801	128	22	1.04	0.05	0	0	15	0	332
2573	114	21	1	0	493	38	15	0.05	309
2698	159	27	1	0	0	0	21	0	306
2490	123	20	1.21	0	435	0	15	0	333
2501	113	17	1.01	0	500	38	15	0.05	316

**Table 3.** ExampleSet

Row No.	MYTHIC+	prediction(MYTHIC+)	prediction(HIGH)	confidence(LOW)	Hero	Win	Popularity	Banned
1	HIGH	LOW	0.433306419	0.566693581	Rafaela	0.5694	0.0133	0.1538
2	LOW	HIGH	0.770063276	0.229936724	Argus	0.5403	0.0023	0.0017
3	HIGH	HIGH	0.805117389	0.194882611	Khaleed	0.5308	0.0018	4.00E-04
4	HIGH	HIGH	0.804136143	0.195863857	Freya	0.5227	0.004	0.003
5	LOW	LOW	0.202542328	0.797457672	Alice	0.5151	0.0012	7.00E-04
6	HIGH	HIGH	0.799617267	0.200382733	Yu Zhong	0.5127	0.0125	0.0029
7	HIGH	LOW	0.381287917	0.618712083	Brody	0.5113	0.0103	0.0031
8	HIGH	HIGH	0.608041496	0.391958504	Lylia	0.5111	0.0071	0.0024

**Table 4.** ExampleSet

K-Nearest Neighbors (KNN) is a machine learning algorithm utilized to forecast outcomes by assessing the similarity among instances. In our study, it's employed to anticipate the rank of heroes (MYTHIC+, HIGH, LOW) utilizing attributes outlined in the ExampleSet table.

1. Euclidean Distance:

- Compute the Euclidean distance between the hero under scrutiny and all other heroes within the dataset.
  - $Distance = \sum_{j=1}^n (X_{ij} - X_{kj})^2$ , where  $X_{ij}$  and  $X_{kj}$  represent attribute values for feature  $j$  of the hero under scrutiny and hero  $k$ , respectively, and  $n$  denotes the number of features.
2. Identifying Nearest Neighbors:
    - Choose the  $k$  nearest neighbors based on the smallest distances.
  3. Determining Rank Prediction:
    - Forecast the rank of the hero under scrutiny based on the predominant rank among its neighbors.

accuracy: 61.54%		
	true HIGH	true LOW
pred. HIGH	4	2
pred. LOW	3	4
class recall	57.14%	66.67%

**Table 5.** Performance Vector

The application of the K-Nearest Neighbors (KNN) algorithm in our study has provided valuable insights into hero performance within the dynamic Mobile Legends meta. Let's explore these insights by focusing on the key aspects derived from our analysis: [15]

**1. Outcome Prediction:**

- The KNN algorithm predicts outcomes based on the majority class of the  $k$  nearest neighbors.
- Hero performance data are meticulously collected and preprocessed to facilitate accurate predictions.

**2. Validation and Refinement:**

- Accuracy and reliability of predictions are ensured through rigorous validation against real-world outcomes.
- Iterative validation enhances prediction accuracy and reinforces analytical credibility.

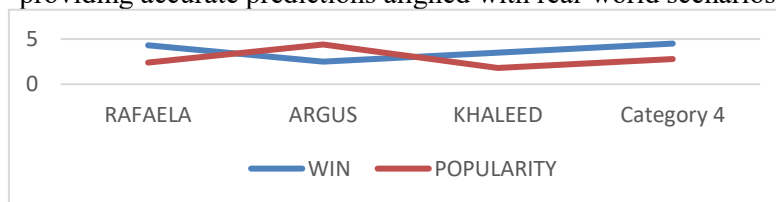
**3. Performance Metrics:**

- Predictions for hero attributes, including MYTHIC+ rank, confidence levels, and corresponding hero information, are presented.
- Probability of winning and overall accuracy of the KNN algorithm are visualized.

**4. Effectiveness of KNN Algorithm:**

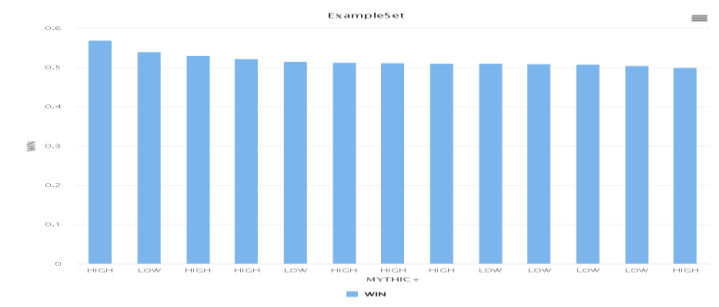
- The algorithm, based on the proximity principle, predicts outcomes by considering the similarity of hero attributes.
- Nuanced insights into hero interactions within the dynamic Mobile Legends meta are provided.
- Uncovering complex patterns contributes to actionable insights for players, analysts, and game developers.

In conclusion, the KNN algorithm effectively predicts hero performance, enhancing understanding of the Mobile Legends meta. Its iterative validation process ensures practical utility in gaming contexts, providing accurate predictions aligned with real-world scenarios.



**Figure 3.** Probability of Winning

Figure 3 visualizes the probability of winning based on the predictions made by the K-Nearest Neighbors (KNN) algorithm. The x-axis represents different instances, while the y-axis shows the corresponding probability of winning. This graph provides an overview of the algorithm's predictive performance in estimating the success of heroes within the Mobile Legends meta.



**Figure 4.** Accuracy

Figure 4 depicts the comprehensive accuracy of the KNN algorithm in forecasting hero attributes. The x-axis denotes distinct iterations or instances, while the y-axis showcases the accuracy percentage. This graphical representation showcases the algorithm's efficacy in predicting hero ranks (MYTHIC+, HIGH, LOW) using the given attributes. Accuracy serves as a pivotal metric in evaluating the predictive model's dependability.

#### 4. Conclusion

In conclusion, this research aims to conduct a comprehensive statistical analysis of hero performance in the latest Mobile Legends meta using the K-Nearest Neighbor Algorithm (KNN). The study provides valuable insights into the various factors influencing hero success. The methodology involves a rigorous research stage, encompassing the collection of hero performance data from diverse sources and community data-sharing platforms. The dataset undergoes detailed pre-processing to ensure integrity and validity, establishing a solid foundation for subsequent applications of the KNN algorithm. The selected algorithm, renowned for its non-parametric and instance-based learning capabilities, effectively uncovers complex patterns in the multidimensional space of hero statistics. The research results present a comprehensive statistical profile of hero performance, demonstrated through the application of the KNN algorithm. This analysis reveals crucial factors, including win rates, popularity, and hero ban rates, offering different insights into interactions in the latest Mobile Legends meta. The study outlines performance vectors, accuracy metrics, and factors influencing hero performance. Key factors affecting a hero's success encompass win rate, popularity, ban rate, hero characteristics (hero kit), meta adaptation, and player skill. The study underscores the importance of a deep understanding of the meta game, hero abilities, and effective gameplay strategies for proper hero selection. While this research provides valuable insights for Mobile Legends enthusiasts, analysts, and industry professionals, it also acknowledges certain limitations. Future research efforts could address these limitations, refining the methodology used in this study. In essence, this research serves as a valuable resource, offering a detailed exploration of the dynamics of hero performance in the ever-evolving Mobile Legends landscape.

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