AN ENHANCEMENT OF BAUTISTA AND CHAVEZ' LAS VEGAS ALGORITHM USING SUPPORT VECTOR MACHINE APPLIED IN ONLINE GAME MATCHMAKING

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ABSTRACT

The Las Vegas algorithm, a type of random process in computing that consistently delivers precise results or conclusively identifies failure. It is utilized in online game matchmaking systems to ensure equitable and effective player pairings that employ controlled randomness to match players, based on factors such as skill level, experience, and game performance metrics. In the study, it introduces an enhanced Las Vegas Algorithm integrated with Support Vector Machine (SVM) technology to optimize online game matchmaking. Drawing on the significance of efficient matchmaking in gaming, the research addresses scalability challenges and aims to enhance accuracy and runtime performance. The methodology involves loading and preprocessing player data, training the SVM model for player categorization, and integrating the Las Vegas algorithm for match selection. PyCharm, Python, and Microsoft Excel were utilized for implementation, alongside libraries such as NumPy, Pandas, and Scikit-learn. Results demonstrate the Enhanced Algorithm's superiority, achieving 79% accuracy and outperforming Traditional and Hybrid Algorithms across iterations. Runtime analysis indicates a significant improvement, with the Enhanced Algorithm completing tasks in 0.02 seconds, compared to the Hybrid Algorithm's 26.89 seconds. Discussion highlights the role of feature selection in enhancing computational efficiency and the algorithm's ability to maintain accuracy and improve runtime performance, contributing to fair and engaging gaming experiences. The study's findings underscore the potential of the Enhanced Algorithm to transform matchmaking systems, offering a compelling avenue for enhancing player satisfaction and gaming experiences in online gaming environments.

Keywords: Las Vegas Algorithm, Support Vector Machine, Online Game Matchmaking, Feature Selection Algorithm

INTRODUCTION

The Las Vegas algorithm is a random process commonly used in computing to reliably produce precise outcomes or conclusively identify failures. Its runtime depends on the complexity of the input, and it operates based on two rules: either it completes within an expected timeframe, providing a solution, or it stops, signaling an inability to find a solution (CodeDocs, 2021).

In online gaming, the Las Vegas algorithm, alongside other randomized algorithms, plays an important role in matchmaking systems, ensuring fair and efficient pairings among players (Bautista & Chavez, 2023). By incorporating controlled randomness and considering factors such as skill level and experience, these algorithms enhance matchmaking efficiency, ultimately enhancing player experience by facilitating competitive matchups.

Research by Dumrique and Castillo (2018) highlights the significance of online gaming as a preferred leisure activity for many individuals, fulfilling various functions such as stress relief, challenge, competition, relaxation, and social interaction. However, the effectiveness of matchmaking systems significantly influences player satisfaction and, consequently, the longevity of gaming products (Deng et al., 2021).

Player impatience and dissatisfaction can arise from delays in matchmaking or being matched against opponents of significantly different skill levels (IDEAS NCBR, 2022). These challenges underscore the importance of an effective online matchmaking algorithm to maintain player engagement and uphold a positive reputation for gaming companies.

While previous studies have attempted to enhance the Las Vegas algorithm's performance in matchmaking, such as through hybridization with other algorithms, limitations persist, including reduced accuracy with increasing iterations and longer runtimes (Bautista & Chavez, 2023; Hoos & Stützle, 2013). These challenges necessitate further research to develop more efficient and precise matchmaking algorithms.

To address the limitations observed in existing matchmaking algorithms, the researchers propose an enhanced Las Vegas Algorithm integrated with Support Vector Machine (SVM) technology. This integration aims to leverage SVM's classification capabilities to improve player categorization and, subsequently, enhance the precision and efficiency of matchmaking systems.

The primary objective of the study is to design an algorithm for online game matchmaking that prioritizes increased accuracy, thereby promoting more balanced gameplay and enhancing the overall gaming experience for players. Additionally, the researchers aim to optimize the algorithm's runtime performance to minimize execution time while maintaining or surpassing existing accuracy levels. Furthermore, the study seeks to address the scalability challenges posed by the non-deterministic nature of the Las Vegas algorithm, particularly as player bases expand and datasets grow. This objective involves the development of a Feature Selection Algorithm to optimize feature choice, effectively tackling classification and scalability issues inherent in the algorithm. Through these objectives, the research endeavors to create a more efficient and precise matchmaking system capable of accommodating larger player populations and sustaining high levels of performance over time.

Research Questions

1. The challenging analysis of Las Vegas algorithm behavior due to its non-deterministic nature leads to scalability problems, impacting the algorithm's efficiency (Hoos & Stützle, n.d.)
2. The algorithm yields a lower result of accuracy from 57% to 48% as the iteration increases which can affect the fairness of matchmaking.
3. The hybrid algorithm returns a comparatively longer runtime of 26 seconds which affects the efficiency of matchmaking and leads to player dissatisfaction.

METHODOLOGY

The methodology employed by the researchers to address the research question and achieve the study objectives involved several key steps. Firstly, the researchers loaded the Valorant Dataset into the simulator after converting it into CSV format. This dataset contained vital statistics of over 80,000 players, including personal details, location, ratings, agent preferences, and favored weapons. Subsequently, the researchers processed the player data through classification, feature selection, and clustering in both 2-dimensional and 3-dimensional views. This processing enabled the evaluation of player data, with the outcomes presented using Support Vector Machine's (SVM) hyperplane feature to display player classification accuracy and matchmaking evaluation metrics.

Following data processing, the researchers trained the SVM model to assess player skill levels based on diverse gaming parameters. This involved separating features and target players, as well as splitting the data into training sets. Feature selection was then performed to further classify the data, analyzing player skills and performance. Clustering visualization techniques, including dimensionality reduction using Principal Component Analysis (PCA), were utilized to visualize player clusters in both 2D and 3D.

Integration of the Las Vegas algorithm followed, strategically selecting opponents or teammates within desired skill ranges while considering fairness and balance criteria. Throughout the process, the researchers utilized several software tools, including PyCharm Community Edition as an Integrated Development Environment (IDE) for Python development, Python itself for coding and data analysis, and Microsoft Excel for data management and basic computations. Additionally, Python libraries such as NumPy, Pandas, and Scikit-learn were employed for mathematical operations, data manipulation, and machine learning tasks.

The training and testing phase involved the initial collection and preprocessing of data for SVM model training. The SVM model predicted player skill levels, while the Las Vegas algorithm optimized match selection based on skill ranges and randomness for opponent selection. Through continual learning and iterative refinement, the SVM-LVA framework evolved to ensure fair and engaging gaming experiences.

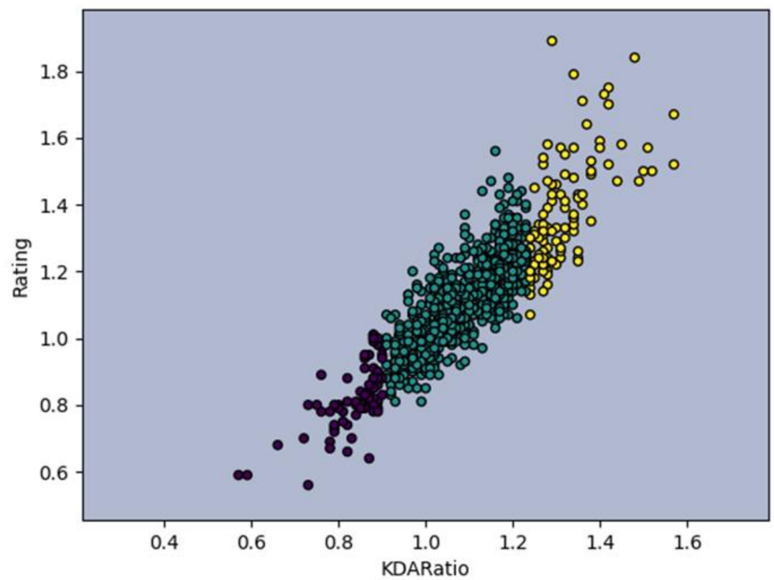
Overall, the simulation of the Enhanced Algorithm yielded promising results, outperforming Traditional and Hybrid Algorithms with an accuracy of 79% across multiple iterations. These findings underscored the efficacy of the proposed Enhanced Las Vegas Algorithm-Support Vector Machine fusion for online game matchmaking, demonstrating its potential to enhance player satisfaction and gaming experiences.

RESULTS

A.) Results of Traditional, Hybrid, and Enhanced Algorithm in Simulation

Figure 1

Visualization of Player Parameters



The figure shows the visualization of the player's parameters as the result of utilizing the Feature Selection Algorithm to enhance the computational efficiency of the traditional algorithm. The first parameter, "Ratings," is shown in the graph as the green colored dots. The second parameter "KD Ratio" as yellow and the combination of both "KD Ratio" and "Ratings" as the violet dots. The intervals at the X-axis indicates the "KDARatio" and the Y-axis as the "Rating".

B.) Results of Traditional, Hybrid, and Enhanced Algorithm in Simulation Using 10, 30, 50, and 100 Iterations

Table 1

Comparison of Results of Traditional, Hybrid, and Enhanced Algorithm

	Traditional Algorithm (LVA)				**Bautista & Chavez' Hybrid Algorithm (LVA & KNN)**				**Enhanced Algorithm: EHL Model (LVA& SVM)**			
No. of Iterations	**10**	**30**	**50**	**100**	**10**	**30**	**50**	**100**	**10**	**30**	**50**	**100**
Accuracy	*0.3%*	*0.7%*	*0.5%*	*0.2%*	*30%*	*57%*	*48%*	-	*77%*	*78%*	*78%*	*78%*
Precision	*0.25%*	*0.66%*	*0.5%*	*0.28%*	*40%*	*67%*	*54%*	-	*61%*	*61%*	*61%*	*61%*
Recall	*0.2%*	*0.8%*	*0.6%*	*0.4%*	*40%*	*67%*	*54%*	-	*77%*	*78%*	*77%*	*77%*
F1 Score	*0.22%*	*0.72%*	*0.54%*	*0.33%*	*40%*	*67%*	*54%*	-	*79%*	*79%*	*82%*	*84%*

Table 1 displays the results obtained from three different algorithms which are the Traditional Algorithm (referred to as the Las Vegas Algorithm), the Chavez – Bautista Hybrid Algorithm (a combination of the Las Vegas algorithm and K-Nearest Neighbor), and the Enhanced Algorithm or the EHL Model (which integrates the Las Vegas Algorithm with Support Vector Machine).

Each algorithm's performance was evaluated across various metrics, including accuracy, precision, recall, and F1 score. For the LVA, LVA & KNN, and LVA-SVM algorithms, 4 columns represent the number of iterations: specifically, 10, 30, 50, and 100 iterations.

The traditional algorithm (LVA) shows a low and inconsistent percentage of accuracy, precision, recall and F1 score. At **10 iterations** its performance ranges between ***0.2 - 0.3%***. At **30 iterations** it ranges from ***0.66-0.8%***. At **50 iterations** ranging from ***0.5-0.6%***. And at **100 iterations** ranging from ***0.2-0.4%***.

The hybrid algorithm (LVA-KNN) on the other hand shows an inconsistent percentage of accuracy, precision, recall, and F1 score with results at **10 iterations** ranging from ***30-40%***. At **30 iterations** ranging from ***57-67%***. And at **50 iterations** ranging from a lower ***48-54%*** than the previous iterations.

Lastly, the enhanced algorithm EHL model (LVA-SVM) performs with a consistent and higher percentage of accuracy, precision, recall, and F1 score than the previous algorithms. At both **10 and 30 iterations** ranging from ***61-79%*. 50 iterations** ranging from ***61-82%***. And lastly at **100 iterations** with performance ranging from ***61-84%.***

C.) Results of Runtime of Traditional, Hybrid, and Enhanced Algorithm in Simulation

Table 2

Comparison of Runtime of Traditional, Hybrid, and Enhanced Algorithm

	Traditional Algorithm (LVA)				***Bautista & Chavez' Hybrid Algorithm (LVA & KNN)***				***Enhanced Algorithm: EHL Model (LVA& SVM)***			
No. of Iterations	***10***	***30***	***50***	***100***	***10***	***30***	***50***	***100***	***10***	***30***	***50***	***100***
Runtime	*0.10*	*0.13*	*0.11*	*0.14*	*26.89*	*26.37*	*26.89*	*-*	*0.02*	*0.02*	*0.02*	*0.02*

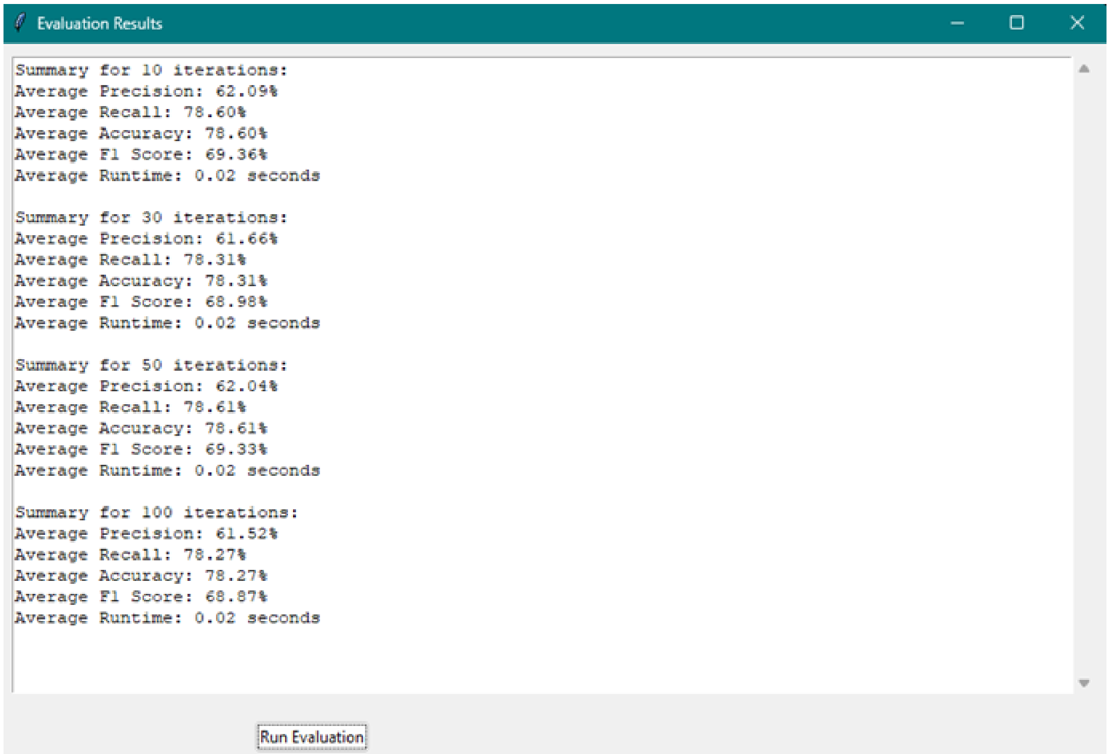
The data showcased in Table 2 presents the runtime of the Traditional Algorithm (LVA), Hybrid Algorithm (LVA-KNN) and Enhanced Algorithm's (LVA-SVM) runtime with varying iterations of 10, 30, 50 and 100.

The Traditional Algorithm (LVA) exhibits a low runtime of ***0.10 seconds*** at **10 iterations**, ***0.13 seconds*** at **30 iterations, *0.11 seconds*** at **50 iterations** and ***0.14 seconds*** at **100 iterations**. The Hybrid Algorithm (LVA-KNN) shows a relatively longer runtime starting at **10 iterations** with ***26.89 seconds***. At **30 iterations** with ***26.37 seconds***. And **50 iterations** with ***26.89 seconds.*** The Enhanced Algorithm (LVA-SVM) exhibits a consistent and low runtime of ***0.02 seconds*** at all **10, 30, 50 and 100 iterations.**

D.) Evaluation Summary

Figure 2

Accuracy Results of the Enhanced Algorithm Using the Application



In Figure 2, a concise overview of the evaluation findings for the enhanced algorithm is presented. The results clearly indicate that the enhanced algorithm performs better than both the traditional and hybrid algorithms, especially in its performance across each iteration. It maintains an accuracy of 78%, unlike the other algorithms that yield much lower accuracy as the iteration increases. Notably, the average precision stands at 62%, recall at 78%, and F1 Score at 69%, all achieved with remarkable efficiency, with a mere runtime of 0.02 seconds. These findings highlight the significant advancements brought by the enhanced algorithm in improving the effectiveness and speed of the matchmaking process.

DISCUSSION

A.) Enhancing Computational Efficiency

To solve the classification of the algorithm and its scalability issue, the researchers utilized Feature Selection Algorithm. By selecting the most relevant requirements for subsequent classification tasks such as player Ratings, KD Ratio, and Ratings/KD Ratio, it makes it more manageable to handle larger datasets.

The first parameter, "Ratings," serves as a critical determinant for match queuing, ensuring players are grouped with others of the same rank. Furthermore, the algorithm adjusts matchmaking choices according to players' skill levels as they change, creating fair and enjoyable gaming experiences. Using Support Vector Machine, it makes matchmaking more efficient, ultimately making the gaming experience more satisfying overall.

Moreover, the KDA Ratio (Kill-Death-Assist) parameter is utilized to assess player performance, calculated as (Kills + Assists) / Deaths, where Kills indicate the number of enemy players defeated, Deaths signify times a player was defeated by enemies, and Assists represent aid in defeating an enemy player.

Weighing the KDA enhances player classification, curbing the influence of experienced players, or "Smurf accounts," who may exploit lower-ranked or novice players. Players with high weighted KDA are categorized as those who typically perform above their rank, thus promoting fair competition.

By integrating these parameters, matchmaking ensures the formation of balanced and equitable five-vs-five matches, pairing players with similar or identical ranks for an optimal gaming experience.

B.) Optimizing Algorithm Accuracy

Each algorithm's performance was evaluated across various metrics, including accuracy, precision, recall, and F1 score. For the LVA, LVA & KNN, and LVA-SVM algorithms, 4 columns represent the number of iterations: specifically, 10, 30, 50, and 100 iterations.

The performance values for each algorithm and iteration are visible in their respective rows, with performance metrics expressed as percentages. The data presented in Table 1 reveals that the EHL model consistently maintains and improves its performance across each iteration, surpassing the results obtained from all other iterations of both the Traditional Algorithm and Hybrid Approach. With an accuracy rate of ***78%,*** coupled with precision, recall, and F1 score rates of ***61%, 77%*** and ***84%*** respectively, the EHL model demonstrates its effectiveness in the classification and categorization of data.

C.) Improving Runtime Performance

The data showcased in Table 2 highlights that the Enhanced Algorithm surpasses both Traditional and Hybrid approaches in terms of runtime efficiency, with 0.02 seconds, which is 99.92% faster. As depicted, the Traditional algorithm exhibits a runtime ranging from 0.10 to 0.14 seconds, attributable to the absence of classification or techniques within the algorithm. The Hybrid Algorithm on the other hand, exhibits a long runtime that can affect the player’s satisfaction. These findings suggest that the EHL model demonstrates superior speed in executing the required task, attributed to its capability to carry out the necessary operations with better efficiency.

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