Optimizing Athletic Performance Analysis with ACED-GBS: A Convolutional Encoder-Decoder Approach

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Optimizing Athletic Performance Analysis with ACED-GBS: A Convolutional Encoder-Decoder Approach

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ABSTRACT

Sports performance improvement and prediction contains the analysis of various factors influencing athletic performance, including player statistics, team dynamics, injuries, and environmental conditions. Challenges of traditional methods in sports performance improvement and prediction include data privacy concerns, over fitting issues, complexity, and interpretability. To overcome these complexities, this paper proposed a novel method named the Adaptive Convolutional Encoder-decoder-based Gooseneck Bernacle Search (ACED-GBS) algorithm. In this study, a Convolutional Neural Network (CNN) is utilized to extract data related to athletes' sports performance. Additionally, the encoder-decoder is employed to efficiently capture the interactions between the information. In this work, the Gooseneck Bernacle optimization with initial search strategy is implemented for hyperparameter optimization to enhance the performance of the ACED-GBS method and the study conducted experiments on the ODI-Players performance dataset. Different evaluation metrics namely precision, accuracy, recall, F1-score, specificity, etc are utilized to evaluate the performance of the ACED-GBS method and compare its performance with existing methods. The experimental outcomes depict the effectiveness of the ACED-GBS method for sports performance improvement and prediction. The experimental analysis demonstrates that the convergence speed of the ACED-GBS method is high, the error is low and the prediction performance is more accurate with high noise immunity and practicality compared to traditional methods.

Keywords: Sports performance improvement; Sports performance prediction; Convolutional Neural Network; Encoder and decoder; Gooseneck Bernacle optimization; Initial search strategy.

1. INTRODUCTION

The advancement of sports technology involves enhancing the competitive edge and performance of competitive sports through the introduction of novel technologies, materials, procedures, and equipment. Its basic characteristics are innovation and practicality. Innovation is reflected in constantly exploring and exploring new technologies, materials, processes, and equipment to achieve higher athletic performance and better competitive levels. Practicality refers to the fact that these technological innovations must be able to be practically applied and have a positive promoting effect on improving the actual level of competitive sports (de Subijana et al., 2020).

With the development of technology, sports technology innovation has increasingly become an important component of the development of competitive sports. The application of technological innovation can play an important role in improving the physical fitness of athletes, optimizing training methods, improving competition management, and enhancing competitive levels. In the process of the development of competitive sports, sports technology innovation continuously promotes the development of competitive sports, becoming an important driving force for the advancement of competitive sports (de Subijana et al., 2020).

In competitive sports, the physical fitness and health condition of athletes are one of the decisive factors for their success or failure in competition. Therefore, the application of sports technology innovation in athlete health management is also receiving increasing attention. The health management of athletes mainly includes the formulation of training plans, monitoring of athlete status, and rehabilitation of sports injuries, and sports technology innovation provides new means and ideas for athlete health management (Logue et al., 2020).

By analyzing and modeling the physical fitness, training volume, and exercise status of athletes, the intelligent training system can automatically generate scientific and reasonable training plans based on the actual situation of athletes, reducing the factors of manual intervention and improving training efficiency and effectiveness. In addition, the intelligent training system can also monitor and provide real-time feedback on the training process of athletes, timely identify and correct problems, and improve the training effectiveness of athletes (Balberova et al., 2021).

To better understand the physical condition and training effectiveness of athletes, modern competitive sports are increasingly emphasizing the application of athlete status monitoring technology. By analyzing these data, abnormal physical conditions of athletes can be identified in a timely manner, and corresponding adjustment plans can be formulated to ensure that the athlete's physical condition is in the best state (Devrim et al., 2021).

Athletes are inevitably prone to various sports injuries during training and competition, such as muscle strains, ligament injuries, etc. For example, physical therapy and rehabilitation training commonly used in sports injury rehabilitation can utilize virtual reality technology and intelligent rehabilitation equipment to make rehabilitation training more precise and efficient. In addition, artificial intelligence technology can also assist doctors and rehabilitation therapists in developing more personalized rehabilitation plans, and provide more timely and accurate rehabilitation guidance through real-time monitoring and data analysis. It is worth mentioning that 3D printing technology also provides new possibilities for sports injury rehabilitation. For example, 3D printing technology can be used to print personalized orthotics and braces, providing athletes with more comfortable and effective rehabilitation assistance tools. In addition, emerging technologies such as gene editing and stem cell technology are also providing new solutions for sports injury rehabilitation, such as repairing damaged tissues through gene editing technology or promoting tissue regeneration and rehabilitation through stem cell therapy (Smith et al., 2022).

Game data analysis can help coaches develop better tactics and lineups. By analyzing the opponent's match data, coaches can understand their strengths and weaknesses and develop better combat plans. At the same time, analyzing the match data of our team can help coaches understand the strengths and weaknesses of our team, and thus carry out targeted training and adjustments (Dos et al., 2018).

Artificial intelligence technology can help coaches and athletes better understand competition and individual performance. Through the application of artificial intelligence technology, competition videos can be analyzed and recognized, providing better video playback and teaching. In addition, artificial intelligence technology can also recognize and evaluate the posture and skills of athletes, helping coaches develop better training plans and adjustments (Prieto et al., 2021).

The technological innovation of sports venues and competition venues is an important aspect of sports technology innovation. Various technologies and equipment have been applied in sports venues and competition venues, greatly improving the viewing and safety of competitive sports. Firstly, the construction of sports venues is increasingly focusing on environmental protection, safety, and sustainable development. Various new technologies and materials have been applied, such as ecological bricks, solar power generation, intelligent control systems, etc., effectively improving the efficiency and environmental protection level of sports venues; Secondly, technological innovation in the competition venue is also an important direction for sports technology innovation. For example, in football matches, the most advanced video referee technology has been applied, which can accurately determine controversial goals and fouls, improving the fairness of the game and the quality of referees. In addition, sports equipment and competition equipment can be manufactured through 3D printing technology, improving the accuracy and quality of equipment and providing athletes with a better gaming experience. In summary, the technological innovation of sports venues and competition venues has played an important role in promoting the development of competitive sports (Jacob et al., 2018)

It will fundamentally change the substantial separation between the education and sports sectors, not only to explore the potential sports reserve talents in the education sector but also to solve the problem of cultural education for the reserve talents in the sports sector. The reserve talents of competitive sports will also not only rely on sports schools alone, but use schools as the basic position, sports schools as the main support, and social forces as a supplement. Efforts will be made to break down the barriers between various sectors, and to make concerted efforts to realize the cause of physical education. In response to the dilemma faced by competitive sports and to promote the development of competitive sports reserve talent training, the following strategies are proposed to actually work on competitive sports. The pathway of competitive sports performance improvement is shown in Figure 1(di et al., 2020).

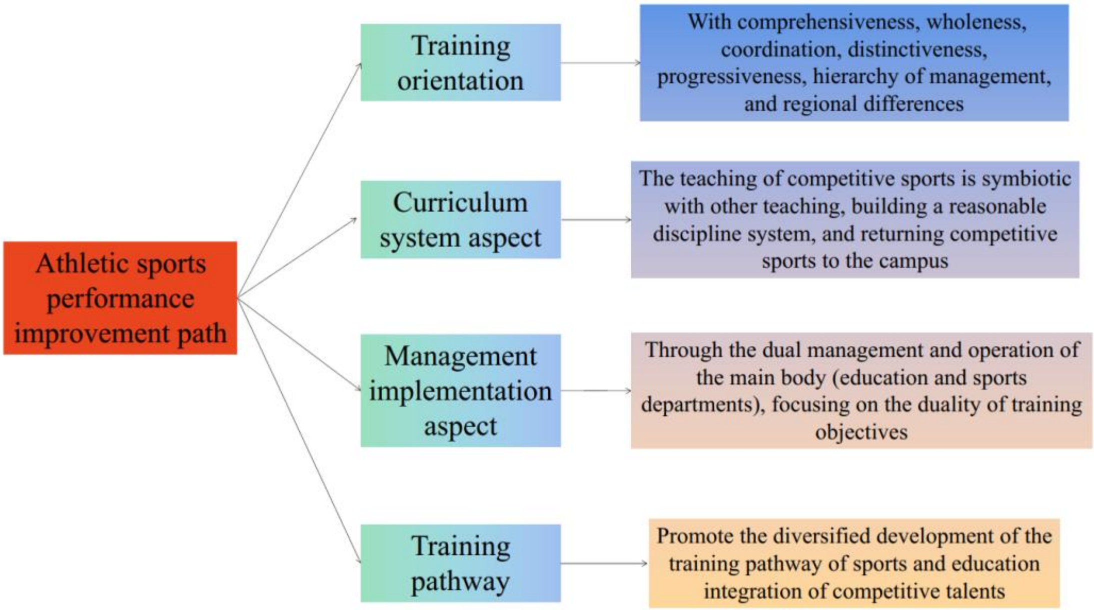

Figure 1: Athletic Sports Performance Improvement Path

Meanwhile, in recent years, more and more students have become too weak, with myopia and obesity rates gradually increasing, and college students have worse physical fitness than primary and secondary school students. It has been reported that the myopia rate among adolescents has increased from 20% to 31% in recent years, and the obesity rate has increased by nearly 50%, with roughly 25% of urban boys being obese. The emergence of test-based education, where more people care only about cultural achievement, and the crowding out of physical education classes in almost every primary and secondary school, as well as parents' fear of their children being hurt in physical education classes, have further limited students' development in physical education. Children's competition has intensified, parents focus on cultural training from early childhood, and only interest in physical, audio, and aesthetic training, with the general improvement of social education and culture (Ravi et al., 2021). In China's rapid development of competitive sports athletic achievements have made great progress, but school sports are not given attention, students do not get comprehensive development, and competitive sports reserve talents in short supply.

For the education sector, the state has now begun to pay attention to students' competitive sports courses, and the proportion of the state's performance in competitive sports in schools is gradually increasing, but for schools, teachers, and parents for the setting of competitive sports activities only on the premise of not affecting learning will allow students to go to competitive sports activities, the importance of competitive sports classes still exists only in the document. It is not possible for students to have systematic and standardized training in school, to develop their interests, to stimulate their sports potential, and to explore the reserved talents of competitive sports. In terms of professional athletes in gymnasiums, the phenomenon of emphasizing physical fitness over education still prevails, athletes' cultural performance is weak, and due to training as well as athletes' own learning attitudes, there is no or lack of systematic cultural study, resulting in professional athletes being in a single line of development and facing a dilemma when facing selection failure and the reality of retirement (Ravi et al., 2021). The athletes' follow-up pathways to higher education cannot be guaranteed, and more and more parents and students themselves refuse to join sports teams for training for fear of having no prospects, resulting in a shortage (Sun et al., 2022).

To make contemporary college students develop morally, intellectually, physically, aesthetically, and laboriously, accumulate the data with huge data of previous college students' competitive sports performance data, analyze the historical competitive sports performance data, and make the prediction of college students' competitive sports performance. Therefore, it has been an important research direction for scholars to find an efficient and accurate method for predicting college students' athletic performance (Liu, 2021).

The neural network is generally applied in the case of uncertain input-output function mapping, where linear correspondence can be determined. It possesses stable validity and adaptability, propagates signals in the forward direction and errors in the reverse direction, and is often applied in various fields. Common neural network methods have some drawbacks, such as training ignoring the old samples to learn only the new samples, slow convergence, and missing the global optimum to generate very small local values. To optimize these drawbacks, particle swarm optimization methods can be invoked based on neural networks. The particle swarm optimization (PSO) method is based on the principle of swarm intelligence, and this method achieves swarm optimization through the biological evolutionary process of random search, which has the characteristics of fast convergence without dependence on the initial value and can effectively optimize neural networks (Chang et al., 2020). This approach represents an inventive and data-driven solution aimed at tackling the challenges in sports talent training, with a specific emphasis on the integration of sports and education. Existing methodologies, including Blockchain-based HMM, ANN-optimized AFSA, AS-LSTM, and OCNN, face limitations such as inadequate data leading to model inaccuracies, ethical considerations, and heightened computational complexity in predicting competitive sports performance. To address these issues, we propose the Adaptive Convolutional Encoder-Decoder-based Gooseneck Barnacle Search (ACED-GBS) algorithm. This algorithm aims to enhance the effectiveness of implementation, data quality, and the ongoing monitoring and refinement of the model. The identified drawbacks mentioned above have motivated the development of this research, which contributes significantly to the field in various ways

- ***Novel Technologies***: Introducing the Adaptive Convolutional Encoder-Decoder Gooseneck Barnacle Search (ACED-GBS) algorithm aims to elevate and forecast sports performance.
- ***Enhanced predictive accuracy***: Leveraging Convolutional Neural Networks (CNNs) consistently enhances predictive accuracy, particularly in tasks related to image and pattern recognition. This advancement ensures more dependable and precise forecasts of athletes' competitive sports performance.
- ***Faster convergence:*** The Gooseneck Barnacles optimization technique detailed in the methodology, involving the refinement of position and velocity through individual and global extremes, accelerates convergence during neural network training. This results in expeditious model development and implementation.

- ***Baseline Techniques:*** Rigorous evaluation of the proposed model involves comparing its performance against existing methods and benchmarks to gauge its effectiveness.
- ***Evaluation outcome:*** Validation of the proposed ACED-GBS method is executed using the ODI-Players performance dataset. The enhanced outcomes attained by this method underscore its potential for predicting sports performance

The main work of this paper is as follows. To improve the accuracy of college athletic performance prediction, this paper proposes a CNN model-based method for college athletic performance enhancement and prediction to achieve high efficiency and high accuracy prediction of college athletic performance.

2. RELATED WORK

This portion provides an extensive examination of the current body of literature concerning crucial subjects related to enhancing scheduling and routing for predicting competitive sports performance. The review covers various aspects, including the evolution of competitive sports, methods for enhancing sports performance and prediction, multi-objective optimization, and deep learning applications. Furthermore, it highlights areas within the literature that exhibit gaps, which the Adaptive Convolutional Encoder-Decoder-based Gooseneck Barnacle Search (ACED-GBS) algorithm seeks to, overcome

2.1. The current situation of competitive sports development

Competitive sports is becoming increasingly widespread, which can help coaches and athletes better understand the competition process and personal performance, thereby achieving better performance and performance improvement. Data analysis and artificial intelligence technology can analyze and predict the physical, technical, tactical, and other aspects of athletes, providing coaches with scientific guidance and training plans. Meanwhile, these technologies can also collect and analyze game data, helping teams develop better tactics and lineups (Chen et al., 2022).

By collecting and analyzing the physiological data of athletes, it is possible to better understand their physical condition and performance and thus develop personalized training plans and adjustments. For example, the analysis of physiological data such as blood oxygen saturation and heart rate can help coaches understand the physical fitness status of athletes during competitions and make timely adjustments. In addition, the competition data of athletes, such as running speed and ball passing success rate, can also be evaluated and improved through data analysis (Taborri et al., 2020).

The integration of sports and education should establish and improve the three major systems of school sports teaching, competition, and training so that competitive sports can return to the campus (Malewska et al., 2023). Take the United States as an example, as a sports powerhouse, they have always used sports as a form of education, believing that the development of competitive sports cannot be separated from education, and the essence of American sports is attributed to education, following the governance framework of the school education system, integrating sports and education, using sports competition as a form of education, integrating sports ability and education into the education system, and allowing athletes to learn in the process of receiving education athletic skills, strengthen their bodies, develop good moral qualities, and be able to explore their athletic potential according to their personal characteristics to promote the overall healthy and coordinated development of students (Demarie et al., 2022). If there is no sports competition in school, young people will not be able to develop a sense of competition and teamwork, and they will be less able to experience the joy brought by sports. Therefore, the sports department should be organically integrated with the education department, and all resources should be open to young people to serve their healthy growth (Wang, 2021).

Actively carry out sports competitions, take advantage of school sports, allow students to participate in sports competitions held within the school while receiving education, select outstanding sports talents, conduct systematic training, continue to participate in higher-level sports competitions, gradually improve their competitive level, form high-level teams of different age groups, and provide reserve talents for competitive sports (TilahunMuche et al., 2021). Allowing athletes to participate in sports training while not being separated from the education system is conducive to understanding, improving skills, and to a large extent, avoiding the problem of secondary employment for athletes. Moreover, in the traditional school sports competition, only a few students can play sports advantages and participate in the competition, most students just play the role of cheering on the field, improve the rules and forms of sports competition, so that most students can participate with to which, in the competition to improve the personality, and competition level (Jelleli et al., 2023).

To create schools with sports characteristics, strengthen the school sports curriculum, develop extracurricular sports activities for students' development, create schools with special sports programs, let each student learn specific sports skills, and promote the construction of "one school, one product", such as soccer special schools (Nien et al., 2020). The integration of sports and education opens the way for outstanding retired athletes to enter schools as physical education teachers and sports coaches, and introduces highly qualified coaches or teachers, so that the level of youth competitive sports can be improved, and high-level sports teams can be established in universities, taking reference from the United States, so that universities become an important part of competitive sports talent delivery. The combination of competitive sports and school sports will improve the competitive level of youth so that they will become participants, builders as well as promoters of popular sports in the future (Zarkeshev et al., 2019).

Youth sports clubs can not only promote the development of mass sports but also serve as a selection channel for the reserve talents of competitive sports. The development of youth sports clubs is conducive to stimulating students' interest in sports and their active participation in sports activities outside school hours, and some students with sports talent can stand out in the clubs, providing a guarantee of human resources for competitive sports (Zarkeshev & Csiszar, 2019). With the increase of sports clubs, the demand for coaches and sports instructors will increase, and the goal of training excellent athletes will not only be to achieve excellent training results on the field of various competitions but also some sports teachers, sports coaches, social instructors, etc (Colyer et al., 2018). The demand for talent becomes more, the social positions increase, and excellent athletes can find jobs and realize their value after retirement, and also solves the problem of wasting sports talent and the problem of shortage of sports talent at the same time, which will increase opportunities for secondary employment of retired athletes in competitive sports. Promoting the development of youth clubs has great benefits for both competitive sports and popular sports (Sarandi et al., 2020).

2.2. CNN model for sports performance improvement and prediction method

Since the founding of New China, our athletes have achieved remarkable results in international competitions, making China a great sports power and demonstrating the superiority of our socialist sports system. However, compared with countries such as the United States and Japan, our country has outstanding athletes in competitive sports, but the level of national competitive sports is low. With external factors such as the increasing education level of families and society, as well as the highly administrative management mode of competitive sports, the current stage of financial investment and talent training needs of supply and demand and other factors, resulting in the shortage of reserve talents for advantageous projects, emerging. The reform of various types of sports schools at all levels has become a key element in improving the national system of competitive sports.

Prediction of physical education results can effectively improve the relevance of physical education training for college students and help academic departments develop physical education training plans.

For the sports performance prediction problem, many scholars have conducted a lot of research, currently, there are mainly 2 types: linear sports performance prediction models and nonlinear sports performance prediction models, linear modeling methods mainly have multiple linear regression, resulting in relatively large sports performance prediction errors; nonlinear modeling methods mainly have artificial neural networks. Although artificial neural networks have strong nonlinear modeling ability, they are prone to over fitting sports performance prediction results, which makes sports performance prediction results unreliable. If the output result is correct, it does not enter this back propagation process; otherwise, it enters the back propagation process of the output layer, the implicit layer, and the input layer based on the calculation error.

2.3 Research gaps

The prediction of competitive sports performance has been carried out through the application of machine and deep learning models. While various methods have been explored in the preceding section, it is noted that these models face challenges in achieving optimal results. These challenges encompass issues such as over fitting, reduced performance, prolonged execution times, insufficient datasets, high computational costs, and the requirement for extended classification periods. In order to overcome these complexities, this study develops a novel model, named the Adaptive Convolutional Encoder-Decoder based Gooseneck Barnacle Search (ACED-GBS) algorithm.

- ***Comparison with alternative models*****:** The proposed method with conventional approaches, further investigation could assess its effectiveness compared to alternative machine learning models or methodologies. This thorough comparative examination has the potential to offer valuable insights into the advantages and limitations of various predictive models within the realm of sports performance.

- **Improved effectiveness:** In this study, the presented model makes use of the Gooseneck Barnacle Algorithm (GBA) to effectively adjust the model weights. The algorithm takes advantage of the initial search strategy, aligning with the objectives of optimizing power. As a result, the efficacy of the developed method is improved.

3. PROPOSED METHODOLOGY

The structural diagram of the proposed CNN model-based method for competitive sports performance enhancement and prediction is shown in Figure 2. The data gathered from the ODI-Players performance dataset and then they are preprocessed with denoising, image resizing, and normalization steps, which contains five graph-void 9 Convolutional layers at different scales and a hierarchical encoder-decoder structure with five graph transformation layers. Also, two original graph9 Convolutional layers are used at the beginning and end of the network for the input encoding and output decoding processes. Notably, the graph null convolution layer effectively expands the perceptual field of the graph convolution kernel and densely learns the multiscale pose context, and the graph conversion layer is used to capture the full director range connectivity. In addition, graph pooling and graph up-sampling are used to ensure the interaction of multiscale information from local to global.

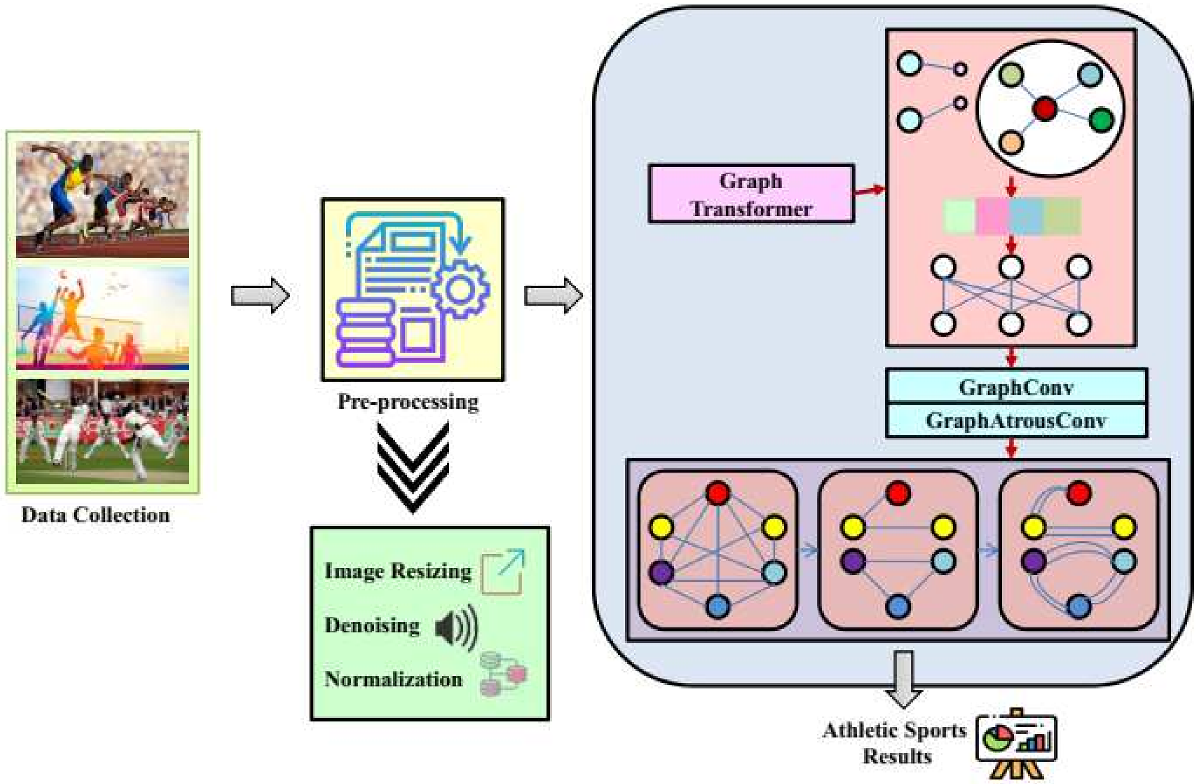

Figure 2: Model Structure

3.1 Pre-processing:

To obtain quality input for processing the detection of distraction, pre-processing steps are needed which can remove the unwanted elements from the images. Here, pre-processing steps are applied and they are explained in the below section including Resizing, Denoising, and normalization.

- ***Image Resizing***:

The process of changing the dimensions of the images is referred to as resizing, generally, this can influence the image's quality and file size. Resizing the images can decrease the bigger file's size for simple use, the pixels can be discarded by the reduction of the image's size.

- ***Denoising:***

In image processing, denoising involves the elimination of noise present in an image. Noise often appears as random fluctuations in pixel values, stemming from factors like sensor constraints, environmental variables, or transmission glitches. The primary objective of denoising techniques is to retain the essential structures and characteristics of an image while diminishing the influence of undesirable noise. One widely employed denoising approach involves the application of filters, with the Gaussian filter standing out as a popular choice for this task. The 2D Gaussian kernel is mathematically represented by the following equation

$$G(w,z) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{w^2+z^2}{2\sigma^2}\right)} \tag{1}$$

The value of the Gaussian kernel at coordinates (w,z) is denoted as $G(w,z)$. The standard deviation of the Gaussian distribution, which governs the width of the filter, is represented by σ

- ***Normalization:***

For setting the data with a range of [0, 1], max-min normalization utilizes minimum values and maximum values and is specified in the below equation.

$$\hat{Z} = \frac{Z - Z_{min\,i}}{Z_{max\,i} - Z_{min\,i}} \tag{2}$$

From the above equation 1, $Z_{\max i}$ is represented as the maximum value of the feature, the sample video is specified as Z, and the number of minimum values is indicated as the $Z_{\min i}$.

3.2 Convolution of graph voids

The graph neural network-based approaches that exist typically use stacked graph convolution modules to extract high-level skeletal information to regress 3D poses. The most used expression for the graph convolution operation is currently as follows

$$X^{(i+1)} = \sigma(WX^{(i)}(\Lambda \Theta M)) \tag{3}$$

Where σ, i, and Λ is the activation function, index of the current layer, and the Laplacian matrix of the normalized graph. W and M signifies the learnable weight matrix and attention mask matrix. In addition to using local graph 10 convolutional networks to extract skeleton features, non-local modules are also introduced to long-range information, which usually refers to the relationship between the current node and all other nodes. The previous method uses a restricted convolution kernel to convolve only the first-order neighbors, ignoring the multiscale context information of the higher-order neighbors. In view of this, a multi-scale graph convolution is introduced in this chapter to extract the multiscale context implicitly in the higher-order neighbors, and the graph convolution is named Graph Atrous Convolution (GAC).

Inspired by the void convolution in image segmentation, the void convolution is a parallel convolution operation with different expansion factors (also called expansion rates). The graph-hole convolution is then represented as a convolution with a root node (root), first-order neighbors (1-hop), second-order neighbors (2-hop), third-order neighbors (3-hop), and even higher-order neighbors. This chapter first formally defines the *k*-th-order neighbor matrix of the pose skeleton graph as A_k, which is calculated as follows:

$$[A_k]_{i,j} = \begin{cases} 1 d(v_i, v_j) = k \\ 1 d(v_i, v_j) = 0 \end{cases} \tag{4}$$

Where $d(v_i, v_j)$ is the length of the shortest path between the nodes v_i and v_j in the human skeleton graph. Similarly, A_k it carries the self-losop operation.

$$Y_k^{(l)} = \sigma\left(W_k X^{(l)} \left(\Lambda_k \Theta M_k\right)\right) \tag{5}$$

where Λ_k is the Laplace matrix of the normalized k^{th} order adjacency matrix. W_k is a learnable weight matrix used for node embedding, and M_k is a $N \times N$ learnable attention mask matrix. $Y_k^{(l)} \in R^{N \times C}$ is the k^{th} order graph null output of the convolution. In addition, to facilitate the extraction of global contextual information, this chapter uses global pooling to process the original skeleton features, which are then stitched with the output of the parallel graph-void convolution in the equation and finally fed into a multilayer perceptron sub network to aggregate the multiscale and global contextual features. It is worth noting that the global average pooling here is done by averaging all the nodal features in the skeleton graph and then copying multiple copies, thus keeping the number of nodes in the skeleton graph constant to adapt the subsequent operations between features. The expression of this process is as follows.

$$\begin{cases} Y_{pool}^{(l)} = AvgPool\left(X^{(l)}\right) \\ Y^{(l)} = Cat\left(\left[Y_0^{(l)}, \ldots. Y_{k-1}^{(l)}\right], Y_{pool}^{(l)}\right) \\ X^{(l+1)} = WY^{(l)}, \end{cases} \tag{6}$$

3.3 Graph encoder and decoder

The graph null convolution introduced in the previous subsection can efficiently extract local multi-scale contexts, while the graph transformation layer can capture the full director range connectivity. To facilitate the interaction from the extracted local features to the global features, this chapter is subjected to the introduction of a human dynamics-based graph encoder-decoder structure in encoder-decoder structure in image recognition. The graph encoder-decoder is employed to efficiently capture the interactions between multi-scale information (e.g., joint-scale and part-scale) in a pose in addition to stacking graph-void convolution and graph-transformation layers, graph pooling, and graph up-sampling. Before graph pooling and up-sampling, the joint points at each scale s are divided into different regions R_i^s according to the physical prior of the human body, e.g., left lower leg, torso, etc.

For the features in the previous scale, this chapter uses averaging pooling for the joints belonging to the same region in the current scale to obtain a point feature to be used as the pooled feature in the next scale. In other words, multiple points are averaged to a single point. The specific graph pooling expression is as follows.

$$X_i^{s+1} = Avg\ pool\left(\left\{X_j^s \mid \forall X_j^s \in R_i^s\right\}\right) \tag{7}$$

Where R_i^s is the feature of the i^{th} region located under scale s, and X_j^s is an element of the nodal feature belonging to the set of $R_i^s \cdot X_i^{s+1}$ the new nodal feature obtained by graph pooling at scale $s+1$. Due to the independence of the partitioned regions, this chapter implements graph up-sampling by copying a next-scale feature multiple times and splicing it to the corresponding region at the previous scale. The specific graph up-sampling expression is as follows:

$$R_i^s = Cat\left(\left\{X_i^{s+1},....,X_i^{s+1}\right\}\right) \tag{8}$$

where the number of iterations X_i^{s+1} is determined by the corresponding set of regions R_i^s. In addition, the features obtained by up-sampling are stitched with the corresponding original features and then sent to the next layer for fusion.

3.4Novel Initial Search Gooseneck Barnacle Optimization

In aquatic environments worldwide, numerous barnacles thrive, exhibiting the ability to swim (Ahmed et al., 2023). These microorganisms adhere to objects in the water and develop shells as they age. Notably, barnacles possess elongated penises that surpass the length of their bodies, facilitating alterations to the aquatic environment and ensuring a stable lifestyle. Additionally, barnacles are hermaphrodites, capable of both female and male reproduction. Mating involves communication between neighboring barnacles, with the exchange of sperm forming mating groups. The competition among barnacles for mating partners is crucial, significantly influencing mating success. Among crustaceans, Gooseneck barnacles, also known as stalked barnacles, stand out. Characterized by long, flexible, and curved stems resembling goosenecks, these barnacles attach to surfaces. This unique feature enables high-density reproduction, a notable advantage of gooseneck barnacles. To facilitate the fertilization of eggs, male and female barnacles release their reproductive cells into the surrounding water. This mechanism enables fertilization to take place, even in instances where individual barnacles are spatially distant from each other. However, the reproductive process of gooseneck barnacles is influenced by the presence of waves.

GBO algorithm

The key features of the gooseneck involve reproductive behavior through sperm casting, with influences from air and waves impacting the process. These characteristics form the basis for the design of the GBO algorithm, which is expressed mathematically in the following equation:

$$(W+k)_{j+1} = (W+k)_j + XC_j + S_{\dim} + T((W+1)_j (Tp_{water})_i) + Gt.(W+l)_j \tag{9}$$

The above equation WD denotes the direction of the wind; $S_{\dim}$ and represents the target dimension to move towards the best solution, $(W+k)$ which is the location of the goose barnacle in j^{th} iteration. To decide the next position to visit, the gooseneck barnacle executes a probabilistic action rule (Kurilovas et al., 2014). In this, R selects the next position m for moving when $k \le k_o$

$$k_p^o = \begin{cases} 1, & if\ M = \arg\left\{ \max_{c \in R_m} i\, Z_s . \tau_{dv}^r \left(1+\psi_{dv}^r\right) . \omega_{dv}^{\delta_G} \right\} \\ 0, & otherwise \end{cases} \tag{10}$$

Else

$$k_p^o = \frac{\sum_{i-1}^{4} Z_t \left| \tau_{rv}^r (1+\psi_{rv}^1) \right|^{\alpha_G} \left| \omega_{rv} \right|^{\beta_G}}{\sum_{\mu_G \in R_v^o} \left(\sum_1^4 Z_s \left| \tau_{v\mu}^r \left(1+\psi_{p\mu_G}^r\right) \right|^{\alpha_G} \left| \omega_{v\mu_G} \right|^{\beta_G} \right)}, if\ r \in R_v(p) \tag{11}$$

Further, the $Sperm\_region$ is given below,

$$Sperm\_region = \begin{bmatrix} (s_r)_{1,1} & (s_r)_{1,2} & \cdots\cdots & (s_r)_{1,c} \\ \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots \\ (s_r)_{m,1} & (s_r)_{m,2} & \cdots\cdots & (s_r)_{m,c} \end{bmatrix} \tag{12}$$

Here c and m represent the number of variables and the gooseneck, respectively. The gooseneck barnacles harbor two potential solutions, namely, position and sperm areas. Consequently, this method consistently stands out as the optimal choice for addressing gooseneck-related challenges. Moreover, the calculation of wave height involves the application of the following equation

$$Gt = 4\sqrt{G\hat{}2S} \tag{13}$$

In the GBO algorithm, the calculation of wave height involves the utilization of the following equation. This equation indicates that the wave intensity can be sustained within the range of 0.2–1.5 or 3.0 meters. The iterative process aims to identify the optimized reproduction area for investigating wave intensity, with each iteration progressively decreasing the parameter Gt.

$$Gt - 1.5 - \left(\frac{itr(1.5 - 0.2)}{\max\_itr} \right) \tag{14}$$

Moreover, equation (15) delineates the mathematical representation of the adjacent logarithmic spiral region relevant to sperm casting

$$T\left((W + k)_j (Tp_{water})_i\right) = C_j.e^{cs}.\cos(2\pi s) + (Tp_{water})_i \tag{15}$$

The provided formula s characterizes a random number within the interval of [-1, 1]. The variable a signifies a constant that defines the configuration of the logarithmic spiral, while the distance is quantified by equation (16).

$$C_j = (W + k)_j - (Tp_{water})_i - (Tp_{water})_i \tag{16}$$

Where C_j is the distance of the j^{th} barnacle and for the i^{th} sperm casting region and $(W + k)_j$ and $(Tp_{water})_i$ denotes barnacle and sperm casting region respectively.

Off-spring generation

To improve the visibility of recently introduced gooseneck barnacles in the exploration zone and streamline the transition to the next iteration, we will employ the vector equations outlined below.

$$\Delta(W + 1)_{j+1} = XC_j + S_{\dim} + G_t.\Delta(W + 1)_j \tag{17}$$

$$(W + 1)_{i+1} = (W + 1)_j + \Delta(W + 1)_{j+1} \tag{18}$$

$$(W + 1)_{j+1} = (W + 1)_j + levy * (W + 1)_j \tag{19}$$

Where the wind direction is XC_j and $S_{\dim}$ denotes in the target dimension value;

$$levy(M) = 0.01 \times \frac{q_1 \times \sigma}{|q_2|^{\frac{1}{\alpha}}} \tag{20}$$

Next, α is a constant given in the equation (23) further, q_1 and q_2 are random numbers in the range [0-1].

$$\sigma = \left(\frac{\tau(1+\alpha) \times \sin\left(\frac{\pi\alpha}{2}\right)}{\tau\left(\frac{1+\alpha}{2}\right) \times \alpha \times 2^{\left(\frac{\alpha-1}{2}\right)}} \right)^{\frac{1}{\alpha}} \tag{21}$$

The search agents take into account the wind direction and specific wave functions as they adjust their positions within the target. They continuously update their positions iteratively to meet the specified requirements

3.5 Hyperparameter tuning of T-RGB for enhancing sports performance

This study addresses challenges related to efficient sports performance detection. We carefully examine the ODI-Players performance dataset using a prediction approach, focusing on minimizing computational complexities while achieving better accuracy. To improve prediction performance, we employ a hybrid model that incorporates more than two distinct and suitable models. The literature review reveals predictions using Deep Learning models or a hybrid of DL, Machine Learning, and Convolutional Neural Network models. We propose the Adaptive Convolutional Encoder Decoder-based Gooseneck Barnacle Search (ACED-GBS) algorithm for sports performance prediction. This algorithm utilizes the Convolution technique, a graph encoder and decoder, and the Gooseneck Barnacle algorithm. The ACED-GBS approach is implemented to enhance sports performance using the provided dataset. Optimal hyperparameters for the proposed ACED-GBS approach are carefully selected to enhance system performance. The adjustment and tuning of parameters are crucial for obtaining the best results, and the Gooseneck Barnacle Search is employed for parameter optimization. During the search process, the Gooseneck Barnacle algorithm faces convergence issues, impacting overall system performance and complicating the prediction process. To address these challenges, an initial search strategy is integrated with the Gooseneck Barnacle optimization. This integration aims to overcome convergence problems and enhance the search process. The GBS algorithm is employed to tune the hyperparameters of the transformer model, overcoming the difficulties mentioned earlier. The optimal solution is obtained by sorting the best candidate solution. Furthermore, the advantages of the GBS algorithm are harnessed to fine-tune hyperparameters, ensuring an effective and efficient tuning process. Figure 3 illustrates the flowchart representation of the ACED-GBS algorithm.

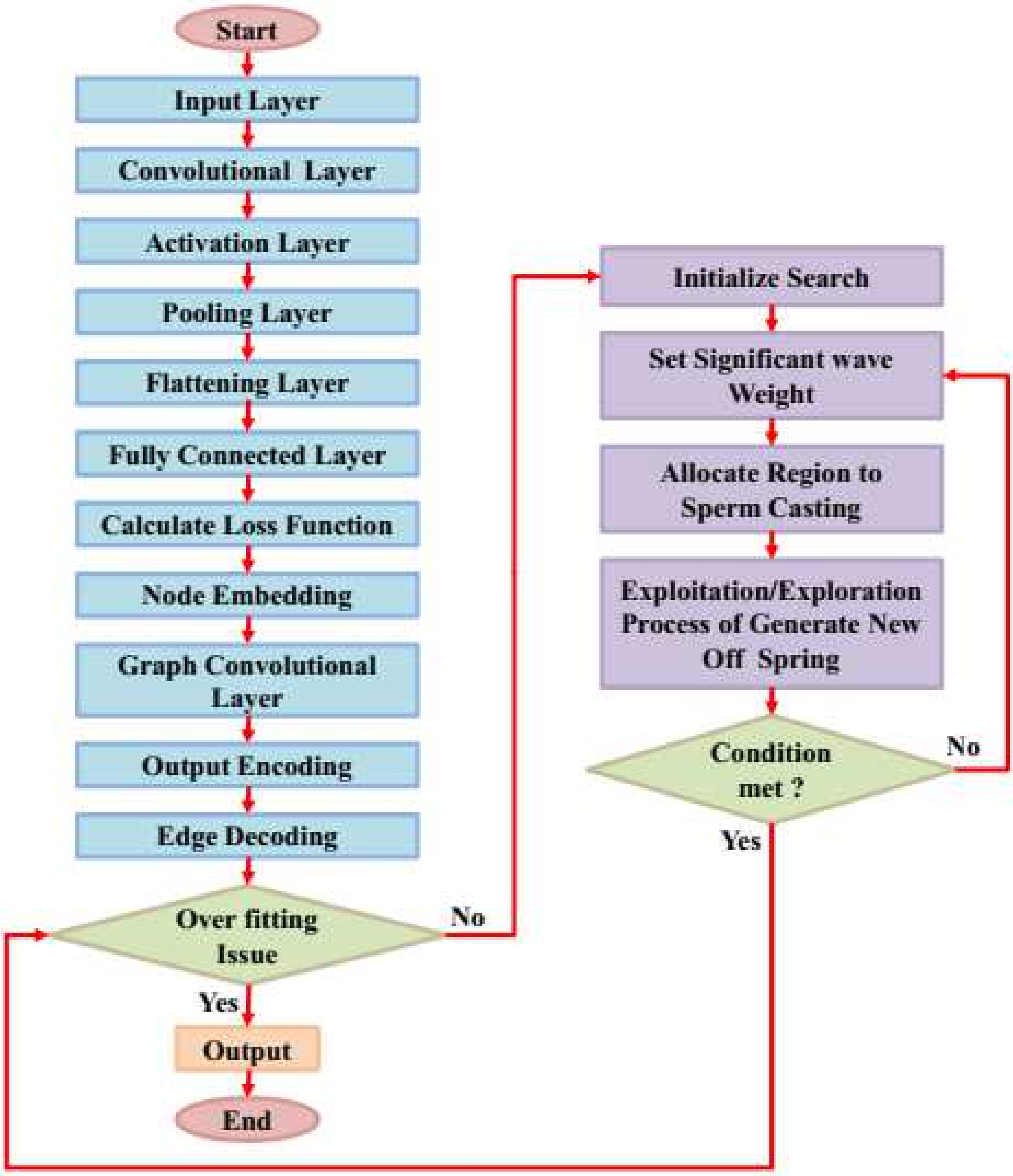

Figure 3: flowchart representation of the ACED-GBS algorithm.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

The performance of the ACED-GBS method for sports performance improvement and prediction and the results achieved from the work are depicted in this section. The ACED-GBS method is evaluated with different evaluation measures namely precision, accuracy, recall, F1-score, specificity, Area Under the Receiver Operating Characteristic (AUC-ROC), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), Matthews Correlation Coefficient (MCC) and execution time and the results are compared with existing methods such as Blockchain-based Hidden Markov Model (HMM) (Cao et al., 2021), Artificial Neural Network optimized Artificial Fish Swarm Algorithm (ANN optimized AFSA) (Wang, 2023), Attention-based sports competition performance improvement and prediction using Long Short Term Memory (AS-LSTM) (Zhang et al., 2022) and Optimized Convolutional Neural Network (OCNN) (Song et al., 2021).

4.1. Experimental Setup

In the experimental setup for the ACED-GBS method in performance improvement and prediction in sports athletics, a systematic approach is employed to ensure the reliability of the ACED-GBS method's performance. In this work, the ACED-GBS method is implemented in Python and the system uses Windows 10 with 16 GB RAM operating at a clock speed of 2.70 GHz. Moreover, certain wearable devices, like Global Positioning System (GPS) trackers and heart rate monitors, are employed to gather real-time physiological information during athletic training sessions. High-speed cameras and video analysis software are utilized to assess athletes' movements.

4.2. Parameter Setting

The parameter configuration of the ACED-GBS method for sports performance improvement and prediction involves set parameters for CNN to capture precise data during training sessions. Also, fine-tune video analysis parameters including frame rates and resolution for detailed assessments of athletes' movements. Table 1 represents Parameter values.

Table 1: Parameter Setting

Parameter	Value
Batch size	100
Learning rate	0.001
Epochs	100
Drop out	0.5
Optimizer	Adam
Momentum	0.9
Iterations	100
Activation function	Relu

The ACED-GBS approach experiences 100 iterations using a batch size of 100, utilizing the Adam optimizer with a learning rate set at 0.001. Additionally, the table presents alternative parameter values for experimentation: dropout rate of 0.5, momentum of 0.9, epochs of 100, and activation function of Relu. In this work, the Gooseneck Bernacle optimization with an initial search strategy is utilized to improve the performance of the ACED-GBS method.

4.3. Dataset Description

1. In this study, the cricket ODI-Players performance dataset (https://www.kaggle.com/datasets/thedevastator/cricket-odi-data-new-insights-into-player-perfor) is utilized to implement the ACED-GBS method for sports performance improvement and prediction. The Cricket ODI - Players Performance dataset is a collection of statistical information capturing the performance of cricket players in One Day International (ODI) matches. The dataset includes individual player statistics such as batting averages, strike rates, total runs scored, centuries, and half-centuries. Bowling figures, including wickets taken, economy rates, and average runs conceded, are also incorporated, offering a well-rounded perspective on players' all-around

performances. Team-specific information, match dates, venues, and outcomes are integrated, providing contextual details for each player's performance. The dataset covers a significant timeframe, allowing for trend analysis and the identification of players who have consistently excelled or faced challenges across different periods. Moreover, it likely includes details on players' fielding performances, adding another dimension to the assessment of their overall contributions on the field. In this research, a dataset comprising 10,000 observations is gathered. These observations are then partitioned into training and testing sets, maintaining an 80:20 ratio. This division is undertaken to assess the effectiveness of the ACED-GBS method in enhancing and predicting sports performance.

4.4. Evaluation Measures

The ACED-GBS method's effectiveness in sports performance improvement and prediction is evaluated through different evaluation measures such as accuracy, precision, specificity, F1-score, AUC-ROC, recall, execution time, RMSE, MSE, and MCC. The mathematical formulations of these metrics are mentioned below.

Accuracy

Accuracy (a_{cy}) gauges the percentage of accurately classified instances out of the total instances. It provides the ACED-GBS method's ability in sports performance improvement and prediction. It can be represented as,

$$a_{cy} = \frac{\omega^{+} + \omega^{-}}{\omega^{+} + \omega^{-} + \mu^{+} + \mu^{-}} \tag{22}$$

Precision

Precision (p_{rn}) measures the performance of the ACED-GBS method in correctly identifying positive instances and minimizing false positives. It can be calculated as,

$$p_{rn} = \frac{\omega^{+}}{\omega^{+} + \mu^{+}} \tag{23}$$

Recall

Recall (r_{l}) is the ACED-GBS method's ability to recognize every pertinent occurrence and assess the accurate prediction of positive outcomes. It can be expressed as,

$$r_{l} = \frac{\omega^{+}}{\omega^{+} - \mu^{-}} \tag{24}$$

F1-score

F1-score $(f1_{score})$ calculating the harmonic mean of precision and recall offers a balanced assessment, striking a compromise between these two metrics. The mathematical representation of the F1-score is given below.

$$f1_{score} = 2 \times \frac{(p_{rn} \times r_l)}{(p_{rn} + r_l)} \tag{25}$$

Specificity

Specificity (s_{py}) is the ability of the ACED-GBS method to identify all negative instances. It measures the proportion of actual negatives correctly predicted. It can be calculated as,

$$s_{py} = \frac{\omega^-}{\omega^- + \mu^+} \tag{26}$$

Area Under the ROC Curve (AUC-ROC)

The Area under the Receiver Operating Characteristic curve represents the trade-off between sensitivity and specificity across various thresholds. AUC-ROC values closer to 1 indicate better performance of the ACED-GBS method. The following equations show the true positive rate $(\omega^+ \ rate)$ and false positive rate.

$$\omega^+ \ rate = \frac{\omega^+}{\omega^+ + \mu^-} \tag{27}$$

$$\mu^+ \ rate = \frac{\mu^+}{\mu^+ + \omega^-} \tag{28}$$

Matthews Correlation Coefficient (MCC)

MCC (M_{CC}) is an evaluation metric for sports performance improvement and prediction, considering true and false positives and negatives. It ranges from -1 to 1, with 1 indicating perfect classification. MCC can be calculated as,

$$M_{CC} = \frac{(\omega^+ \times \omega^- - \mu^+ \times \mu^-)}{\sqrt{((\omega^+ + \mu^+)(\omega^+ + \mu^-)(\omega^- + \mu^+)(\omega^- + \mu^-))}} \tag{29}$$

Execution time

Execution time is the time taken by the ACED-GBS method to make predictions or complete a task. It measures the efficiency of the ACED-GBS method in sports performance improvement and prediction.

Root Mean Squared Error (RMSE)

RMSE $(rmse)$ is the square root of the average of the squared differences between predicted and actual values. It represents the error of the ACED-GBS method's predictions. It can be represented as,

$$rmse = \sqrt{\frac{\sum_{l=1}^{Q} \left\| r(l) - \hat{r}(l) \right\|^2}{Q}} \tag{30}$$

In equation (32), Q denotes total samples, l^{th} measurement, and its equivalent predictions are represented as $r(l)$ and $\hat{r}(l)$ respectively.

Mean Squared Error (MSE)

MSE is the average of the squared differences between predicted and actual values. It quantifies the ACED-GBS method's prediction error. It can be calculated as,

$$mse = \frac{1}{Q}\sum_{l=1}^{Q}\left(r_l - r_l'\right)^2 \tag{31}$$

In equation (33), Q, r_l and r_l' represents the total sample, the actual class of sample, and the predicted class of sample respectively.

4.5. Performance Analysis

This section depicts a comprehensive performance analysis of ACED-GBS and existing methods for sports performance improvement and prediction, as illustrated in several figures. Several key metrics are used to assess the performance of the ACED-GBS method, including accuracy, precision, recall, F1-score, specificity, AUC-ROC, execution time, RMSE, MSE, and MCC. In this study, the performance is evaluated by comparing the ACED-GBS method with the existing methods like Blockchain-based HMM, ANN-optimized AFSA, AS-LSTM, and OCNN. The comparative graphical representation of the ACED-GBS method and the existing methods for different evaluation metrics based on sports performance improvement and prediction are depicted in Figures 4 to 13.

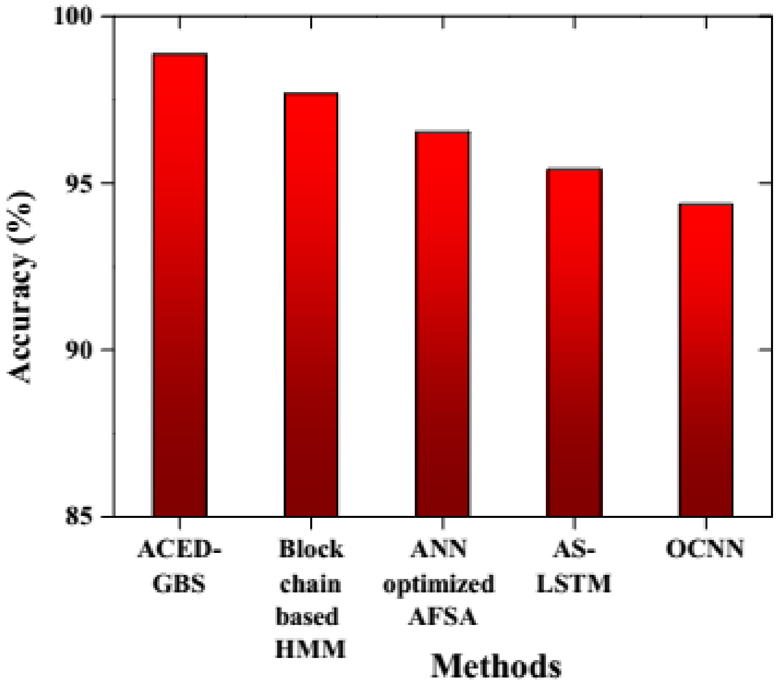

Figure 4: Graphical Representation based on Accuracy

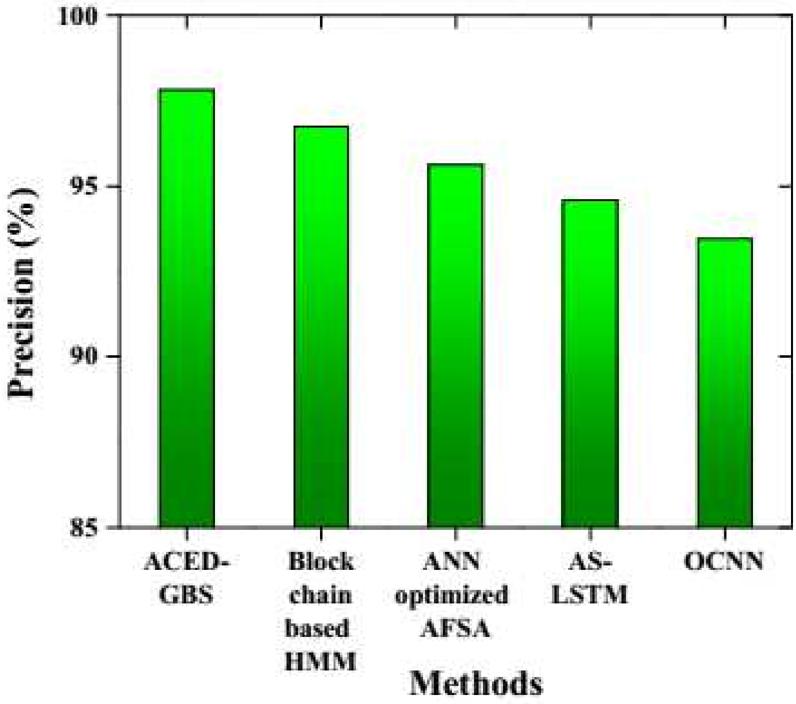

Figure 5: Performance Evaluation based on Precision

A comparative analysis of various methods based on their classification accuracies is presented in Figure 4. The ACED-GBS method stands out with a high accuracy of 98.85%, exhibiting its superior performance compared to other methods. The blockchain-based HMM, ANN-optimized AFSA, AS-LSTM, and OCNN follow closely with an accuracy of 97.68%, 96.54%, 95.42%, and 94.37% demonstrating its effectiveness in sports performance improvement and prediction. Figure 5 illustrates the precision values for different sports performance improvement and prediction methods, and offers the ACED-GBS method's ability to accurately identify positive instances among the predicted ones. The ACED-GBS method leads with a high precision of 97.83%, indicating a high proportion of correctly identified positive cases. Following closely, Blockchain-based HMM, ANN-optimized AFSA, AS-LSTM, and OCNN achieve a precision of 96.75%, 95.62%, 94.58%, and 93.46% showcasing its effectiveness in sports performance improvement and prediction.

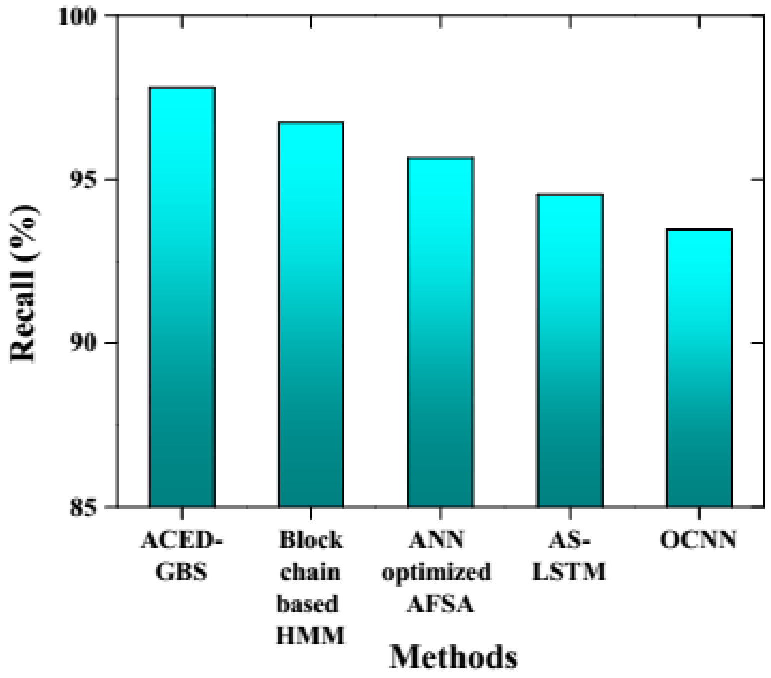

Figure 6: Recall Analysis for Performance Validation

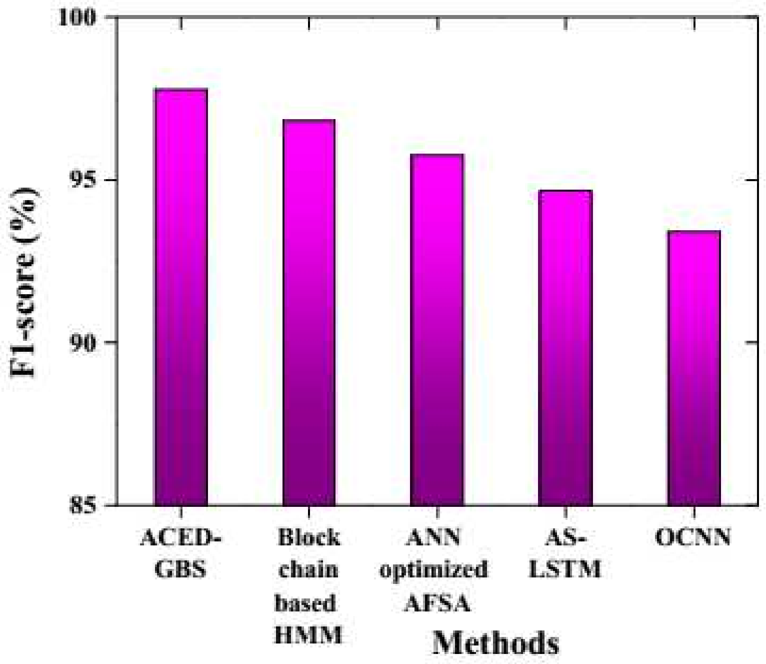

Figure 7: Graphical Representation based on F1-score

In Figure 6, the recall values for different sports performance improvement and prediction methods are depicted, displaying the ACED-GBS and existing methods' abilities to effectively capture and identify positive instances among all actual positive cases. The ACED-GBS method takes the lead with a high recall of 97.81%, exhibiting its excellence in identifying a high proportion of true positive cases. Following closely, Blockchain-based HMM, ANN-optimized AFSA, AS-LSTM, and OCNN exhibit a recall of 96.72%, 95.67%, 94.54%, and 93.48% respectively indicating its competence in capturing positive instances within the dataset. The F1-score values for various sports performance improvement and prediction methods are presented in Figure 7. The ACED-GBS method leads with a high F1-score of 97.78%, signifying a harmonious balance of precision and recall in its prediction performance. Following closely, Blockchain-based HMM, ANN-optimized AFSA, AS-LSTM, and OCNN achieve an F1-score of 96.82%, 95.76%, 94.67%, and 93.41% respectively demonstrating a balanced performance in terms of both identifying true positive cases and minimizing false positives.

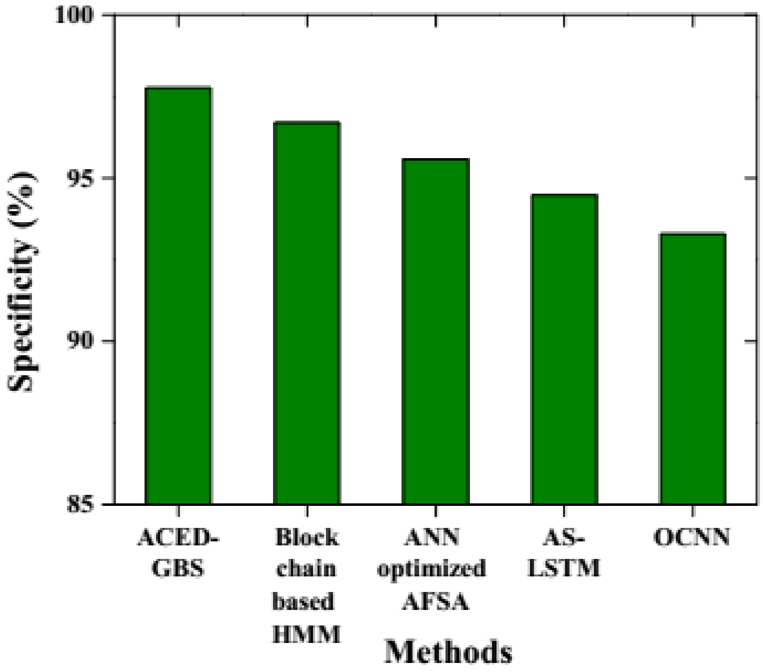

Figure 8: Performance Evaluation based on Specificity

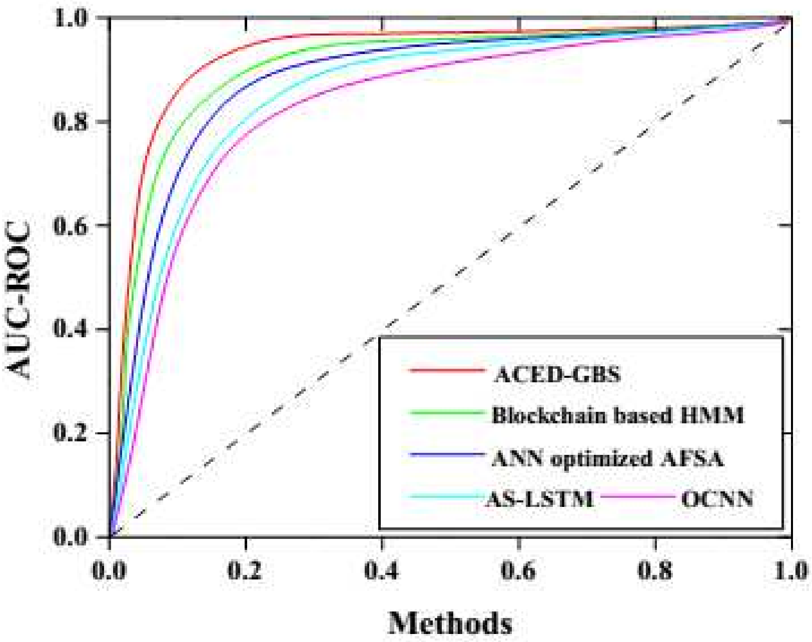

Figure 9: AUC-ROC Analysis for Performance Validation

In Figure 8, a performance evaluation based on specificity is depicted for ACED-GBS and existing sports performance improvement and prediction methods. The ACED-GBS method displays a better specificity value of 97.75%, demonstrating its efficiency in correctly identifying and classifying normal instances. Following closely, the Blockchain-based HMM method exhibits a specificity of 96.68%, highlighting its ability in sports performance improvement and prediction. The ANN-optimized AFSA, AS-LSTM, and OCNN achieve specificity values of 95.57%, 94.46%, and 93.28% respectively. Figure 9 illustrates a performance evaluation based on AUC-ROC for the ACED-GBS and existing sports performance improvement and prediction methods. The ACED-GBS method is achieved with an AUC-ROC of 0.9876, indicating its ability to discriminate between true positive and false positive rates across varying thresholds. The Blockchain-based HMM method follows closely with an AUC-ROC of 0.9768, displaying its effectiveness in achieving a balanced trade-off between sensitivity and specificity. The ANN-optimized AFSA, AS-LSTM, and OCNN achieve AUC-ROC values of 0.9652, 0.9554, and 0.9481 respectively in sports performance improvement and prediction.

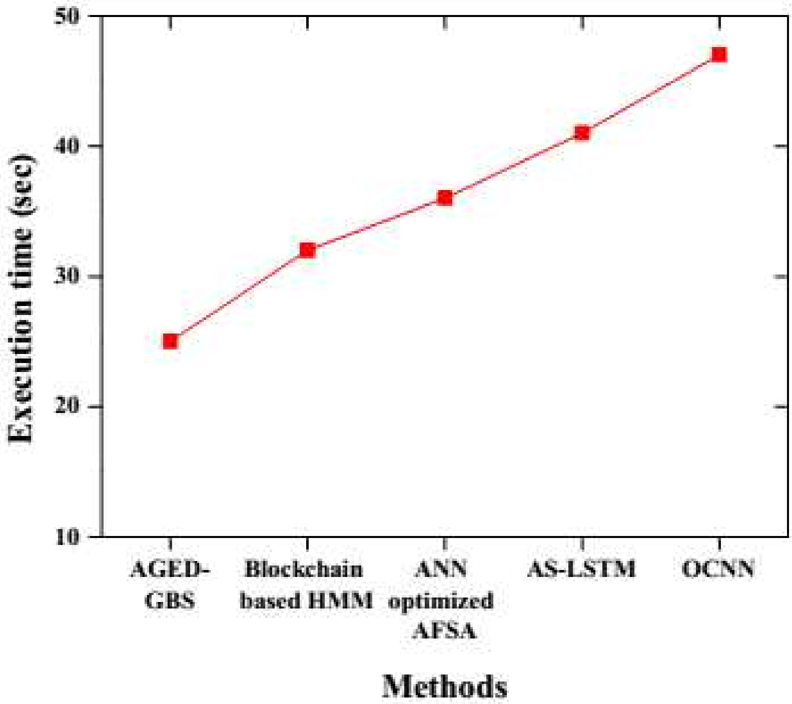

Figure 10: Graphical Representation based on Execution Time

Figure 10 depicts a graphical representation based on the execution time for the ACED-GBS and the existing sports performance improvement and prediction methods. The ACED-GBS method achieves better performance with an execution time of 25 seconds. The Blockchain-based HMM, ANN-optimized AFSA, AS-LSTM, and OCNN methods follow with an execution time of 32 seconds, 36 seconds, 41 seconds, and 47 seconds respectively in sports performance improvement and prediction. Figure 11 illustrates a graphical representation based on RMSE for the ACED-GBS and existing sports performance improvement and prediction methods. The ACED-GBS method achieves a low RMSE of 0.262, indicating better performance in its predictions and minimal deviation from the actual values. The Blockchain-based HMM method follows closely with an RMSE of 0.396, demonstrating its performance but with slightly higher prediction errors compared to the ACED-GBS method.

The ANN-optimized AFSA, AS-LSTM, and OCNN methods exhibit increasing RMSE values of 0.473, 0.585, and 0.674 respectively.

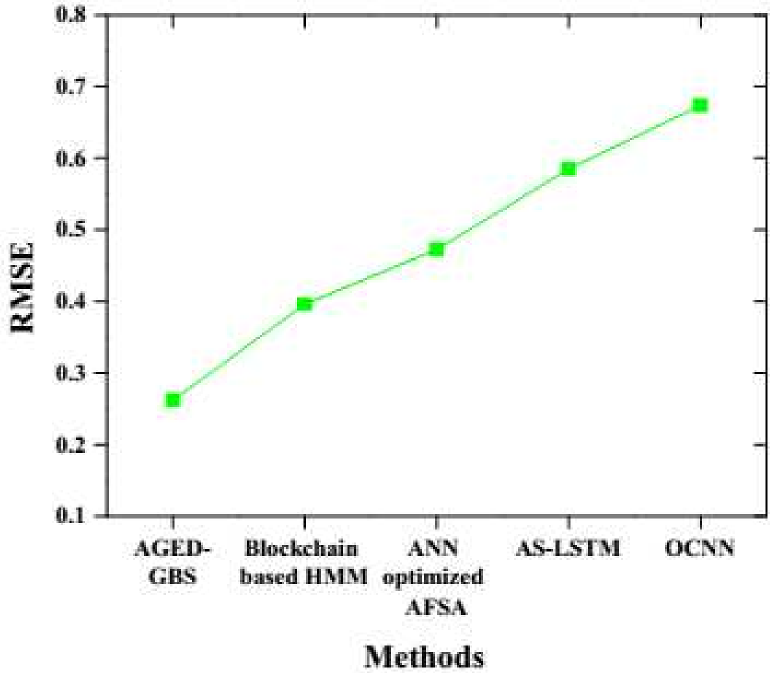

Figure 11: Performance Evaluation based on RMSE

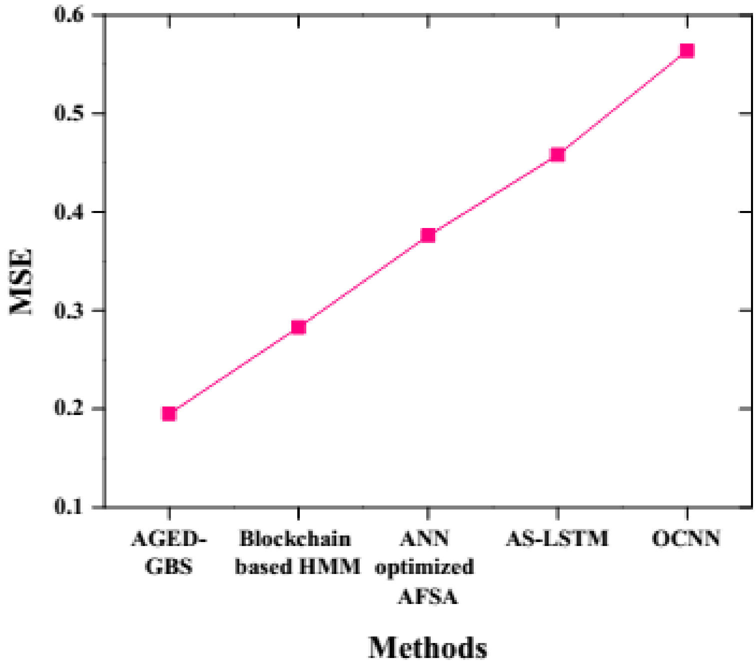

Figure 12: MSE Analysis for Performance Validation

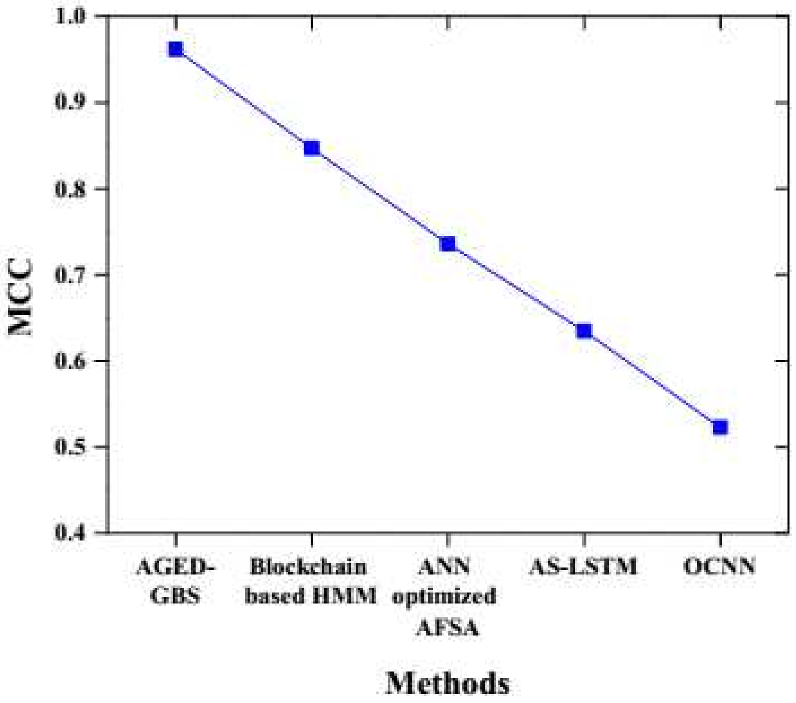

Figure 13: Graphical Representation based on MCC

In Figure 12, a graphical representation based on MSE is presented to assess the performance of the ACED-GBS and existing sports performance improvement and prediction methods. The ACED-GBS method demonstrates better performance with a low MSE of 0.195, indicating minimal prediction errors. The Blockchain-based HMM method follows closely with an MSE of 0.283, displaying accurate predictions but with slightly higher errors compared to the ACED-GBS method. The ANN-optimized AFSA, AS-LSTM, and OCNN exhibit higher MSE values of 0.376, 0.458, and 0.564 respectively. The Matthews Correlation Coefficient (MCC) values for different sports performance improvement and prediction methods are presented in Figure 13, providing a comprehensive evaluation that considers true and false positives and negatives. The ACED-GBS method stands out with an MCC of 0.962, indicating an effective performance in balancing true and false predictions. Blockchain-based HMM follows with an MCC of 0.847, exhibiting a correlation between predicted and actual values. ANN-optimized AFSA, AS-LSTM, and OCNN exhibit MCC values of 0.736, 0.635, and 0.523 respectively, highlighting their effectiveness in predicting true positive and negative instances. The performance evaluation illustrates the ACED-GBS method's efficiency in accuracy, precision, recall, F1-score, specificity, AUC-ROC, RMSE, MSE, MCC, and execution time for sports performance improvement and prediction.

5. CONCLUSION

This paper proposed the ACED-GBS method to provide distinctive advantages in sports performance improvement and prediction. In this study, the CNN is employed for feature extraction and the encoder-decoder is utilized to capture the interactions between the sports performance-related data. Moreover, the Gooseneck Bernacle optimization with initial search strategy is utilized for hyperparameter optimization which enhances the performance of the

ACED-GBS method. Various evaluation measures namely precision, accuracy, recall, F1-score, specificity, AUC-ROC, RMSE, MSE, MCC, and execution time are used to validate the performance of the ACED-GBS method, and these results are compared with existing methods such as Blockchain-based HMM, ANN optimized AFSA, AS-LSTM, and OCNN. The ACED-GBS method achieved accuracy of 98.85%, precision of 97.83%, recall of 97.81%, F1-score of 97.78%, specificity of 97.75%, AUC-ROC of 0.9876, execution time of 25 seconds, RMSE of 0.262, MSE of 0.195, and MCC of 0.962 respectively. The results illustrate that the ACED-GBS method achieved better results for sports performance improvement and prediction. In future work, big data analytics will enable the processing of vast amounts of information and allow the analysis of an athlete's performance based on their specific strengths, weaknesses, and injury risks. Also, the adaptive learning algorithms will be utilized to adjust training routines, optimizing performance enhancement strategies for each athlete.

Ethical Statements:

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Conflicts of interest Statement: Not applicable

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

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Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Authors' contributions

HR agreed on the content of the study. HR collected all the data for analysis. HR agreed on the methodology. HR completed the analysis based on agreed steps. Results and conclusions are discussed and written together. The author read and approved the final manuscript.

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