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A Hybrid Approach to Online Game Matchmaking Using Las Vegas Algorithm and K-Nearest Neighbor

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Abstract— ***Online gaming, particularly video games, is a popular leisure activity. Matchmaking is crucial in e-sports and online gaming as it directly affects player satisfaction and the longevity of gaming products. A proposed solution to address unequal matchmaking in online gaming is to establish a performance-driven system. This study used the Las Vegas Algorithm (LVA) for player selection and K-Nearest Neighbor (KNN) for categorizing and classifying player performance data. This study proposed a hybrid algorithm for online game matchmaking that combined LVA and KNN. The hybrid approach includes improvements such as data classification, runtime optimization, and increased success probability. The study used a dataset of 80,000 raw data and 32 variables that underwent Mutual Information-Based Feature Selection. The study showed that using LVA and KNN together improved data categorization and classification, and a greater probability of success. However, the hybrid algorithm had a longer runtime compared to the Las Vegas algorithm. The hybrid algorithm necessitates an initial data categorization phase prior to selecting players randomly. The existing algorithm disregards player performance when identifying them. The hybrid algorithm takes longer to execute due to the extra computational steps needed for data categorization, which are not present in the current algorithm. Despite its drawback, the hybrid algorithm can enhance player selections by integrating performance rates into the categorization process.***

Index Terms— ***hybrid approach, k-nearest neighbor, las vegas algorithm, mutual information-based feature selection, online game matchmaking.***

I. INTRODUCTION

A. Background of the Study

Online gaming is a popular pastime. Video games offer various advantages such as stress reduction, competition, enjoyment, social interaction, and mental diversion [1].

Matchmaking is a crucial concern in e-sports and online games as it affects player satisfaction and the longevity of gaming products. Matchmaking algorithms typically categorize players into two teams based on predetermined criteria. Matchmaking system design and installation are often labor- and product-intensive. Matchmaking facilitates player competitions. The matchmaking algorithm creates teams for players in line and pits every two teams against one another because of a significant number of players requesting the gaming service and confirming their availability [2].

These algorithms for matchmaking in online games indicate that each technique of matchmaking presents a unique set of obstacles to overcome. Nonetheless, one of our answers to the problem of imbalanced and unfair matchmaking is to build performance-based online game matchmaking. This study utilizes the Las Vegas Algorithm and K-Nearest Neighbor to categorize and classify players' performance data.

Las Vegas Algorithm (LVA) is a randomized algorithm that incorporates a random source into its logic. The Las Vegas algorithms have broad applications in artificial intelligence, games, computer science, and operations research.

K-Nearest Neighbor (KNN) is a simple machine learning algorithm commonly used for classification. Classification is determined by the categorization of neighboring data points.

The purpose of merging KNN with LVA is to solve LVA's classification and categorization, run-time issues, and probability of success. This also allows us to develop a way for identifying and classifying a performance-based matchmaking approach as a potential new method for matchmaking in online games.

B. Statement of the Problem

The research aims to develop a hybrid technique for online game matchmaking that combines the Las Vegas Algorithm and K-Nearest Neighbor. The following statements are addressed in this study:

1. *The data in Las Vegas Algorithm is neither categorized nor classified.* There is no classification or categorization of the data in LVA [3]. Due to the algorithm's failure to classify and organize the data, the process will continue to run until the sought-after information is located. If the algorithm is unable to

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locate the desired data, the program will terminate.

2. *The Las Vegas algorithm has an unpredictable run-time.* The amount of time required to complete it is also dependent on the number of data as well as the random choices that are made [3]. Its run-time is also dependent on the quantity of input and the randomness of its decisions. The process may take some time if the required element cannot be located, resulting in a failure, or it may promptly discover the required element.
3. *The Las Vegas Algorithm has difficulty in determining the probability of success.* The probability of success of the technique is problem-dependent, and it might be challenging to calculate the probability of success for a specific problem [4].

C. Objective of the Study

The overall objective of this study is to find a solution to LVA's incapacity to identify and classify data, improve its run-time, and determine the probability of success. The study's specific objectives are as follows:

1. Combine LVA and KNN to solve the inability of LVA to categorize and classify data.
2. Utilize feature selection to reduce the data scanning procedure's execution duration.
3. The application of LVA and KNN to matchmaking problems will increase the probability of success.

D. Significance of the Study

This study will provide light on the hybrid technique's effectiveness in online game matchmaking. This research study is beneficial and highly significant for the following:

1. *Game Developers* - The study will be helpful to game developers as online gaming becomes more widespread.
2. *Gaming Industry* - This study will be beneficial as we work to enhance matchmaking for 5v5 competitive online games.
3. *Future Researchers* - This research will be useful for their subsequent investigations. It will help them improve and modify this research field in the future.

E. Scope and Delimitation

This research project aims to create a modern hybrid solution for the matchmaking process in online games by combining the K-Nearest Neighbor Algorithm and the Las Vegas Algorithm. The Las Vegas Algorithm and K-nearest Neighbor are combined to create a precise and effective approach for categorizing and matching data according to its key matches. This study is limited to examining matchmaking features in online games and improving data classification and categorization to enhance run-time and determine success probability.

II. REVIEW OF RELATED LITERATURE

A. Online Game Matchmaking

Recent industry research from Spil Games shows that 1.2 billion people are now playing games worldwide, with 700 million playing games online as just another reminder of how swiftly the gaming market is expanding (Soper, 2014). Global video gamers totaled 3.03 billion in 2022, a modest decline from the 3.2 billion recorded the year before. The COVID-19 pandemic drove the popularity of gaming purchases to rise even faster in 2020 and 2021 before leveling out in 2022 as more alternatives to gaming became available (Clement, 2022) [5].

According to [6] the most common source of entertainment for both children and adults is playing online games. By 2020, they may be recognized as e-Sports and included in the Olympic Games on a regular basis. According to [7], due to the popularity of online team games, systems that can construct and match teams are now necessary because traditional matchmaking systems only deal with the development of one-player versus one-player (1v1) matches.

Software support architectures used in the digital gaming sector, such as game engines and online services, require ongoing improvement to meet user expectations and technical advancements. Current matchmaking methods for multiplayer online games (MOGs), the vital function that enables players to discover opponents, create significant concerns regarding the user experience. They frequently result in mismatches where strong players compete against inferior ones, which is an outcome that benefits none of the individuals. Furthermore, the wait for a game session to start can be exceedingly long, lasting up to hours [8].

One of the most crucial features of online gaming is matchmaking. The experience can be ruined by playing against someone who has much more or less ability and knowledge of the game, regardless of how well-planned the game is. In the meantime, according to [9], if matchmaking takes too long and gamers get bored waiting in line, the experience might never even start a game. Therefore, matchmaking systems must be quick to produce balanced pairings and computationally efficient.

Matchmaking is a key component of practically every online game. It is an important component because it adds to the enjoyment of a game. Matchmaking essentially makes sure that players never confront opponents who are either better or worse than them. Both good and bad players are discouraged by a poor matchmaking system. Veteran gamers will become disinterested, while novices will become upset [10].

Players enjoy themselves and feel satisfied when they engage in competitive play by playing a close match. However, playing against easy opposition or winning comfortably may feel less enjoyable or give players awful feelings. The matchmaking procedure is therefore unfair.

For online games to be more evenly balanced, matchmaking needs to be improved. A competitive games developer must effectively set up fair matchmaking between players and guarantee that player satisfaction is at its highest level. In order to reach those results, we should gather more player data and select the information that may be relevant to their ability and how they contribute to the team, taking it into consideration for a better and fair matchmaking system to get better results at matchmaking [11].

B. Las Vegas Algorithm in Different Applications

For more than a century, randomization has been recognized as helpful in research and engineering. Numerous disciplines, including computer science, optimization, and numerical analysis, have benefited from its important techniques. The development of probabilistic and sampling-based systems and control approaches has been considerable over the past years [12].

Randomized algorithms pose a promising approach to solving such highly complex computations and problems [13]. A randomized algorithm uses random integers to forecast the next step in its logic. It is often applied to decrease the running time, time complexity, space complexity, or memory usage of a common method [14]. In general, there are two different types of randomizations: the Montecarlo Algorithm and the Las Vegas Algorithm but let us concentrate on the latter.

In a different study, [15] converted the elliptic curve discrete algorithm problem into a linear algebra problem and used the Las Vegas algorithm to solve it. The exhaustive search would randomly select a set and then check the total points, but the LVA selects and checks any random point simultaneously. That is why they opted for LVA over the exhaustive search.

One of the key benefits of using LVA is that it produces effective procedures and outcomes. In another study by [16], the researchers presented "A Las Vegas Method for Offline Approximate Nearest Neighbor Search." The algorithm utilized was able to equal the Monte Carlo algorithm's best running time. However, it often has a shorter run-time than the Las Vegas algorithm. Instead of using a single random sample, the researchers used random partitions in the context of the Quick Sort example. The probabilistic polynomials that were produced either provided the proper response or a value indicating an error had occurred due to the researchers making one crucial alteration at each phase. Although the run-time was cut down, it was still possible for the incorrect response to be output.

In a study conducted [17], the Las Vegas Algorithm is used with the Naive Bayes Algorithm to produce a precise and effective method for classifying and dividing the data into groups based on critical matches. Their next step was to choose a group based on the required parameter from the database. Filtering techniques typically result in higher generalization due to their learning independence. However, because they frequently select larger feature groups, they occasionally call for threshold usage. When there are many features, filtering methods must be utilized since they are quicker than the alternatives.

C. K-Nearest Neighbor in Different Applications

The supervised machine learning technique known as the k-nearest neighbors (KNN) can be used to tackle classification and regression issues. It is simple to use and comprehend, but it has the important problem of becoming noticeably slower as the amount of data in use increases [18].

A study by [19], stated that they used KNN to show how the effects of autism spectrum disorder (ASD) significantly impact a person's entire life. ASD is primarily characterized by a lack of social contact and communication, repetitive behavioral patterns, and fixed interests and activities. Early ASD diagnosis is crucial for successful treatment. The classification approach for diagnosing ASD in children aged 4 to 11 years was utilized in this study. The K-Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA) methods are used for classification.

In the study of [20], the KNN Algorithm in Puzzle Games performs well, compared to the other puzzle games without this technique. This technique allows the node that drags and drops the fixing will be simple. If the problem and KNN function match, then It might enable the object's node to recognize the nearby node. without putting the object in the appropriate place, from the object a drawing of the object in place the item that KNN corrected closer node will pull, couple, and match in the closer node-based node immediately closer. If we do not use the KNN algorithm, the object must match the object sketch exactly and if the object doesn't match, it can go back to its initial position.

In a proposed study by [21], three machine learning concepts—Supervised Learning, Gradient Descent, and K-Nearest Neighbor (KNN) Classification—are presented conceptually in ML-Quest, a game. Using the TAM model, the game's usefulness and player experience were assessed in a controlled experiment with 41 higher-secondary students.

Considering K-Nearest Neighbor (KNN) has proven to be effective in the gaming industry and other industries, in our study, we suggest merging the Las Vegas Algorithm (LVA) and K-Nearest Neighbor (KNN) to handle LVA's classification and categorization, run-time issues, and the probability of success. We will then use this algorithm to improve online game matchmaking. According [22], in order to retain each player's rank during actual matchmaking, K-Nearest Neighbor can be used to identify the shortest path between the data that needs to be evaluated and its K-nearest neighbors in the training data.

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III. THEORETICAL FRAMEWORK

A. Existing Las Vegas Algorithm

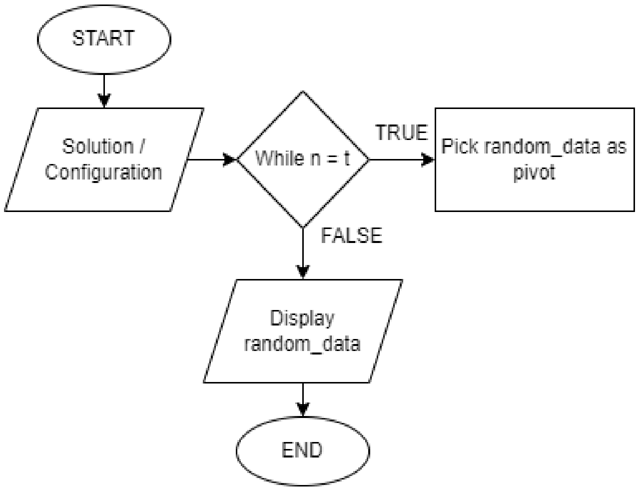

Figure 1: Flow of Existing Las Vegas Algorithm

Along with other branches of computer science and operations research, Las Vegas algorithms are widely used in the field of artificial intelligence [23]. Las Vegas Algorithm (LVA) is a randomized algorithm that consistently yields the correct answer—or simply fails to do so—but it is unable to guarantee a time limit because the time complexity depends on the input. In the worst-case scenario, however, it ensures an upper bound. Almost every time someone searches for something, Las Vegas algorithms appear. When a Las Vegas algorithm solves a problem, it is completely confident that it has found the correct answer, but the road to that point may be difficult to follow [24].

The randomized quick sort algorithm is a well-known example of a Las Vegas algorithm. It randomly selects a pivot and divides the elements into three sets: all the elements that are less than the pivot, all the elements that are equal to the pivot, and all the elements that are greater than the pivot [25].

B. K-Nearest Neighbor Algorithm

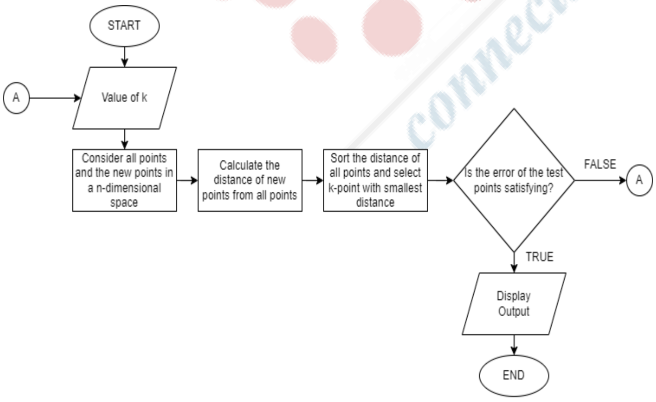

Figure 2: Flow of K-Nearest Neighbor

According to [26], K-Nearest Neighbor Algorithm (KNN) is used to resolve complex problems since it can resolve a variety of difficult problems in daily life. KNN's organizational structure was created to make searching quicker.

According to [27], KNN operates by calculating the distances between a query and each of the examples contained in the data, selecting the predetermined number of examples (K) that are the most like the query, and then either voting for the label that occurs the most frequently (in the case of classification) or averaging all the labels (in the case of regression).

Clearly, this exemplifies the adaptability of KNN. It can be utilized for classification, regression, and searching.

C. Hybrid Approach Using LVA and KNN

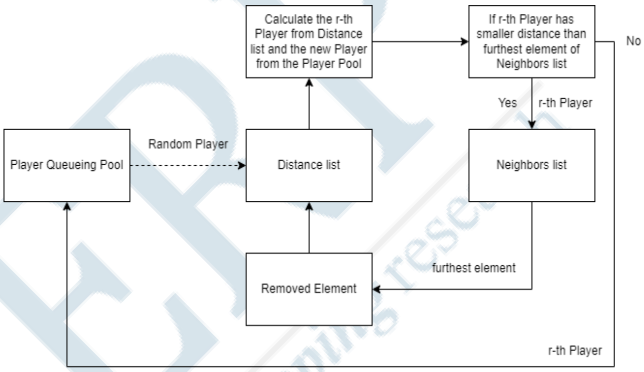

Figure 3: Theoretical Framework

Matchmaking for online games has never been developed with or improved upon using LVA. With this research, KNN and LVA will be merged to resolve LVA's classification difficulties. This also allows us to build a mechanism for detecting and qualifying a performance-based approach to online game matchmaking as a viable new method for matchmaking in online games.

[28] devised a skill rating system that requires a prediction of no more than a 55%-win rate for a match, and if the anticipated winning probability for one side is more than 55%, we toss away the teams and form two whole new teams,

Which is comparable to our study's goal. Instead of making predictions about the outcome of matches or win rates, our study will instead be based on the 5-man team skill rating, where the team members are chosen at random but not completely at random because it is also not far from the skill rating of each team member using a hybrid approach of LVA and KNN.

D. Feature Selection

One feature selection technique that may be suitable for use in a hybrid approach combining the Las Vegas Algorithm and K-Nearest Neighbor classification is mutual information-based feature selection.

This technique could be a good fit in this hybrid case because it can incorporate the probabilistic nature of KNN classification, and it could be used to filter out features that are not important for the classification. Also, it could be used with Las Vegas Algorithm considers random feature subsets and therefore adds an element of randomization that allows an exploration of the feature space efficiently in high-dimensional feature space.

IV. METHODOLOGY

A. Dataset

The dataset was obtained from Kaggle, an open-source data repository hosting datasets from various groups. The collection contains valuable player stats. The dataset contains personal identification, location, rating, agent choices, and weapon preferences for 80,000+ participants. The data comprises players' K/D ratio, win rate, and average round damage. The dataset facilitates the analysis of Valorant players and pattern recognition. The dataset can aid in identifying popular agents and effective weapons. The dataset facilitates cross-regional player performance comparisons and longitudinal player tracking.

B. Pre-processing

During the study, the advocates opted to employ the software application known as Visual Studio Code as their primary tool in authoring the computer code. This decision was made based on the software's reputation for being a highly efficient and user-friendly integrated development environment (IDE) that is widely used by software developers and programmers across various industries.

Data cleaning and preparation for machine learning models is a key application. This study analyzes the method of identifying the key features for forecasting player ratings in an online gaming dataset. The columns 'region', 'name', 'tag', 'agent_1', 'agent_2', 'agent_3', 'gun1_name', 'gun2_name', and 'gun3_name' were eliminated from the dataset as they were not pertinent to the task at hand. The 'rating' column was excluded from the feature matrix (X) as it should have been the objective variable (y) or a class.

C. Mutual Information-Based Feature Selection

A mutual information classification approach with k=3 was used for feature selection. Upon analysis, it was determined that the three primary attributes that were identified and deemed significant were "victories," "headshots," and "kills." These metrics were found to be of utmost importance in evaluating the overall performance and success of the individual or team in question. It is worth noting that these attributes were identified through a rigorous and comprehensive examination of the data, which was conducted with the utmost care and attention to detail. The chosen attributes exhibit a substantial degree of mutual information with the target variable, which is indicative of their potential to serve as reliable predictors of a player's rating. This finding suggests that these specific characteristics possess a strong association with the outcome variable, and thus, may be instrumental in forecasting the performance of a given player.

D. Training and Testing

The dataset has been divided into distinct training and testing subsets, with a particular emphasis on utilizing the most significant k features. The training data was utilized to instantiate and train a K-nearest neighbors' classifier. A single row was randomly selected from the feature matrix X to serve as the test data, and the classifier made a prediction of its corresponding label. Subsequently, the precision of the K-nearest neighbors' algorithm was calculated. In addition, the classifier's precision, recall, and f-score were computed.

The outcomes were appended to a roster, which was subsequently transformed into a structured data object known as a DataFrame. Ultimately, the outcomes were recorded in a Comma Separated Values (CSV) format.

E. Performance Metrics

Accuracy, precision, recall, and F1 score are used to evaluate a classification model in machine learning. Each of these indicators helps us understand the model's strengths and flaws. By looking at all four indicators, we can assess the model's performance. Based on classification results, these metrics are calculated:

True Positives (TP) are events that were accurately categorized as positive. *True Negatives (TN)* are instances that were appropriately categorized as negative. *False Positives (FP)* are instances that were wrongly labeled as positive. *False Negatives (FN)* are situations that were misclassified as negative.

The metric of accuracy, refer to (1), serves as a means of comprehending the proportion of correctly classified instances in relation to the total number of instances. The metric informs us about the ratio of accurate categorizations in relation to the overall quantity of occurrences.

$$accuracy = \frac{(TP+TN)}{(TP+TN+FP\ FN)} \quad (1)$$

Precision, refer to (2), helps determine positive classification accuracy by comparing the proportion of true positives to the sum of true and false positives. When we forecast a positive outcome, this helps us assess our accuracy.

$$precision = \frac{TP}{(TP+FP)} \quad (2)$$

Recall, refer to (3), tests the model's positive recognition. It quantifies the ratio of accurate positive classifications to positive instances. Recall shows how well a model captures positive cases.

$$recall = \frac{TP}{(TP+Fn)} \quad (3)$$

The F1 score, refer to (4), provides a complete model efficacy assessment. Harmonic means integrating precision and recall. A model that accurately identifies positive instances and captures all relevant positive examples has a high F1 score.

$$f1 = 2\frac{(precision * recall)}{(precision + recall)} \quad (4)$$

V. RESULTS AND DISCUSSION

A. Results

The initial stage involved training the model for a duration of 10 iterations. An iteration refers to one iteration over the training dataset. Stated differently, the model is exposed to the entire set of training data in a single iteration.

Following that, the model underwent a training process spanning 30 iterations. This was undertaken to assess whether there would be an enhancement in the precision. Following the observed improvement in accuracy, the subsequent course of action involved further training of the model for additional iterations.

After that, the model was trained for a total of 50 iterations. Nevertheless, the precision exhibited a decline in contrast to the outcomes obtained after 30 iterations. This occurrence is frequently observed in the field of machine learning. With an increase in the number of iterations, the model may exhibit overfitting tendencies toward the training data.

The last phase involved terminating the model training process upon completion of 50 iterations. This decision was made due to the lack of improvement in accuracy and the observed phenomenon of overfitting the model to the training data.

A. Problem 1

Table I: Comparison of Existing Algorithm and Hybrid Algorithm

k = 3	Existing Algorithm (LVA)			Hybrid Algorithm (LVA & KNN)		
Average	*10*	*30*	*50*	*10*	*30*	*50*
Accuracy	0%	7%	6%	30%	57%	48%
Precision	0%	7%	6%	40%	67%	54%
Recall	0%	7%	6%	40%	67%	54%
F-Score	0%	7%	6%	40%	67%	54%

Table I presents the outcomes of two distinct algorithms, namely the existing algorithm (the Las Vegas Algorithm) and the hybrid algorithm (the Las Vegas algorithm and K-Nearest Neighbor), across varying iterations. The performance of each algorithm was assessed using distinct metrics, namely accuracy, precision, recall, and F-score.

Below each algorithm, there are three columns denoting the number of iterations, specifically 10 iterations, 30 iterations, and 50 iterations. The performance values for each algorithm and iterations can be observed in their respective columns. The performance metrics are expressed in the form of percentages.

The findings presented in Table 1 indicate that the hybrid algorithm, when subjected to 30 iterations, yields superior results in comparison to all other iterations of the existing algorithm. The hybrid algorithm's impressive accuracy rate of 57%, as well as its precision, recall, and f-score rates of 67%, suggest that it is effective in the classification and categorization of data.

B. Problem 2

Table II: Comparison of Existing Algorithm and Hybrid Algorithm in its Average Runtime

	Existing Algorithm (LVA)			Hybrid Algorithm (LVA & KNN)		
Average	*10*	*30*	*50*	*10*	*30*	*50*
Runtime	0.22	0.23	0.22	26.89	26.37	26.89

The data presented in Table II indicates that the existing algorithm outperforms the hybrid approach in terms of runtime. The results indicate that the existing algorithm may exhibit superior speed for the given task, owing to its ability to perform the necessary computations in a comparatively shorter duration than its hybrid counterpart. The hybrid algorithm exhibits a comparatively longer runtime as it involves the preliminary categorization of data prior to the selection of random players, in contrast to the existing algorithm, which directly identifies players without considering their performance rate.

B. Problem 3

Table III: Comparison of Existing Algorithm and Hybrid Algorithm in its Average Distance

	Average	Distance
Existing Algorithm (LVA)	*10*	58.58%
	30	63.44%
	50	58.91%
Hybrid Algorithm (LVA & KNN)	*10*	3.60%
	30	5.32%
	50	2.80%

The results presented in Table III demonstrate that the hybrid algorithm displays a shorter distance from other players, which can be interpreted as a reflection of a restricted spectrum of performance ratings. This observation, in turn, implies that the competencies of the players utilizing the hybrid algorithm are relatively comparable to one another. When comparing the existing algorithm with the implementation of a random player selection approach, it can be observed that the latter yields a significantly greater distance. The difference can be attributed to the fact that the random selection process introduces a higher level of variability in the selection of players, resulting in a wider distribution of distances between the selected players. The findings of the study demonstrate the successful assessment of the amalgamation of two distinct algorithms, namely the Las Vegas Algorithm and K-Nearest Neighbor, which is commonly referred to as the Hybrid Algorithm.

VI. CONCLUSION

This paper proposed a hybrid approach to online game matchmaking using the Las Vegas Algorithm and K-Nearest Neighbor with the following enhancements: classifying or categorizing data, improving its runtime, and increasing the probability of its success. This study showed that the combination of LVA and KNN helped in the categorization and classification of data and contributed to its probable success. However, the hybrid algorithm was characterized by a relatively longer runtime compared to the existing algorithm, the Las Vegas algorithm. This is due to the fact that the hybrid algorithm involves an initial step of data categorization before the selection of random players. In contrast, the existing algorithm directly identifies players without considering their performance rate. The hybrid algorithm's longer runtime can be attributed to the additional computational steps required for data categorization, which are not present in the existing algorithm. Despite this drawback, the hybrid algorithm has the potential to yield more accurate player selections by considering performance rates in the categorization process.

To improve the work of future researchers, it is recommended by the authors of this study to apply the hybrid algorithm in a different field. This would allow for the exploration of the algorithm's versatility and potential applicability in various fields. By conducting further research in this manner, a more comprehensive understanding of the algorithm's strengths and limitations could be obtained, ultimately contributing to the advancement of knowledge in the field. The medical domain has the potential to contribute significantly towards the prediction of various diseases. Through the utilization of advanced technologies and techniques, medical professionals can identify and analyze various risk factors associated with a particular disease, thereby enabling them to predict the likelihood of its occurrence. This proactive approach toward disease prediction can aid in the development of effective prevention and treatment strategies, ultimately leading to improved health outcomes for individuals and populations. In addition to the recommendation, the authors of the study propose that it would be advantageous to explore alternative feature selection techniques that have the potential to boost the accuracy of the hybrid algorithm. By incorporating different feature selection methods, the algorithm may be able to more effectively identify and utilize relevant data points, ultimately leading to improved accuracy and performance.

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