Enhanced Soccer Training Simulation Using Progressive Wasserstein GAN and Termite Life Cycle Optimization in Virtual Reality

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Abstract: *Virtual Reality (VR) offers the possibility of creating engaging and intensive training programs to enhance sports performance. Football, a widely popular sport worldwide, attracts millions of spectators. However, the physical demands and risks inherent in the game necessitate the creation of a training environment immune to external influences, minimizing sports-related injuries while enhancing player immersion. Existing training methods are affected by external factors like, weather, injuries, and space limitations, hindering effectiveness and skill development. To overcome these issues, in this research, enhanced soccer training simulation using Progressive Wasserstein GAN and Termite Life Cycle Optimization in Virtual Reality (PWGAN-TLCOA-ST-VRT) are proposed. This study begins by analyzing the fundamental features of computer-generated soccer training techniques and introduces the implementation of VRT in football training via PWGAN technology. The goal is to develop virtual systems resilient to external factors and provide theoretical support for the expansion of virtual football sports software. By overcoming constraints like, weather, player injuries, space limitations, and financial constraints, the proposed approach aims to enhance training effectiveness, teaching techniques, and football skill development. Software tools like Poser 8.0, 3Ds MAX and EON Studio are introduced for system development. Evaluation of the proposed PWGAN-TLCOA-ST-VRT method is examined using performance metrics including, precision, accuracy, F1-score, recall, specificity, error rate, computation time, and Receiver Operating Characteristic (ROC) analysis. The proposed PWGAN-TLCOA-ST-VRT technique achieves significant improvements compared to existing approaches like, Analysis of the application of virtual reality technology in football training (AI-ST-VRT), Cortex VR: Immersive analysis and training of cognitive executive functions of soccer players using VR and machine learning, Predict the value of football players using FIFA video game data and machine learning techniques (MLR-ST-VRT).*

Keywords: *Football, progressive Wasserstein generative adversarial network, soccer training termite life cycle optimization, virtual reality.*

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1. Introduction

The Virtual Reality (VR) is referred as Virtual Environments (VEs) are the popular topic in recent years due to the development and growth of technology [8]. Since 1965, the fundamental idea behind VR technology has been in existence. However, the device's high price is a barrier to its general adoption [27]. The adoption of VR technology is decreased as a result of the prolonged overhypes and hype around it. Because of this, many experts had been pessimistic about the widespread adoption of VR technology [7]. The introduction of affordable consumer-grade VR headsets for gaming and entertainment has helped VR technology gain traction [11]. Nowadays, VR utilized in a wide range of industries, like games, sports, movies, education, and construction as well as enormous economic value for society [22]. Future research into VR technology is quite promising. Participants move around Virtual Environment (VE), view it in dissimilar perceptions and direct computer to tasks by using the sophisticated human-computer interface known as VR. This new technology involves several different fields like computer science, engineering, social sciences [20]. VR employs computer technology to produce realistic, 3 dimensional animations that combine real and virtual worlds for an immersive experience [16]. It combined by sensor to create a place like actual world in sight, sound, touch, smell [6]. VR technology allows user engagement and sensory immersion. Therefore, through digital created imagery, enthusiastic characters, avatars, users move about the VE, pick up virtual objects and interact with them [19]. Since people engage with media and influence how a situation or understanding unfolds in real time [21]. Customers interact with VR equipment efficiently using this way, due to computers and accompanying gear. Other important element in VR technology is immersion because of perceptual enveloped VE, users of immersive VR are marginally aware of their surroundings [15]. As a result, the sensory awareness of actual world is muted and offers impression that a person has entered VE and engaged actively [30]. The VR technology aim is to enable participant interaction with the VE and realistic experiences [5, 17]. The VR system users engaged themselves completely in a VE to make immersive experience; nevertheless, the pricey and demanding technology required renders the system's commercial growth challenging. The viewing window for desktop VR systems is a computer screen or projection screen. To interact with things in the VE, such as on a real-world game console, a portable input device or position tracker is required [4].The basic objective of VR technology is to allow for organic user-virtual world interaction to produce a realistic experience [24]. The goal of immersive VR systems is to immerse users in a digitally produced world, but the required technology is complex and costly, which makes commercial development challenging [18]. The desktop VR method uses a computer screen or projection screen as the VE's viewing window [2]. To manipulate objects in the virtual world like a real-world game console, a portable input device or position tracker is required. Football is widespread sports, viewed by millions people. However, football's intense physical contact, demanding movements, risky ball-tackling cause various physical damage. Therefore, it is important to create training setting free from outside distractions, protectors against sports injuries, and encourages an immersing sense in the athletes. VR has vital role to play in enhancing football training because of interactive, immersive, creative features [29]. In today's globalized contemporary culture, technology drives social growth and professional football is no exception. Football coaches observing to establish a long-lasting competitive edge now have access to a market for technology-based innovation because to the sport's intense competition [26]. VR technology offers wide potential applications in football training since it help players exercise more effectively without being constrained by time or physical area [10]. VR technology is useful enough to monitor the body motions made by players while playing sports, allowing coaches and players to analyze the data.

Existing research on soccer training simulations and VR technology lacks a cohesive approach to addressing the challenges posed by external factors such as weather, injuries, and space limitations. Despite advancements in VR and machine learning techniques, there remains a gap in optimizing training effectiveness while minimizing injuries and external influences. The presented gap underscores the need for a comprehensive solution that integrates Progressive Wasserstein Generative Adversarial Network (PWGAN) with Termite Life Cycle Optimization Algorithm (TLCOA) for soccer training simulation in VR. The motivation behind this research stems from the potential to revolutionize soccer training by providing an immersive, injury-free environment that overcomes the constraints of traditional training methods. By leveraging cutting-edge technology and optimization algorithms, the presented research aims to address this gap and provide the advancement of VR technology in sports training.

The novelty of the proposed research exists in proposing a comprehensive approach to soccer training simulation in VR using PWGAN technology. By collecting and synthesizing athlete physiological data, and optimizing PWGAN parameters with a new variant of the TLCOA, the study creates realistic training scenarios. This methodology demonstrates superior efficiency and effectiveness, offering innovative insights for VR-based sports training with the Implementation on Python and examined with existing models.

The major concepts of this research paper are abridged below:

- Introducing a novel approach to soccer training in VR utilizing PWGAN technology.
- Utilizing PWGAN to generate synthetic data resembling real athlete performance metrics, facilitating the creation of personalized soccer skill learning scenarios for assessment purposes.
- Introducing a new variant of the TLCOA to optimize PWGAN parameters, enhancing its ability to generate realistic synthetic data for training simulations.
- Implementing the PWGAN-TLCOA-ST-VRT model in Python and evaluating its effectiveness using performance metrics.
- Comparing the efficiency of the proposed technique with existing models demonstrates superior performance of training effectiveness and computational efficiency.

Remaining manuscript is organized as: section 2 portrays the literature review, section 3 describes the proposed method; section 4 shows the result, section 5 gives the conclusion.

2. Literature Review

Several researches were suggested in the literature related to deep learning based on Football training in VR, some of recent studies are divulged here,

Zhao and Guo [32] suggested analysis of the application of Virtual Reality (VR) technology in football training with the combination of sports training and VR technology. The feasibility of VR football training systems was investigated using Poser 8.0, 3Ds MAX, and EON Studio. The presented approach offers theoretical support for creating and analyzing virtual football sports system software, overcoming constraints like weather, player injuries, and financial constraints. This enhances training techniques, technical movement knowledge, and football abilities. It offers high Accuracy and higher Error Rate.

Krupitz *et al*. [12] presented Cortex VR: Immersive analysis and training of cognitive executive functions of soccer players by VR and machine learning. The presented strategy was to evaluate the systems utility for cognitive training and EF analysis using VR-critical performance metrics. The architecture of the system provides better experience compared with standard desktop apps, while the application's effort was not adversely affected by the foreign interaction paradigm. The systems modular design enables users to engage in natural virtual world. Game modes blend gameplay with simulation material to focus on particular aspects of training. The technology separates coaching sessions from training sessions, and a database keeps track of user performance and advancement. It delivers distraction-free immersion training in a completely virtual setting, together with an intuitive analysis tool and an automated, adaptive training mode. It provides high Precision. It has higher F1-Score.

Al-Asadi and Tasdemır [1] presented predict the value of football players using FIFA video game data and machine learning methods. Their main argument was that transfer prices and market values are vital in transfer negotiations since football was a large business and popular sport. Experts estimate market values, but data analytics offers an alternative. Here, the objective quantitative method using machine learning algorithms decides football players' market values. The data used was FIFA 20 video game data from sofifa.com. Random forest performed better than other methods with the greater accuracy score and lesser error ratio. Negotiations between football teams and player agents were expedited using the presented method. The presented method provides high Recall. It provides higher Specificity.

Tian *et al*. [23] presented the path of college football teaching and training reform along intelligent innovation based on mixed teaching mode. Their main objective was to demonstrate that computers and network information technology were impacting education, with higher education information integrating technology and education. The presented paper explores innovative teaching development depend on college football training. The essay develops football training reform experiment employing smart sensor technologies and questionnaires to track dietary modifications with literature investigation and questionnaire surveys. The trial demonstrates that the football teaching as well as training development program improves students' football training experiences with 95% confidence level. The utilization of Massive Open Online Course (MOOC) resources in the classroom develop students' capacity for autonomous learning, move them from passive to active learning, boost learning motivation, nurture a deep interest in football. The presented method provides high error rate. It has greater computation time.

Li *et al*. [13] presented an approach for enhancing football teaching quality instruction in mobile internet context by AI and Meta verse. Their main contribution was to generate the meta-verse, which developed the influence of science and technology. Artificial Intelligence (AI) was crucial for addressing meta-verse errors in meta-verses. The quality of traditional physical education was currently changing. So, the integration of AI and the meta-verse was increasing, particularly in football teaching. Were physical education includes teaching the game of football, VR offers immersion quality, interaction, creativity that create a virtually authentic football teaching experience. The presented study explores methods to improve football instruction; the meta-verse and K-means algorithm were used to power 360-degree panoramic VR films in mobile Internet contexts. It provides high Receiver Operating Characteristic (ROC). It has greater F1-Score.

Zhang and Tsai [31] presented application of adaptive VR through AI-enabled techniques in modern sports training. The main approach was to develop a sports training structure by VR technology. Then designing motion detect data technique depend on behavior strings. The research compares traditional and virtual training methods, revealing that the training psychology approach was more effective than traditional methods. Training psychology provided greater internal motivation than traditional training methods, a significant improvement. The presented approach increases motivation, improves training outcomes, and encourages psychological motivation to continue training. It provides high Recall and higher Accuracy.

Wood *et al*. [28] presented soccer players of both amateur and professional were used to test the construct validity of a VR simulator adapted to the sport. The main contribution of the presented method was to provide VR, which has the possibility of immersive, engaging training solutions that improve sport performance. The thorough evaluation of the simulation's validity was required if VR training implemented and used in an effective and research created way. The simulation's construct validity measures how well it captures the essential elements of the activity. If the training exercises in the VR environment were appropriate for the talents needed there, athletes who excel in the real world of sport also succeed in the virtual one. The presented method provides high F1-Score. It has higher ROC.

Chen [3] presented the use of offensive and defensive linkage in a virtual football game using an Internet of Things (IoT) decision-making structure. Their main contribution is to football's popularity across the globe. Football may help players develop their offensive and defensive abilities in addition to strengthening their bodies and increasing their physical condition. Football matches are well-attended activities everywhere. Virtual football games have grown in popularity along with science and technology. The virtual football game was a creative endeavor which blends VR and computer technology to examine the link between offense as well as defense in virtual football game. The presented methods comprehend decision-making process and apply to IoT decision-making system, enabling to make decisions as quickly and precisely as virtual players. It reached greater Specificity, but high Error Rate.

The following limitations are observed using previous techniques depending upon the literature survey presented,

Transitioning from the literature review to the background of the research problem requires clarity to guide readers seamlessly. The existing literature highlights various approaches utilizing VR and AI technologies in soccer training. However, there are notable gaps and contradictions. While some studies focus on the presentation of VR technology in football training, others emphasize cognitive analysis, player valuation, or IoT decision-making structures. These diverse approaches reflect the evolving landscape of sports technology but also reveal gaps in addressing comprehensive training needs, including skill development, injury prevention, and performance evaluation. Despite advancements, there remains a lack of integration between AI-driven simulations, physiological data analysis, and immersive VR training environments. Therefore, there is a clear need to bridge these gaps and develop a holistic solution that optimizes soccer training effectiveness while addressing the limitations of existing methodologies. By integrating AI, VR, and physiological data analysis, our research aims to fill this gap by offering a comprehensive framework for soccer training simulation and evaluation. This research problem builds upon existing literature by offering a unified approach that leverages the strengths of AI and VR technologies to enhance soccer training outcomes.

3. Proposed Methodology

In this section, enhanced soccer training simulation using Progressive Wasserstein GAN and Termite Life Cycle Optimization in Virtual Reality (PWGAN-TLCOA-ST-VRT) are discussed. Figure 1 depicts proposed PWGAN-TLCOA-ST-VRT approach.

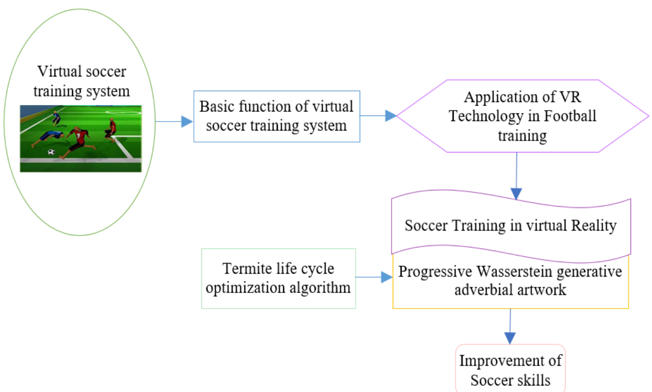

Figure 1. The proposed PWGAN-TLCOA-ST-VRT approach.

3.1. Virtual Soccer System

In the virtual soccer system, the basic structure system is based on the real-time ontology. A virtual soccer system is built in a 3 dimensional method and converted to virtual world. Through displays, sensors, and other devices, the virtual world generates tight feedback loop with internal system to enable user-controlled interface among the virtual and actual world. It stressed that the 3 dimensional model database stores 3 dimensional models and uses them in variety of scenarios to satisfy the requirements of real-world circumstances. At initial, the VE is generated via 3D data, which is collected from the real world and leads to the creation of a 3D model and by combining each 3D model one after other to produce VE that is identical to the real one, Through hardware tools like data suits, data gloves, position trackers, the computer gathers movement data from people and inserts it through 3D sensors into the user's virtual world. Auxiliary devices like the mouse, keyboard assist the user in switching and controlling the interface, interactive features at the same time.

3.2. Basic Functions of Virtual Football Training System

To satisfy the necessities for football training, the virtual football training system completes a number of necessary tasks. The few steps are detailed below:

3.2.1. A Realistic Feel of Football Training Ground

It should be felt realistic while developing a football training ground. So, to create a virtual training area for football it should contain the models like football, grass, the surrounding trees and sky. By utilizing this, it can provide a genuine feel of virtual training.

3.2.2. Physiological Data Collection of Athlete

Collection of data includes the important physiological and psychological health data of the athlete, according to this; they can collect the data like physiological and psychological health data which will be helpful while training.

1. Motion Signal of Reenactment and Demonstration.

The virtual system used by athletes or coaches able to record and depict technical motions. So that, it indicate the deficiencies between their movements and the repair of faults and the display of technical proficiency is made simple.

2. Analysis of Graph Result in Training

Here, error analysis and graph results show the impacts of training on athletes' performance as well as the degree of movement uniformity, which is helpful for teaching and training.

3.3. Application of VR Technologies in Football Training

Development tool called EON Studio was built for integrated creation of 3dimensional or VR content and the creation of interactive 3 dimensional apps. Other 3 dimensional programs simply linked with EON Studio to create VR items and scenarios without modifying them. Frame function nodes are chosen from EON simulation tree window and imported to virtual scene. They are changed to an avatar file and stored in internal database, where EON simulation tree construction is built. Finally, the nodes are dragged from simulation tree to logic window and connect to create logical relationship route. Finally, the animation technique is applied and used in the VE.

3.4. Soccer Training in Virtual Reality based on Progressive Wasserstein Generative Adversarial Network (PWGAN)

In this section, soccer training in VR using PWGAN is discussed [25]. Generative Adversarial Networks (GANs), a popular technique in machine learning. GANs consist of two neural networks - a generator and a discriminator-trained adversarially to generate realistic data samples. Wasserstein GAN (WGAN) is an extension of GANs that addresses some key challenges like mode collapse and training instability. This is accomplished by including the Earth Mover's Distance, or Wasserstein distance, as a metric of dissimilarity between probability distributions. WGAN offers a more stable training process and generates higher-quality samples compared to traditional GANs. In the context of VR, WGAN holds promise for enhancing the generation of VE s, including soccer training simulations. By leveraging the Wasserstein distance, PWGAN produces more realistic and diverse VEs, allowing for more effective and immersive soccer training experiences. Additionally, PWGAN's ability to adjust output types based on conditional information enables the integration of label information from soccer training and VR, further enhancing its applicability in this domain. PWGANs offer a transformative approach to enhancing the generation of VEs for soccer training simulations. By leveraging the Wasserstein distance as the training objective, PWGANs ensure improved stability, mitigating issues like mode collapse and providing a robust framework for generating consistent and realistic training scenarios. Additionally, the PWGANs produce higher-quality samples that closely resemble real-world data distributions, enabling the creation of immersive and visually appealing VEs. Moreover, the diversity of scenarios generated by PWGANs allows for comprehensive training experiences, encompassing various playing conditions, player interactions, and tactical scenarios. Furthermore, PWGANs can be conditioned on specific parameters, enabling the customization of training environments to meet individual player needs and coaching objectives. Through these capabilities, PWGANs enable the creation of tailored and effective virtual training experiences, ultimately contributing to the development of more skilled and proficient soccer players. Two portions make up the overall loss of the PWGAN: generator and discriminator. The generator's goal is revealed in, due to its convexity, differentiability, and symmetry, distance is typically employed as a default loss function. It is expressed in derived Equation (1).

$$M_2 Loss = \frac{1}{PQ} \left\| F(C) - a \right\|_2^2 \tag{1}$$

Here *P* and *Q* denotes the height and width of network. *F(C)* Indicate the data training process. M_2Loss function, this is frequently stuck at local minima and leading to strange results. Comparing to M_2Loss function, M_1Loss function considered as effective in suppressing data. Considering the minimal value, M_2Loss function is lower than the M_1Loss function value. It is formulated as Equation (2).

$$M_1 Loss = \frac{1}{PQ} \left| F(C) - a \right| \tag{2}$$

Here M_1Loss function is considered as more effective in suppressing data, *F(C)* Indicate the process of data training. It is the advanced motivated metrics. Here, *a* denotes *F(C)* and *SSIM* depicted below Equation (3).

$$SSIM(a,b) = \frac{2\mu_a\ \mu_b + K_1\ 2\sigma_{ab} + K_2}{\mu_a^2 + \mu_b^2 + k_1\ \sigma_a^2 + K_2} \tag{3}$$

here μ_a, σ_a denotes *mean and standard deviation a*. μ_b, σ_b implies mean and standard deviation of created solution *b*. σ_{ab} denotes the cross-covariance among *a* and *b*, K_1 *and* K_2 signifies constants to eliminate numerical uncertainty. *SSIM* denotes an index to evaluate VR human visual perception performance and the structural loss function expressed in Equation (4).

$$M_{SSIM} = 1 - SSIM\,(a,b) \tag{4}$$

Here M_2Loss function suffers from some problems in the training procedure. M_1Loss function is better than M_2Loss function in number of ways compared with M_2Loss function, 1-*SSIM* is shown as sensitive loss function to train de-noising technique. Therefore, weighted structurally-sensitive hybrid loss function proposed combines structural loss and M_1Loss function. It is expressed in Equation (5).

$$M_{wshi} = \tau M + (1-\tau) M_{ssim} \tag{5}$$

Here τ *denotes* weight to regulate the balance between every parameter. Then, weight balance of different terms in hyper-parameter is given Equation (6).

$$M_{total} = \alpha M_{WGAN} + M_{wshi} \tag{6}$$

Here α denoted as weight balance different terms in hyper-parameter. Finally, PWGAN improves the training skills of football players. The AI-based optimization technique is used in the PWGAN classifier owing to its convenience, pertinence. The TLCOA is used to enhance the PWGAN optimal parameter α. Here, TLCOA is used for tuning the PWGAN weight and bias parameter.

3.5. Optimization under Termite Life Cycle Optimization Algorithm (TLCOA)

Weights parameter of PWGAN is improved by the TLCOA [14]. The primary goal of using the TLCOA optimization method is to improve PWGAN's accuracy and presentation in the learning environment [9]. TLCOA is integrated into the PWGAN to optimize its weight parameter, thereby enhancing the network's ability to generate realistic soccer training simulations. TLCOA mimics the foraging behavior of termites, utilizing exploration, exploitation, and dispersion phases to iteratively adjust the weights and biases of PWGAN. During exploration, TLCOA explores the weight space to identify potential solutions, while exploitation refines promising solutions based on local information. Finally, dispersion helps maintain diversity in the search process to avoid stagnation. By leveraging TLCOA's capabilities, PWGAN effectively navigates the weight space to find optimal configurations, resulting in improved training outcomes for football players in VR environments.

3.5.1. Stepwise Procedure for Termite Life Cycle Optimization Algorithm

- *Step* 1. Initialization

In the initialization phase the populace of termite life is expressed using the Equation (7).

$$Y(m) = \sum_{i=1}^{m} D_i = D_1 + D_2 + \ldots + D_m \tag{7}$$

where, $D_i = D_1 + D_2 + \ldots + D_m$= denotes as a step length.

- *Step* 2. Random Generation

The input weight parameters generated randomly after initialization through TLCOA method.

- *Step* 3. Fitness Function

The fitness function generates random solution using initialized values. It is measured by Equation (8).

$$Fitness\ Function = optimizing\ [\alpha] \tag{8}$$

- *Step* 4. Exploration Phase

Exploration phase is used to improve the searching ability in optimization problem. The character of termite when it spots predator is expressed in Equations (9) and (10).

$$tA_{n,workers}^{M+1} = tQ(M+1) \otimes \left| A_{best}^{M} - A_{n,workers}^{M} \right| \tag{9}$$

$$tQ(M+1) = (Rand(1,T) + D(M+1)) \tag{10}$$

Here *tQ(M+1)* signifies scalar vector representing the change in 1 the value of step length of $D(M+1)$, *R and* (1,*T*) signifies scalar vector with value between0,1 while having dimension *D*. $A_{n,wor\ ker\ s}^{M+1}$ is intelligent movement strategy of termite workers to explore new search space at *D(M+1)* iteration. The $\otimes$ symbol denotes point-to-point multiplication. A_{best}^{M} denotes best solution recorded at A^{th} iteration.

- *Step* 5. Exploitation Phase for Optimizing

The Exploitation phase concentrates that gazelles are pasturing calmly without termite life cycle. It is considered that the termite's movement expressed in Equation (11).

$$A_{n,worker}^{M+1} = \alpha + \theta_1 (tA)_{n,worker}^{M+1} \tag{11}$$

Here θ_1 signifies scalar number with valuebetween-1 and 1. $(tA)_{n,worker}^{M+1}$ used to regulate the termite workers movement direction, $A_{n,workers}^{M+1}$ denotes termite workers intelligent movement strategy to explore new search space in $D(M+1)$ iteration. Figure 2 shows Flowchart of TLCOA for optimizing PWGAN parameter.

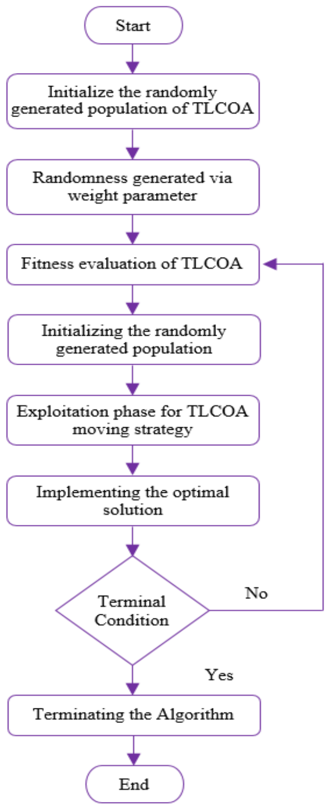

Figure 2. Flowchart of TLCOA for optimizing PWGAN parameter.

Step 6. Termination

Finally, the factor value of generator α from PWGAN optimized using TLCOA, repeat iteratively step 3 until fulfill the halting criteria $D=D+1$.

4. Result and Discussion

The stimulation outcome of proposed PWGAN-TLCOA-ST-VRT technique is discussed. The implementations are performed in Poser 8.0, 3ds MAX, EON Studio Windows version. Then, obtained outcomes of proposed PWGAN-TLCOA-ST-VRT are compared with existing AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

4.1. Performance Measures

The performance of proposed approach is examined utilizing the following metrics.

4.1.1. Accuracy

It is defined as the accurately categorized detection rate. This is calculated in Equation (12).

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{12}$$

4.1.2. Precision

This estimates positive result count while detecting the intrusion. It is calculated through Equation (13).

$$\Pr ecision = \frac{TP}{(TP+FP)} \tag{13}$$

4.1.3. F1-Score

F1-score referred to as the F-measure evaluate the performance in binary categorization tasks. Since this metric is the harmonic mean of recall and precision, it provides a balance between the two metrics. This is determined by Equation (14).

$$F1-Score = 2 \times \frac{recall \times precision}{recall + precision} \tag{14}$$

The performance equation is provided in and the evaluation parameter of F-score is analyzed.

4.1.4. Recall

It is commonly utilized in binary categorization tasks, such as medical tests, where the goal is to correctly identify the negative cases (non-events or healthy individuals). It is computed by Equation (15).

$$\text{Recall} = \frac{TN}{(FP+TN)} \tag{15}$$

4.1.5. ROC

It is a graphical representation commonly employed to scale the performance of a binary categorization mode. ROC is calculated through Equation (16),

$$ROC = 0.5 \times \left(\frac{TP}{TP+FN} + \frac{TN}{TN+TP} \right) \tag{16}$$

4.1.6. Error Rate

The rate of error is the ratio of true positive cases to true negative cases that is incorrectly forecasted and expressed in Equation (17).

$$ErrorRate = (1 - Accuracy) \tag{17}$$

4.2. Performance Analysis

Figures 3 to 10 portrays the simulation result of PWGAN-TLCOA-ST-VRT technique. The performance metrics are comparing to the existing AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

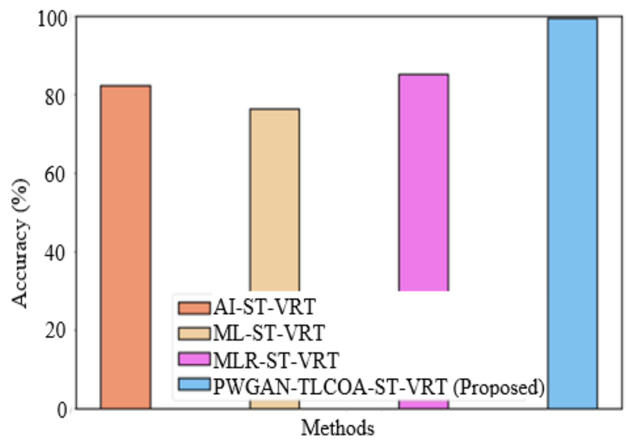

Figure 3. Performance analysis of accuracy.

Figure 3 depicts Accuracy analysis. The PWGAN-TLCOA-ST-VRT achieves 9.12%, 8.32%, 7.84% greater accuracy over existing AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

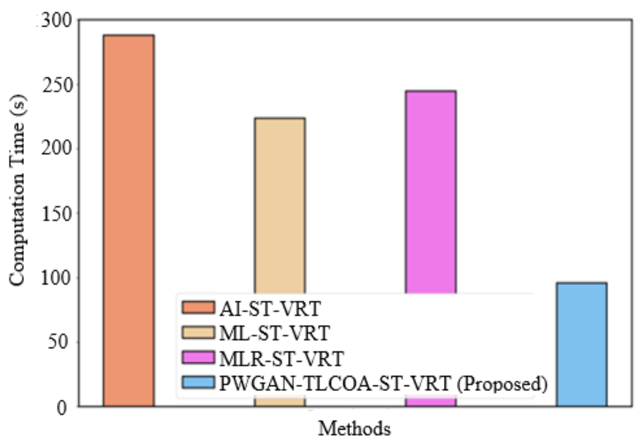

Figure 4. Depicts the analysis of computation time.

Figure 4 depicts computation time of proposed PWGAN-TLCOA-ST-VRT method attains 10.1%, 10.26% and 11.20% lower computational compared to the existing AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

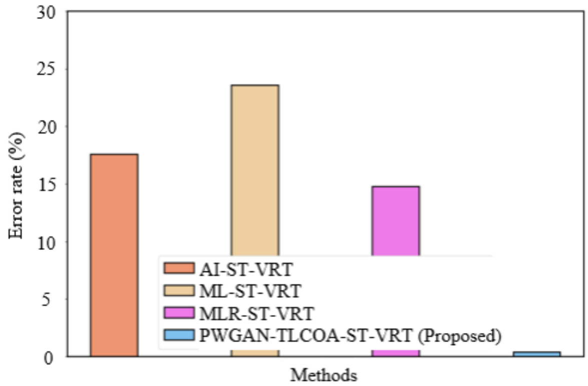

Figure 5. Performance of error rate analysis.

Figure 5 shows error rate analysis. The proposed PWGAN-TLCOA-ST-VRT achieves 10.87%, 15.01%, 18.02% lesser error rate compared with existing AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT models.

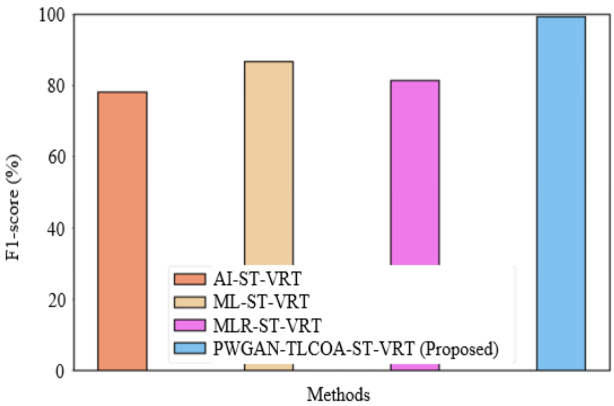

Figure 6. F-score analysis.

Figure 6 displays F1-score analysis. Here, PWGAN-TLCOA-ST-VRT achieves 2.31%, 8.47%, 9.23% greater F-score comparing with existing AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

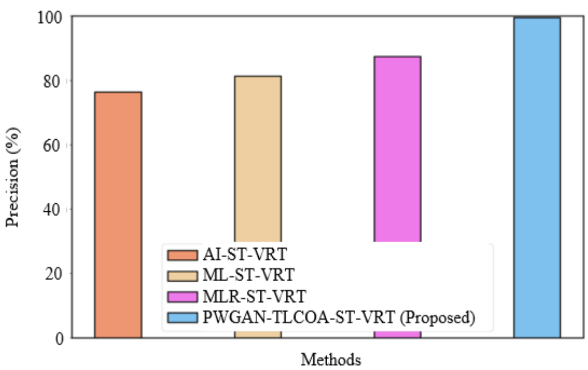

Figure 7. Precision analysis.

Figure 7 depicts precision analysis. The proposed PWGAN-TLCOA-ST-VRT achieves 13.12%, 12.32%, 11.84% greater precision than previous AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

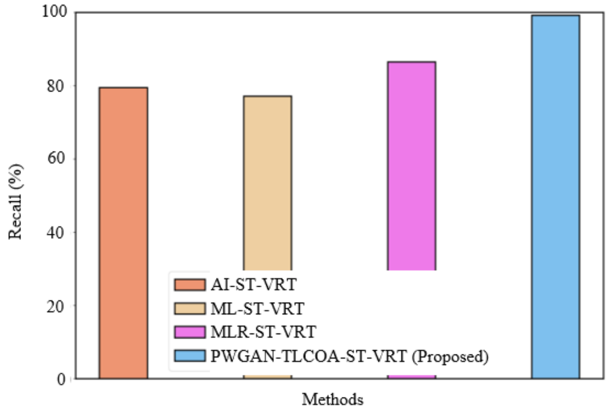

Figure 8. Recall analysis.

Figure 8 shows recall analysis. Here, PWGAN-TLCOA-ST-VRT achieves 11.99%, 14.27%, and 12.09% greater recall evaluated with existing AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

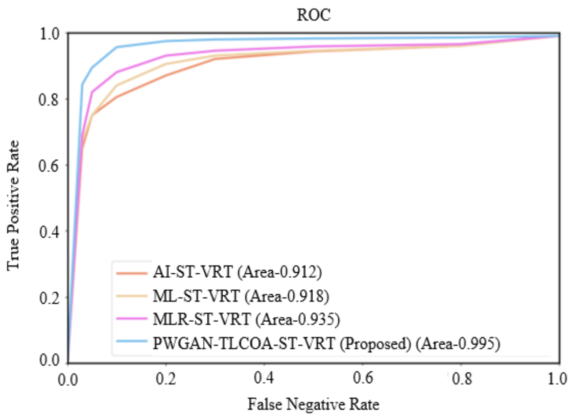

Figure 9. Performance analysis of ROC.

Figure 9 depicts ROC analysis. The PWGAN-TLCOA-ST-VRT attains 3.41%, 2.63%, and 6.95% greater AUC comparing with existing AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

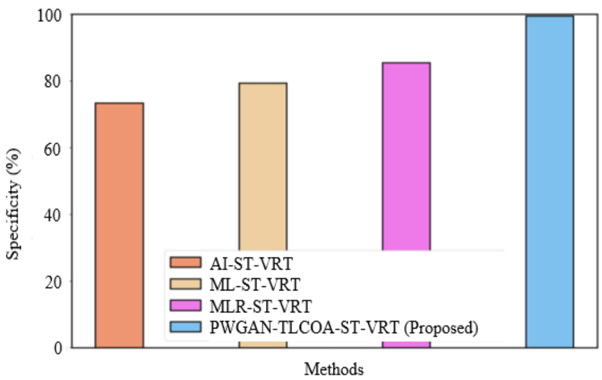

Figure 10. Specificity analysis.

Figure 10 shows Specificity analysis. Here, PWGAN-TLCOA-ST-VRT attains 3.41%, 2.63%, and 6.95% greater Specificity comparing to the AI-ST-VRT, ML-ST-VRT and MLR-ST-VRT methods.

4.3. Ablation Study

The proposed PWGAN-TLCOA-ST-VRT is divided down into its component parts through performing an ablation analysis both with and without each individual component.

Table 1. Ablation study of the proposed PWGAN-TLCOA-ST-VRT method.

Performance metrics	Methods		
	PWGAN	TLCOA	PWGAN-TLCOA-ST-VRT (proposed)
Accuracy (%)	86.92	92.53	99.87
Recall (%)	65.03	74.32	98.5
F1 score (%)	84.4	86.9	98.3
Precision (%)	70.8	75.4	98.7
Error rate (%)	59.02	33.98	19
Computation time (s)	227	215	160

Table 1 illustrates the ablation study of the PWGAN-TLCOA-ST-VRT method, here the performance of PWGAN, TLCOA and the proposed PWGAN-TLCOA-ST-VRT method has evaluated. The study considered various performance metrics. The results indicate that the proposed PWGAN-TLCOA-ST-VRT method outperforms PWGAN, TLCOA in terms of accuracy, with significantly higher values. Additionally, it achieves substantial improvements in precision and f1score, suggesting that the proposed method enhances quality. The proposed PWGAN-TLCOA-ST-VRT method exhibits a remarkable reduction in computation time and error rate, making it not only more accurate but also computationally efficient. These findings demonstrate the effectiveness of the PWGAN, TLCOA fusion in improving detection of spam email enhancement across a range of challenging datasets.

4.4. Discussion

The integration of VR technology into soccer training simulations, coupled with deep learning techniques and optimization algorithms, revolutionizes the immersive experience for players and coaches. By harnessing the power of PWGANs, VEs is generated with unparalleled realism, closely mimicking real-world scenarios. Additionally, optimization algorithms like TLCOA can fine-tune the parameters of these models, further enhancing the fidelity of the simulations. Through this integration, players engage in highly realistic training sessions tailored to their specific needs and skill levels, while coaches analyze performance metrics and design personalized training regimens to maximize player development. The synergy between VR, PWGAN, and TLCOA transforms soccer training into a highly effective and immersive experience, pushing the boundaries of player improvement and performance optimization. To increase accuracy, precision, F1-score, recall, ROC, error rate, and specificity in the classification of fostered soccer training, this fine-tuning method makes sure that the PWGAN is well-adapted to the particular requirements of the course. By using their nurtured football skills in real-world environments, students can gain stage presence, confidence, and flexibility to various performance conditions through this immersive experience. Fostering football training in VR offers kids a greater appreciation for the game and improves their comprehension of difficult football principles. Some metrics are used to examine the efficacy of the proposed method. These metrics show how well the system is at predicting football training elements. The model's error rate measures its overall prediction inaccuracy, demonstrating its dependability in real-world teaching situations. In addition, computing time is an essential parameter to assess the effectiveness of the model and its practicability for practical use. A PWGAN with TLOA is well-optimized and guarantees that the computational time of the VR-based football education system is controlled and does not hinder its real-time interactive features. Students have a deeper knowledge and enjoyment of the benefits of VR football training. The complete evaluation with mentioned metrics confirms that the PWGAN-TLCOA-ST-VRT method is effective, efficient, and appropriate for VR-based football teaching system.

5. Conclusions

In this section, enhanced soccer training simulation using PWGAN-TLCOA-ST-VRT are successfully implemented. The PWGAN-TLCOA-ST-VRT technique is applied in EON Studio. The performance of proposed PWGAN-TLCOA-ST-VRT method achieves 14.69%, 11.64%, and 12.76% greater precision; 18.24%, 16.78%, and 11.17% high F-1 Score; 12.13%, 13.15% and 12.19% less error rate; 12.98%, 10.98%, 15.65% higher Recall compared with existing AI-ST-VRT,ML-ST-VRT and MLR-ST-VRT techniques. Limitation of the proposed method lies in the reliance on synthetic data generated by the PWGAN. While synthetic data can mitigate data scarcity issues, ensuring the representativeness and diversity of the generated data remains a challenge. It is imperative to acknowledge the constraints of the ablation study as well as any potential biases induced by the experimental design for the research findings to remain credible and authentic. In this study, several limitations and biases warrant consideration. Firstly, the ablation study may not encompass all possible variations and combinations of parameters or methodologies, potentially limiting the generalizability of the results. Additionally, the experimental design itself may introduce biases, such as selection bias if certain samples or conditions are overrepresented or underrepresented in the study.

In future, several promising avenues for advancement can be pursued to enhance the proposed method's effectiveness and applicability. Firstly, exploring advanced data augmentation techniques to enhance the quality and diversity of training data could significantly improve the method's performance. Additionally, conducting extensive validation studies in real-world soccer training environments will be crucial for assessing its practical utility and performance. Building upon the insights gained from the ablation study, further exploration of variations and combinations of parameters could provide deeper insights into the method's effectiveness across different settings and conditions. Furthermore, integrating real-time feedback mechanisms and adaptive learning algorithms into the VR simulations could enhance the interactive and personalized nature of the training experience, ultimately leading to more effective skill acquisition and performance improvement in soccer training. By addressing these areas in future research, the proposed method can evolve into a more robust and versatile tool for enhancing soccer training outcomes.

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