Utilization of MLP and LSTM Methods in Hero Selection Recommendations for the Game of Mobile Legends: Bang Bang

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Abstract

Mobile Legends is one of the popular MOBA games played in real-time. The game begins with each player selecting one hero in the draft pick phase. Choosing the right hero is very important because it can affect the chances of winning. This study uses datasets from rank mode matches conducted by streamers, top global heroes, and top leaderboards in Indonesia to compare the accuracy of the MLP and LSTM methods in recommending the fifth hero for one's team. The Concatenate Layer is used in model development. Modifying the dataset was also done by reducing the number of target classes and performing data augmentation to increase data variation. The results show that LSTM excels in top-1 recommendations with an accuracy of up to 59%. Meanwhile, MLP outperforms in top-3 and top-5 recommendations, indicating that this model is more flexible in providing multiple hero alternatives. The conclusion is that players can use the LSTM method if they only want to select the best single hero. However, if players prefer a broader range of hero recommendations, the MLP method is more suitable.

Keywords: Deep Learning, Multi Layer Perceptron, Long Short-Term Memory, Mobile Legends, Draft Pick Recommendation.

I. INTRODUCTION

The development of games continues to attract public attention nowadays [1]. The ease with which the general public can obtain game content through the Google Playstore may be the turning point for it. The Google Playstore offers a wide variety of games, including MOBAs, for the general public to play [2], [3], [4]. Multiplayer Online Battle Arena (MOBA) is a game genre that combines real-time strategy and role-playing. In order to win a match, players must control their characters, work as a team, and understand the game [5]. One of the most popular MOBA games at the moment is Mobile Legends.

Mobile Legends: Bang Bang, also known as MLBB, is a Multiplayer Online Battle Arena (MOBA) game developed and released on July 11, 2016, by Moonton, a Shanghai-based game development company [6]. Millions of people around the world have played this game. This is demonstrated by the number of downloads on the Google Play store, which surpassed 100 million in April 2021. In Indonesia, there are more than 50 million monthly active users.

MLBB is a MOBA game in which 5 players compete against another 5 players, each of whom is part of a single team [7], [8]. The match is played in real time, with each player controlling a single in-game character known as a hero. Before the game begins, players compete to choose a hero to play, a process known as the draft pick (Figure 1). This phase is critical because selecting the right hero and effectively combining them can significantly improve your chances of winning the match [2], [3], [4], [9]. However, many players make mistakes or are not precise in their hero selection, resulting in difficult gameplay and defeat.

Figure 1. The Draft Pick Phase Display in the MLBB Game

In previous research, there are several journals that discuss prediction or recommendation systems for heroes during the draft pick in MOBA games to assist players in selecting the the heroes. Zhang et al. wrote in 2020 about improving Dota2 draft picks with an RNN-based recommendation system and modifying it with a concatenation layer [2]. Inzitari et al. (2022) discusses predicting the order of hero picks in the game League of Legends (LoL) using one of the RNN developments, namely LSTM [3]. Lastly, a new study published in 2023 by Zhu et al. discusses several Deep Learning methods such as

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MLP and LSTM used to predict draft pick compositions in the MOBA game Dota2 [4].

Deep Learning (DL) is an artificial intelligence method used to teach computers how to process data like the human brain [10]. Deep Learning is a part of Artificial Intelligence (AI) and Machine Learning (ML). In DL technology, according to Abdul Raup (2022), there are several types of models that are commonly used, namely Multilayer Perceptron (MLP) and Recurrent Neural Network (RNN) [11]. Multi Layer Perceptron (MLP) is one type of model in DL that consists of 3 main layers: the input layer, the hidden layer, and the output layer [12]. MLP can be said to be a method that capable to classifying an object from several perspectives. As a result, MLP is capable of obtaining accurate classification results by utilizing extensive and complex information from various data features.

Recurrent Neural Network (RNN), also known as a feedback network, is one type of model in DL that uses looping as a feedback connection within its network [13]. The output of the RNN network can be fed back into the same network and then used to generate new output. RNN is one of the popular types of DL and is often used to solve classification problems [14]. RNN also has an architecture suitable for use with sequential data. The RNN architecture can be seen in Figure 2.

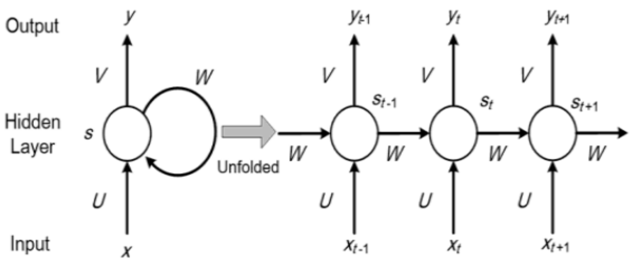

Figure 2. RNN Architecture

Although RNN is thought to be powerful, it does have a weakness: the vanishing gradient. Vanishing gradient is a state in which the model can no longer retain long-term memory, making it difficult to remember previous or outdated information [15]. An illustration of the vanishing gradient can be seen in Figure 3. This issue can be resolved using the Long Short-Term Memory method.

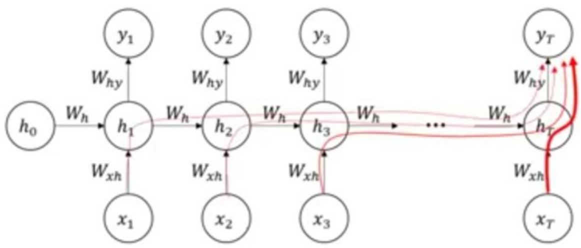

Figure 3. Illustration of Vanishing Gradient in RNN

Long Short-Term Memory (LSTM) is a method developed from the RNN method [16]. LSTM has more memory than RNN so that LSTM is able to learn more than 1000 previous steps. This is contrary to RNN which is only able to learn less than 10 steps [17]. The difference between RNN and LSTM architectures can be seen in Figure 4. Therefore, RNNs often face difficulties in retaining information from far back in time and can only remember limited information from the previous time.

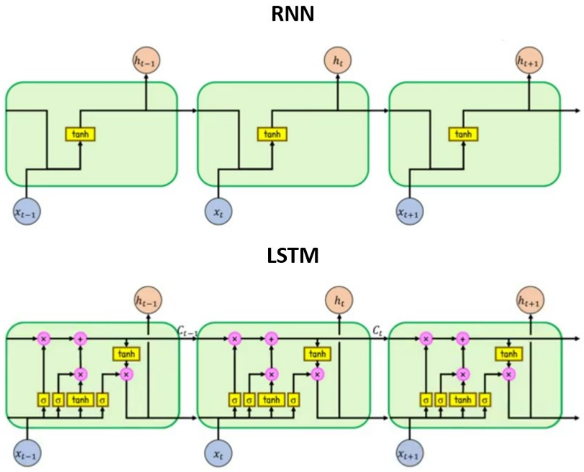

Figure 4. The Difference in Architecture between RNN and LSTM Models

The LSTM algorithm's structure consists of a neural network and several memory blocks known as cells. The information obtained by the LSTM algorithm is stored in the cell, which is then manipulated by components known as gates. The LSTM algorithm uses three types of gates. First, the forget gate determines whether information should be retained or discarded. Second, the input gate receives information from both the previous cell's hidden state and the current input. Then it is combined and processed by the activation function (usually sigmoid or tanh). Third, the output gate plays a role in selecting the information that will be passed on to the next cell.

One of the challenges in this study is the limited availability of reputable journal references discussing draft pick analysis in the MLBB game. Some previous studies on similar topics did not use MLBB as their research subject. Therefore, the researchers are interested in exploring the theme of draft pick analysis specifically for MLBB. In this study, the researchers compare the MLP [4] and LSTM [2], [3] methods in providing accurate hero recommendations during the draft pick phase, as MLBB players often struggle to choose the right hero. Accurate hero recommendations can increase a team's chances of winning. A new approach was introduced by dividing the recommendations into three categories: top-1 (displaying 1 recommended hero), top-3 (displaying 3 recommended heroes), and top-5 (displaying 5 recommended heroes). This categorization helps evaluate the model's effectiveness across different levels of choice. The focus of this study is on selecting the fifth hero based on the four previously chosen heroes in the team's composition. The fifth hero selection in the draft pick phase plays a crucial role in shaping the team's strategy and creating better synergy among the previously selected heroes. Besides optimizing team composition, the final hero selection also serves as an adaptive step against the opponent's hero composition. The hero chosen at this stage is often used to counter the opposing team's strategy (counter pick).

II. RESEARCH METHOD

Before starting the research, several steps must be carried out to ensure a systematic process and achieve the best possible outcome. These stages include dataset collection, preprocessing, implementation and testing, result analysis, and finally, drawing conclusions. The complete diagram can be seen in Figure 5.

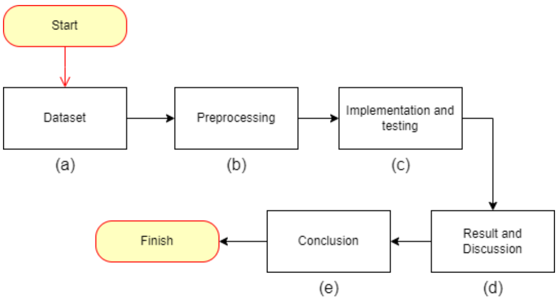

Figure 5. Research Method

A. Dataset

This study employs a dataset obtained from kaggle.com. The dataset created by Gerry Zani and Muhammad Rizqi Nur can be found at www.kaggle.com/datasets/gerryzani/mlbb-draft-breakdown-patch-1768/ and www.kaggle.com/datasets/rizqinur/mobile-legends-match-results. The datasets are 5,056 and 5,440, which add up to 10,496 data. The MLBB game with patch note 1.7.68 uses 119 heroes. This dataset is based on the match history of ranked mode played by Indonesian streamers, certain top global heroes, and the top leaderboard players in the Indonesian region, which can be found in the game and on the MLBB website.

The dataset contains match history where all results ended in victory. It also includes the draft pick data, consisting of 5 heroes selected by the allied team and 5 heroes selected by the opposing team. Because there is no hero ban data in the dataset source, the researchers did not include ban data as part of the dataset [2]. The data was organized according to the planned research scheme. However, preprocessing needs to be done by performing feature extraction or encoding on the dataset.

B. Preprocessing

The Preprocessing begins by assigning heroes to two model draft picks, first pick and second pick. First pick is a situation in which the player selects one hero before being replaced by the player who selects another hero later. Furthermore, the second pick is a continuation of the first pick. Tim's first or second pick is determined at random by the MLBB system. The detailed information can be found in the Table 1 and Table 2.

Table 1. Order of Hero Draft Picks During the First Pick

Pick	1	2	3	4	5	6	7	8	9	10
Allied Team	✓			✓	✓			✓	✓	
Opponent Team		✓	✓			✓	✓			✓

Table 2. Order of Hero Draft Picks During the Second Pick

Pick	1	2	3	4	5	6	7	8	9	10
Allied Team		✓	✓			✓	✓			✓
Opponent Team	✓			✓	✓			✓	✓	

After compiling the list of heroes, preprocessing continues with feature extraction for each hero. Feature extraction is the process of taking or filtering important information from raw data to be used as input in a machine learning model. The main goal of feature extraction is to transform data from unstructured text into structured data so that it can be further processed in the classification stage [18]. This is done to make it easier for the model to recognize patterns and generate accurate predictions. The researchers referred to this process as Multi-Hot Encoding.

The Multi-Hot Encoding process begins by separating the input data and the target class. At the first pick, the draft pick order is taken from order 1 to 9, whereas for the second pick, all orders are taken. The input data for the first pick consists of orders 1 to 8 (4 allied team heroes and 4 enemy team heroes), while the second pick consists of orders 1 to 9 (4 allied team heroes and 5 enemy team heroes). For the last order, whether in the first pick (order 9) or second pick (order 10), it is designated as the target class. Each hero that serves as input data is processed into 30 features based on lane position value, type, combat ability, and initial statistics. Except for the initial statistics, heroes with the condition "true" are valued at 1 and if "false" are valued at 0. In the initial statistics, a rating scale between 0.1 and 1.0 is used. Specifically for the target class, the One-Hot Encoding technique is used. This technique is useful for converting categorical variables into a numeric format or binary columns (0 and 1) that can be used in machine learning modeling [19]. The features used can be seen in the Table 3.

Table 3. Feature Extraction for Each Hero

No.		1.	2.	...	119.
Feature		Miya	Balmod	...	Arlott
Lane Position	Roamer	0	0	…	1
	Midlaner	0	0	…	0
	Jungler	0	1	…	0
	Explaner	0	1	…	1

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	Goldlaner	1	0	…	0
Type	**Tank**	0	0	…	0
	Fighter	0	1	…	1
	Assasin	0	0	…	1
	Mage	0	0	…	0
	Marksman	1	0	…	0
	Support	0	0	…	0
Ability in Fighting	**Finisher**	1	0	…	0
	Damage	1	1	…	0
	Regen	0	1	…	0
	Charge	0	0	…	1
	Poke	0	0	…	0
	Burst	0	0	…	1
	Crowd Control	0	0	…	0
	Chase	0	0	…	0
	Magic Damage	0	0	…	0
	Guard	0	0	…	0
	Initiator	0	0	…	0
	Control	0	0	…	0
	Push	0	0	…	0
	Support	0	0	…	0
	Mixed Damage	0	0	…	0
Initial Statistics	**Durability**	0,4	0,2	…	0,3
	Offense	0,7	0,3	…	0,9
	Ability Effects	0,1	0,8	…	0,3
	Difficulty	0,1	0,1	…	0,6

C. Implementation and Testing

The researchers created two models using two different methods (MLP and LSTM), whose algorithm illustrations can be seen in Figure 6 and Figure 7. The dataset, which consists of 10,496 data points, was split into 80% for training data and 20% for testing data. The free version of Google Colab was used by the researchers in this study, and the installed tools can be seen in the Table 4.

Table 4. The Tools Used in the Research

No.	Tools	Version
1.	Python	3.10.12
2.	Keras	3.4.1
3.	TensorFlow	2.17.0
4.	Sklearn	1.5.2
5.	Matplotlib	3.8.0
6.	Numpy	1.26.4
7.	Pandas	2.2.2

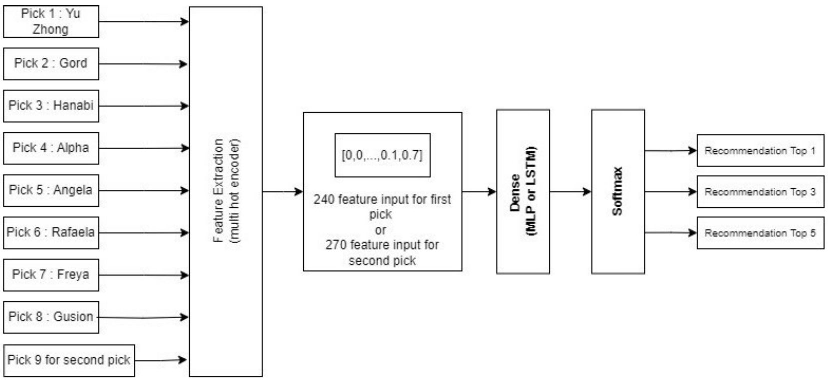

Figure 6. The Structure of the First Model Without the Concatenate Layer

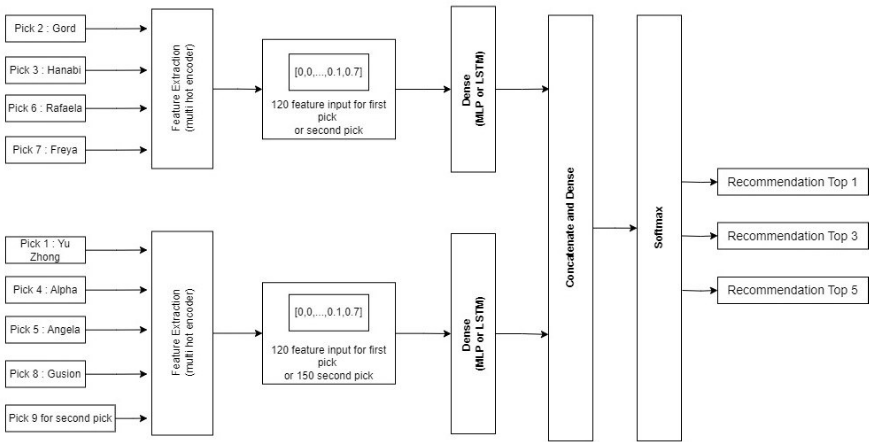

Figure 7. The Structure of the Second Model With a Concatenate Layer

The first model is depicted in the Figure 6, with input data of 8 heroes (4 enemy heroes and 4 team heroes) for the first pick and 9 heroes (5 enemy heroes and 4 team heroes) for the second. Each hero generates 30 input features, totaling 240 for the first pick and 270 for the second pick. The features are then processed using MLP or LSTM. The researchers used softmax activation to identify the top 1, 3, and 5 recommendation sequences. This occurs because the softmax activation function can convert a numerical vector to probabilities. The probability is used to determine multi-class classification with the class output based on the highest probability [20].

In the second model (Figure 7), the researchers separated the features of their own team's hero draft picks from the features of the enemy team's hero draft picks. The method used is the same as the first model, with the distinction that the researcher uses a concatenate layer here. The Concatenate Layer is a layer in a neural network that is used to combine two or more features into one [2]. In the output layer, the researchers also used the softmax activation function.

The goal of this research is to develop a model that can accurately classify or display the correct target class. The model's success can be evaluated based on the model's final results, which are represented by accuracy values against the testing data. The accuracy value represents the percentage of the model's precision required for the output hero in the target class to be included in the recommendation list. If illustrated, for example, if the target hero in the training data is supposed to be Bane, then Bane must be included in the recommendation list (top 1, 3, or 5). If Bane is not present, the recommendation is considered wrong, and the team is deemed to lose. Conversely, if Bane is present, the recommendation is correct, and the team wins.

III. RESULTS AND DISCUSSION

In this study, researchers tested each model five times and used the average to calculate accuracy. The following Table 5 and 6 shows the average accuracy of the testing data from the models that were created. Sorted by the best accuracy value of top 1, researchers display two tables, namely the accuracy results at the time of the first and second pick.

Table 5. Accuracy Results During the First Pick

No.	Method	Top 1	Top 3	Top 5
1.	LSTM with concatenatelayer	59%	63,3%	67,7%
2.	MLP with concatenate layer	58%	63,1%	67,6%
3.	MLP	57,4%	62,2%	66,2%
4.	LSTM	57,4%	60,8%	63,7%

Table 6. Accuracy Results During the Second Pick

No.	Method	Top 1	Top 3	Top 5
1.	LSTM with concatenate layer	59%	63,5%	67,8%
2.	MLP with concatenate layer	58,4%	63,4%	67,7%
3.	LSTM	57,4%	61,5%	65%
4.	MLP	56,9%	62,2%	66%

The study results outperform previous research on the same topic conducted by Lei Zhang in 2020 [2]. Lei Zhang employs the Bidirectional LSTM technique (an RNN development method). The method is used to develop a model that can recommend the fifth hero in the MOBA game Dota2. Lei Zhang achieved an accuracy of only 50.63 percent.

After analyzing the results, the researchers attempted to modify the dataset in the hopes of improving accuracy (for example, above 70%). The first modification involves reducing and balancing the target class. The researcher refers to this as target class filtering. Because, as shown in the Figure 8, the target class distribution is uneven across the dataset used.

Figure 8. Target Classes are not Evenly Distributed

Target class filtering is done by removing target classes with data below 50 and reducing the dataset size to a maximum of 100 data for each target class that has more than 100 data. This reduces the dataset to only 5,941 draft pick data. This is done to limit the heroes that are frequently picked from appearing in the recommendations. So that the distribution of classes becomes quite even. This change can be seen in the Figure 9.

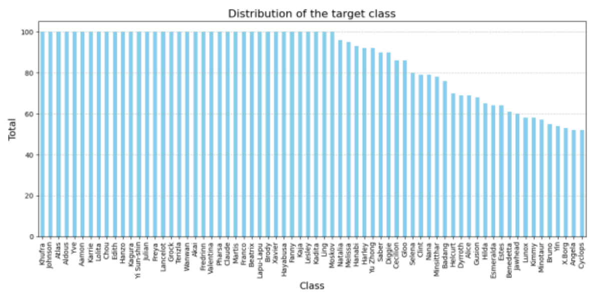

Figure 9. Distribution of the Target Class After Dataset Reduction and Normalization

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Data augmentation is the second modification. The objective is to enhance the variability of the data [21]. In this study, augmentation was performed by randomizing the draft pick order of both the own team and the opposing team. Augmentation was performed in 12 combinations (random) resulting in a total of 136,279 data points. The illustration can be seen in the Figure 10.

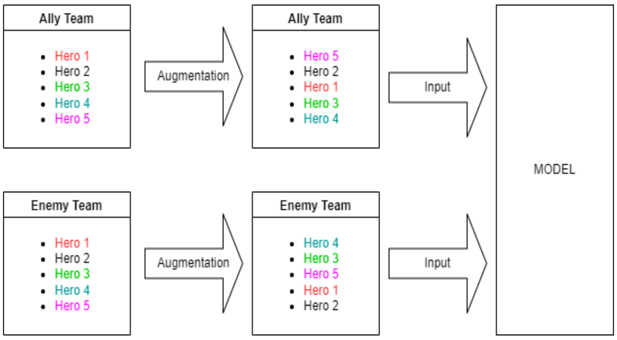

Figure 10. Illustration of Dataset Augmentation

The third modification is to perform both (filtering the target class followed by data augmentation), resulting in a total of 77,233 data points. This modification is illustrated in figure 10. The accuracy results obtained from the dataset modifications conducted by the researchers can be seen in the Table 7, 8, and 9, which are sorted based on the highest accuracy at the top 1.

Table 7. The Model's Accuracy Results After Dataset Reduction and Normalization

No.	Draft Pick	Method	Top 1	Top 3	Top 5
1.	first pick	LSTM with concatenate layer	45.5%	51%	56.6%
2.		MLP with concatenate layer	44.9%	50.6%	55.8%
3.		MLP	43.9%	50.4%	55.3%
4.		LSTM	42.8%	46.8%	50.6%
5.	second pick	LSTM with concatenate layer	44.9%	50.7%	56.5%
6.		MLP with concatenate layer	44.8%	49.4%	55.2%
7.		LSTM	43.9%	49.4%	54.6%
8.		MLP	43.3%	49.8%	55.5%

Table 8. The Accuracy Results After Data Augmentation

No.	Draft Pick	Method	Top 1	Top 3	Top 5
1.	first pick	MLP with concatenate layer	57.8%	63.3%	67.6%
2.		MLP	57.1%	63.4%	68.2%
3.		LSTM	53.8%	59.9%	64.6%
4.		LSTM with concatenate layer	53.1%	61.2%	65.8%
5.	second pick	MLP with concatenate layer	57.9%	63.7%	67.6%
6.		LSTM with concatenate layer	57.4%	63.6%	67.9%
7.		MLP	55%	62.9%	67.6%
8.		LSTM	48.7%	60.7%	66%

Table 9. The Accuracy Results After Normalization and Dataset Augmentation

No.	Draft Pick	Method	Top 1	Top 3	Top 5
1.	first pick	MLP	43.9%	51.4%	57.8%
2.		LSTM with concatenate layer	43.8%	51.6%	57.7%
3.		LSTM	43.6%	50.2%	56.1%
4.		MLP with concatenate layer	43.6%	50.7%	57.4%
5.	second pick	MLP with concatenate layer	58%	63.8%	68.3%
6.		LSTM with concatenate layer	43.8%	51.7%	58.1%
7.		LSTM	41.8%	50.1%	56.4%
8.		MLP	41.3%	50.8%	57.8%

From the 3 tables above, it was found that the results are not better than the model created without modifying the dataset. Even the accuracy obtained could be less than 50%. Despite the fact that data augmentation (with or without target class filtering) produced very good accuracy results (exceeding previous tests). However, training a model on a dataset that is 12 times larger will undoubtedly require more resources and time. Certainly, this will be taken into account if you decide to build a model using this method.

The suboptimal accuracy obtained after modifying the dataset may be due to the fact that the data does not fully reflect optimal strategies. In ranked mode gameplay, players often choose heroes based on personal preference, comfort level, or simply experimenting with popular heroes, rather than focusing on team synergy or countering enemy heroes. This can lead to inconsistent patterns, making it challenging for the model to capture relevant relationships for accurate predictions. However, despite these factors and possibilities, the researchers concluded on the most suitable model to use for generating recommendations for the top 1, top 3, and top 5 heroes. The results can be seen in the Table 10 and 11.

Tabel 10. Best Accuracy in the First Pick

No.	Method	Recomendation	Best Accuration
1.	LSTM with concatenate layer	Top 1	59%
2.	MLP with augmentation data	Top 3	63,4%
3.	MLP with augmentation data	Top 5	68,2%

Tabel 11. Best Accuracy in the Second Pick

No.	Method	Recomendation	Best Accuration
1.	LSTM with concatenate layer	Top 1	59%
2.	MLP with concatenate, normalization and dataset augmentation	Top 3	63,8%
3.	MLP with concatenate, normalization and dataset augmentation	Top 5	68,3%

Several facts have emerged as a result of the research, including which model is better suited to finding each recommendation in the top 1, top 3, and top 5. Among them are:

1. Using an LSTM model with a concatenate layer produces the highest the accuracy of up to 59% when determining the top recommendation. Whether as the first or second pick.
2. The MLP model with data augmentation achieved the highest accuracy for top three recommendations (63.4%) and top five (68.2%). But only for the first-choice condition.
3. The MLP model with a concatenate layer, augmentation, and target class balancing achieved the best accuracy for top 3 recommendations at 63.4% and top 5 at 68.2%. But only for the second pick condition.

IV. CONCLUSION

The selection of the best model highly depends on the specific strategic needs. If the focus is on providing the most optimal single hero recommendation, then LSTM is the more suitable choice, with accuracy and winning probability reaching up to 59%. On the other hand, if the goal is to provide several hero alternatives to support strategic flexibility, MLP performs better, with accuracy and winning probability reaching up to 68%.

To improve the model's performance, it is recommended that future research use data that more accurately reflects optimal gameplay strategies. In ranked mode games, players often choose heroes based on personal preference, comfort level, or simply following the trend of popular heroes, without paying much attention to team synergy or countering enemy heroes. This inconsistent pattern can make it difficult for the model to capture relevant relationships to produce accurate predictions. Although data augmentation can expand the variation in the dataset, the quality of the initial data remains an important factor in improving the model's accuracy. Therefore, future research could consider using data from professional tournament matches such as MPL, MSC, M-Series, or other official MLBB tournaments, where strategies and counter plays tend to be more structured and consistent. Other methods, such as CNN (Convolutional Neural Network), could also be considered as an alternative for development, as this method has a similar architecture to MLP.

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