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Molecular & Cellular Biomechanics 2024, 21(4), 458.
https://doi.org/10.62617/mcb458

Article

Biomechanical analysis and tactical awareness cultivation of badminton players' variable speed running training

Weiguo Li

School of Physical Education and Health, Zhaoqing University, Zhaoqing 526061, China; 18316200129@163.com

CITATION

Li W. Biomechanical analysis and tactical awareness cultivation of badminton players' variable speed running training. Molecular & Cellular Biomechanics. 2024; 21(4): 458. https://doi.org/10.62617/mcb458

ARTICLE INFO

Received: 3 October 2024
Accepted: 17 October 2024
Available online: 24 December 2024

Abstract: In recent years, the combination of machine learning (ML) and computer vision has influenced sports training approaches, notably for monitoring player performance. This research gives a detailed biomechanical analysis of badminton players during speed-running training, using insights from ML techniques. Key biomechanical metrics such as gait, speed, and acceleration are assessed by tracking players' motions and the dynamics of their running patterns using computer vision techniques. The badminton stroke video dataset was collected from the Kaggle source. To ensure high-quality input for analysis, the data preprocessing stages include video stabilization with the Kalman filter, noise reduction with Gaussian smoothing, and frame extraction using temporal sampling. Feature extraction approaches like the histogram of oriented gradients (HOG) are used for shape recognition and optical flow for motion tracking. The study provides the use of a simulation environment built on a Modified Ant Lion Optimized Decision Trees (MALO+DT) model trained on historical training data, which allows for the prediction of player movement and biomechanical adjustments based on contextual features such as environment variations and player fatigue. The findings demonstrate that speed running training improves tactical awareness and decision-making in dynamic environments. The performance of the suggested approach was evaluated on the Python platform. The model achieves good prediction accuracy (98.3%), recall (97.4%), F1-score (98%), and precision (97.5%), demonstrating a model's abilities for analysis the effect of training on player biomechanics. Furthermore, the significance of this study is assessed for tactical awareness development, providing coaches and analysts with actionable insights to enhance practices and increase player performance. The findings show that combining biomechanical analysis with speed running training significantly improves players' adaptability and responsiveness during matches, resulting in a more strategic approach to badminton teaching.

Keywords: speed running training; tactical awareness; Modified Ant Lion Optimized Decision Trees (MALO+DT); biomechanical analysis; badminton players; and player performance

1. Introduction

One of the fastest racquet sports is badminton that demand a set of technical, mental, and physical skills on the court. Some of these qualities are speed and tactical awareness [1]. Badminton is a dynamic game requiring rapid movement by effectively changing places with actions to the opponent. It becomes a valuable resource in terms of improving the biomechanical performance and strategic decision-making skills of better players when training in VSR [2]. Biomechanics, which is the training of motion and forces, plays a huge role in the enhancement of sports performance. Understanding the biomechanical knowledge base for movement enables players to increase their sprinting efficiency, decrease their possibility of injury, and enhance their performance [3]. Rapid pace changes, sudden start and stop motions, and turning are seen in badminton movements and this contributed to the analysis of running strategy. Biomechanical parameters such as joint angles, impact forces loading rates, and step length measures may be used by the coaches and the athletes to find areas where adjustments in training are necessary [4]. The variation of pace at which a player has to play in a badminton match is well complemented by VSR training. A player often requires changing running styles from rapid bursts and sudden acceleration to rapid deceleration and side-to-side movements. Such player conditioning for the unpredictability of the game may be insufficient with traditional exercises of steady-state running. However, to assimilate the variation in the length of a badminton rally, VSR training employs intervals of varied speeds. This training method makes players more ready to face some situations that occur in the games while improving anaerobic and aerobic fitness, muscular coordination, and movement patterns [5].

Another crucial aspect of playing badminton is tactical awareness or the capability of analyzing the match and making wise decisions based on changing dynamics of play. Such players can always anticipate the moves of their opponents, modify game plans according to such moves, and exploit the lack of defense in the opponent's game. Preparation in intellectual, although very helpful in the way it makes players recognize patterns and make rapid choices during pressure, is as important as physical preparation for this kind of skill. The integration of strategic awareness into VSR training, therefore allows players to hone their agility and speed and make situational decision-making perfect [6].

This is especially possible when training the VSR because it is even easier to increase the extent of enhanced strategic awareness through the incorporation of game-like situations into training sessions. For instance, coaches can arrange several workouts that will help the athletes train at the same time at different speeds as they demand quick decisions [7]. It also enhances their analytical skills in emergency circumstances as well as their physical ability. By combining biomechanical evaluation with strategic training, the coaches may be able to establish a training program that addresses the physical and mental load in badminton [8]. The manner, in which the players move about on the court, again supports the integration between biomechanics and strategic awareness [9]. Maintaining stability, balance, and accuracy appears to be less difficult as the rates of direction change and speed change with higher mechanical compliance by the player with the moves. A player may exploit the weakness of an opponent by targeting his biomechanical strengths [10]. To list out the used acronym in this study in Appendix.

This research presents an innovative MALO + DT model for anticipating player actions and biomechanical changes.

Contributions

- The badminton stroke video data was obtained from the Kaggle source.
- Employing the Kalman filter for video stabilization, Gaussian smoothing for noise reduction, and temporal sampling for frame extraction, the data preprocessing procedures ensure excellent input for analysis.

- The feature extraction method includes motion tracking by optical flow and identifying the shapes through the HOG. It enhances understanding of the player's movements during training activities.
- The paper introduces a new MALO + DT model for training the previous training data. This model simulates player action and biomechanically adapts it based on certain contextual features such as player fatigue levels and additional changes in the playing field.

The remaining portion of this research is as follows: Section 2: Related works; Section 3: Methodology; Section 4: Result; Section 5: Discussion; and Section 6: Conclusion.

2. Related works

To obtain information about the footwork response of individual badminton players, the research by Luo et al. [11] proposed novel methods. For instance, binocular positioning was used to physically position the shoes to their respective 3D positions whilst DL was used to get the image positions (2D) of the respective shoes. The findings showed that the suggested approach achieved a target placement accuracy of 74.7%. For the biomechanical investigation, the research by Peng and Tang [12] connected the DL approach with the batting position preferred by tennis players. The findings demonstrated that the novel proposed DL-based-GAN technique outperformed the conventional approaches in PSNR and SSIM direction by about 4.5db and 0.143. Coaches and players may want to use adaptive learning and information analysis to customise physical games and help athletes attain their most ability via incorporating the ANN technique into essential fitness programs, inside the research by Ma et al. [13]. The consequences demonstrated that records-pushed strengthening exercises specifically designed for badminton can be incorporated into huge programs to maximise physical capabilities and lift overall performance standards.

A sensor-based technique to acquire participant movement information for specific shots, examine it, and broaden an LSTM-based framework to categorize exceptional shots changed into offered in the research by Malik and Jain [14]. The outcomes tested that there has been a 98.6% correlation among the teach's rankings and the LSTM-based totally ML version. Through the proposed sensor-based totally way of obtaining players' movement facts for the numerous shots, the evaluation of the shot and the system of the LSTM framework to categorize the diverse photographs have been highlighted within the research. The effects validated that a 98.6% similarity become attained between the very last ratings of the teach and the LSTM-based totally ML version. Utilizing AI and NN technology, the research by Yu [15] investigated the identity of badminton moves. Utilizing NN technology to analyze the statistics, AI became used to accumulate statistics on numerous badminton racket motions, inclusive of swings. The TA had greater than 95% accuracy; while the swing movement becomes examined simultaneously, it became observed that the TA's accuracy handed 96%. By the usage of movement records from wearable sensors, research by Mekruksavanich et al. [16] centered at the identification of badminton movement and participant assessment. A participant assessment model that used a DRN was trained the use of the movement information. The consequences established that the cautioned DRN done well and had the best accuracy while it got here to figuring out badminton hobby and assessing badminton players.

A DL-based totally badminton training aid system was designed and evolved with the aid of Jian et al. [17] to allow customers to practice independently without having to meet with coaches in man or woman. The method advanced the usage of deep mastering and the ensuing gadget identified specific training poses with an accuracy of more than 80%. A modern nearby feature extractor using the CNN method became proposed by Rahmad and As'ari [18] employing a pre-trained DL-based CNN method. SVM became then used to classify the functions that have been set up. According to the results, the best performance accuracy of 82.0% was achieved by a single local characteristic extractor that used AlexNet-based CNN algorithms.

A DL-based totally motion identification gadget for badminton gamers became proposed in the studiesby Liu and Liang [19]. It trained through decoupling using an LSTM community and re-encodes human hitting event collection records with multi-relational houses into relational triples. The findings confirmed that the cautioned method improved the accuracy of recognizing human hitting actions via attaining 63%, 84%, and 92% recognition accuracy on numerous benchmark datasets. SA DeepConv-LSTM hybrid DL method was developed through the investigationby Deng et al. [20] for identifying badminton activities. The results confirmed that the cautioned framework handed traditional tactics with a badminton activity identity accuracy of 97. 83%. It moreover furnished the blessings of fast convergence and less schooling time. A good-sized exam of the Multi-Modal AGNES method and its use in numerous fields, consisting of movement pattern calculation, modal feature calculation, coordinate calculation, and badminton feature calculation, become supplied within the article by Wang and Wu [21]. The effectiveness of the technique turned into mounted by means of significant checking out and evaluation. It may want to reliably hit upon movement trends, efficaciously extract functions from lots of datasets, locate objects particularly in 3 dimensions, and estimate badminton-particular signs.

A new technique for reliably recognizing badminton starting, based on enhanced DL, was presented in the research by Lianju and Haiying [22]. The results demonstrated that the human skeleton structure could precisely replicate human motion and help extract action elements. The enhanced CNN's ability to accurately identify starting actions had significantly increased. An ML-based approach for automating the evaluation of badminton players' strikes and techniques during a match was presented in the researchby Van Herbruggen et al. [23]. The suggested 2D-CNN had a shot categorization accuracy of 90.9% and an LSTM approach detection accuracy of 80%. An innovative technique of reporting the actual assessment of the fitness of college badminton players was described in the research by Xu and Zhu [24]. It examined present methods used in assessment, then proposed a new method that incorporated PSO-BPNN and data mining. The model introduced a new idea and approach to evaluating the movements of the athletes because the investigation showed that the fit was perfect, and the accuracy of the assessment was also perfect.

3. Methodology

The data is preprocessed using various strategies, such as the Kalman filter for video stabilizing, Gaussian smoothing for noise reduction, and temporal sampling for frame extraction. Then, feature extraction approaches, such as HOG for shape recognition and optical flow for motion recognition are employed, and a novel model is introduced for biomechanical changes and player movement prediction called the MALO + DT. **Figure 1** displays the overall flow of MALO + DT.

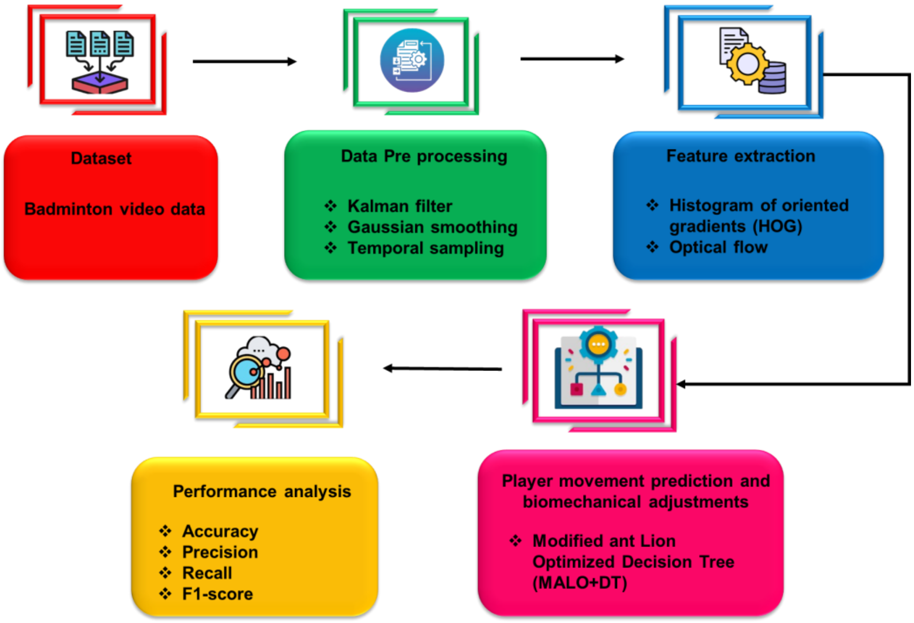


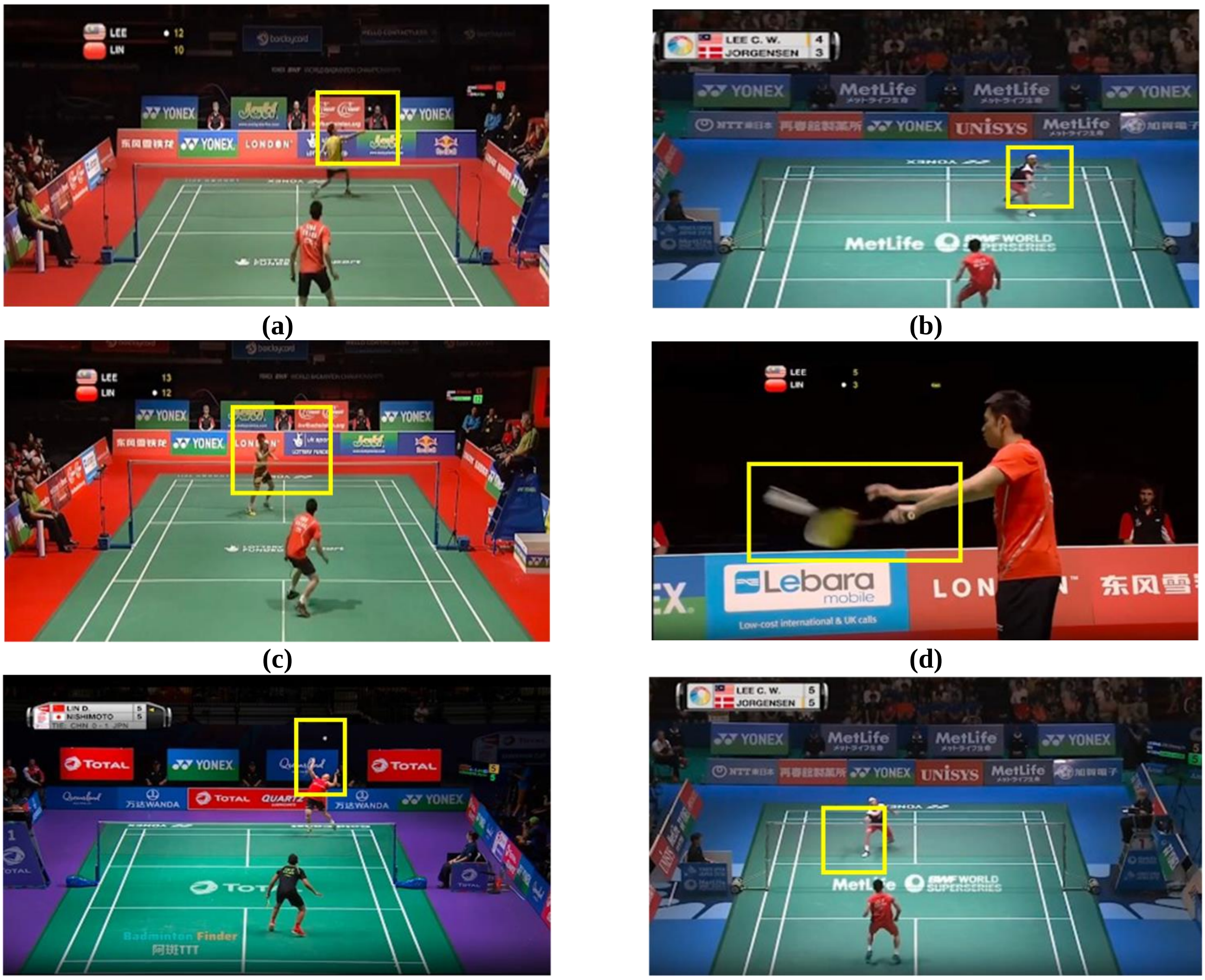
Figure 1. Overall flow of MALO + DT.

3.1. Data collection

The badminton stroke video dataset was gathered from the Kaggle source [25] which contains a collection of videos that capture six key movements performed by badminton players. Each video shows a specific stroke performed multiple times, providing a comprehensive view of the biomechanics involved in each motion (**Figure 2**).

1) Forehand net shot: A quick, controlled stroke aimed at keeping the shuttle close to the net.
2) Forehand lifts: Shot aimed at lifting the shuttle high into the opponent's court, typically from a lower position.
3) Forehand drive: A powerful, flat stroke sent across the court in a fast, straight line.
4) Backhand net shot: Similar to the forehand net shot but performed on the backhand side.
5) Backhand drive: A flat, fast shot performed with the backhand.
6) Forehand clear: A high and deep shot meant to push the opponent to the back of the court.

Each stroke represents different technical skills and physical demands, making this dataset ideal for assessing variations in biomechanics, such as posture, acceleration, and muscle engagement. The total number of videos and sample distribution among the different strokes provide sufficient training data for the ML model. The movement recognition of six types of strokes is shown in **Figure 2**.



(a) **(b)** **(c)** **(d)** **(e)** **(f)**

Figure 2. Movement recognition of the dataset **(a)** Backhand-drive; **(b)** Backhand-net shot; **(c)** Forehand-lift; **(d)** Forehand-net shot; **(e)** Forehand-clear; **(f)** Forehand-drive.

3.2. Data pre-processing

In the data preprocessing process known as the steps that provide high-quality input for analysis, video stabilization uses the Kalman filter, noise reduction with Gaussian smoothing, and frame extraction using temporal sampling.

3.2.1. Kalman filter

The Kalman filter is employed in video stabilization to calculate the camera's intended global movements based on predicted absolute frame placements. To acquire a jitter on a video, reduce the Kalman filter's output from the predicted relative frame locations because Kalman filters create intentional movements.

Consequently, stabilization is carried out with these acquired jitter estimates. The state transition and observation calculations of the Kalman filter for the constant speed model are represented by Equations (1)–(3).

$$\begin{bmatrix} w_s \\ n_s \end{bmatrix} = \begin{bmatrix} 1 & S \\ 0 & 1 \end{bmatrix} \begin{bmatrix} w_{s-1} \\ n_{s-1} \end{bmatrix} + [x] \tag{1}$$

$$[y_s] = [1 \quad 0] \begin{bmatrix} w_s \\ n_s \end{bmatrix} + [u] \tag{2}$$

where

y_s—Measured absolute frame location of the frame,

n_s—Velocity of the frame, and

w_s—Predicted absolute frame location of the frame,

$$B = \begin{bmatrix} 1 & S \\ 0 & 1 \end{bmatrix}, G = [1 \quad 0] \tag{3}$$

With a specified time interval S serving as a break in the video between subsequent frames, the previously mentioned equations are applied to each of the measured relative frame locations in the w and z directions separately, because the goal of video stabilization is to reduce jitter in both directions. L and K values can be changed to modify the Kalman filter's properties. Measurement noise correlation is denoted by an L value, whereas process noise correlation is represented by a K value. As an outcome, estimates with higher L values appear to be smoother, while those with higher K values appear to be closer to the noisy observations. Kalman filter is used to monitor the player's limb movement and racket motion, eliminate noise, and ensure that all the considered movements are noise-free and consistent.

3.2.2. Gaussian smoothing

Using function assessments to create a direction, Gaussian smoothing (GS) calculates the directional derivative across the direction, multiplies the directional derivative by the direction, and finally calculates the gradient of a function. Gaussian smoothing is a broadly used zero-order strategy since the calculation may be applied to any gradient-based optimization technique.

In particular, the gradient estimator of Gaussian smoothing is Equation (4),

$$\nabla_\theta E^{HT}(\theta) = \frac{1}{d} E(\theta + d\epsilon)\epsilon, \;\; \epsilon \sim \mathcal{N}(0, J) \tag{4}$$

The following improved objective's gradient can be estimated using Monte Carlo methods and smoothed using a conventional normal random variable in Equation (5).

$$E_d(\theta) \triangleq \mathbb{E}_{\epsilon\sim\mathcal{N}(0,J)}[E(\theta) + d\epsilon], \;\; d > 0 \tag{5}$$

The improved objective's gradient is provided by Equation (6),

$$\nabla_\theta E_d(\theta) = E_{\epsilon\sim N(0,J)} \left[\frac{1}{d} E(\theta + d\epsilon)\epsilon\right] \tag{6}$$

The antithetic (AT) estimator and the forward-difference (FD) estimator, which include control variates, are popular alternatives for $\nabla_\theta E_d(\theta)$ since they frequently exhibit significant variance in practice: for$\epsilon \sim N(0, J)$.

$$\nabla_\theta E^{EC}(\theta) = E_{\epsilon \sim N(0,J)}\left[\frac{1}{d}E(\theta + d\epsilon)\epsilon\right] \tag{7}$$

$$\nabla_\theta E^{BS}(\theta) = \frac{1}{2d}[E(\theta + d\epsilon) - E(\theta - d\epsilon)]\epsilon \tag{8}$$

Each estimator's variability can be minimized by averaging over numerous directions. It concentrates on the FD estimator due to its simplicity and minimal computing overhead.

Employing gradients determined by Equations (7) and (8), iterative optimization leads to a fixed location for non-convex objectives and an ideal location for convex ones when $E(\theta)$ meets some moderate regularity constraints. Some of the characteristics of a video frame are random noise and variations that can be minimized through GS. It is most important when observing players' motion that the number of clear boundaries and shapes from the edges of limbs should be precisely defined for feature extraction. Feature extraction is particularly crucial when monitoring player movements. Smoother video does not cause video interference; it is easier to identify other biomechanical parameters, such as acceleration and speed.

3.2.3. Temporal sampling

Temporal sampling is a video feature extraction technique that takes out frames from the video at set amounts of time. This method helps preserve such important visual information for analysis purposes while at the same time offering a way of minimizing the amount of data needed. It can be applied in a fully consistent way or can be applied unpredictably depending on the situation in the working process. The calculations of temporal sampling are described below in Equation (9),

$$f_k = I(t_0 + k.\Delta t), \quad k = 0, 1, 2, 3, \ldots, N-1 \tag{9}$$

where

$I(t)$—Video frame at time$t$,

f_k—k^{th}Extracted frame,

Δt—Temporal sampling interval,

t_0—Initial timestamp, and

N—Total number of frames to be extracted.

The video is split into equal segments, and a frame is taken after each segment to guarantee that the data is sampled consistently throughout the video. Temporal samplings are a process of locating key frames of each stroke and are dependent on time intervals based on motion activity.

3.3. Feature extraction

Feature extraction methods such as histogram of oriented gradients (HOG) are employed for shape recognition, while for motion data, we utilize optical flow.

3.3.1. Histogram of oriented gradients (HOG)

The purpose of HOG is to familiarize the program with the target object. Based on vector theory, HOG can be separated down into three required phases. First, the image of interest is evaluated by identifying the object from the background. This method searches the image for differences in magnitude. As a result, simply take the vector's magnitude into account for the time being and disregard its direction. Equation (10) could be used to determine the image's size.

$$n(v,u) = \sqrt{e_v(v,u)^2 + e_u(v,u)^2} \tag{10}$$

Equation (10) provides the size n of a feature vector at location $(v,u).n(v,u)$ comprises of $e_v(v,u)$ and $e_{u(v,u)}.e_v(v,u).\ e_u(v,u)$ is components in the $v\ and\ u$ directions, respectively. Once the program has assessed the object's location within the image, then train it to identify the object with greater accuracy. Considering the vector's direction into consideration is the second stage. This can be compared to the minor modification.

$$\Theta(v,u) = \tan^{-1}\frac{e_u(v,u)}{e_v(v,u)} \tag{11}$$

Equation (11) demonstrates how it may utilize arctangent to calculate an angle based on $e_u(v,u)$, and $e_v(v,u)$. Equation (11) offers a detailed description of vector direction, which allows the object to be presented as a constant gradient that varies based on the vector direction. It separated the image into a large number of pixels since the outcome, which is displayed as a gradient, is hard to understand. A histogram displays the overall outcome following pixel definition. It shows how pixels from the object have a substantially higher cumulative result than pixels from the background. This program accurately and precisely distinguishes between an object and its background by analyzing the data from the histogram. HOG is extremely helpful for identifying shapes and player postures during various strokes.

3.3.2. Optical flow

Optical flow estimation's main goals are to produce an optical flow field vector for the moving object and to distinguish moving foreground objects from their surroundings. Optical flow computes the movement of each pixel in a frame between two frames that were captured at distinct times. It is a discriminative approach that considers the object to be monitored as a local image area binary categorization problem. One of the most widely used methods for monitoring moving objects is optical flow, often known as optic flow. This one can detect the moving object from the backdrop with more accuracy and can provide comprehensive movement data. When the collected frames are filtered by the noise filter, this approach becomes helpful for tracking objects.

Let's assume an object that moves in time δs by a distance δw in the w-direction and a distance δz in the z-direction. The background's brightness is taken to be constant. An equation connecting the brightness pattern's movement to the variation in image brightness at a given position will be derived.

Let (w,z) be the brightness of the image at time q at the position in the image plane. Now analyze the instance where the pattern shifts. A certain location in the pattern has a constant brightness, indicating that $\frac{dj}{ds} = 0$.

The 2D static brightness functions of $J(w,z,)$ and s can be represented by the Taylor series equation below. With further simplification of Equation (12) and the use of Taylor series expansion on the right side of the formula, which can be written.

$$J_w . u_w + J_z . U_z = -J_s \tag{12}$$

Here $\vec{u}$is the optical flow field vector in this instance, and ∇J is the spatial gradient of intensity.

$$\nabla J . \vec{u} = -J_s \tag{13}$$

The local flow estimating method is a different term for the Lucas and Kanade approach. The global error propagation issue can be avoided with this technique. The same smoothness and brightness parameters form the basis of the local flow estimate. These assumptions can be used for the small areas that constitute each video frame. Less computing time is needed and greater accuracy is achieved with the approach. For biomechanical analysis of the running or stroke movements, it is necessary to measure the movement speed and acceleration, and dynamic changes of form between frames, which depend on the optical flow.

3.4. Modified Ant Lion Optimized Decision Trees (MALO + DT)

A unique prediction tool known as the MALO-DT technique is used in predicting and profiling players' movements and biomechanical adjustments in sports. DTs, which are easy to understand and interpret, are integrated with the MALO algorithm, an adaptive computing approach based on the hunting technique of the ant lion.

DTs are also very useful in presenting complex relationships that are not simple when it comes to biomechanical information, for instance, the position, walking, and strength applied during sports events when previewing player movement. The MALO also enhances the DT by offering better handling for the selection of features and criteria for splitting, using the most relevant biomechanical features results in better and more accurate forecasts.

The MALO-DT algorithm improves the DT's branch generation strategy by using an optimization technique to reduce errors to avoid overfitting. The model is used to predict future movements and changes in performance by the model refining every estimation until it perceives small differences in players' movements and responds to each player's biomechanics. This makes it applicable in sports workouts, the recovery from, and the improvement of performance outcomes. Algorithm 1 shows the pseudocode for MALO + DT.

Algorithm 1 Pseudocode for MALO + DT

```
import numpy as np
from sklearn.tree import DecisionTreeClassifier
def modified_ant_lion_optimization(data, labels, iterations, num_ants):
ant_positions = initialize_ants(num_ants, data)
best_solution = None
best_score = infinity_value()
for iteration in range(iterations):
for ant in ant_positions:
fitness = evaluate_fitness(ant, data, labels)
if fitness < best_score:
```

Algorithm 1 (*Continued*)

```
best_score = fitness
best_solution = ant
ant_positions = update_ant_positions(ant_positions, best_solution)
return best_solution
def build_decision_tree(data, labels, features):
tree = DecisionTreeClassifier()
tree.fit(data[features], labels)
return tree
def malo_dt(data, labels, iterations, num_ants):
optimized_features = modified_ant_lion_optimization(data, labels, iterations, num_ants)
decision_tree = build_decision_tree(data, labels, optimized_features)
return decision_tree
if __name__ == "__main__":
data, labels = load_data()
iterations = parameter_value()
num_ants = parameter_value()
model = malo_dt(data, labels, iterations, num_ants)
predictions = model.predict(new_data)
```

3.4.1. Decision tree

The DT is a sequential hierarchical framework made up of the following: nodes, which are arbitrary vertices where potential events can develop; branches with characteristics that establish the OF; and leaf nodes, which have OF values that indicate the results of merging several objects and choosing a certain attribute value. Classification trees and regression trees are the two categories of DTs based on the type of anticipated indicator. Classification trees are useful for investigating specific characteristics, such as assigning objects to a previously identified class; hence, using them is recommended when creating a prediction-establishing system. DTs group data and produce an if-then hierarchy of operators that classify the information.

To split the nodes into useful functions, let’s establish an OF. The partitions where the increment is maximized are Equation (14),

$$IG(C_l, e) = T(C_l) - \sum_{i=1}^{n} \frac{M_i}{M_l} T(C_i) \tag{14}$$

where

e—Characteristic that splits the data

T—Measure of heterogeneity,

C_i and C_l—Parent node,

M_i—Number of samples in the $i-th$ child node,

$i-th$ Child nodes,

M_l—Total number of samples in the parent node.

Binary DTs are implemented for simplicity and to minimize the overall search space. $C_{left}$and C_{right} child nodes in Equation (15):

$$IG(C_l, e) = T(C_l) - \frac{M_{left}}{M_l} T\left(C_{left}\right) - \frac{M_{right}}{M_l} T(C_{right}) \tag{15}$$

C_l—Dataset of the parent node,

C_i—Dataset of $i-th$ child nodes,

M_{left}—Numbers of patterns in left child nodes,

C_{left} and C_{right}—Child nodes,

M_{right}—Numbers of patterns in right child nodes.

Entropy calculation for all non-empty classes $\{o(t/p)\} \neq 0$ 2

$$T(s) = 1 - \max\{l\left(\frac{t}{p}\right)\} \tag{16}$$

where $l\left(\frac{t}{p}\right)$ represents the percentage of samples that are class and p is the single node.

As a result, the entropy is highest when there is a uniform distribution of classes and zero when all samples in a node fall under an identical class in Equation (17).

$$T_G(p) = -\sum_{j=1}^{d} l(t|p)log_2 l(t|p) \tag{17}$$

The parameter that reduces the probability of incorrect classification can be understood as the Gini measure of heterogeneity in Equation (18).

$$T_H(p) = \sum_{j=1}^{d} l\left(\frac{j}{p}\right)\left(1 - l\left(\frac{j}{p}\right)\right) = 1 - \sum_{t=1}^{d} l\left(\frac{t}{p}\right)^2 \tag{18}$$

where

$l(t/p)$is the percentage of samples that belong to a class and a single node p,and

$J_\varepsilon(p)$is the Gini measure of heterogeneity.

Classification error is an additional metric for heterogeneity,

$$t_\varepsilon(p) = 1 - \max\{l(t/p)\} \tag{19}$$

where

$l(t/p)$—Classification error and

$t_\varepsilon(p)$—Percentage of samples that belong to a class and a single node$y$.

This criterion is appropriate for pruning trees, but it is not suggested for tree growth because it is less responsive to variations in the nodes' classes' capacities.

3.4.2. Ant lion optimization

An innovative swarm intelligent optimization technique is called Ant Lion Optimizer. The actual optimization issue is addressed by modeling the natural process of antlions preying on ants. The antlion digs a pit in the sand that resembles a cone using its jaw. The antlion hides itself beneath the cone's base after digging the trap. Ant walks might fall into it at random. The antlion throws sand to the edge of the hole and waits for the fallen ant to catch prey. For its subsequent hunt, the antlion restores its trap after consuming its prey. The following is an assessment of the specifics of the ALO method.

- Mathematical model

The following equation is created to imitate the random motion of ants because they travel randomly in nature in Equation (20).

$$W(s) = [0, cumsum(2q(s_1) - 1), \dots, cumsum(2q(s_m) - 1)] \tag{20}$$

The following is the definition of the $cumsum$ function, where the $q(s)$function assesses the array's accumulated value in Equation (21),

$$q(s) = \begin{cases} 1 & ifrand > 0.5 \\ 0 & ifrand < 0.5 \end{cases} \tag{21}$$

where

$rand$—Random number that falls between [0,1] and

s—Number of iterations.

To normalize Equation (22) and create random paths of ants in the search space, use the subsequent equation.

$$W_j^s = \frac{\left(W_j^s - b_j\right) \times \left(c_j^s - d_j^s\right)}{\left(a_j - b_j\right)} + d_j^s \tag{22}$$

where

d_j^s—Lower border of j^{th} space at s^{th} iteration,

b_j—Minimum of random walk array$w(s)$, and

c_j^s—The higher boundary of j^{th} space at s^{th} iteration.

The area's border is influenced by the antlion's location, which is moved randomly by the ants. The computation equations for c_j^s and $d_j^s$are the following, where

$$d_j^s = Antlion_i^s + d^s$$

$$c_j^s = Antlion_i^s + c^s$$

c_j^s—Upper boundary at s^{th} iteration, and

d_j^s—Lower boundary at s^{th} iteration.

The location of the i^{th} antlion by the roulette wheel choice at the s^{th} iteration is displayed by $Antlion_i^s$.

The antlion removes the sand from around the hole to force the ant to fall into the bottom of the hole as soon as it reaches the trap, preventing it from escaping. This mechanism can be considered as the ant random walk's reducing radius. Following are the Equations (23) and (24).

$$d^s = \frac{d^s}{J} \tag{23}$$

$$d^s = \frac{d^s}{J} \tag{24}$$

where j represents the border contraction ratio and its equation is expressed as follows in Equation (25),

$$J = \frac{10^{\circ}\, s}{S} \tag{25}$$

where S is the maximum number of iterations, and s is the current iteration. ω is a constant value that can be used to change how quickly an ant moves toward an ant lion.

$$Ant_j^s = \frac{Q_B^s + Q_F^s}{2} \tag{26}$$

The elite approach states that the ant with the greatest level of fitness is regarded as an elite and that the elite can influence all ants' random movements. Ant walking paths are impacted by elites and ant lions. The following is the equation for the ant's location change.

where Q_B^s represent an ant randomly walking around an antlion chosen by a roulette wheel, and Q_F^s represent this ant randomly walking around the elite.

The ant is captured and eaten by the antlion if the changed ant's fitness exceeds that of the specified antlion. The ant's location is then adjusted to match the antlion's location. The two equations are employed as follows in Equation (27).

$$Antlion_i^s = Ant_j^s if e\left(Ant_j^s\right) > e(Antlion_i^s) \tag{27}$$

where

e-Value of the fitness function, and

Ant_j^sAnt displays the j^{th} ant with the highest fitness value at the s^{th} iteration.

The ALO algorithm's shortcomings include decreased search accuracy and an easy fall into the local optimum. This section suggests a modified version of the ALO algorithm. To provide opposed solutions, MALO employs an opposition-based learning technique, which helps in the search for more productive areas. The ideal threshold is then found by MALO by maximizing Otsu and Kapur's entropy techniques.

➢ Opposition based learning

The creation of opposing solutions is the basic principle of the opposition-based learning (OBL) approach. Excellent individuals can make their way into the next generation by contrasting their solutions with the ones that are currently in place. The approach has the following mathematical definition:

In the D-dimensional search space, where $w = (w_1, w_2, \ldots, w_C)$is a point that may be considered as an acceptable solution, $w_i = [b_i,\ a_i],\ i = 1,2, \ldots, C$ and its opposite point, $\widetilde{w} = (\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_C)$, are described as Equation (28),

$$\widetilde{w} = b_i + a_i - w_i \tag{28}$$

The present solution's and the opposing solution's fitness values are evaluated. In contrast, the ideal fitness value solution remains unchanged.

➢ Modified Ant Lion Optimization

The benefits of the ALO algorithm include a simple concept, fewer parameter sets, and more. It also suffers from less search accuracy, a slower convergence speed, and an easy drop into the local optimum. The native ALO incorporates the OBL approach to enhance the ALO algorithm's exploration and exploitation.

There is a higher chance that the global optimum will be reached. The location of ant $Ant_j^s$is determined for every iteration using Equation (20). It is possible, that Ant_j^sant is located in opposition to or close to the optimal location within the search space. Consequently, OBL is employed to produce the opposite solution $\widetilde{Ant_k^s}$following Equation (29).

$$(\widetilde{Ant_k^s}) = ub + lb - Ant_j^s \tag{29}$$

The lower bound is indicated by the lb, and the upper bound is represented byub.

Fit values are compared between the updated and original positions. High fitness value positions are kept after assessment. Subsequently, each iteration of the modification algorithm includes more search attempts.

Four elements, including the number of search agents (M), the number of dimensions (C), the highest number of iterations (S), and the cost of function E, are used to calculate the time complexity (TC) of MALO. The TC of the initialization operation is $P(M)$. The sorting process has a TC of $P(M \times logM)$. Function evaluation has a TC$(S \times M \times E)$. To change the locations, the TC is indicated as $(S \times M \times C)$. The OBL's modifying stage has a $P(S \times M \times C)$TC. MALO has a $P(S \times (1 + logM + S \times (E + 2C)))$total TC.

4. Result

The suggested MALO + DT technique is run on a Windows 11 laptop with an Intel i5 core processor and 8GB RAM, and Python 3.10 is used. The effectiveness of the suggested MALO + DT approach is verified by the utilization of the traditional Bi-directional Long Short-Term Memory (BiLSTM), Space-Time Graph Neural Network fused Bi-directional Long Short-Term Memory (STGNN fused-BiLSTM), and Convolutional Neural Network (CNN) [26] techniques.

The detection accuracy of the six types of stroke data is displayed in **Figure 3**. The detection accuracies of the forehand net shot are 82%, forehand lift is 84%, forehand drive is 81%, backhand net shot is 86%, backhand drive is 90%, and the forehand clear stroke has a detection accuracy of 92%.

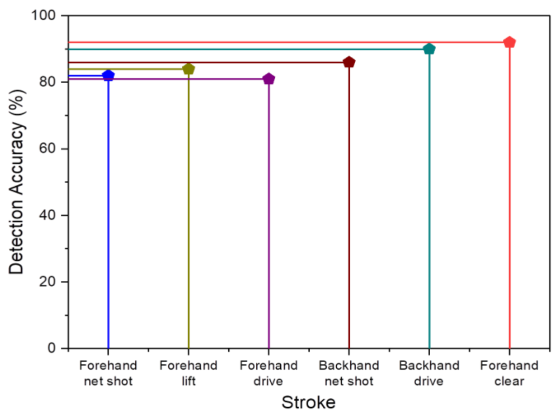


Figure 3. Result of detection accuracy.

4.1. Accuracy

The evaluates the true ability of the model to predict the actual movements by checking if the anticipated movements correspond with the real data as indicated and establishing how closely the predictions will line up with real-time performance to enhance training and prevent injuries. In comparison to the suggested MALO + DT approach, which has a high accuracy value of 98.3%, traditional methods yield accuracy values for BiLSTM (83%), CNN (77%), and STGNN fused-BiLSTM (94.34%), as shown in **Figure 4**.

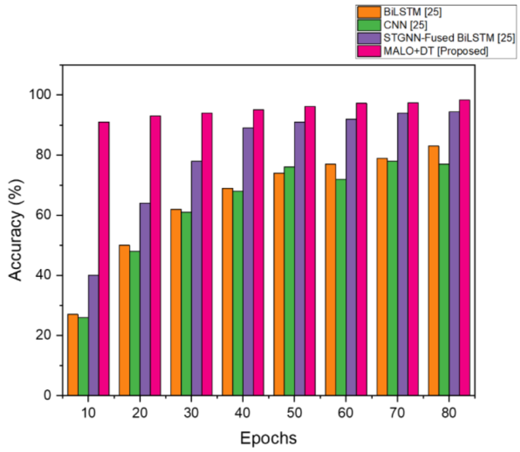


Figure 4. Result of accuracy.

4.2. Precision

It measures how good the model is at detecting and accurately predicting the actual occurrence of a particular action or change in stance during the game. It improves performance-based approaches; it computes the number of true positives divided by all expected positives. Compared to the proposed MALO + DT strategy, which has a high precision value of 97.5%, conventional procedures provide precision values for BiLSTM (76%), CNN (73%), and STGNN fused-BiLSTM (92.35%), as displayed in **Figure 5**.

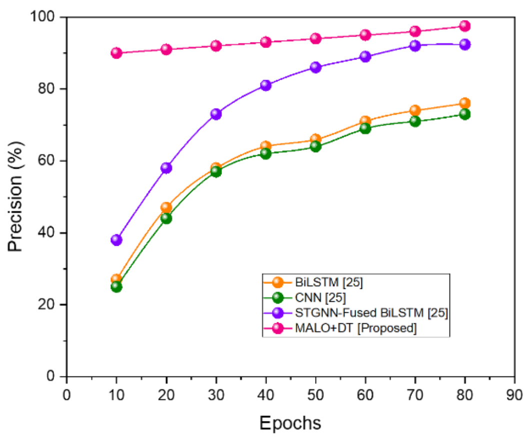


Figure 5. Output of precision.

4.3. Recall

The performance of the predictive algorithm when predicting motions by players and consequently biomechanical changes, it proves the predictive ability of the model in recording appropriate motions by computing the ratio of true positive forecasts to the total number of true positive cases. The conventional BiLSTM (75%), CNN (73%), and STGNN fused-BiLSTM (90.44%) techniques have recall rates respectively, whereas the recall rate of the suggested MALO + DT approach is 97.4%, which is displayed in **Figure 6**.

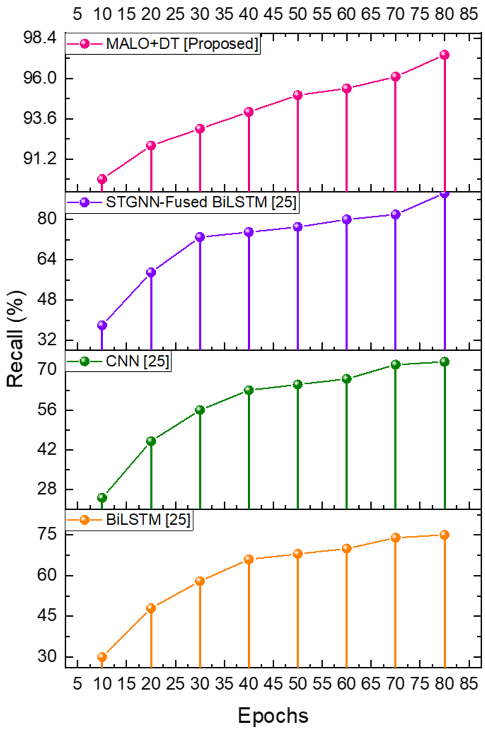


Figure 6. Output of recall.

4.4. F1-score

It measures the capacity of a model to predict player motion and biomechanical adaptations by balancing precision and recall. It reduces false positive and negative results, thereby enhancing performance evaluation accuracy in correctly identifying the relevant actions. Conventional approaches yield F1 scores for BiLSTM (71%), CNN (67%), and STGNN fused-BiLSTM (89.22%) compared to the suggested MALO + DT strategy, which has a high F1 score of 98% and is shown in **Figure 7**. **Table 1** shows the result of the proposed MALO + DT with traditional methods.

Table 1. Result of MALO +DT.

Methods	Precision (%)	F1-score (%)	Accuracy (%)	Recall (%)
BiLSTM [26]	76%	71%	83%	75%
CNN [26]	73%	67%	77%	73%
STGNN fused-BiLSTM [26]	92.35%	89.22%	94.34%	90.44%
MALO+DT [Proposed]	97.5%	98%	98.3%	97.4%

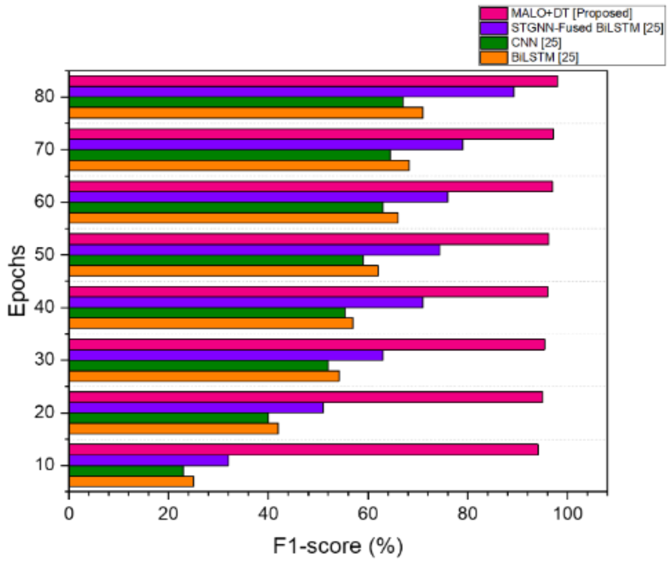


Figure 7. Result of F1-score.

5. Discussion

The STGNN fused-BiLSTM method is generally constrained by its dependency on the proper graph representations of spatial relations that might not accurately describe shifting relations involving player action. Besides, interpreting and training models can be complicated by multiple data modalities. Further, the computing stress may result in slower inference times, reducing its suitability to embedded applications such as real-time tracking and adaptation during gameplay [26]. High-dimensional data do not capture long-range dependencies well, making BiLSTM models inaccurate at predicting player movement over huge periods. Moreover, they are not fit for real-time usage since they require substantial computation resources [26]. CNNs have issues with capturing temporal dynamics because they primarily focus on spatial information and thus typically fail when trying to predict patterns of motion over time. It's often the instance that, to learn well, their architecture demands a substantial amount of labeled data, which is difficult to collect in this area of sports analytics [26]. To overcome these issues, a novel MALO + DT approach is introduced for player movement prediction and biomechanical adjustments. Compared to more conventional methods like STGNN fused BiLSTM and CNNs, the suggested MALO + DT approach has several benefits, especially when it comes to player movement prediction and biomechanical modifications. Its capacity to manage spatial-temporal relationships efficiently without the need for explicit graph representations-which may be constrained in constantly shifting sports environments is one significant gain. While MALO + DT is more computationally efficient and better suited for real-time applications like gameplay monitoring and adaptation, BiLSTM models frequently struggle with long-range dependencies and need significant processing resources. Furthermore, the MALO + DTs decision tree component is similar to understanding, which helps to overcome the complexity and training difficulties that come with a model that includes several data modalities. Even with little labeled data, the MALO + DT method is excellent at predicting motion patterns over time, which makes it perfect for sports analytics where data collection can be difficult. This is in contrast to CNNs, which mainly concentrate on spatial information and may overlook temporal dynamics. The model guarantees enhanced prediction accuracy while lowering computing load by utilizing the MALO algorithm's optimization capabilities, which makes it ideal for embedded and real-time applications.

6. Conclusion

This research underscores the transformative potential of integrating computer vision and machine learning in sports training methodologies, particularly for enhancing player performance tracking. By introducing the Modified Ant Lion Optimized Decision Trees (MALO + DT) model, we provide a robust framework for predicting player movements and biomechanical adjustments during badminton training. The impressive metrics achieved accuracy (98.3%), recall (97.4%), F1-score (98%), and precision (97.5%) demonstrate the model's effectiveness in a dynamic environment. The ability of MALO + DT to outperform traditional methods highlights its significance in advancing sports analytics, offering coaches and analysts actionable insights into player performance. However, challenges remain in adapting to the rapidly changing dynamics of player interactions and contextual factors, which can limit the model's applicability during live competitions. Nonetheless, the findings of this study lay the groundwork for future enhancements in real-time analytics and training methodologies. Ultimately, by continuing to refine and adapt our approaches, we can create more responsive systems that contribute to the strategic development of athletes, fostering improved decision-making and performance in the fast-paced world of competitive sports.

Limitation and future work

Despite its promising results, this study faces limitations, including the complexity of dynamic contexts, where changing player relationships and environmental factors may challenge the MALO + DT model's predictive capabilities. The computational demands may also impede real-time applications during sporting events. Future work should focus on enhancing the model's adaptability to varied environments, reducing computational complexity, and improving processing speed for near-real-time performance. Incorporating additional data sources, such as player physiological metrics and environmental conditions, could further refine the model's predictive accuracy and applicability in competitive settings.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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Appendix

VSR	Variable speed running	ANN	Artificial Neural Network
GAN	Generative adversarial network	DL	Deep Learning
AlexNet	Alex Krizhevsky Network	LSTM	Long short-term memory
PSO-BPNN	Particle Swarm Optimization with Backpropagation neural networks	SSIM	Structural Similarity Index Measure
2D	Two-dimensional	SADeepConvLSTM	Self-attention based-CNN-LSTM
CNN	Convolutional Neural Network	NN	Neural network
AGNES	Agglomerative Nesting	PSNR	Peak Signal-to-Noise Ratio
DRN	Deep residual network	SVM	Support vector machine
3D	Three dimensional	OF	Objective function
AI	Artificial intelligence		
DT	Decision tree	TA	Technical algorithm
ML	Machine learning		