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# Real-Time Decision Modeling of Basketball Game Tactics Based on Video Analytics

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***Abstract: -*** Basketball games, real-time adjustment of defense strategy according to the changes on the court can greatly improve the team's chance of success in defense and thus win the game. In sophisticated team sports, it can be particularly difficult to judge these kinds of talents. This study attempted to develop an accurate and dependable video-based decision-making evaluation for young basketball in order to solve this problem. In this manuscript, Progressive Graph Convolutional Networks based onreal-time decision modeling of basketball game tactics based on video analytics (RDBGT-PGCN-GOA) is proposed. First, the image is taken from the NBA basketball video collection, and the pre-processing section receives the acquired data after that. When preparing, Unsharp Structure Guided Filtering (USGF) is used to remove background noise from the image. Then the preprocessed output is fed to Progressive Graph Convolutional Networks (PGCNs) is successfully used to classify the game tactics such as the Body Postures, Player Positions and Player Actions. Progressive Graph Convolutional Networks (PGCNs) classifiers, in general, do not express adaptive optimisation procedures to find the best parameters to guarantee accurate classification of player positions, player actions, and body postures. Hence, proposed GOOSE Optimization Algorithm (GOA) enhances Progressive Graph Convolutional Networks (PGCNs), accurately classify game tactics such as Body Postures, Player Positions and Player Actions. The weight parameter of the PGCN optimized with GOOSE Optimization Algorithm (GOA) for accurate prediction. The proposed RDBGT-PGCN-GOA proposed is implemented on the Python working platform. The performance of proposed method examined utilizing performance metrics likes Accuracy, Precision, Recall,F1 score, Error rate, and specificity were looked at. The proposed RDBGT-PGCN-GOA approach contains 23.52%, 22.72% and 24.92% higher accuracy; 23.52%, 24.72% and 21.92% lower Error rate compared with existing methods, such as Basketball video analysis using deep learning algorithms for technical features (TFBV-DNN), offline reinforcement learning for tactical strategies in professional basketball games (TSPBG-RNN), and real-time defensive strategy optimization using motion tracking and deep learning (RTBDS–CNN) are the three approaches that are being examined.

***Keywords:*** Basketball, GOOSE Optimization Algorithm, Progressive Graph Convolution Networks, Unsharp Structure Guided Filtering, Video.

## I. INTRODUCTION

### *a) Background*

Basketball, being a competitive and dynamic sport, places significant demands on players' quick decision-making and reactive skills during gameplay [1]. Defensive strategies are pivotal in basketball for attaining success. However, conventional defensive tactics predominantly hinge on the intuition and experience of coaches and players, lacking scientific analysis of real-time data and opponent behavior [2]. The quick advancement of IoT and artificial intelligence in recent years has brought brand-new technical means to basketball [3]. Artificial intelligence scrutinizes basketball game data, offering coaches enhanced data support to refine tactical arrangements and decision-making [4]. Concurrently, IoT technology enables real-time monitoring of game data, delivering instant feedback and data support for both coaches and players [5]. Moreover, with the evolution of motion tracking technology and deep learning algorithms, researchers are delving into leveraging these advanced technologies to optimize basketball defensive strategies [6].Through analyzing real-time data and on-court motion trajectories, coupled with integrating them into deep learning models to anticipate the actions of opposing players, coaches and players can access sharper and more effective defensive strategies [7]. This research holds significance as it anticipates aiding coaches and players in comprehending game dynamics through real-time data assistance, thereby empowering them to make more informed decisions [8].Simultaneously, employing this method offers teams the chance to enhance their competitive edge and tactical prowess through the utilization of cutting-edge technological resources [9]. Within the realm of artificial intelligence, computer vision technology stands out as one of the most rapidly evolving areas, finding extensive applications in basketball [10].

### *b) Literature Review*

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Numerous studies based on deep learning have already been published in the literature; the basketball game tactics and classification based on deep learning and aspects. Some of them are reviewed here,

Kang, [11] have suggested that a player posture estimation algorithm leveraging local spatial constraints, utilizing both motion tracking and deep learning technologies. This algorithm builds upon the foundation of a general human body pose estimation algorithm, where it specifically constrains the image based on athlete detection frames. By isolating and focusing solely on the athlete within the image, the algorithm inputs the processed image into a general human body pose estimation model for pose detection. Subsequently, the detected pose was mapped back to the original picture, culminating in the comprehensive estimation of the athlete's posture. This method provides high accuracy and low precision.

Li Chen and Wenbo Wang [12] have developed that a video analyzes the technical attributes of basketball players and introduces a behavior analysis approach leveraging deep learning. First, a method for mechanically extracting stadium and court markings was developed. Next, a spatiotemporal scoring approach was used to identify key frames in the video. Later on, an encoder-decoder architecture was used to add a behaviour identification and prediction mechanism. This method provides high accuracy and low error rate.

Chen et al. [13] have suggested that an introducing ReLiable, It focuses on investigating how player decisions could be influenced by reinforcement learning (RL). For the purpose of training an offline deep Q-network (DQN), we utilised past National Basketball Association (NBA) game data. This method provides high precisionand low accuracy.

Soroush, BabaeeKhobdeh et al. [14] have presented a deep fuzzy LSTM network used with YOLO to recognise basketball actions. In human-computer interaction (HCI), recognising human behaviours in uncertain settings is important, particularly for sports, since it provides players, coaches, and analysts with essential information about movement patterns and aids referees in making decisions on sportsmanship. Notably, diverse backdrops, obscured actions, and different lighting conditions make it difficult to identify human activities in basketball scenarios. This study described a method using YOLO and a deep fuzzy LSTM network to get around these problems. This method provides high Recall and low precision.

Bin Yuan et al. [15] have suggested a Basketball technology and systems for assessing physical fitness both employ motion sensors based on neural networks. In order to provide more precise diagnostic recommendations, the system uses clever algorithms to objectively analyse pertinent data. Motion sensors are needed to collect a variety of body data for human movement detection. Strong computer equipment is incorporated into the system's data collecting components for the purposes of training, data preprocessing, and recognition model implementation, while prioritising mobility and low power consumption. This method provides high accuracy and low F1 score.

Dongxu Du et al. [16] have suggested that using machine vision to extract characteristics in real time from basketball players' foul acts. The demand for basketball has noticeably increased as the world economy continues to grow quickly and the standard of living of people keeps rising. This method provides high accuracy and low specificity

Ghazi Rekik et al. [17] have presented that a In order to study how gender differs in basketball tactical action learning using static picture and video modelling, There were eighty enrolled secondary school pupils (Mage = 15.28, SD = 0.49). In order to ensure gender parity, participants were split into two groups: the dynamic condition (20 men, 20 women) and the static condition (20 males, 20 women). Assignments were made in a quasi-random way. Participants immediately completed an exam on card rotations, a test of game performance, and an evaluation of their mental effort related to learning after being exposed to either dynamic or static presentations of the playing system during the learning phase. This method provides high Recall and low error rate.

*c) Research Gap and Motivation*

The overall analysis of the most current studies demonstrates that, However, the unique nature of basketball presents numerous challenges for computer vision technology. Firstly, the environment within basketball games is complex and dynamic, with factors such as player interactions, rapid movements, and occlusions. Secondly, defensive strategies in basketball require real-time adjustments to accommodate changing circumstances. Numerous academics are addressing this issue in the literature using various technologies, similar to convolution neural networks (CNN), recurrent neural networks (RNN), and deep neural networks (DNN). Implementing CNNs for real-time analysis of player movements and strategic decision-making requires substantial computational power and memory resources. This could lead to challenges in deploying the system in real-world settings, especially in scenarios where real-time responsiveness is critical, such as during live basketball games, While DNNs excel in pattern recognition, understanding the rationale behind their classifications or predictions can be complex, making it difficult for coaches or analysts to trust and incorporate these insights into their strategies effectively. This lack of interpretability may hinder the adoption of deep learning approaches in basketball analytics, where transparency and comprehensibility are crucial for decision-making. The Recurrent Neural Networks (RNNs) for creating strategic plans for professional basketball matches is the challenge of accurately representing the full complexity of game dynamics solely based on historical data. The above mentioned technologies have impact on the Noise increasing. There aren't many approach-based publications in the literature that address this issue; these shortcomings and issues are what spurred this study effort.

*d) Challenges*

Developing a real-time decision modeling system for basketball game tactics based on video analytics presents several challenges. Ensuring the accuracy and reliability of the video analytics algorithms in real-time scenarios is crucial, as any delays or inaccuracies could significantly impact the effectiveness of the tactical decisions made during the game. Integrating the video analytics system seamlessly into the fast-paced environment of a basketball game requires robust infrastructure and high-performance computing capabilities to handle the processing demands in real-time. Interpreting the insights generated by the video analytics system and translating them into actionable tactical decisions poses a cognitive challenge for coaches and players, who must quickly understand and implement the recommended strategies during the game. Moreover, ethical considerations regarding player privacy and to keep the confidence, data utilisation needs to be carefully considered and acceptance of the system within the basketball community.

*e) Contribution*

The following list summarizes the important contributions of this manuscript:

- Initially data gathered from NBA basketball video dataset.
- To remove background noise from the image using an Unsharp Structure Guided Filtering is applied in the pre-processing section.
- The Progressive Graph Convolutional Networks then receives the pre-processed data and used to classify the game tactics such as the Body Postures, Player Positions and Player Actions.
- To improve the PGCN, the weight parameter is optimised by the GOOSE Optimisation Algorithm (GOA).
- The proposed RDBGT-PGCN-GOA method is implemented, and performance measures that are analysed include F1 score, specificity, accuracy, precision, recall, and error rate.

*f) Organization*

Section 1 describe the introduction is explain the literature review and background of the research work, Sector 2 includes the proposed methodology, Sector 3 includes the results and discussion, Sector 4 clarifies the Conclusion and Sector 4 the manuscript concludes.

## II. PROPOSED METHODOLOGY

This section explains the RDBGT-PGCN-GOA proposed technique. The NBA basketball video dataset is useful for automating the camera operator's work during a match, allowing the ball to be efficiently kept in frame, forestry, and urban planning applications. Lacklustre Organisation During the pre-processing phase, background noise is eliminated from the image using guided filtering. The categorization stage receives the output from the pre-processing phase, where the Body Postures, Player Positions and Player Actions Progressive Graph Convolution Networks. The Goose Optimization algorithm is utilized to enhance the Progressive Graph Convolution Network for classifying the neural network's predictions of Body Postures, Player Positions, and Player Actions. Figure 1 depicts the Block schematic illustrating the proposed strategy

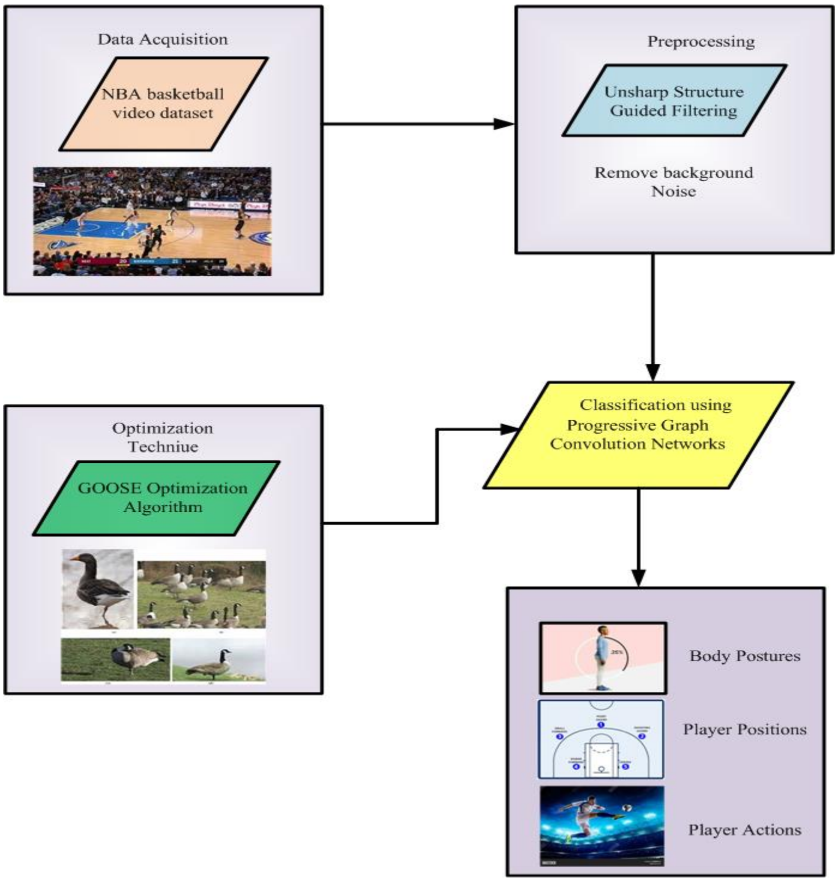


Fig 1: Block schematic illustrating the proposed strategy

*A. Data Acquisition*

The NBA basketball video dataset served as the original source of the dataset [11]. One hundred pictures underwent testing, featuring an average of 7.73 athletes per image. To ensure equitable and consistent testing conditions, all algorithms in this experiment operated within identical hardware and software environments. The maximum allowable number of people detectable in each picture was capped at 10.However, the count of individuals within the image surpasses this threshold significantly, indicating that the bottom-up player pose estimation method undertakes numerous unnecessary operations, leading to inefficient utilization of computational resources and time. To maintain the stability of experimental outcomes, the average value for each iteration was computed across all images in the test set to yield the final test result.

*B. Image Preprocessing using Unsharp Structure Guided Filtering(USGF)*

In this section, a USGF [18] is discussed. The method of Unsharp Structure Guided Filtering is employed to enhance images by effectively preserving edge details while simultaneously reducing noise and artifacts. It achieves this by leveraging the unsharp mask to emphasize edges and structures in the image, guiding the filtering process to maintain sharpness in these regions while smoothing out noise in the flat areas. This approach is particularly useful in various image processing applications such as denoising, sharpening, and enhancing visual quality, offering a balance between noise reduction and edge preservation that traditional filtering techniques may struggle to achieve.

In this instance, $G$'s information is sent to $I$. The input statistics determine this kind of association. The following formula may be used to calculate the statistics, assuming that wk is a local window with pixel $k$ at its centre:

$$a_k = \frac{\frac{1}{|w|}\sum_{i \in w_k} I_i G_i - \bar{I}_k \overline{G}_k}{\sigma_k^2 + \in} \tag{1}$$

$$b_k = \bar{I}_k - a_k \overline{G}_k \tag{2}$$

Here $|w|$ is the number of pixels in $w_k$, $\sigma_k^2$ is the variance of $G$ in $w_k$, $\overline{G}_k$ and $\bar{I}_k$ stand for the mean of G and I in $w_k$, and E is a regularisation term. Based on the linear coefficients $a_k$ and $b_k$, the anticipated result $P$ may be written as follows:

$$P_i = a_k G_i + b_k, \forall_i \in w_k \tag{3}$$

Since the entire image contains several windows $w_k$ s converging pixel $i$, the filtered results for that point are different. The average of all $P_i$ values may be used to get the final result:

$$p_i = \frac{1}{|w|}\sum_{k\in w_i}(a_k G_i + b_k) \tag{4}$$

But in order to get the best $a_k$ and $b_k$, typical guided filtering necessitates empirical parameter change, which significantly reduces denoising performance. Furthermore, using a self-supervised learning network to estimate two coefficients at once may make training more unstable and result in inconsistent structure in the predicted pictures. Thus, by combining Eq. 2 with Eq. 4, the coefficient $b_k$ may be removed:

$$p_i = \frac{1}{|w|}\sum_{k\in w_i} a_k G_i + \frac{1}{|w|}\sum_{k\in w_i}(\bar{I}_k - a_k \overline{G}_k) \tag{5}$$

Then, the following formulation can be obtained:

$$p_i = \frac{1}{|w|}\sum_{k\in w_i} a_k (G_i - \overline{G}_k) + \frac{1}{|w|}\sum_{k\in w_i}\bar{I}_k \tag{6}$$

To determine the value of $G_i^*$, a mean filter is used in this research. As a result, $G_i^*$ in the window is quite close to its mean $\overline{G}_k$. This means that we can rewrite Eq. 6.

$$p_i = a_i^*(G_i - G_i^*) + I_i^* \tag{7}$$

It is evident that $(G - G^*)$ indicates the guiding pictures' unsharp structures where $a_i^* = \frac{1}{|w|}\sum_{k\in w_i} a_k$, $I_i^* = \frac{1}{|w|}\sum_{k\in w_i}\bar{I}_k$ appears. The intensity of structures is regulated by coefficient $a^*$. In particular, the filtered picture $I^*$ can get the structural information thanks to the term $a^*(G - G^*)$. Finally, remove background noise from the image using an Unsharp Structure Guided Filtering. Then the Pre-processed image is given to the Progressive Graph Convolution Networks for Classification.

*C. Classificationusing Progressive Graph Convolutional Network*

In this section, a Progressive Graph Convolution Networks (PGCNs) [19] is discussed. The Progressive Graph Convolution Networks (PGCNs) offer significant benefits in graph-based learning tasks. They excel at capturing hierarchical structures within graphs by progressively refining node representations across multiple layers, thereby facilitating the extraction of intricate patterns and relationships. Progressive Graph Convolutional Networks (PGCNs) are employed across diverse graph-based learning tasks owing to their proficiency in capturing intricate relationships and structures within graphs. Particularly beneficial in contexts where data demonstrates hierarchical organization or multiple levels of granularity, these algorithms are valued for their ability to handle complex graph structures effectively. PGCNs demonstrate proficiency in node classification, graph clustering, link prediction, and graph generation tasks. Through their progressive refinement mechanism, they iteratively enhance node representations, resulting in improved performance in capturing both local and global structural features of graphs.

The objective is to assign greater weight to nodes possessing similar power, irrespective of their spatial proximity. The trend similarities between nodes in a network are measured by the cosine similarity of their power metrics. Assume there is a single input feature for the node power $x_t^i$. The definition of the cosine similarity ($s_{ij}$) between two nodes ($v_i$ and $v_j$) is:

$$s_{ij}^t = \tilde{x}_t^{i(T)^T} \cdot \tilde{x}_t^{j(T)} \tag{8}$$

Where $\bar{x}_t^{i(T)}$ is indicated as the min-max normalised power of node $v_i$ at time $t$ and $\tilde{x}_t^{i(T)} = \bar{x}_t^{i(T)} / \left\|\bar{x}_t^{i(T)}\right\|$ is a unit vector.

Basketball clubs frequently use expert employees to analyse replay data, such as data analysts and video coordinators, in an effort to improve tactical and strategic decision-making. In order to adjust to patterns and unpredictability, it also added a learnable component, $W_{adj} \in R^{T\times T}$, to the similarity of cosine. Every member of the progressive adjacency matrix $A_{P_{ij}}^t$ has a specified $W_{adj} \in R^{T\times T}$.

$$A_{P_{ij}}^t = soft\max\left(\mathrm{Re}LU(\tilde{x}_t^{i(T)^T}\, W_{adj}\, \tilde{x}_t^{j(T)}\right) \tag{9}$$

The progressive adjacency matrix is normalised using the soft-max function, and the negative connections are removed by ReLU activation. After applying $W_{adj}$ to each vector, the parameter $W_{adj}$ discovers the link between the two powers, $\tilde{x}_t^{i(T)}$ and $\tilde{x}_t^{j(T)}$. In other words, $W_{adj}$ encodes the power-based linear transformations used to get the final similarity value.

The diffusion convolution for a K-step diffusion process with filter $f_W$ on a directed graph may be described using the transition matrix $p = A/rowsum(A),$ as

$$Z_t = X_t * g\ f_W = \sum_{k=0}^{k-1} p^k X_t W_{k,1} + P^{T^K} X_t W_{k,2} \tag{10}$$

Where $*g f_W$ is is the filter-based convolution operation on a graph $f_W$, and $W_{k,1}$, and $W_{k,2} \in R^{C\times D}$ are learnable parameters, $P$ and $P^T$ are employed to depict the diffusion process both forward and backward.

A convolution kernel $\gamma \in R^P$ and a power feature time-series input $x_t^{i(T)} \in R^T$ at time $t$ are given, the dilated causal convolution applied on $x_t^{i(T)}$ can be represented as

$$x_t^{i(T)} * T\,\gamma = \sum_{p=0}^{p} \gamma(p)\, x_t^{i(T)}\,(T - D\times P) \tag{11}$$

A basketball team's ultimate objective is to outscore their opponent and win the game by scoring more points. Where $d$ is the dilation factor, The scalar values in the brackets are the vector indices, while $*T\gamma$ is a dilated convolution operation with kernel $\gamma$. In order to retrieve the temporal element of the input sequence, $X_t^{(T)} \in R^{N\times T\times C}$, the input is passed to gated activation units after the dilated causal convolution. Equation (12) classify the game tactics such as the Body Postures, Player Positions and Player Actions

$$H_t = \tanh(X_t^{(T)} * T\Gamma 1) \otimes \sigma(X_t^{(T)} * T\Gamma 2) \tag{12}$$

Where $\otimes$ stands for multiplication of elements, $\sigma(\cdot)$ is an activation function of the sigmoid and $\Gamma 1$ and $\Gamma 2 \in R^{P\times C\times D}$ are the dilated causal convolutions kernels. Finally, PGCN classify the game tactics such as the Body Postures, Player Positions and Player Actions. In this work, GOA is employed to optimize the PGCN optimum parameters $H_t$ and $Z_t$. Here, the weight and bias parameter of the PGCN are adjusted using GOA.

*D. Optimization using GOOSE Optimization Algorithm*

In this section, GOOSE Optimization Algorithm (GOA) [20] is described. The GOA improved the PGCN weight parameters $H_t$ and $Z_t$ in order to improve the suggested RDBGT-PGCN-GOA techniques classify to remove background noise from the image. The Goose Optimization Algorithm (GOA) because of its efficacy in solving optimization problems across diverse domains. Inspired by the foraging behavior of geese, GOA strikes a balance between exploration and exploitation, enabling it to effectively navigate complex search spaces and converge towards optimal solutions. Its simplicity, ease of implementation, and ability to handle large-scale problems make it an attractive choice for researchers and practitioners seeking efficient optimization techniques. Additionally, GOA's versatility and ability to escape local optima make it can serve a number of functions, including engineering design, logistics planning, financial modeling, and machine learning optimization. Overall, the GOA's robustness, scalability, and adaptability make it a valuable tool in addressing complex optimization challenges.

***Step1:*** Initialization

Set the input parameters to their initial values. In this case, the input parameters are the HIPN weight parameters, which are indicated as $H_t$ and $Z_t$

***Step2:*** Random generation

The initialized populations are randomly created by using random generation, which is described by,

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{13}$$

Here, $X$ is the GOA population matrix, $X_i$ represents the $i^{th}$ frilledlizard, $m$ is denoted as the amount of decision variables, $x_{i,d}$ denotes its dth dimension within the field of search, $N$ gives the number of frilled lizards.

***Step 3:*** Fitness Function

The outcome is derived from the random response and initialized judgements. In order to evaluate the fitness function, weight parameter optimisation effects $H_t$ and $Z_t$ are utilised. Equation (14) is used to compute it.

$$fitness\ function = Optimizing\,[H_t \text{ and } Z_t] \tag{14}$$

Where, $H_t$ denotes the increasing the accuracy, $Z_t$ represent decreasing the error.

***Step 4:*** Exploration Phasefor Optimizing $H_t$

As demonstrated in Eq. (15), determining a $BestX_{it}$ is required to resolve a new $X$ in the population or to reawaken the individual in the flocks. This formula consists of the $Free\_Fall\_Speed$ speed of the falling object multiplied by the average duration, plus the goose $Distance\_Goose_{it}$'s distance. $Time\_Average$.

$$X_{(it+1)} = Free\_Fall\_Speed + Distance\_Goose_{it} * Time\_Average^{\wedge\,2} \tag{15}$$

However, In the event when both variables indicate the stones' weight $Stone-Weight_{it}$ and $pro$, respectively, less than 12 and less than or equal to 0.2, then use the formula in Eq. (17) below to get the new $X$.

$$Free\_Fall\_Speed = Time\_of - Average - Object_{it} * \frac{Stone-Weight_{it}}{9.81} \tag{16}$$

In the new mathematical equation, on the other hand, we discover a new *X*. All variables, including the distance travelled by the geese, the average time, In Equation (17), the coe and the falling object's speed are multiplied sequentially by one another.

$$X_{(it+1)} = Free\_Fall\_Speed * Distance\_Goose_{it} * Time\_Average^{\wedge\,2} * Core \tag{17}$$

It employed two equations, such as Eqs. (15) and (17), to find a new X during the exploitation phase. The equation that was used was decided by the values of variables $pro$ and $Stone-Weight_{it}$.

***Step 5:*** Exploitation Phase for Optimizing $Z_t$

Variable alpha has a value between 2 and 0, and as demonstrated by Equation (18), its value drastically decreases with each iteration of the loop. Its purpose is to enhance the outcome of a new X in the search space.

$$alpha = \left(2 - \left(\frac{loop}{\frac{Max-It}{2}}\right)\right) \tag{18}$$

Here $Max-It$ is denoted asthe most iterations that are feasible. Calculating the two parameters $Minimum-Time$ and alpha is essential to directing the search phase towards the solution that is most likely to be the best one.

In Eq. (19), the minimum of time and alpha are multiplied by a random number and then added to the best location in the search space.

$$X_{(it+1)} = randn(1,\dim) * (Minimum-Time * alpha) + Best - pos \tag{19}$$

If $Best - pos$, or the best location found in the search region, is the $BestX$ and dim is the number of issue dimensions.

***Step 6:*** Update the Best Solution

The procedure is finished if the best result is achieved.

***Step 7:*** Termination

The process will end if the chosen solution is the best one; if not, it will go to the step 3 fitness calculation and go through the remaining stages until a solution is found.

## III. RESULT AND DISCUSSION

In this manuscript, the quantitative performance evaluation technology This section discusses the RDBGT-PGCN-GOA approach, which is based on a Deep Learning technology. The Python working platform is used for the simulations. Python is used to simulate the proposed method under various performance criteria. Results of RDBGT-PGCN-GOA examined using the RTBDS-CNN, TFBV-DNN, and TSPBG-RNN techniques.

### *A. Performance Measures*

There is also a comparative study of the performance indicators, which include specificity, F1 score, accuracy, precision, recall, and error rate.

#### *1) Accuracy*

It is the proportion of the entire number of predictions produced for a dataset divided by the count of precise forecasts. It is quantified using equation (20).

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{20}$$

Where, $TN$ s denotes as true negative, $TP$ is symbolizes true positive, $FN$ is characterizes false negative and $FP$ is denotes false positive.

#### *2) Precision*

A statistic called precision counts the number of correctly predicted favourable outcomes. Equation (21) is used to scale this.

$$\Pr ecision = \frac{TP}{(TP+FP)} \tag{21}$$

#### *3) Recall*

Positive examples can be detected by a machine learning model using recall measures. To put it another way, it gauges your chances of receiving a favourable outcome. Thus it is given an equation

$$\mathrm{Re}call = \frac{TP}{(TP + FN)} \tag{22}$$

*4) F1-Score*

It is crucial to select the right performance measures for assessing deep learning and machine learning techniques.

$$F1 - sore = 2 * \frac{(precision * \mathrm{Re}call)}{(precision + \mathrm{Re}call)} = \frac{TP}{TP + \frac{1}{2}(FN + FN)} \tag{23}$$

Here, $TP$ is signifies true positive, $FP$ is characterizes false positive, and $FN$ is characterizes false negative.

*B. Performance Analysis*

Fig 2 to 7 portrays the simulation outcomes of proposed RDBGT-PGCN-GOA technique. Then, the proposed RDBGT-PGCN-GOA method is likened with existing RTBDS–CNN, TFBV-DNN and TSPBG-RNN methods respectively.

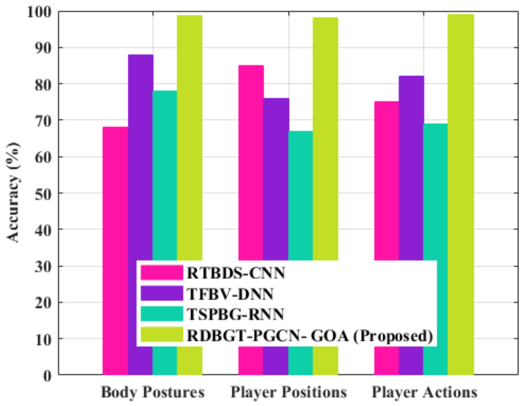


Fig 2: Accuracy performance analysis

The Accuracy performance analysis is depicts in Fig 2. The performance of the proposed technique results in accuracy that are 23.52%, 21.72%, 24.92% higher for the classify the game tactics such as the Body Postures, Player Positions and Player Actions, when evaluated to the existing RTBDS–CNN, TFBV-DNN and TSPBG-RNN models correspondingly.

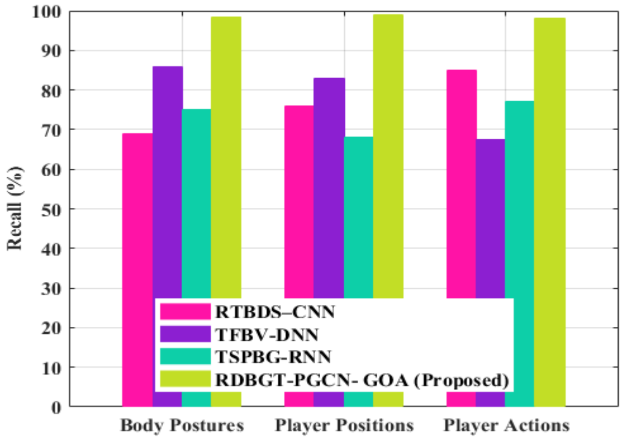


Fig 3: Recall performance analysis

The Recall performance analysis is depicts in Fig 3. The performance of the proposed technique results in accuracy that are 23.52%, 22.72%, 24.92% higher for the classify the game tactics such as the Body Postures, Player Positions and Player Actions, when evaluated to the existing RTBDS–CNN, TFBV-DNN and TSPBG-RNN models correspondingly.

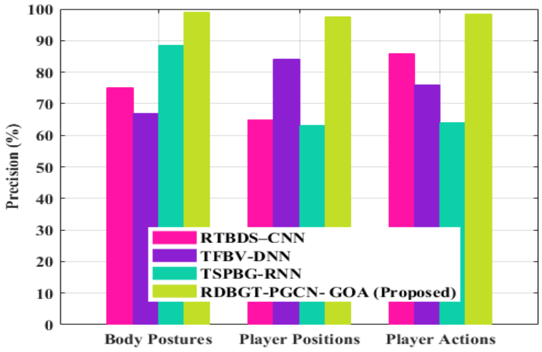


Fig 4: Precision performance analysis

The Performance analysis of precision method is depicts in Fig 4. The performance of the proposed technique results in accuracy that are 23.52%, 21.72%, 24.92% higher for classify the game tactics such as the Body Postures, Player Positions and Player Actions, when evaluated to the existing RTBDS–CNN, TFBV-DNN and TSPBG-RNN models correspondingly.

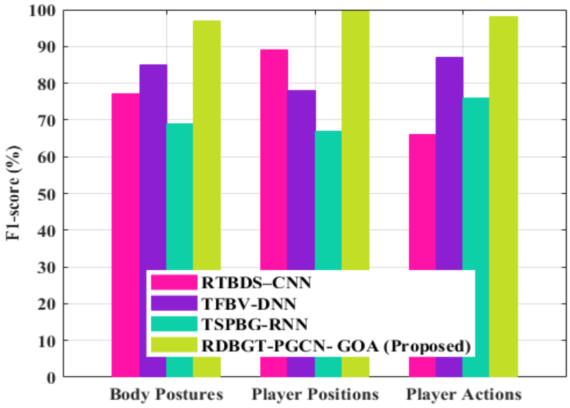


Fig 5:F1-score performance analysis

The F1-score performance analysis is depicts in Fig 5. The performance of the proposed technique results in accuracy that are 23.52%, 20.72%, 24.92% higher for the classify the game tactics such as the Body Postures, Player Positions and Player Actions, when evaluated to the existing RTBDS–CNN, TFBV-DNN and TSPBG-RNN models correspondingly.

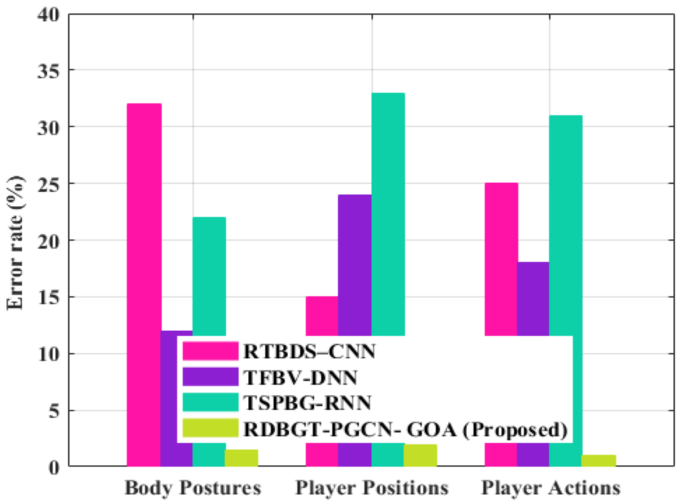


Fig 6: Error rate performance analysis

The Error rate performance analysis is depicts in Fig 6. The performance of the proposed technique results in accuracy that are 23.52%, 24.72%, 24.92% higher for the classify the game tactics such as the Body Postures, Player Positions and Player Actions, when evaluated to the existing RTBDS–CNN, TFBV-DNN and TSPBG-RNN models correspondingly.

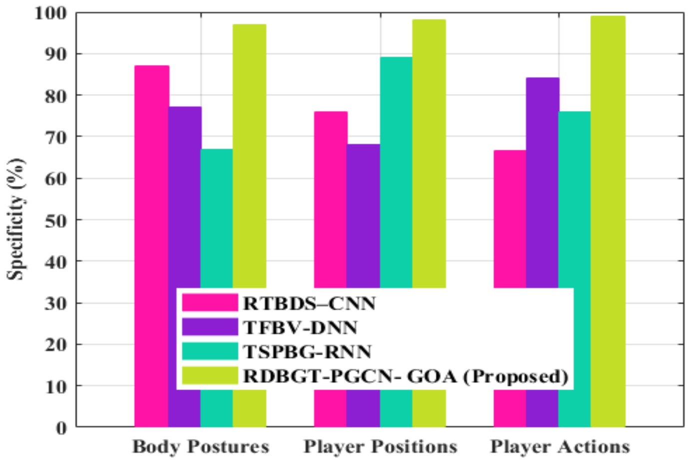


Fig 7: Analysis of specificity performance

The Analysis of specificity performance is depicts in Fig 7. The performance of the proposed technique results in accuracy that are 23.52%, 22.72%, 24.92% higher for the classify the game tactics such as the Body Postures, Player Positions and Player Actions, when evaluated to the existing RTBDS–CNN, TFBV-DNN and TSPBG-RNN models respectively.

*C. Discussion*

The performance analysis across various metrics demonstrates the superiority of the proposed technique in classify the game tactics such as the Body Postures, Player Positions and player actions compared to existing models such as RTBDS–CNN, TFBV-DNN, and TSPBG-RNN. Notably, the accuracy rates achieved by the proposed approach are consistently higher, the proposed RDBGT-PGCN- GOA method attains 23.52%, 22.72% and 24.92% higher accuracy classify the Body Postures, Player Positions and player actions. The proposed RDBGT-PGCN- GOA method attains 23.52%, 24.72% and 21.92% lower Error rate for classify the Body Postures, Player Positions and Player Actions. Moreover, the method exhibits lower error rates, further bolstering its reliability in decision-making scenarios. By leveraging advanced techniques like Progressive Graph Convolutional Networks (PGCNs) enhanced with the GOOSE Optimization Algorithm (GOA), the proposed model achieves unparalleled performance, paving the way for more accurate and robust video-based decision-making assessments in youth basketball.

## IV. CONCLUSION

In this section, Basketball game tactics based on video analytics (RDBGT-PGCN- GOA) was successfully implemented. The proposed RDBGT-PGCN- GOA method is executed in the Python working platform utilizing the dataset of NBA basketball video dataset. The performance of the RDBGT-PGCN- GOA method containsF1 score, specificity, accuracy, precision, recall, error rate, and specificity. The proposed RDBGT-PGCN- GOA method attains 23.52%, 22.72% and 24.92% higher accuracy classify the Body Postures, Player Positions and Player Actions. The proposed RDBGT-PGCN- GOA method attains 23.52%, 24.72% and 21.92% lower Error rate for classify the Body Postures, Player Positions and Player Actions. Future work in Real-Time Decision Modeling of Basketball Game Tactics Based on Video Analytics could focus on advancing player tracking algorithms to improve accuracy and reduce latency, allowing for more precise analysis of player movements. Additionally, integrating predictive analytics techniques could enable the anticipation of opponent actions, facilitating real-time strategy adaptation. Interactive coaching tools could be developed to provide coaches with actionable insights during games, leveraging visualizations and scenario planning capabilities.

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