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Optimization of Table Tennis Players' Technical Movements based on Genetic Algorithm

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Abstract

Table tennis players employ rapid footwork, accurate racket movements, and strategic ball placement. They use topspin, backspin, and side spin to control the ball, adjusting their posture and grip accordingly. To improve table tennis players' presentation, we suggested an inventive Redefined Genetic Algorithm (RGA) for optimizing their industrial movements and refining sports play strategy efficiently. By competently identifying edges in imagery, our technique can reduce error and speed of negative response while growing identification accuracy. Furthermore, this study builds a tactical analysis framework for table tennis video games by combining the techniques of trajectory prediction and tracking of targets. We obtained a dataset that comprises table tennis player performance metrics, gameplay videos, and trajectory data. Image processing is performed to pre-process the gathered raw image data. Utilizing Scale-Invariant Feature Transform (SIFT) for efficient feature extraction enhances the robustness and accuracy of identifying key points and descriptors. Long Short-Term Memory (LSTM) and Radial Basis Function Support Vector Machine (RBF-SVM) algorithms were utilized to recognize and analyse movement patterns in table tennis gameplay videos effectively. The proposed model is implemented in Python software. We evaluate the effectiveness of the proposed method using various key metrics such as precision, recall, f1 score, and accuracy. The experimental findings demonstrate the effectiveness of the proposed recognition model.

Keywords: Table Tennis Players, Technical Movements, Redefined Genetic Algorithm (RGA), Recognition Model, Tactical Analysis.

1. INTRODUCTION

Table tennis is a fast-paced sport where players must learn a number of technical moves to succeed. Players must possess agility, accuracy, and imaginative thinking. Gamers need to continuously improve their approaches to play better and avoid frequent errors that might negatively affect their performance. Helping athletes to recognize and solve these mistakes is largely dependent on effective coaching **[1]**.Examine common mistakes and impacts also discuss the significance of technical motions in table tennis, and investigate how players can develop their skills through specialized instruction. Figure 1 shows the table tennis players of technical movements.

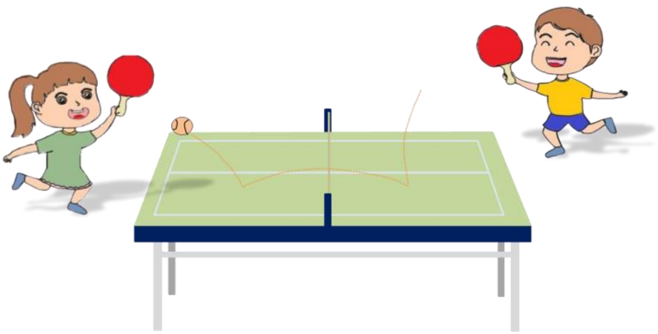

Figure 1: Table tennis player's technical movements

1.1. Starting with a strong foundation

Building a solid base is essential for playing table tennis with effectiveness, to maintain balance; players should stand with their feet shoulder-width apart, their knees slightly bent, and their weight equally positioned in the balls on their feed. Rapid responses and lateral motions are made possible by the arrangement. Furthermore, retaining control and producing the necessary spin need mastery of the proper grip, whether it is pen-hold or shake hand **[2]**. A strong establishment lays the stage for higher approaches and dependable presentation while proving constancy and suppleness that enable precise and forceful shots. Table tennis engages a wealth of technical motion, such as grip, posture, footwork, stroke methods, and serves. To achieve shots with precision, speed, and spin, every of this equipment is essential. Professional who masters these plans is able to administer the ball superior, respond quickly to shots from rivals, and conserve an advantage over their rivals **[3]**.

1.2. Common mistakes and their Issues

Table tennis players frequently make mechanical mistake that have an extremely unhelpful effect on their game. The inability to conserve a precise grip is one of the recurrent issues. The incorrect grip can bound an assortment of connection and decrease the capability to make spin, which can effect in weaker shots and a greater weakness to come back from other players **[4]**. Several players' also regularly put great effort with unfortunate footwork, which makes it harder to attain the ball and causes them to move more gradually, which results in wasted possibilities and poor returns. These typical issues restrict a player's advancement and minimize their potential for improvement, in addition to making it more difficult for them to perform complex techniques. To improve a player's technical skill and overall game performance, it is important to identify and solve these shortcomings through concentrated practice and targeted coaching **[5]**.

1.3. Addressing and improving technical issues

Players in table tennis need to practice purposefully and receive focused instruction to conquer technical problems. Analysis of videos can yield insightful information that instructors can use to identify particular mistakes and model proper techniques **[6]**. Drills that emphasize follow-through, footwork, and stroke mechanics can assist in building muscle memory for accurate execution when practiced consistently. Players can enhance their abilities and make the required modifications during workouts because of immediate feedback. Setting strength and conditioning as the primary focus also improves speed, endurance, agility, and overall table effectiveness **[7]**. Players can improve their technical deficiencies and reach higher levels of performance with focused effort and supervised teaching.

1.4. Objective of the study

The objective of the research is to assess and improve table tennis players' professional shots using an RGA. The study uses evolutionary concepts to find the greatest movement patterns and tactics that improve players' performance and advance comprehension of table tennis tactics.

1.5. Key contributions

- The integration of trajectory prediction and target tracking techniques in table tennis video games offers a comprehensive tactical evaluation framework that enables better strategy development and player training.
- The SIFT enhances descriptor extraction and key point identification, edge recognition effectiveness, and reducing mistakes, thus enhancing identification precision in images.
- To improve technical strokes and gaming tactics for table tennis players, the RGA is a revolutionary technique that has been developed. Through specialized optimization methods, players can be able to improve their performance by utilizing RGA more effectively.

The rest of the paper was arranged and added to the related works in section 2. Section 3 included a thorough methodology. Section 4 presents a result and discussion. Section 5 provides the conclusion.

2. RELATED WORKS

Machine learning (ML) was used to analyse the table tennis professionals ‘electroencephalograms (EEGs) in an effort to increase the accuracy of stress identification **[8]**. The researchers collected EEG data by means of intellectual data pre-processing, the Stroopcolour, and word tests. Random forest (RF), logistic regression (LR), support vector machines (SVM), decision trees (DT), regression trees (RT), and extreme gradient boosting (XGBoost) were a few of the numerous techniques used. The study outcomes recognized that XGBoost executes accurately in the three levels of pressure categorization. High, moderate, and low levels of pressure can illustriously use the stress-detecting model that was developed using EEG data. The recognition of sports, which embrace both participant and audience, has amplified the alertness of judgment made by manager **[9]**. To reduce score errors and slanted awareness, the study optionally developed a novel deep residual network (DRN) and deep learning (DL) of the table tennis score technique. The organization collected image information and trained a DL model by using an included camera for image evaluation. A microcontroller component was incorporated with the qualified model to show the score instantaneously. The deep Convolutional Neural Network-Long Short Term Memory (DCNN-LSTM) representation was suggested to monitor and recognize the real-time trajectory of table tennis in demanding situation. The LSTM approach was used to forecast the trajectory of the ball after extracting motion cues from the deep neural network (DNN). A self-constructed video dataset was used to evaluate the model, and it was contrasted with other methods **[10]**. The Deep Deterministic Policy Gradient (DDPG) approach achieved superior feature extraction with maximum precision and least mean square error (MSE), the DCNN-LSTM model excels in comparison to traditional methods. Difficulties with rotation measurement and table tennis tracking can be resolved by using automated detection techniques. Table 1 shows the objectives, methods, results, and limitations of previous works.

Table 1: Objective, methods, results, and limitations in related works

Reference	Objective	Methods	Results	Limitations
[11]	To address the growing psychological strain that table tennis players experience in the highly competitive large tournaments and to offerpractical recommendations for psychological education with the technological assistance of DL.	The study evaluated the psychological strain of table tennis players using a facial recognition heart rate measuring method based on DL, and using video heart rate technique, incorporating team members' understanding of stress sources and real-time monitoring.	Table tennis players can find relief from psychological swings with the help of a video heart rate measurement method, which has an error rate and post-exercise states.	Further study was required to address possible constraints including scalability, reliability, and execution concerns, as the existing dynamic heart rate measuring technique has low detection accuracy.

[12]	With the objective of creating an upgraded player performance system for sports analytics utilizing computer vision, the section presented a novel approach to gathering table tennis video data for stroke recognition and categorization.	A temporal convolutional neural network (CNN) model was created, and ML and DL methods for stroke detection were contrasted in the study, which gathers footage of table tennis strokes from players.	The table tennis neural network model was designed to obtain validation accuracy for the multiclass classification of strokes and the best accuracy for new strokes from players omitted from the dataset.	The drawbacks were the demand for validation across various situations and abilities, the applicability to other sports, and possible difficulties in taking the suggested approach into practice because of the necessary computing power and data.
[13]	The research created and assessed action recognition models using YOLOv8-Alphapose 2s-STGCN for technical table tennis actions. It also suggested a fresh framework for assessing players' styles and tactics.	Using YOLOv8-Alphapose-2s-STGCN, the study developed two action recognition models using high-definition action images of top players. It evaluated the models' performance with seven different artificial intelligence (AI) algorithms and used DNN evaluation.	By recognizing tactical styles and trends using DNN, the YOLOv8-Alphapose-2s-STGCN models outperformed other models in table tennis identification, offering important insights into players' tactics and strategic decisions.	The study's shortcomings include the possibility of biases resulting from high-quality table tennis recordings and the necessity for more research to establish whether the findings apply to other sports or players at lower levels.
[14]	The study presented a control approach that addresses issues such as calculating spin velocity and guaranteeing the desired ball landing position and height above the net, allowing table tennis robotic to precisely regulate ball motion during play.	The method involved using DRL to approach the stroke plan of a table tennis robot. The DRL-based approach calculates ball spin velocity and learns the best stroke method iteratively through interaction with the environment, while also creating a virtual table tennis playing environment for proper pre-training.	According to experimental data, the suggested control system works superior to conventional aerodynamics-based techniques, with a greater table landing frequency and an average landing error.	The study emphasized how difficult it was to measure a ball's spin speed precisely in real-world situations and to estimate it from visual clues since the ball's surface lacks roughness.
[15]	Table tennis was an excellent application for motor development in virtual reality (VR) since it's a physically demanding sport that calls for a high degree of motor skills. The study looked at how effective feedback is when	Using a unique physics approach for proper posture and paddle handling, researchers developed a training system for beginning table tennis players that offers multi-modal teaching and real-time posture coaching.	After using a VR system for training, the participants showed enhanced technique and quality of ball return, demonstrating the technology's efficacy in motor training for table tennis.	The study's inadequate sample size restricted the findings' adaptability, even though it showed how beneficial real-time feedback was for VR table tennis training. Furthermore, the effectiveness of various feedback modalities and long-term skill

	teaching table tennis in virtual reality (VR).			maintenance were examined in the investigation.

3. METHODOLOGY

The following activities can be completed using the proposed approach, the data were gathered in game-play videos and trajectory data, and the collected raw image data is pre-processed by image processing. In the section, a Redefined Genetic Algorithm (RGA) is suggested to accomplish the greatest results in terms of table tennis professionals' technical moves based on a genetic algorithm with feature extracting capability of the Scale-Invariant Feature Transform (SIFT) method. Figure 2 shows the flow of the proposed method.

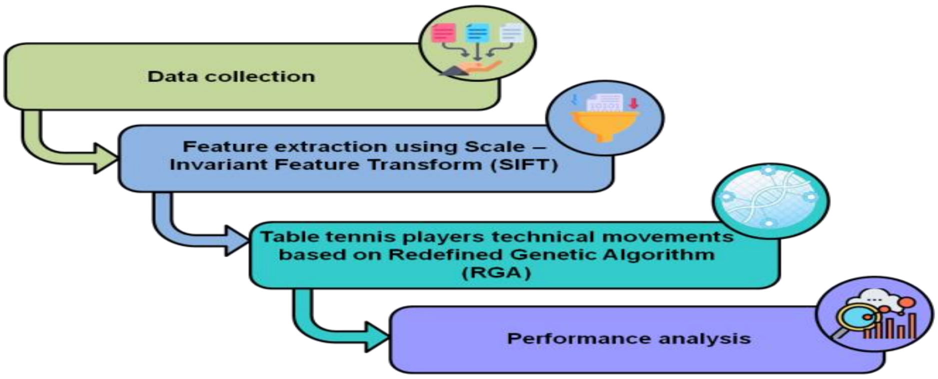

Figure 2: Flow of the proposed method

3.1. Data collection

The resolution and color depth of this model are 755 x 1130 pixels with a 30-bit depth the shooting frequency ranges from 1010 frames to 100,015 frames per second with customizable speed and the transmission speed is 105/1008-Mbps Ethernet with a wireless remote. Downloading the films to local and distant PCs is quick and easy. Six different types were chosen from the video footage, preparation, slides, hits, throwing a tennis ping-pong ball, serves, and short pushing. The whole data set for data balancing consisted of 35 video clips chosen for the various categories. A test set of 150 samples is randomly picked for every training period, with the remaining samples serving as the training set. The experiment incorporates the guiding principle of super-parameter modification.

3.2. Pre-processing

Data preprocessing is a kind of data preparation that involves processing unprocessed data to prepare it for further video data preprocessing. To improve the quality and extract pertinent information from raw video data, preprocessing the video data includes cleaning, converting, and organizing the data.

3.3. Feature extraction using Scale-Invariant Feature Transform (SIFT)

Table tennis players' motions can be inspected using the SIFT, which distinguishes restricted key points in their events independent of scale or direction change. When SIFT make possible the monitoring and evaluation of contestant schedule by recognizing and associating these uniqueness in numerous scenes of the play. This helps with appearance analysis, method growth, and skill appraisal. Furthermore, SIFT is more useful for analysing complex moves in dynamic sports environment such as table tennis because of its pliability to changes in conditions, difficulty and illumination.

- **Identification of SIFT**

The initial stage is to determine key points that are dependable with scale difference by penetrating across a variety of scales and image location. A SIFT is utilize to identify the areas in an image that remain steady in size regardless of modification in scale level. As explained, the Gaussian function $H\ (w, z)$represents the only workable scale-space kernel. A convolution of the variable-scale Gaussian function$H\ (w, z, \sigma)$ using an input image $J\ (w, z)$ yields the scale space of an image $K\ (w, z, \sigma)$ using equation (1).

$$K\ (w, z, \sigma) = \ H\ (w, z, \sigma) * J\ (w, z) \qquad (1)$$

Hereσ is the Gaussian function's extent. $w$and$z$ are the image apparatus. The Difference of Gaussian (DoG) function defines a stable key-point position in the SIFT. The variation among two images with scales of $k$and$l\sigma$, where k is a multiplicative factor, that used to determine the SIFT, which is found in$C(w, z, \sigma)$,as denoted in the equation (2).

$$C(w, z, \sigma) = \big(H(w, z, l\sigma) - H(x, z, \sigma)\big) \times I(w, z) = K(w, z, l\sigma) - K(w, z, \sigma) \qquad (2)$$

To make the key-point rotation-invariant, it receives an orientation previous to the extraction of a description. This indicates that there can be a possible key point at (w, z) with scale σ. The direction of the key point is determined using the orientation histogram of local gradients from the nearest smoothing image$K(w, z, \sigma)$. Following is the calculation of the gradient's direction and magnitude using equation (3).

$$n(w, z) = \sqrt{(K(w + 1, z) - K(w - 1, z))^2 + (K(w, z + 1) - K(w, z + 1))^2}(3)$$

The overall SIFT integration with motion analysis systems provides useful data on table tennis players' tactics, advantages, and potential areas for development this eventually advances coaching methods and player progression in table tennis.

Once the probabilities for each base classifier are known, they cannot be changed, and any variation between them is completely disregarded. Weak classifier weights determine the initial GA population, which in turn determines the number of decision groups. The constant T, which is unlimited at zero, limits the maximum number of iterations. The crossover and mutation probability have a significant bearing on the method's optimization impact. If you want to utilize these definitions in parameter equations (4-6), they come from the literature:

$$T_f = \gamma \qquad (4)$$

$$T_n = 0.1(1 - \gamma) \qquad (5)$$

where γ is a control variable.

To specify the fitness value, we can suggest:

$$\text{fit} = \frac{\sum_{x=1}^{M} X(j(I_x) = j_x}{M} \qquad (6)$$

A typical GA is seen in Figure 3 below.

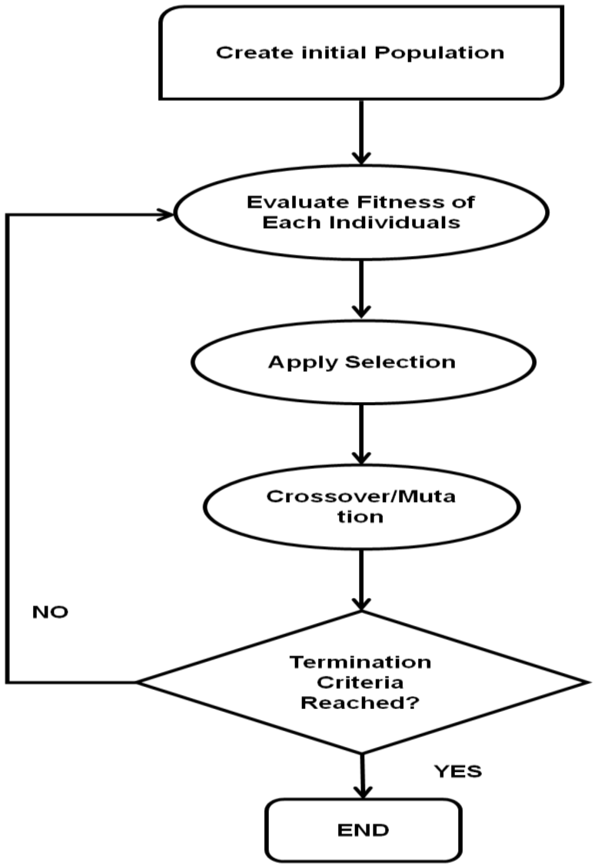

Figure 3: Typical GA flow chart

Genetic algorithms share components that depend on the task, such as the encoding and evaluation functions. The researcher started by encoding the problem in order to start translating it into computer language. Specifics usually dictate the best method to characterize the problem. There are various kinds of representations, such as:

• Binary encoding: This method uses a sequence of ones and zeros to represent each chromosome. One situation where binary encoding could be helpful is the knapsack issue.

• Permutation encoding: This method employs a sequence of integers to represent the position of a chromosome. This method may be useful for ordering issues such as the Traveling Salesman problem (TSP).

• Encoding as a set of values: Chromosomes can be encoded as a set of values that include letters, numbers, or even actual objects. The values could be anything from letters to numbers.

The "tree encoding" encoding method depicts the chromosomes as branches of a tree that holds programs or instructions. Tree encoding is handy for genetic programming, which makes use of algorithms that evolve over time. After chromosomal encoding, GA operates as summarized in the following outline.

i. Begin: Creating a starting population of randomly selected individuals is the initial step in every GA. Afterwards, we represent each new person as a chromosome using a string sequence of length L that meets the problem encoding. Finally, a "genotype" population is created at random.

ii. Fitness: After that, we need to figure out how fit an individual is in comparison to the rest of the population. A person's fitness value and the assessment's prioritized values determine their pairing. Despite the fact that the terms are sometimes used interchangeably, there is a notable distinction between fitness and evaluation in the context of GA.

iii. Evaluation: An evaluation function, also known as an objective function, is used to rate performance based on predefined criteria. The performance metric of the fitness function is used to construct a spectrum of reproductive alternatives.

iv. The Reproduction Process: Selection The number of offspring produced by each chromosome and which ones are utilized in mating and reproduction are both decided by natural selection. With the guiding principle that "the better an individual, the higher its chance of being a parent," this is the main objective of the selection procedure. Whether practitioners utilize tried-and-true or user-defined selection techniques depends on the nature of the issue.

• Crossover: The selecting process determines which parents will have a hybrid child. Crossover occurs when two parents exchange genetic material at a randomly selected spot on a chromosome. Crossover offspring are those whose parents' genetic material has been transferred at a precise location.

Mutation is a common issue that arises following a crossover. The operator in question alters several "genes" at random to produce fresh "offspring," resulting in adaptive solutions that are less prone to converge to a local optimum. One example is binary encoding, which allows for the random flipping of bits between 0 and 1 or 1 and 0.

• Conditions for ending: Before revealing the optimal answer, GA can be ended in a number of ways, including:

i. The maximum number of generations has been reached.

ii) There is less than a predetermined threshold of overall population fitness variation.

The maximum attainable fitness level has remained same.

3.4. Proposed method Redefined Genetic Algorithm (RGA)

The RGA improves performance by repeatedly creating techniques to maximize the technical motions of table tennis players. RGA simulates natural selection by using a genetic framework to improve grip, footwork, and stroke mechanics.Identifying the most effective combinations of these components across multiple generations improves players' agility, accuracy, and strength. The adaptive nature of RGA enables it to customize tactics to the unique attributes of each player, hence optimizing their performance at the table. RGA transforms training approaches and produces the next generation of top table tennis players with unmatched accuracy and efficiency by fusing biomechanics insights and performance data. The description above makes it clear that RGA offers a generic framework for solving large system optimization issues, independent of the domain and related difficulties. The fitness function is the cornerstone of the RGA. By applying genetic operations to every individual, a player's repeating process for entity structure rearrangement is accomplished. Some basic RGA approaches are as follows in equation (7):

$$SGA = (D, F, O_{P,} M, \emptyset, \Gamma, \psi, S) \tag{7}$$

D -Individualized coding methodology, F - activities that assess an individual's level of fitness, $O_{P,}$ -initial population, M- several of people, $\emptyset$- operator for the choice, Γ -operator in the crossover, ψ- operator of the mutation, S- The requirement for terminating a genetic surgery. Finally, we identified the player's technical moves using our novel method accurately.

The fitness function guides the selection, crossing, and mutation of individuals within the initialization population. The following formula shows our fitness definition as the goal function:

$\text{fitness} = -t_{end}$ (8)

t_{end} shows the most last time it took to do the job, hence a faster time indicates that the population as a whole is more fit.

For genetic operators, we opted for the most popular tournament selection approach. Two individuals are chosen at random from each generation's population to be compared; the one with the higher individual fitness is kept in the next generation.

In a population, the crossover genetic operator couples people and swaps out chromosomes based on the crossover probability; in a mutation genetic operator, gene values at specific chromosome sites are changed to various alleles. The crossover operator uses single-point crossover to randomly swap chromosomal fragments. In order to improve population variety, the mutation operator uses single-point mutation, which involves adding a disturbance value to a randomly selected location on the chromosome to rearrange the order of certain activities. Below are the formulas (9-10) for adaptive crossover and mutation probability that are defined in this paper:

$$p_c = k_c - \frac{f' - f_{avg}}{f_{max} - f_{min}}\lambda \qquad (9)$$

$$p_m = k_m - \frac{f_i - f_{avg}}{f_{max} - f_{min}}\mu \qquad (10)$$

p_c is the adaptive crossover probability; k_c is the basic crossover probability; λ is the crossover factor; f' is the larger fitness value of the two individuals for crossover; k_m is the basic mutation probability; μ is the mutation factor; f_i is the current individual fitness. When the population fitness tends to the local optimal value, appropriately reduce the crossover probability and increase the mutation probability to prevent premature convergence of the algorithm; when the fitness difference between chromosomes is relatively large or individuals in the population are dispersed in the solution space, the formula can appropriately increase the crossover probability and reduce the mutation probability, so that superior individuals can be retained to help the population conduct a more extensive search in the solution space.

P_c is the bigger fitness value of the two individuals for crossover; k_c is the basic mutation probability; λ is the mutation factor; f' is the current individual fitness; k_m is is the adaptive crossover probability; and μ is the basic crossover probability. λ is the crossover factor. If the population fitness is approaching the local optimal value, then it is appropriate to decrease the crossover probability and increase the mutation probability to avoid the algorithm from convergent too soon. On the other hand, if there is a large fitness disparity between chromosomes or if the population members are scattered across the solution space, then it is appropriate to increase the crossover probability and decrease the mutation probability according to the formula. This allows the population to retain better individuals and search the solution space more thoroughly.

Algorithm 1 shows the pseudo code for RGA.

Algorithm 1: RGA

Function run Evaluations (o)

Population_size =size (o)

For (i = 1 to populations_size) **do**

begin

The crossover operator defines crossover

Apply the mutation operator probability to mutations

end for

Surpass the new population o”(s) towards the next generation 0(s) = o’(s)

Elitist $= \text{highestFitness}\ (O)$;

$O''(s) = o''(s) + \text{elitist}$;

Return $o''(s)$;

end function

Function GA

Set $j = 0$

Initialize $(o(j))$;

Evaluate fitness $o(j))$;

For (gen $=$ 1 to generation_size) **do**

begin

$O_{gen} = \text{runEvaluations}(O_{gen-1})$

end for

end function

4. RESULT AND DISCUSSION

Throughout the investigation, Python 3.2 was utilized. It provides Windows 8 and Intel Core i7 laptops with 35GB SSDs. Accuracy, Precision, Recall, and F1-score are some of the assessment measures used to assess the efficacy of the proposed system.Long Short-Term Memory (LSTM) [16], Radial Basis Function Support Vector Machine (RBF-SVM), and RGA have all been used in a comparison.Table 2 shows the numerical comparison of parameters.

Table 2: Numerical comparison of parameters

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LSTM	81.30	83.37	81.91	80.82
RBF-SVM	76.96	84.37	76.96	74.88
RGA [Proposed]	92.82	90.63	90.12	86.98

4.1. Accuracy

Accuracy in table tennis is essential and is attained by using exact technical motions, such as the right stance, grip, and shot implementation. For optimum positioning, a player has to be proficient in both front and backhand strokes in addition to footwork. To place the personality in the greatest probable position, a performer has to be proficient with both the forehand and backhand shots as well as footwork. Technical ability such as correct spin and control of velocity, strategic position, and enhanced accuracy are essential for competitive play. LSTM scored 81.30%, and RBF-SVM scored 76.96%, the suggested RGA algorithm has the maximum accuracy of 92.82%. These percentages show the effectiveness and performance of each method, with the proposed RGA algorithm showing tremendous potential in its categorization tasks. Figure 4 shows the outcome of accuracy.

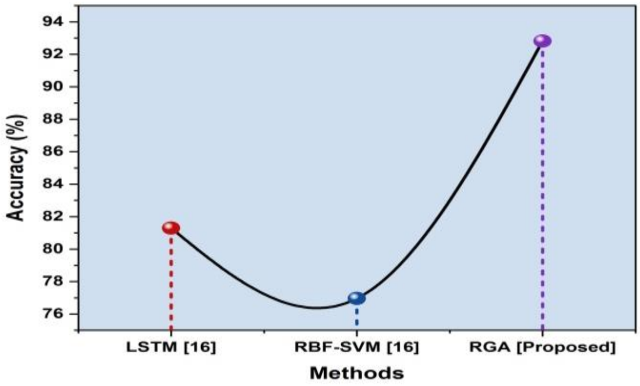

Figure 4: Outcome of accuracy

4.2. Precision

The ability to execute technical activities using manage and accurateness is necessary for table tennis precision. This entail maintenance a steady grip, using precise footwork for perfect assignment, and using exact wrists and arm activities to implement stroke like topspin, backspin, and sidespin. To out-maneuver opponent and succeed points, one have to be capable in these approach since this guarantee precise placement and spin control. LSTM scored 83.37%, and RBF-SVM scored 84.37%, respectively, the proposed algorithm has the greatest precision of 90.63%. The proposed RGB algorithm shows a lot of potential in its classification tasks, as seen by these percentages that show how well each approach performs. Figure 5 shows the outcome of precision.

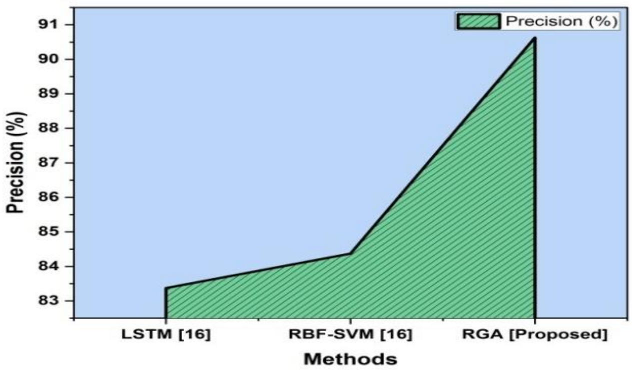

Figure 5: Outcome of precision

4.3. Recall

Recognizing the opponent's upcoming move by analysing their past tendencies is known as recall in table tennis. Footwork spins like backspin and topspin, and forehand and backhand strokes are illustrations of technical motions. Accuracy and precision are needed to master these moves, which allow players to dictate the pace of competition and successfully out-maneuver other players. LSTM scored 81.91%, and RBF-SVM scored 76.96%, the proposed approach RGA has the greatest recall level of 90.12%. These percentages show the way that each method performed and how successful the recommended RGA algorithm was in its classification tasks. Figure 6 shows the outcome of the recall.

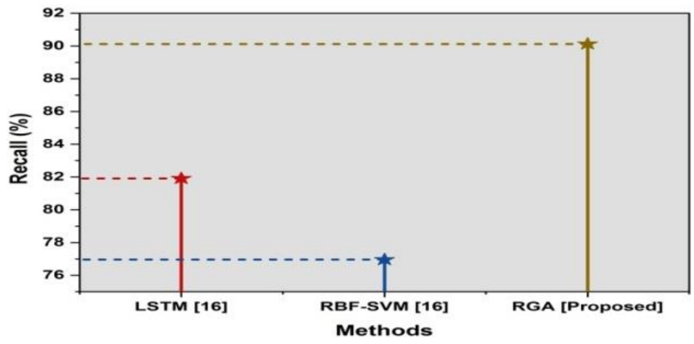

Figure 6: Outcome of recall

4.4. F1-score

Precision and recall are balanced in the F1-score, a statistic used in classification tasks. Table tennis players use precise tactical maneuvers for prevailing games, such as backhand flicks and forehand looping. LSTM scored 80.82%, and RBF-SVM scored 74.88%, respectively. With an outstanding accuracy of 86.98%, the proposed algorithm, RGA greatly surpassed the others. The effectiveness of each technique and the suggested RGA algorithm in identifying the tasks are demonstrated by these percentages. Figure 7 shows the outcome of the F1-score.

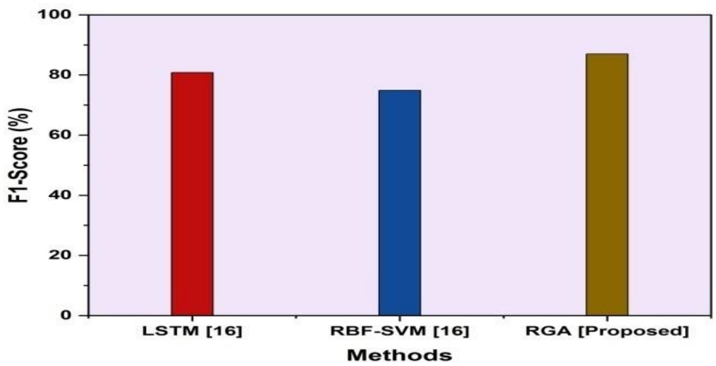

Figure 7: Outcome of F1-score

4.5. Discussion

Identifying long-term dependencies in consecutive data is strength of LSTM networks **[16]**. Their shortcomings include lengthy training durations, gradients that disappear, which makes it impossible to handle very long sequences, and high determining complexity. Additionally, it is difficult to tune efficiently and demands a lot of memory. The scaling inputs to higher parameters, RBF-SVM is useful for non-linear classification. The principle drawback of this methodology is its elevated processing expenses, especially when handling large datasets, which can result in extended training and prediction times. The suggested technique RGA maximizes the effectiveness of training and memory use to overcome the limitations of LSTM and RBF-SVM. To effectively modify LSTM parameters, RGA uses GA, which shortens training periods and helps to mitigate gradient vanishing problems. Furthermore, to reduce the computational intensity and speed up the processing of huge datasets, RGA optimizes the RBF-SVM hyperparameters. This strategy overcomes the drawbacks of conventional techniques while improving performance.

5. CONCLUSION

Technical movements in table tennis refer to the precise motions and methods used during play, such as forehand and backhand strokes, footwork for positioning, spin manipulation, and offensive or defensive tactics, all of which are essential for efficient play and success in competition. A dataset containing game-play videos, trajectory data, and performance measurements of table tennis players was acquired. To pre-process the collected raw image data, image processing has occurred. It improves the resilience and accuracy of finding important locations and descriptors by employing SIFT for effective feature extraction. When the RGA model was compared to other conventional techniques, the study found that there were significant improvements in performance metrics for our suggested method such as accuracy (92.82%), precision (90.63%), recall (90.12%), and F1-Score (86.98%). This study emphasizes table tennis player's technical movements, with a focus on RGA models. The physical limits include speed and agility; table tennis players have trouble making precise shots because of their limitations in technical moves. The trajectory of the ball is influenced by environmental variables, including surface conditions and illumination. Further difficulties arise from the psychological components of focus and decision-making, which affect shot accuracy and consistency. Future developments in table tennis professionals' technical moves focus on enhanced biomechanical assessment that combines camera footage and AI for accurate movement evaluation. It improves performance optimization, avoiding injuries, and training methods. VR simulators can also provide intense practice settings that allow players to develop their talents to levels that were previously unattainable.

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