Online Game Outcome Prediction Model Using Weighted-Based Feature Approach

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Abstract

Recently, the popularity of online games has risen drastically due to the latest technology that can connect players globally. League of Legends (LoL) holds the title of being the most extensively played Multiplayer Online Battle Arena (MOBA) game globally. This issue compels a substantial volume of preceding research that still analyzes and predicts the game outcomes with traditional methods that can be inaccurate and imprecise. Furthermore, these methods are frequently associated with the high rates of both false positive and false negative results. Hence, this paper presents a weighted-based feature predictor model to enhance the prediction accuracy. The approach predicts the game outcome of League of Legends matches in the Latin America North (LAN) and North America (NA) regions. We utilize player mastery and win rate for each summoner as the features. The data preparation process includes a weighted algorithm calculation and then evaluation using Naïve Bayes and Support Vector Machine algorithm. The outcomes illustrate that the weight-based feature approach can predict the outcome of LoL matches with an average accuracy of over 97 percent. This approach can be a valuable technique for players, teams, and coaches to analyze their performance and make strategic decisions.

Keywords: Weighted based; Prediction Model; Player Mastery; Player Win rate; League of Legends.

1. Introduction

At present, most users play online games due to easy access to the internet either to play on their own or with others. League of Legends (LoL) was develop by Riot Games [1]–[3]. It is presently the most approximately played Multiplayer Online Battle Arena (MOBA) game in the creation [4]. LoL has 180 million players, with its highest number of daily players at more than 32 million in 2022 [1], [5]. This shows that LoL was popular among users in the creation. A main feature of LoL is the combative ranked gameplay. With the rapid growth of LoL in 2023, most of the preceding researchers conducted a study to predict the result of the LoL's matches. The data there includes from such as big-scale events such as the world championship to small-scale matches as personal solo que ranked matches [6]–[9]. However, the persistent need for accurate and precise prediction models in online games like LoL is driven by the inherent complexity of these games, the growth of their player bases, the competitive nature of the gaming environment, and the limitations of current models in addressing these challenges. [8]. They have utilized different models, including deep neural networks, machine learning-based models, and logistic regression [7]. Nevertheless, these models have limitations, such as low accuracy and the inability to consider all relevant features [9]. The main problem is the ability to accurately predict match results still not being discovered. This is very crucial for fans and analysts. The current prediction methods often don't work well because the game is very complex. with the current methods, traditional analyzing and predicting game outcomes can be commonly inaccurate and unreliable [10], [11]. In accumulation, Typically, these methods yield elevated rates of both false positives and false negatives [12]. To solve this, we'll use weighted features, which

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means we'll give more importance to certain in-game things and player stats. This should make our predictions more accurate and dependable.

Therefore, this paper proposed a weighted-based feature prediction model to forecast the result of a LoL competition founded on various in-game features. We introduced the effectiveness of utilizing weighted features in predicting the outcome of LoL's matches. Utilizing Pearson's correlation test, it was uncovered that the win rate of players with specific champions and the mastery points associated with those champions were the sole features exhibiting correlation with the match outcome [13]. Similarly, it was discovered that the overall number of games played and the recent games played specifically on a particular champion had no impact on the match outcome [6]. Through analysis of past match results, key features that have a noteworthy influence on the outcome of a game will be identified and assigned weights based on their relative importance. These features will then be utilized to develop a weighted-based feature predictive model. The primary aim of this paper is to assess the effectiveness of the proposed approach in predicting the outcomes of League of Legends matches. Furthermore, it aims to offer insights into strategies for teams to improve their performance. Additionally, the study will explore different predictive models developed for League of Legends, examining their strengths and limitations. Ultimately, the overarching goal of prediction in League of Legends is to attain a comprehensive understanding of the game, its players, and the most effective strategies [14], [15]. It is important to note that the game is constantly evolving, thus it is imperative to continually update predictive models as new data becomes available [16], [17]. Objective of this paper are:

- To propose a prediction model that utilizes weighted features based for online game.
- To develop an online game outcome prediction model using weighted based features on the experience and skill level of the players.
- To evaluate the performance of prediction model based on accuracy, precision recall and F-Measure using classification algorithm.

1.1 Online Game

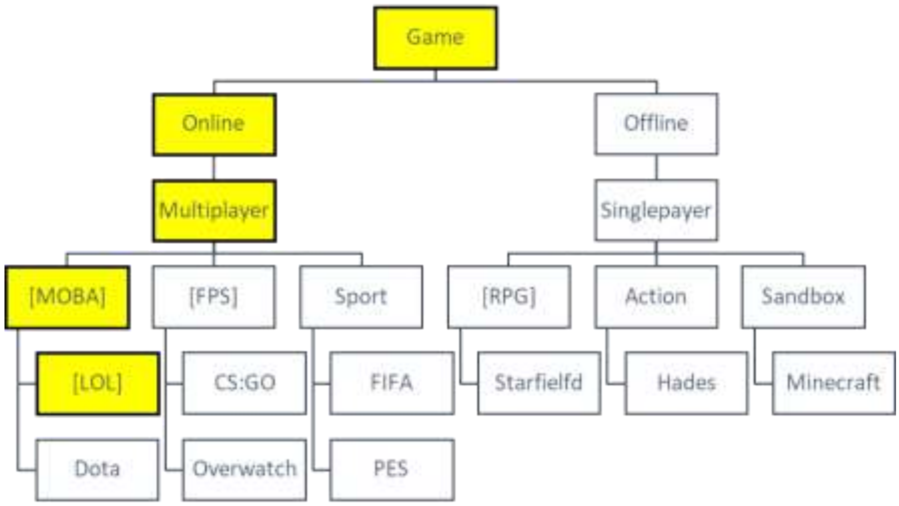

Figure 1: The Game Tree Diagram

The advent of online gaming has ushered in a new era of interactive entertainment, reshaping the way individuals engage with digital media and socialize in virtual spaces [18]. As technology has advanced, so too have the possibilities for immersive experiences and global connectivity. A plethora of online games now exist as shows in Figure 1, catering to various genres and preferences, such as the vast and immersive realms of World of Warcraft, the creative sandbox of Minecraft, the competitive battles of Fortnite, and the strategic clashes of Counter-Strike: Global Offensive [19]. However, as shown in Figure 1, amidst this diverse landscape, one game has emerged as the epitome of online gaming excellence: League of Legends [20]. Developed by Riot Games, this multiplayer online battle arena (MOBA) game has captivated the hearts of millions of players globally, establishing itself as the unrivaled pinnacle of online gaming. We chose League of Legends because it's one of the highest well-known and challenging games in the MOBA category. This decision came after looking at many options and considering how many different things, like player strategies and performance, come together to decide who wins a match in League of Legends.

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One of the most widely embraced online multiplayer games globally, League of Legends draws in millions of players on a daily basis [21]–[24]. It has a thriving competitive scene that has captured the attention of gamers and the esports community alike[25]. One of the core components of this competitive landscape is the Solo Queue Ranked Match (SQRM), which allows players to compete against each other and climb the ranks to prove their worth [26].
In an SQRM, players are matched up against each other based on their skill level and then compete in a 5v5 battle for dominance. The goal is to reach the highest rank possible by earning League Points (LP) for wins and losing LP for losses [27], [28].
Several preceding research already being conducted to analyze and predict online game matches. Even though a variety of advanced mathematical algorithms was being used, the potential to increase the prediction rate was not being implemented. Therefore, this paper will introduce the weighted-based feature predictor model that will help enhance the prediction score for SQRM. To be more efficient, this weighted-based feature predictor model should be suitable and flexible to be used in any domain of prediction task.

1.2 Online Game Predictor Approach

The preceding researchers for Multiplayer Online Battleground Arena game prediction highly focused on League of Legends (LoL). They used LoL for game prediction [29]. Work by Chen et al. [29] suggests that League of Legends has a greater variety of skill compositions compared to Dota. They incorporate player-champion experience, champion experience, and player experience as features, providing insight into players' in-game progress and skills. However, their achieved accuracy of 60.24% appears relatively low, indicating room for enhancement.
Lee et dal. [30] adopt a comprehensive approach by considering essential in-game metrics like kill difference, gold difference, and towers destroyed. While their model performs reasonably well at 5 minutes (62.26%) and 15 minutes (73%), the variation in accuracy across time intervals suggests potential challenges in making consistent predictions as a match unfolds.
Silva et al. [31] employ a Recursive Neural Network, showcasing a sophisticated approach for capturing intricate patterns within the data. Although their accuracy at 5 minutes (63.91%) is reasonable, the substantial improvement at 25 minutes (83.54%) raises questions about the model's initial predictive power and its ability to provide early insights.
Ani et al. [32] achieved an impressive accuracy of over 90%, indicating the effectiveness of their approach. However, it is essential to note that their model relies solely on ban data, potentially oversimplifying the complexity of LoL matches. Additional details about the dataset and methodology would provide a more comprehensive evaluation.
Tiffany et al. [33] introduce a Deep Neural Network, a modern and potent technique for prediction. Their accuracy of 75.10% is reasonable, though there is room for improvement to reach higher levels of precision.
Gonzalez et al. [34] combine Deep Neural Network and Gradient Boosting, achieving a relatively high accuracy range of 82-90.48%. While this result is promising, the variability inaccuracy suggests the need for further investigation into factors contributing to this wide range.
According to the discoveries of the preceding paper, all the comparative studies shown in Table I mainly focus on player champion experience as the feature. As stated by this study, the study by Gonzalez [34] will be applied and improved with the weighted-based features by this research to achieve a higher accuracy than the preceding research by using the weighted-based feature predictor model to enhance the prediction higher than preceding studies.

Table 1: THE COMPARISON AND SUMMARY OF THE RELATED STUDIES

Work By	Dataset	Features Used	Algorithm	Acc (%)
Chen et al. [29]	LOL	Player-champion experience, champion experience, player experience	Logistic Regression	60.24
Lee et al. [30]	LOL	Kill difference, gold difference, towers destroyed	Random Forest	62.26 (at 5 min)

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Silva et al. [31]	LOL	Kill difference, gold difference, towers destroyed	Recursive Neural Network	73 (at 15 min)
Ani et al. [32]	LOL	Ban data	Random Forest Trees	63.91 (at 5 min)
Tiffany et al. [33]	LOL	Player-champion experience, champion experience, player experience	Deep Neural Network	83.54 (at 25 min)
Gonzalez [34]	LOL	Player-champion experience, champion experience, player experience	Deep Neural Network. Gradient Boosting	>90

The remaining sections of this paper are organized into the following chapters. Section 2 describes the design of the prediction model adopted to accomplish the objectives of the research. This contains the research framework, data sources, instrumentation, and result analysis. Section 3 emphasizes the development of the features algorithm that aims to find the outcome of the online game's matches. This algorithm will describe the features used in the prediction model in the next chapter. Finally, section 4 displayed the overall conclusions of the research, the contribution, and proposed topics for future research.

2. Methods and Materials

2.1 Weighted Based Feature Approach

Figure 2 illustrates the weighted-based feature predictor model and its overall processing steps. The processing phases encompass requirement analysis and data preparation, the incorporation of weighted-based features, the development of prediction and analysis, and the subsequent evaluation [35]. The model is constructed employing a general data mining approach with the goal of building a classifier for the Game Predictor. The classifier's objective is to accurately categorize all samples as either a win or defeat.

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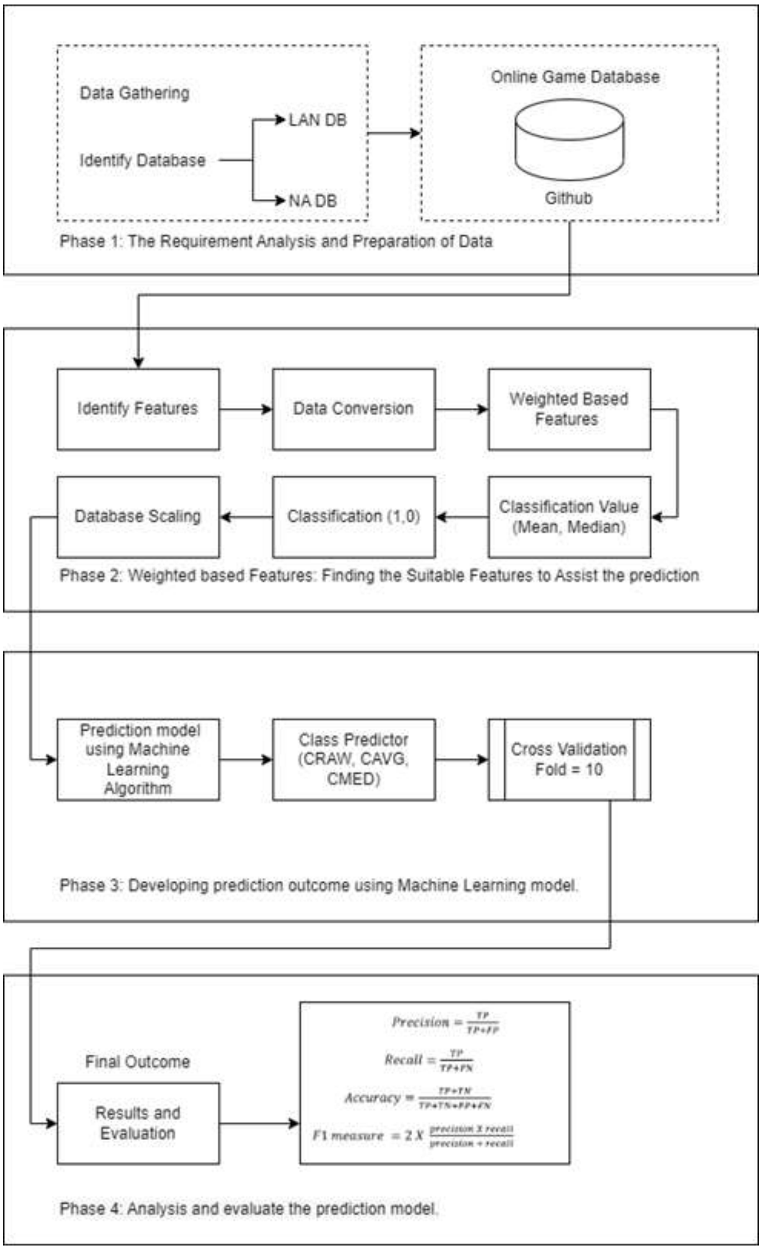

Figure 2: Weighted Based Features Approach

Phase 1: The Requirement Analysis and Preparation of Data: The first phase focused on the fundamental requirements. The LoL database that has been selected is a combination of two sources: from the region of North America (NA) and Latin America North (LAN) players. The collected data were 4552 matches from the NA region and 12458 matches from the LAN region. The benchmark data was extracted from GitHub which has been used by [34].

Phase 2: Weighted-Based Feature: Two categories of features being selected for both teams are the mastery and the win rates. To enhance the representation of each team's collective player-champion experience, additional features were generated for each match through mathematical calculations. These calculations included features such as the team's average, median, coefficient of excess kurtosis, coefficient of skewness, standard deviation, and variance of the players' champion win rate and their champion mastery points for both teams.

The dataset comprised 44 features per match, incorporating two features per player for 10 players and 12 features per team. Subsequently, we extracted 22 Online Game Predictor features per match, as outlined in Table 2, to be utilized in the experiment. Finally, the permission-based feature was selected using the weighted-based feature algorithm.

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Table 2: THE COMPARISON AND SUMMARY OF THE RELATED STUDIES

Work By	Dataset	Features Used	Algorithm
Mastery	M1	Player 1 mastery	{1,0}
	M2	Player 2 mastery	{1,0}
	M3	Player 3 mastery	{1,0}
	M4	Player 4 mastery	{1,0}
	M5	Player 5 mastery	{1,0}
	MAVG	Player mastery average	{1,0}
	MMED	Player mastery median	{1,0}
	MKURT	Player mastery kurtosis	{1,0}
	MSKEW	Player mastery skewness	{1,0}
	MVAR	Player mastery variance	{1,0}
	MSTD	Player mastery standard deviation	{1,0}
Win Rate	W1	Player 1 win rate	{1,0}
	W2	Player 2 win rate	{1,0}
	W3	Player 3 win rate	{1,0}
	W4	Player 4 win rate	{1,0}
	W5	Player 5 win rate	{1,0}
	WAVG	Player win rate average	{1,0}
	WAMED	Player win rate median	{1,0}
	WKURT	Player win rate kurtosis	{1,0}
	WSKEW	Player win rate skewness	{1,0}
	WVAR	Player win rate variance	{1,0}
	WSTD	Player win rate standard deviation	{1,0}

Then both the 22 features of each team will be assigned as 1 or 0 to represent the dominance score of each data. The feature's value indicator is a binary value of 1 if the blue team won and 0 if the blue team did not win. This data classification step is crucial to ensure that the data is in the correct format for the algorithm to understand and make predictions. Then the whole database will be separated into 7 groups that increasing with 1000 values each group. This will help prove this predictor model justify that it is suitable will small- and large-scale database.

2.2 Weighted Based Feature Predictor Model

A weighted based feature predictor model will be developed that utilizes the selected features to predict the outcome of online game matches. This process to remove any bias toward every feature by classified every data for each feature with the weighted value.

For Phases 2

For Identify Features and Data Conversion

1. Identify the features for each data point.
2. Calculate the dominance value of features in every match as follows:
    - If team A's performance is better than team B's for a feature, assign a value of 1; otherwise, assign 0.

For data classified as 1:

1. Count the total number of data points classified as 1 for each feature.
2. Repeat step 3 for all features.
3. Sum the total counts of data points classified as 1 across all features.
4. Count the total number of unique features in the dataset.
5. Implemented the Weighted Based Features calculation

For data classified as 0:

1. Count the total number of data points classified as 0 for each feature.
2. Repeat step 1 for all features.
3. Sum the total counts of data points classified as 0 across all features.
6. Implemented the Weighted Based Features calculation

Figure 3: The Identify Features and Data Conversion

In Phase 2 of the process, we focus on two key tasks: "Identify Features and Data Conversion." To begin with, we identify the features associated with each data point. Following this, we calculate the dominance value for these

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features in every match. This is achieved by assessing whether team A's performance surpasses that of team B for a given feature. If it does, we assign a value of 1; otherwise, we assign a value of 0.
For data points classified as 1, we proceed with further steps. Initially, we count the total number of data points that have been classified as 1 for each individual feature. This count is repeated for all features in the dataset, and the results are then summed to obtain the total count of data points classified as 1 across all features. Simultaneously, we determine the total number of unique features present in the dataset. These preliminary steps set the stage for the subsequent implementation of the Weighted Based Features calculation specific to data classified as 1.
Similarly, for data points classified as 0, we follow a parallel process. Initially, we calculate the total number of data points classified as 0 for each individual feature, repeating this calculation for all features. We then sum these counts to derive the total count of data points classified as 0 across all features. As with data classified as 1, we also perform the Weighted Based Features calculation for data classified as 0. This phase serves as an essential preparatory step for evaluating and attributing weighted features based on the performance dominance of features in matches, facilitating a more comprehensive analysis of the data.

For Phases 2

For The Weighted Based Features:

1. This is the crucial step where a weighted feature predictor model is constructed for data classified as 1. The (count of 1s in a feature) is divided by the sum from (total count of 1s across all features) and then multiplied by the count of features. This calculation generates a weighted value for each feature. This process is repeated for all features, with one feature being replaced at a time.
2. The same steps as above are repeated for data classified as 0 to calculate the weighted values for each feature when the second team is winning.

For Classification Value (Mean and Median):

1. The weighted values obtained for each feature for both 1s and 0s are used to calculate the total weight of each match. This is done by averaging the weighted values for all features in a match.
2. A two-class predictor is applied to the total weight of each match. It measures both the average and median total weight of matches.
3. The results from the two-class predictor in step 2 are classified as 1 or 0 again to indicate the prediction of whether the first team (team blue) won or lost.

Figure 4: The Weighted Based Feature and Data Classification

Figure 4 shows specifically focusing on the Weighted Based Features, we delve into a pivotal stage of the process. Here, we construct a predictive model designed to assign weighted values to features for data points classified as 1. This intricate process involves a series of steps. Firstly, we calculate the ratio of the count of 1s in a particular feature to the sum of the counts of 1s across all features. This ratio is then further multiplied by the count of features, generating a unique weighted value for each feature. This meticulous computation is executed iteratively for all features, systematically replacing one feature at a time to ensure a comprehensive evaluation.
Subsequently, we apply an analogous process to data classified as 0, replicating the aforementioned steps to compute weighted values. This operation considers scenarios where the second team prevails, making it a crucial facet of our analysis.
Moving on to the Classification Value, we employ the previously derived weighted values for both 1s and 0s. These values are instrumental in calculating the total weight for each match. This summation is accomplished by averaging the weighted values across all features within a given match.
A two-class predictor is then deployed, factoring in the average and median total weights of matches. This predictor provides valuable insights into the outcomes of these matches. Finally, the results from the two-class predictor, as outlined in step 2, undergo classification once more. This final classification serves as an indicator, signaling whether the first team (team blue) emerged victorious or suffered defeat, providing a comprehensive prediction based on the weighted feature analysis. Then the whole database will be separated into 7 groups that increasing with 1000 values each group. This will help prove this predictor model justify that it is suitable will small- and large-scale database. All the preceding process will be conduct again for each database.
Phase 3: Developing the Prediction Outcome: In the machine learning phase, we employed Naïve Bayes (BayesNet) and Support Vector Machine (SMO) algorithms. The models were formed and trained with the Waikato Environment for Knowledge Analysis (WEKA) software. The class with the highest vote was deemed the optimal output by assessing the voted classes from all individual trees. Furthermore, BayesNet and SMO algorithms are well suited for complex classification tasks and have methods to address the issue of unbalanced class populations. The cross validation will being set at 10-fold value. Two algorithms been selected to justify the flexibility of the weighted based feature predictor model that can been used on any algorithm.
Phase 4: Analysis and Evaluation the Prediction Model: When assessing the performance of a weighted-based feature prediction model, we rely on four crucial metrics: Precision, Recall, Accuracy, and F1-Measure. These

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metrics provide us with valuable insights into how well our model is performing in a straightforward and meaningful manner. Precision gauges the accuracy of positive predictions, informing us about the proportion of correctly predicted positive cases (1). Recall, on the other hand, gauges the model's capability to correctly identify all actual positive cases, ensuring that none are overlooked (2). Accuracy offers a broad overview of overall correctness, considering both positive and negative predictions (3). Lastly, the F1-Measure strikes a balance between Precision and Recall, providing a harmonious measure that considers both the accuracy of positive predictions and the model's capability to uncover all positive cases (4). These metrics collectively assist us in evaluating the effectiveness of our weighted-based feature prediction model, guiding us in making informed decisions about its real-world applicability.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$F1\ Measure = 2\ X \frac{Precision\ X\ Recall}{Precision + Recall} \tag{4}$$

Based on the four-evaluation metrics that being used to analysis the result, TP and FP represents the true positive and false positive, meanwhile TN and FN represent true negative and false negative (1)-(4). Firstly, the precision score is employed to assess the model's performance by measuring the count of true positives correctly identified out of all positive predictions made (1). Subsequently, the recall score is utilized to evaluate the model's performance by measuring the count of true positives accurately identified out of all the actual positive values (2). The accuracy score serves to measure the model's performance by determining the ratio of the sum of true positives and true negatives out of all predictions made (3). Finally, the F1-score, as the harmonic mean of precision and recall scores, is employed as a metric in scenarios where opting for either precision or recall may lead to compromises in terms of the model yielding high false positives and false negatives, respectively (4).

3. Result and Discussion

3.1 Experimental Setup

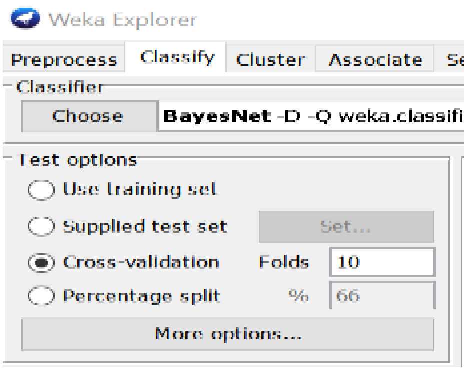

Figure 5: Experimental Setup

Based on Figure 5, the experiment was carried out using WEKA software. We used 12,458 samples of online game matches from Gonzalez for the experiments [34]. The dataset consisted of 22 features and was tested on two types of algorithms, BayesNet and SMO algorithms. All the experiments will be trained and tested using 10-fold cross-validation.

3.2 Results and Discussion

In this study, the discovery was carried out with WEKA software. We utilized a dataset of 28000 samples of online game matches for the experiments. The dataset is partitioned into several sizes, 1000, 2000, 3000, 4000, 5000, 6000, and 7000 data sizes. The dataset consisted of 22 features and was tested on three types of class data, denoted

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as class raw, class avg, and class med. The first class utilized permission-based features and was tested using Gonzalez [34] as the class raw predictor. While class avg and class med employed a weighted-based feature prediction model as the feature selection method. All the experiments will be run into cross-validation with a fold value of 10.

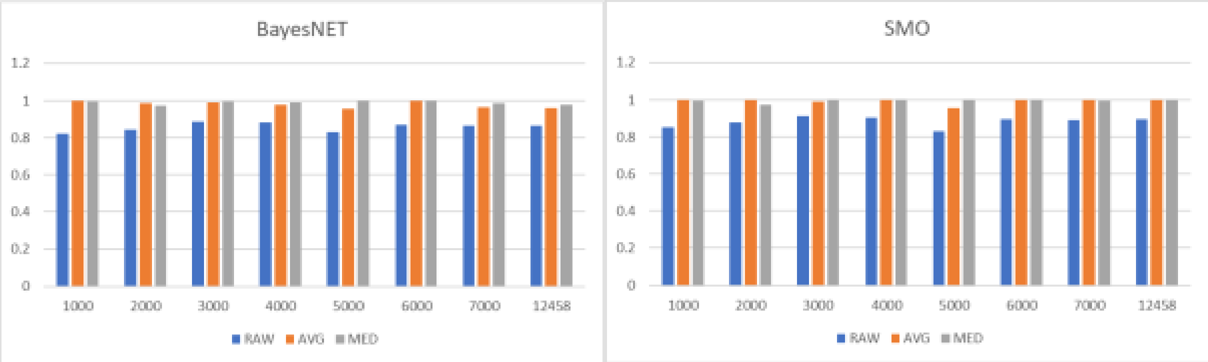

Figure 6: Precision Evaluation

Figure 6 the precision evaluation of the BayesNET and SMO algorithms across different classes (1000, 2000, 3000, 4000, 5000, 6000, 7000, and 12458), key performance metrics, including precision for each class, average precision (AVG), and median precision (MED), were examined. In the BayesNET algorithm, the raw precision values ranged from 0.8228 to 0.8866. Notably, the AVG and MED precision metrics demonstrated improvements over the raw values. The AVG precision ranged from 0.9557 to 1, showcasing an overall enhancement in precision, while the MED precision values ranged from 0.9741 to 1, indicating a consistent improvement across various classes. These results suggest that AVG and MED precision metrics offer a more nuanced and reliable assessment of the BayesNET algorithm's precision compared to raw precision values.
Similarly, in the SMO algorithm, the raw precision values varied from 0.8309 to 0.9143 across different classes. The AVG and MED precision metrics consistently outperformed the raw values, with AVG precision values ranging from 0.9557 to 1 and MED precision values ranging from 0.9731 to 1. This highlights that the SMO algorithm's precision performance is better captured by AVG and MED precision metrics compared to raw precision values. In summary, the utilization of AVG and MED precision metrics in both BayesNET and SMO algorithms provides a more comprehensive and nuanced understanding of their precision across diverse classes, emphasizing the significance of these refined evaluation measures in critical analysis of algorithmic performance.

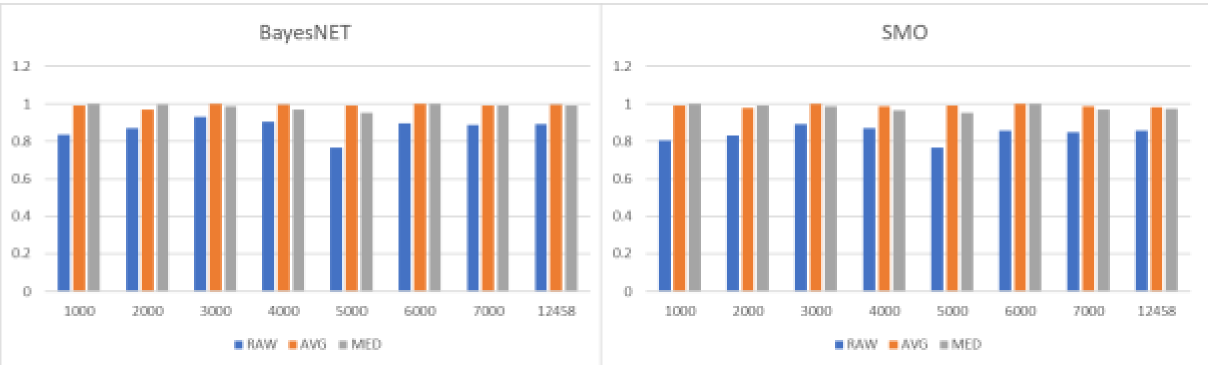

Figure 7: Recall Evaluation

Figure 7 illustrates the recall evaluation of the BayesNET and SMO algorithms across various classes (1000, 2000, 3000, 4000, 5000, 6000, 7000, and 12458), the analysis focused on key performance metrics, including raw recall values, average recall (AVG), and median recall (MED). In the BayesNET algorithm, raw recall values ranged from 0.7666 to 0.9328. Notably, AVG and MED recall metrics exhibited improvements over the raw values. AVG recall ranged from 0.9933 to 1, indicating an overall enhancement in recall, while MED recall values ranged from 0.9546 to 1, showcasing consistent improvement across different classes. This suggests that AVG and MED recall metrics provide a more nuanced and reliable assessment of the BayesNET algorithm's recall compared to raw recall values.
Similarly, in the SMO algorithm, raw recall values varied from 0.7666 to 0.8949 across different classes. The AVG and MED recall metrics consistently outperformed the raw values, with AVG recall values ranging from

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0.9933 to 1 and MED recall values ranging from 0.9546 to 1. This emphasizes that the SMO algorithm's recall performance is better captured by AVG and MED recall metrics compared to raw recall values. In summary, the utilization of AVG and MED recall metrics in both BayesNET and SMO algorithms provides a more comprehensive and nuanced understanding of their recall performance across diverse classes, underscoring the significance of these refined evaluation measures in critical analysis of algorithmic performance.

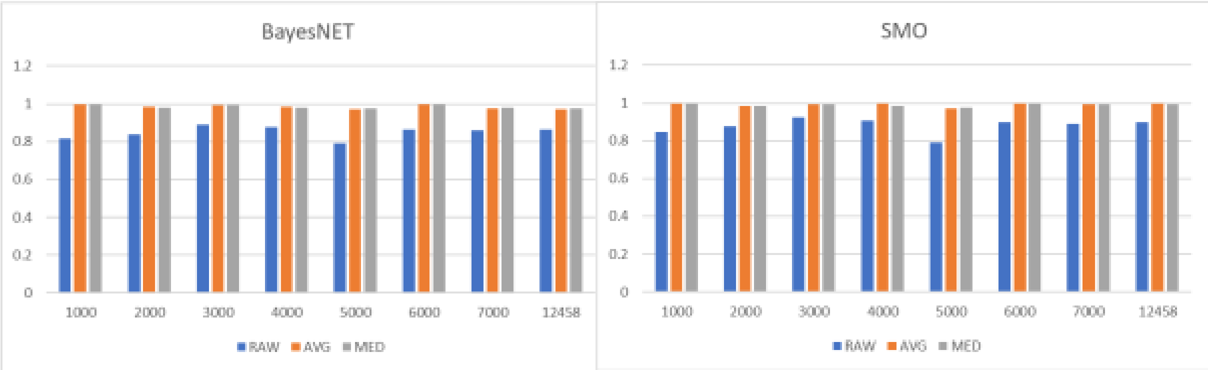

Figure 8: Accuracy Evaluation

In the Figure 8 is the accuracy evaluation of the BayesNET and SMO algorithms across different classes (1000, 2000, 3000, 4000, 5000, 6000, 7000, and 12458), the analysis included raw accuracy (RAW), average accuracy (AVG), and median accuracy (MED) for a comprehensive understanding of performance. In the BayesNET algorithm, the raw accuracy values ranged from 0.817 to 0.890. Remarkably, AVG and MED accuracy metrics displayed consistent improvements over the raw values. AVG accuracy ranged from 0.9734 to 1, indicating an overall enhancement in accuracy, while MED accuracy values ranged from 0.9762 to 1, demonstrating a consistent improvement across various classes. This highlights that AVG and MED accuracy metrics provide a more nuanced and reliable assessment of the BayesNET algorithm's accuracy compared to raw accuracy values.

Similarly, in the SMO algorithm, the raw accuracy values varied from 0.845 to 0.9233 across different classes. AVG and MED accuracy metrics consistently outperformed the raw values, with AVG accuracy values ranging from 0.9734 to 1 and MED accuracy values ranging from 0.9762 to 1. This emphasizes that the SMO algorithm's accuracy performance is better captured by AVG and MED accuracy metrics compared to raw accuracy values. In summary, the utilization of AVG and MED accuracy metrics in both BayesNET and SMO algorithms offers a more comprehensive and nuanced understanding of their accuracy across diverse classes, underscoring the importance of these refined evaluation measures in critical analysis of algorithmic performance.

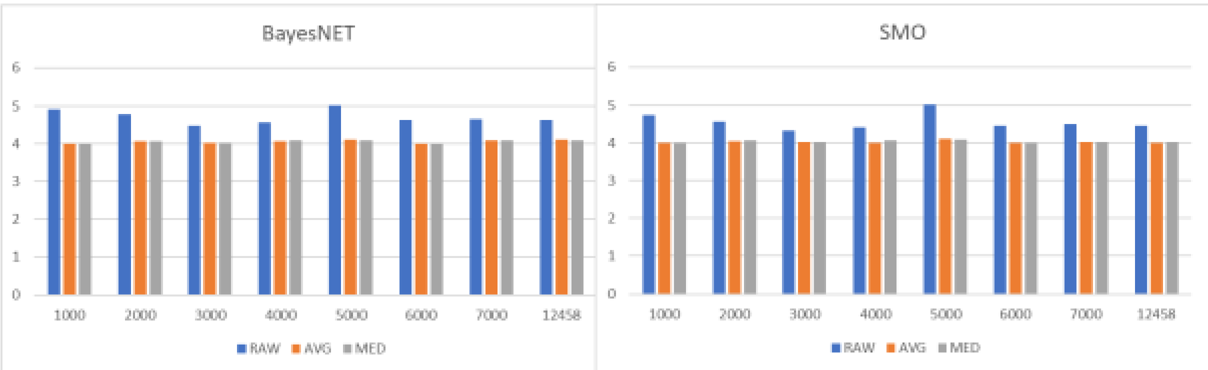

Figure 9: Accuracy Evaluation

Finally, in the figure 9 display the f-measure evaluation of the BayesNET and SMO algorithms across various classes (1000, 2000, 3000, 4000, 5000, 6000, 7000, and 12458), comprehensive analysis was conducted on f-measure values, average f-measure (AVG), and median f-measure (MED). For the BayesNET algorithm, the RAW f-measure values ranged from 4.4907 to 5.0160. The AVG and MED f-measure metrics exhibited improvements over the RAW values, with AVG values ranging from 4.0000 to 4.1104 and MED values ranging from 4.0000 to 4.0918. This indicates that AVG and MED f-measure metrics provide a refined and enhanced assessment of the BayesNET algorithm's performance compared to RAW f-measure values.

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Similarly, in the SMO algorithm, RAW f-measure values varied from 4.3317 to 5.0160 across different classes. The AVG and MED f-measure metrics consistently outperformed the RAW values, with AVG values ranging from 4.0000 to 4.1063 and MED values ranging from 4.0000 to 4.0186. This underscores that the SMO algorithm's f-measure performance is better captured by AVG and MED metrics compared to RAW f-measure values. In summary, the utilization of AVG and MED f-measure metrics in both BayesNET and SMO algorithms provides a more nuanced and reliable understanding of their f-measure across diverse classes, emphasizing the importance of these refined evaluation measures in the critical analysis of algorithmic performance.

4. Conclusion

The surge in popularity of online gaming, particularly the globally played Multiplayer Online Battle Arena (MOBA) game League of Legends (LoL), has necessitated a fresh approach due to the inaccuracy inherent in traditional methods used to predict game outcomes, often resulting in high rates of false positives and false negatives. In this regard, the application of a weighted based feature approach, the results demonstrate the potential of this approach, with an average accuracy exceeding 97% and the achievement of a fully accurate prediction rate of 100%, thereby providing a powerful tool for performance analysis and strategic decision-making for players, teams, and coaches, potentially reshaping the competitive landscape of online gaming. Future research opportunities may be included in the examination of other areas of online gaming such as for politician to predicted their voters' percentage or more critical domain such as medical department to predict the potential of diseases spreads.

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