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Article

Optimizing badminton training plan with artificial intelligence assisted system: A preliminary study

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Abstract: Sports today are heavily reliant on modern technology, making it significant to device efficient methods for receiving valuable information from data. Because machine learning (ML) procedures can handle large datasets, they have been shown to be useful in the treatment of biomechanical data. Sympathetically, these aspects are essential to exploiting training in badminton, where quick reflexes, agility, and accurate actions are significant for presentation. To recover training and assist coaches and athletes in receiving the best out of their training plans, this development aims to develop a system that employs artificial intelligence (AI) to classify among beginner and expert badminton players. Using wearable sensors in a cross-sectional study in a badminton training center, assembly anthropometric and biomechanical data are achieved from both skilled and beginner players. Movement data, such as shuttlecock speed, muscle activity, and footwork dynamics, were recorded by these sensors. Adaptive jelly fish searches Optimized extreme gradient boosting (AJFSO-XGB) method was trained on this data, with the most precise model being further refined through hyper parameter tuning. It is interesting to observe that the AJFSO-XGB technique showed a significantly higher capacity to categorize expert players, an ability that is essential for customizing practices and tactics to enhance performance. These results indicate that improving player growth and optimizing badminton practices can achieve accuracy of 97.05%, F1-scoreof 97.23%, precision of 97.52%, recall of 97.27% and training time of 350 (sec) with the help of an AI-assisted system.

Keywords: badminton training; machine learning (ML); adaptive jelly fish search optimized extreme gradient boosting techniques (AJFSO-XGB); biomechanical data; training strategies

1. Introduction

The sport of badminton is known for its quick tempo and requests for quick decisions. Players have to move quickly while possessing their equilibrium and replying almost promptly to the shuttlecock's path [1]. These supplies emphasize the implication of developing speed and finely adjusted motor abilities; they are important for a competitor to prosper [2]. Players must constantly hone their athletic abilities and tactical approach to the game because the sport also emphasizes emphasis on skill, endurance, and attention to detail [3]. In the modern sports world, technology has emerged as a vital tool for enhancing training regimens and performances by athletes [4]. As the need for accuracy, productivity, and improved outcomes grows, data-driven methods are being used more and more to provide insights into areas before unreachable [5]. Technology has immensely improved sports like badminton, where precision, agility, and fast reactions are essential for success [6]. Understanding and improving such crucial elements requires far more than simply cautious training techniques; additional creative explanations that are not amenable to independent investigation are also preferred [7]. The size to examine and recover various parts of a society gets more multifaceted as expertise develops extra [8]. Top businesses and coaches today have access to a collection of data that could enable them to make better decisions, enhance their training regimens, and ultimately improve their performance in difficult situations [9]. As a result, there is currently more stress on exploiting all features of sports planning, from injury evasion and suitability to polishing particular approaches provided to separate troupes [10]. The possibility for technological inventions in badminton is huge, since even little variations may have a noteworthy impact. This can provide players and coaches with strong tools to help them achieve at their uppermost levels. These growths additionally give players a detailed grasp of biological mechanics, allowing them to optimize their strengths and rectify their areas of susceptibility that recuperate the action as a whole [11].

The Aim of the study: An AI system that uses wearable device data to examine morphological and mechanical data to classify between beginner and professional badminton players. The study aims to improve training strategies and plans that are modified to each player's skill level by using the AJFSO-XGB technique. This is predictable to increase player attainment and growth in badminton via statistically knowledgeable choices and attentive performances.

Key contributions:

- The dataset contains detailed biomechanical and anthropometric data from badminton players, allowing exact skill-level categorization and performance improvement powered by AI training models.
- The Z-score normalization allows for the standardization of biomechanics data from badminton players and the creation of assessments among beginner and experienced athletes was more perceptive. The dependability of AI models in examining presentation is improved by this plan that improves data honesty by effectively addressing the influences of dissimilar balances.
- The LDA in this work allows for the unmistakable parting of novice and experienced badminton players by removing judicial features from presentation data. LDA improves correctness in organization by enhancing class departure, which helps to create more individualized and effective badminton training agendas.
- By professionally regulating hyperparameters, the AJFSO-XGB method greatly improves model accurateness in badminton player organization. This technique makes use of sophisticated search algorithms to enhance prediction competence, allowing customized training plans that more effectively address the particular requirements of beginner and professional athletes.

Organization of the study: Part 2 presents the related work, the methodology is established in Part 3, the result and discussion are displayed in Part 4 and the conclusion is illustrated in Part 5.

2. Related work

Zhang et al. [12] investigate a badminton training aid powered by AI that improves player efficacy and efficiency. The system architecture made use of a filter called Kalman for observation and prediction, virtual reality, along with 3D-capable MAX capabilities. To handle ambiguity and statistical reasoning, the posture estimation process employed the Bayesian method. The AI-based training system beats current techniques in a variety of actions, increases reliability of the system, and operates better during contests, according to testing. Wei et al. [13] stated that AI is changing many parts of life, including training for sports, very quickly. AI can help athletes by offering simulation and information analysis. This study examined three particular situations in athletic instruction and assessed the literature on AI applications. It emphasized the benefits of AI, with use, suitability, and innovation, and examined the close connection among sports instruction and these technologies. Wu and Chen [14] highlighted the difficulties in both hardware and software engineering while discussing the growing popularity of badminton as a form of exercise and health. It suggested convolutional computing network architecture called Region Proposal Network (RP-ResNet), which used a Squeeze-and-Excitation Network (SENet) and pyramid pool to gather feature images and increase accuracy. To enable real-time recognition of badminton dynamics, the research also presented a dynamic identification technique for badminton hitting using windows that slide. The enhanced Hidden Markov Model (HMM) reduced gratitude time by 0.07s and increased the accuracy of recognition by 1.25%. It would be beneficial to advertise this cognitive data analysis tool to coaches and professional athletes. Lin et al. [15] analyzed locations on the human skeleton were identified and badminton training postures were estimated using the Open Pose algorithm. The model was utilized for the extraction of features and was housed on a cloud calculation stage. The report made recommendations for optimizing training resources to increase the effectiveness of training strategies. Players' badminton skills significantly improved as a result of the tailored training regimens, especially in backhand high ball hits and smashes. Gao and Wang [16] suggested that Decision Support System (DSS) was transforming the sports business by using innovative technologies, like ML, AI, the network of everything, and augmented and virtual reality. By enabling coaches to make accurate decisions regarding players' abilities and performances, these technologies help to maintain a calm environment and reduce the risk of injuries. Sports staff can make educated decisions because DSS can also forecast weather patterns. Newcomers can enhance their skills and fitness by using actual time evaluations of game films. ACO is a technique that was used to determine the best characteristics for both individual and team sports competition performance. He et al. [17] investigated the use of AI in badminton audio visual examination to improve education then play. For applications like real-time object detection, it made use of lightweight algorithms like YoloV5. When it comes to player placements and court borders, the YoloV5 engine does better than other models. This kind of equipment could completely change teaching and gameplay in tennis. Cheng and Kim [18] offer a big data-driven badminton players' tempo training methodology that integrates reaction and cardiovascular training. The model satisfied research criteria while optimizing assessment methods. Experiments meet research needs and demonstrate a high degree of applicability. Hao et al. [19] offered basketball sporting events; the research used sophisticated mobile devices to gather physiological markers and current information from students. It was suggested to use the supportive Vector Machine (SVM) classification algorithm to track data such as human posture. The fashionable smart device serves as an additional teaching tool to assist pupils in mastering fundamental movement abilities. The wearable gadget enhanced four actions, long-throw movement, and physiological quality, according to a 32-credit education experiment. Chen and Xiao [20] indicated that multimedia-based robot technology is becoming more and more prevalent in several sectors, notably aerospace, medicine, education, and services. This essay examined the elements of badminton competition, such as the tactical and technical components as well as the necessity of on-site training. Yao and Liang [21] suggested digitization of gait-based perceptions and linked databases were also covered. To improve the finish operator's game data, the study suggested a position optimization plan for tennis pair that enables operators to assess players' strategic and technical skills using human-computer interactions. Zhang [22] examine the use of national fitness intelligence in badminton and identify research themes, areas of interest, and evolutionary pathways. Hotspots incorporate AI monitoring indications, big data technology, and intelligent sensing badminton instruction. Liu and Ding [23] provided an AI in sports, particularly table tennis, which was investigated in this work. It introduced a TTB trajectory prediction system utilizing Feature Fusion Network (FFN) and convolutional neural networks, attaining over 98% accuracy and 5.3 ms reaction time.

3. Methodology

Wearable sensors were initially used to gather performance data from badminton competitors, such as shuttlecock speed, footwork dynamics, and muscle activity. Z-score normalization was used to pre-process the data to normalize the measures and guarantee reliable comparisons between novice and expert players. To maximize the separation across player groups, class-discriminatory features were extracted from the pre-processed data using linear discriminant analysis (LDA). After that, the player performance levels were classified using the Adaptive Jellyfish Search Optimized Extreme Gradient Boosting (AJFSO-XGB) algorithm. To improve the accuracy of the model even further, hyperparameter tuning was used. The suggested process for improving badminton training plans is shown in **Figure 1**

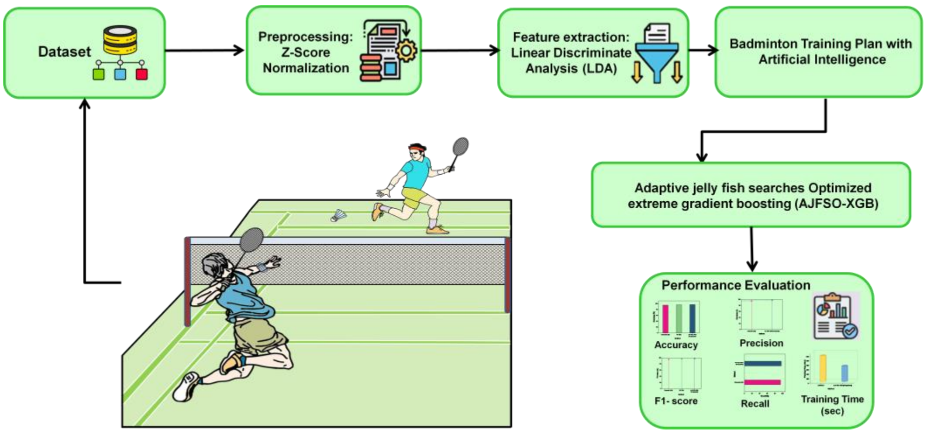

Figure 1. Methodology flow.

3.1. Dataset

The dataset consists of biomechanical and anthropometric data from 120 badminton players, collected to analyze and classify their skill levels during training sessions. Wearable sensors tracked real-time performance metrics, including shuttlecock speed, muscle activity, and footwork dynamics, and **Table 1** presents the collection of the sensor. These sensors recorded key movement data throughout the players' training to identify differences between beginner and expert athletes. Additionally, anthropometric data such as height, weight, and wingspan were gathered to enhance the dataset's comprehensiveness.

Table 1. Dataset-sensors.

Device	Wearable Sensor	Position of the Sensor	Purpose
Smartwatch	Heart Rate Monitor	Wrist	To monitor heart rate during training sessions
Accelerometer	Motion Sensor	Ankle	To track footwork dynamics and acceleration
Electromyography (EMG)	Muscle Activity Sensors	Upper Arm/Legs	To analyze muscle activity and fatigue
Speed Sensor	Shuttlecock Speed Sensor	Racket or Hand	To measure the speed of the shuttlecock
GPS Tracker	Location Sensor	Back (waist)	To track movement patterns and distance covered
Force Sensor	Pressure Sensor	Shoe Sole	To measure foot pressure during footwork

3.2. Preprocessing using the *Z*-score normalization

The data was gathered and the *Z*-score normalization approach was used to normalize several performance parameters, including muscle activity, shuttlecock velocity, and foot mechanics. *Z*-score standardization converts these numbers into an average of zero and a standard deviation of one, enabling an evaluation of players' accomplishments on the same scale. This ensures that variations in units or measures do not impact the accuracy with which the assessments of beginner and expert players are carried out and assessed in Equation (1).

$$W_{\text{new}} = \frac{W - \mu}{\sigma} = \frac{W - \text{Mean}(W)}{\text{StdDev}(W)} \tag{1}$$

here, W_{new} is the new value derived from normalized findings, and$W$ is the previous number, with μserving as people average and σas the average variation.

3.3. Feature extraction using the linear discriminant analysis (LDA)

To distinguish between beginner and skilled badminton players is utilized as a crucial classification method utilizing biomechanical and anthropometric data. By pinpointing the linear feature combinations that most effectively divide between the two levels of skill, LDA improves the optimization of training regimens. As a result, coaches and trainees can more successfully customize training plans by concentrating on problem areas. Because LDA is integrated into this AI-assisted system, data-driven insights are made easier, leading to more effective and individualized badminton techniques, which are evaluated in Equations (2) and (3).

$$T_X = \sum_{j=1}^{D} \sum_{w \in x_j} (w - \mu_j)\,(w - \mu_j)^s \tag{2}$$

$$T_A = \sum_{j=1}^{D} M_j(\mu_j - \mu)\,(\mu_j - \mu)^s \tag{3}$$

everywhere μ is the cruel course of all explanations then$T_S = T_X + T_A$ is the entire throw matrix. For x_j , it can be absolute by columns in a plan matrix $X = [x_1|x_2| \cdots |x_{D-1}]$, as shown in Equation (4).

$$z_j = x_j^S w \Rightarrow z = X^S w \tag{4}$$

Given that the projection isn't a scalar, the scattering matrices' determinant was incorporated into the criteria function, which therefore becomes Equation (5).

$$|I(X)| = \frac{X^S X_A X}{X^S T_X X} \tag{5}$$

The eigenvalue/eigenvector system can be solved by finding X that maximizes $I(X)$, as shown in Equation (6).

$$T_B X = \lambda T_X W \tag{6}$$

While PCA is an unsupervised method for extracting r (rank of data) principal features, LDA is overseen and may abstract (C-1) topographies. Because LDA's derived features make use of class knowledge, it is a more effective extraction of features approach in controlled training than PCA.

3.4. Badminton training plan with artificial intelligence using adaptive jelly fish search optimized extreme gradient boosting techniques (AJFSO-XGB)

The study employed an advanced ML algorithm, Adaptive Jellyfish Search Optimized Extreme Gradient Boosting (AJFSO-XGB), to optimize badminton training regimens. The AJFSO-XGB includes the standard XG Boost technique, advances solution quality, speeds up merging, and keeps the perfect from being surrounded in local optima. Due to this combination, the program can assess real-time presentation data more successfully and provide badminton athletes with exact and modified exercise information.

3.4.1. Gradient Boosting Techniques (XG BOOST)

The XGBoost algorithm is a sophisticated gradient boosting tree method that incorporates a second-order Taylor expansion of the cost function and supports parallel computing to improve performance. This approach is especially useful for evaluating badminton conditioning measures since it makes it possible to distinguish between beginner and expert players using a variety of data inputs gathered from wearable sensors. To improve prediction accuracy and decrease overfitting, XGBoost adds a regularization factor to its objective function that is correlated with the amount of bulges in the leaf and their values. The technique also effectively manages sparse data, enabling designated alternative routes for branches in the event of missing values. This feature is critical for improving training programs by appropriately modeling complex connections in the data.

$$z_j^{(s)} = \sum_{l=1}^{s} e_l(w_j) + e_s(w_j), \quad e_s \in E \tag{7}$$

where z_j characterizes the presentation metrics of badminton players, w_j signifies several training pointers, s is the entire amount of sub-models, and $e$is a set of all regression trees. To assess the model presentation, the loss purpose is distinct as in Equation (8):

$$k(z_j, \hat{z}_j) = (z_j - \hat{z}_j)^2 \tag{8}$$

This function quantifies the error between actual and predicted performance metrics, facilitating the model 's optimization of training strategies. The optimal solution can be defined as Equation (9).

$$E^*(w) = \arg minF(w, z)\left[K\left(z, E(w)\right)\right] \tag{9}$$

Equation (10) represent the normalization term$\Omega(e_s)$.

$$\Omega(e_s) = dS + \frac{1}{2}\delta \sum_{i=1}^{S} \omega_i^2 \tag{10}$$

where w and $\Omega(e_s)$are parameters adjusted to prevent overfitting, abridging the model while being connected with the number of bulges. The impartial purpose that indicates the loss purpose and the regulation term, is articulated as Equation (11).

$$P(s) = \sum_{j=1}^{m} \left(z_j - z_j^{(s+1)} + e_s(w_j)\right) + \Omega(e_s) + D \tag{11}$$

To enhance the accuracy and speed of the gradient descent process, a Taylor expansion is applied to Equation (12).

$$e(w + \Delta w) = e(w) + e'(w)\Delta w + \frac{1}{2}e''(w)(\Delta w)^2 \tag{12}$$

Then, the ideal objective purpose can be identified as Equation (13).

$$P^*(s) = \sum_{i=1}^{S} H_i + \frac{1}{2}\sum_i G_i \omega_i^2 + dS \tag{13}$$

To manage computational complexity, a greedy algorithm is utilized to determine the optimal tree structure by incrementally adding new partitions to existing leaf nodes and evaluating the associated gains Equation (14).

$$\text{Gain} = \frac{1}{2}\left(\frac{H_L^2}{G_L + \delta} + \frac{H_K^2}{G_K + \delta} - \frac{(H_L + H_K)^2}{G_L + G_K + \delta}\right) \tag{14}$$

here, “Gain” is a critical metric for assessing the effectiveness of training strategies in badminton. By leveraging the high exactness and strong stability of the XGBoost algorithm, this study aims to enhance training plans, finished AI-assisted assessments, and attractive performance outcomes for badminton players at various skill levels.

3.4.2. Adaptive jellyfish search optimization (AJFSO)

Various enhancements that precision, speed up convergence, and improve solution quality were suggested to overcome the shortcomings of the Adaptive Jellyfish Search optimized (AJFSO) Algorithm in badminton training plan optimization. The sine and cosine exercise factors are first presented. During Type B mobility, these characteristics enable jellyfish to study by selecting both chance and the finest individuals. This combination improves alternative solution quality by guiding the algorithm toward the optimal solution more efficiently and speeding up resolution. Second, a Local Escape Operator (LEO) is added to protect the AJFSO method from becoming stuck in local optima. By enhancing the algorithm 's exploitation capabilities, the LEO makes training plan optimization more robust by helping it avoid local traps and find globally optimal solutions. Finally, the diversity of candidate populations is increased by including Quasi-Opposition Learning (QOL) and Opposition-Based Learning (OBL) techniques. These strategies broaden the search space and ensure that better individuals are selected for the next iteration, improving solution quality and accuracy. These changes make the AI-assisted badminton training optimization system more effective and precise.

Components of Sine and Cosine Learning: In the exploratory stage of the AJFSO algorithm, the jellyfish transfer in Category B gesture within the jelly gathering, and the modified location of the jellyfish are solely associated with extra jellyfish randomly picked. Stated differently, jellyfish pick up random knowledge from different jellyfish. People in the contemporary population who are partially blind and do not have adequate information sharing among the populace. This procedure might cause the algorithm to change. Extending beyond the optimal candidate solution 's direction, and concurrently, the rate of convergence can slow down. To make up for these shortcomings, the jellyfish are taught from both random and optimal people inside the search range by introducing sine and cosine training variables, orω_1 and ω_2,, respectively. Through expedited convergence speed and faster search for the optimal site, this technique enhances the standard of the potential solution throughout the exploration phase in the Equations (15)–(17).

$$G\omega_1\omega_2 \tag{15}$$

$$\omega_1 = 2.\sin\left[\left(1-\frac{s}{S}\right).\frac{\pi}{2}\right] \tag{16}$$

$$\omega_2 = 2.\cos\left[\left(1-\frac{s}{S}\right).\frac{\pi}{2}\right] \tag{17}$$

$\overrightarrow{\text{step}}$ Since the original JS algorithm used a random learning technique, jellyfish pick up knowledge from the current person at random. Restricted convergence speed will come from the learned jelly species' poor fitness values. Consequently, the jellyfish learns from chance explanations and follows the best solution inside the exploration range, using the sine and cosine learning parameters added to the AJFSO algorithm. This rapidly enhances the quality of the solution and quickens conjunction.

Local Escape Operator (LEO): Efficiently assessing and balancing the algorithm 's capacity for exploration and exploitation is the fundamental task of swarm intelligence. The AJFSO algorithm can explore more locally when both cosine and sine learning variables are included, but its capacity to exploit globally is diminished. Finding new regions and improving the exploitation capabilities are the goals of the LEO, an around a GBO. This is used during the jellyfish phase when they follow the ocean current. Remarkably, the candidate$O_j(s+1)$can have its position updated by the local search operator. By doing this, any local optimum answers are bypassed by the algorithm. This allows it to increase the pool of potential candidates to find the worldwide optimums using the Equations (18)–(20).

$$ifrand < 0.5$$

$$O_{LEO}(s) = O_j(s+1) + e_1\left(v_1 O^* - v_2 O_l(s)\right) + e_2\rho_1\left(v_3\left(O2_j(s) - O1_j(s)\right)\right) + v_2\left(O_{q1}(s) - O_{q2}(s)\right)/2 \tag{18}$$

$$O_j(s+1) = O_{LEO}(s) \tag{19}$$

else

$$O_{LEO}(s) = O^* + e_1\left(v_1 O^* - v_2 O_l(s)\right) + e_2\rho_1\left(v_3\left(O2_j(s) - O1_j(s)\right)\right) + v_2\left(O_{q1}(s) - O_{q2}(s)\right)/2$$
$$O_j(s+1) = O_{LEO}(s) \tag{20}$$

End

where$o$ 2 ~M (0, 1) and o 1 is any number that is evenly distributed in [−1, 1]. Three random numbers, v_1, v_2, and v_3, have the following mathematical Equations (21)–(23).

$$v_1 = K_1 \times 2 \times Q1 + (1 - K_1) \tag{21}$$

$$v_2 = K_1 \times Q2 + (1 - K_1) \tag{22}$$

$$v_3 = K_1 \times Q3 + (1 - K_1) \tag{23}$$

where $K_1 = 0\ or\ 1$ and is a binary parameter. When $\mu_1 < 0.5, K_1 = 1$, $K_1 = 0$, else it equals 0, and ε_1 can be any integer between 0 and 1. Furthermore, $Q1 = rand(0,1)$ $Q2 = rand(0,1)$ $Q3 = rand(0,1)$ comprise three random integers from 0 and 1. ρ_1 is the adaptation factor. Here are some specific definitions in Equations (24)–(26).

$$\rho_1 = 2 \times rand(0,1) \times \alpha - \alpha \tag{24}$$

$$\propto = \left|\chi \times \sin\left(\frac{3\pi}{2} + sin\left(\beta \times \frac{3\pi}{2}\right)\right)\right| \tag{25}$$

$$\chi = \chi_{min} + (\chi_{max} - \chi_{min}) \times \left(1 - \left(\frac{s}{S}\right)^3\right)^2 \tag{26}$$

$\chi_{min} = 0.2$ $\chi_{max} = 1.2$ $O1_j(s)O2_j(s)$ Additionally, the next two mathematical equations offer two randomly generated Equations (27)–(30).

$$O1_j(s) = Ka + Q4 \times (Va - Ka) \tag{27}$$

$$O2_j(s) = Ka + Q5 \times (Va - Ka) \tag{28}$$

$$O_l(s) = K_2 \times O_o(s) + (1 - K_2) \times O_{rand} \tag{29}$$

$$O_{rand} = Ka + Q6 \times (Va - Ka) \tag{30}$$

Learning approaches: OBL and QOL are crucial devices for improving the diversity and coverage of applicant solutions in the AJFSO algorithm used for optimizing badminton training plans. These strategies help enhance the solution's precision by updating the jellyfish individuals according to a probability$O$, thereby improving the overall performance of the algorithm using Equations (31) and (32).

$$\breve{O}_j^c = rand\left(\frac{Ka^c + Va^c}{2}, Ka^c + Va^c - O_j^c\right) \tag{31}$$

$$O_j^{new} = \begin{cases} \tilde{O}_j \; ifrand < 0 \\ O_j \; ifrand \geq o \end{cases} j = 1,2, \dots., M \tag{32}$$

Using methodical methodology, the AJFSO maximizes badminton training regimens. Before randomly initializing candidate solutions that reflect different training tactics, it first establishes parameters for important elements, including shuttlecock speed, muscle activity, and footwork dynamics. These include population size, maximum iterations, and boundary restrictions. As the algorithm develops, jellyfish mimic ocean currents to mimic exploration, enabling training regimens to progressively adjust to the unique strengths and limitations of every athlete. During the active swimming phase, every potential solution modifies its location to improve training efficiency and movement skills. The algorithm uses a LEO to ensure that performance improves continuously by increasing the range of training techniques and preventing stalling in local optima. The procedure keeps on until the halting requirements are satisfied, which finally results in an ideal training schedule that improves badminton players' accuracy, speed, and agility.

The AJFSO Algorithm's Time Complexity: A collection of procedures used to handle data and resolve coding problems is referred to as an algorithm. For a given task, while multiple algorithms can yield identical results, their time and resource requirements might differ significantly. Analyzing the benefits and drawbacks of various algorithms is therefore essential. Time complexity, which calculates how long it takes for a program 's instructions to execute, will be used in this article to demonstrate this. When utilizing the AJFSO method to optimize badminton training programs, variables like the number of candidates (N), issue dimensions (D), and total number of repetitions (T) affects the time complexities. The way the AJFSO method works is as follows: candidates model ocean current dynamics; a stalemate is avoided by applying the LEO; applicants actively change under the guidance of sine and cosine knowledge influences; and new individuals are created using OBL and QOL. The iterative process of the following generation is then initiated for the best candidate solutions. Through an analysis of these components, the total time complexity can be computed efficiently, offering information on how effective the algorithm is at optimizing badminton training regimens using Equation (33).

$$\mathrm{P(EJS)} = \mathrm{P}\big(\mathrm{S}(\mathrm{ND} + \mathrm{ND} + \mathrm{ND})\big) = \mathrm{P(TND)} \tag{33}$$

To ensure accuracy and variety in the solution, this method employs a badminton training plan with Artificial Intelligence using Adaptive Jelly Fish Search Optimized Extreme Gradient Boosting Techniques (AJFSO-XGB) as outlined in **Algorithm 1**.

Algorithm 1 AJFSO-XGB

1: Establish T repetitions and initialize N contenders with parameters (muscle contraction, footwork, shuttlecock speed).

2: From t = 1 to T, perform:

3: For every j in N candidates, perform:

4: Use the XG Boost model to compute the anticipated metrics z_jEquation (8):

5: Use sine and cosine learning to update locations Equations (16) and (17):

6: Use LEOif a local optimum is found Equations. (18) and (19):

7: Use QOL to accommodate variety Equation (31):

8: Conclude With

9: Using opponent training as a guide, choose the top candidates and make updates Equation (32):

10: Finish For 11. Provide training conditions that are optimal for every participant.

11: Utilize the gain measure Equation (14) to assess the end performance.

4. Evaluation metrics

Accuracy: The degree of agreement between the ML training suggestions and actual player performance results is referred to as accuracy when discussing badminton training plan optimization using an ML-assisted system. It gauges the degree to which the system accurately forecasts gains in abilities, methods, and general training effectiveness. Instructors can depend on the ML system's insights to optimize player growth and enhance training efficacy since high accuracy signifies that the algorithm successfully directs players toward reaching their objectives for performance using the Equation (34).

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{34}$$

Precision: Precision of a badminton coaching effectiveness system means the reliability and accuracy of the suggestions given by the system to the training camp. It evaluates the ability and effectiveness with which the abovementioned system identifies or targets specific training needs and player development areas, respectively. Coaches and athletes may focus on perfecting specific skills and mask training routines when the latter affects the generation of invaluable information and optimized training methods with a high degree of accuracy are evaluated in an Equation (35).

$$\mathrm{precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{35}$$

Recall: Recall is the ability of a system, which enables the detection of all related instances within a given set. Recall measures the proportion of truly positive instances, or actual proper identification, compared to all the real positive cases or relevant instances, emphasizing its importance in enhancing badminton training regimes by

ML. This reflects a good capacity for the system to pick important items or information to pass through for analysis; hence, aspects of athlete development and training effectiveness do not slip through using the Equation (36).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (36)$$

F-1 Score: The harmonic hardness of the recall and precision that improves is used to compute the F1 Score. The badminton training with the aid of an AI-based system working with an uneven class distribution is beneficial because it emphasizes how important correct identification of significant cases is, as well as minimizing false positives. From a higher F1 Score, it is quantified that the current solution acquires more pertinent training data with higher efficacy and equal or higher accuracy using the Equation (37).

$$F - 1\text{ score} = 2 \times \frac{\text{precision. recall}}{\text{precision} + \text{recall}} \quad (37)$$

Training Time: The training time is the time required to train an algorithm in an ML learning process on a concerning dataset. Consequently, when it comes to the use of AI-supported technologies for managing training schedules to improve badminton players 'performance, the training time, as previously explained, pertains to the amount of time required for the algorithm to acquire data from various inputs, including data obtained from wearable devices on the kind of movement being made by particular body parts. Training time efficiency is important because it affects the model 's ability to quickly adapt to changes in the training environment; in addition, the decision-making skills of coaches/athletes are improved using the Equation (38).

$$\text{Training} = \text{N} \times \text{E} \times \text{S} \quad (38)$$

The training time size is N, number of epochs is E, and average time per epoch is S.

5. Performance analyses

The Python framework was used in conjunction with a Windows 13 operating system that was powered by an Intel® Core i9 CPU and equipped with 16.00 GB of RAM. This setup provided the means of obtaining and examining movement data with the view to enhancing training routines in badminton. The results reveal that the proposed AJFSO-XGB model is superior in analyzing an existing product in comparison to time-tested methodologies implemented with Decoach [24] and RF [25] algorithms. When player performance can be increased and analyzed on an individual basis, AI-aided systems can enhance training strategy and therefore increase the overall effectiveness of badminton training and athlete advancement. This growth is evidenced by this advancement.

Figure 2 displays a correlation matrix for biomechanical and anthropometric data for badminton players. It highlights the relationship between some factors, including the speed of the shuttlecock, locomotor tone, dynamics of shuffle, shuttlecock height, weight, span and width. Lighter tones of purple are taken to mean less strong, with positive or negative correlations, while darker tones signify stronger, either positive or negative correlation. For each cell, the precise correlation coefficient is noted, which gives a clear numerical understanding. Labeled axes and a color bar to the heat map enhance understanding of directions and strengths of variable interactions, respectively.

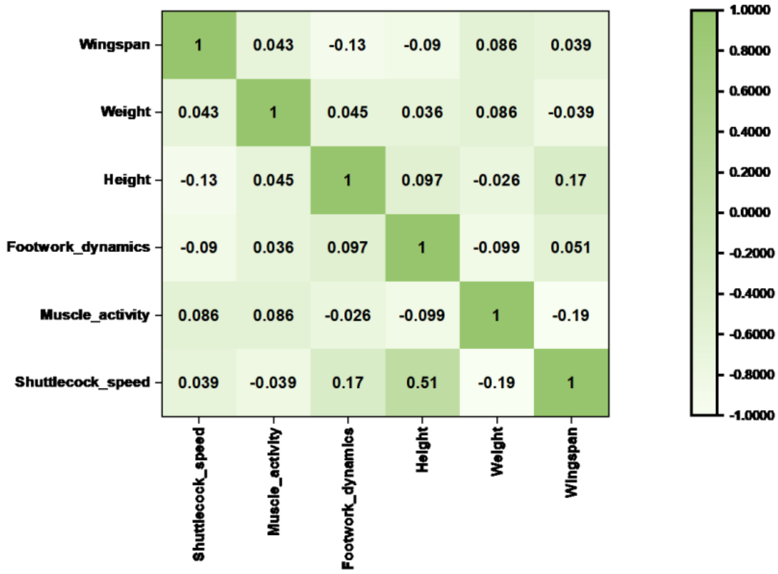

Figure 2. Biomechanical and anthropometric data correlations.

Accuracy: The accuracy percentages of different methods are presented in **Table 2**. The overall performance of a classification model is measured using a statistical metric called accuracy. It represents the model’s percentage of right predictions, including true positives and true negatives, among all forecasts. Accuracy is the percentage of correct predictions generated by a predictive model for badminton training optimization, accuracy represents how well the model identifies players’ ability levels, discriminating between beginners and specialists. **Figure 3** compares the proposed methodology’s accuracy to existing approaches. The accuracy ratings for the DeCoach achieved a 95.21%, the RF had a96.53%. Our suggested method, AJFSO-XGB utilizes AI and ML approaches to optimize badminton training, attaining an outstanding 97.05% accuracy in classifying players, hence improving training plans and overall performance.

Table 2. Comparison outcomes of accuracy and F1-score.

Method	Accuracy %	F1-score %
DeCoach [24]	95.21	95.21
RF [25]	96.53	96.27
AJFSO-XGB (Proposed)	97.05	97.23

F1-score: A F1-score that considers both recall and precision represent the model ’s ability to anticipate and optimize badminton training regimens while minimizing false positives and negatives. A high F1-score guarantees that implementing personalized training plans. **Figure 4** shows the F1-score comparisons of two standard models: RF (96.27%) and DeCoach (95.21%). Our suggested AI-

Assisted System using AJFSO-XGB has an F1-score of 97.23%. These findings demonstrate the superiority of our technique in improving the effectiveness of badminton training plans. **Table 2** presents a full comparison of the F1-score.

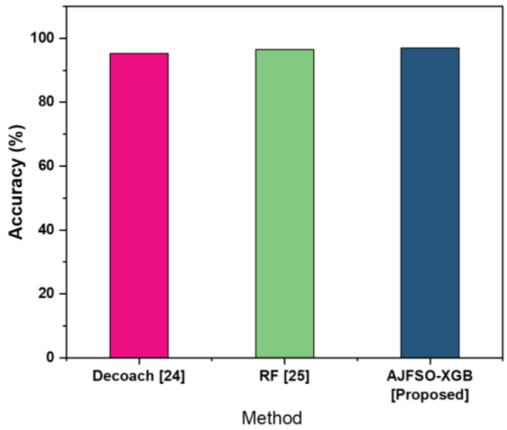

Figure 3. Histogram of accuracy.

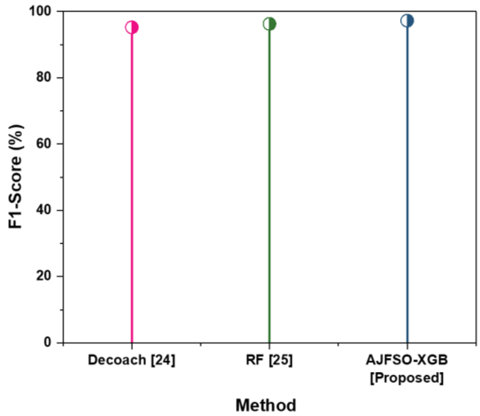

Figure 4. Comparison of F1-Score.

Precision: Precision refers to a model's capacity to precisely identify positive results related with improving Badminton Training Plan. The total number of true positives is computed by dividing it by the total number of actual positives. **Figure 5** compares the precision of the unique approach to that of previous approaches, as well as its performance. The precision percentages for the methods are illustrated in **Table 3**. DeCoach achieved a precision of 95% and the precision of the proposed AJFSO-XGB approach was higher with 97.52% of measures. This also shows that for the instances relevant to this study, AJFSO-XGB is significantly more accurate than DeCoach in its application.

Recall: Recall is a measure of a model's ability to recognize and improving Badminton Training Plan. It is also known as the sensitivity rate or the rate of true positives. The percentages of recall for the methods revealed that DeCoach received the basic recall of 95%, while the improved proposed method AJFSO-XGB received a recall of 97.27%. This enhancement indicates that the proposed method, AJFSO-

XGB, has a better capability to find all related cases than DeCoach, which is proved by the t-test of recall indexes depicted in **Table 3** and **Figure 6**.

Table 3. Comparison outcomes of precision and recall.

Method	Precision (%)	Recall (%)
DeCoach [24]	95	95
AJFSO-XGB (Proposed)	97.52	97.27

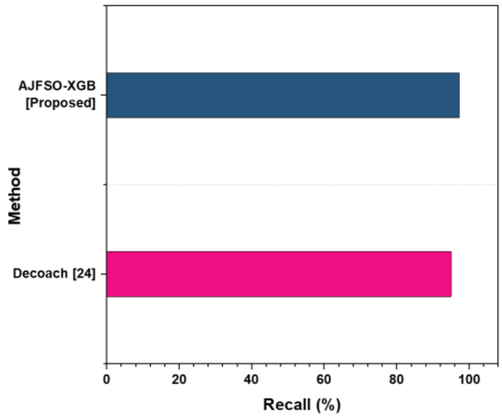

Figure 5. Comparison of recall.

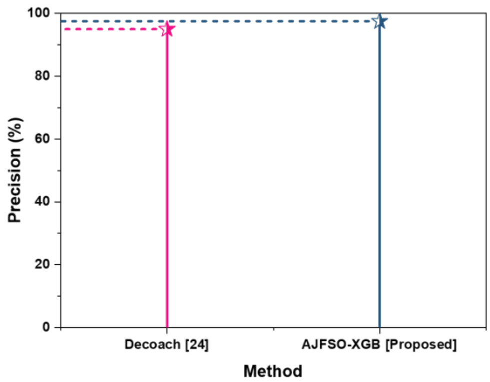

Figure 6. Graphical represent of precision.

Training Time: **Table 4** compares the training times of two methods: LSTM, which took 583 seconds to train, and the suggested AJFSO-XGB model, which took 350 seconds. This huge difference of 233 seconds implies that the AJFSO-XGB model is more efficient, reducing redundant features and the usage of Extreme Gradient Boosting (XGB), which is known for its speed and performance enhancement. Overall, the AJFSO-XGB model's shorter training period makes it a better fit for applications that require speedy deployment and easy computing expenses.

Table 4 and **Figure 7** present the training times of two methods: LSTM and the proposed AJFSO-XGB. LSTM training was completed in 583 seconds; meanwhile, the AJFSO-XGB reduced the training time to as small as 350 seconds only. This reduction shows that the proposed method outperforms LSTM regarding efficiency.

Table 4. Comparison outcomes of training time (sec).

Method	Training time (sec)
LSTM [25]	583
AJFSO-XGB (Proposed)	350

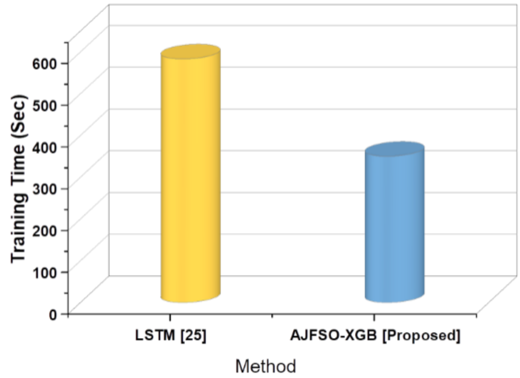

Figure 7. Comparison of training time.

6. Discussion

In that instance, although LSTM and DeCoach [24] can potentially encounter difficulties impeding their functionality, RF [25] can experience problems that impact its performance in specific scenarios. While for coaching systems, DeCoach gives quite satisfactory results, in terms of size and variety of problems, it often runs into complexity and scalability problems, leading to a decrease in accuracy. This is because it relies on fixed rules, and hence is not prepared to alter its configurations according to new patterns in data. LSTM [25] is a bit effective in sequential data, but it cannot really be used in real-time analyses because of the huge amount of computation and the time it takes in training for big problems. In addition, while using LSTMs sometimes, the information can be overfit and this reduces the extent of generalization. While arguing that RF demonstrates excellent robustness, its interpretability remains questionable and its performance tends to deteriorate on unbalanced datasets, which yields heavily shifted predictions toward the dominating class. However, there are some disadvantages with the approach; AJFSO-XGB manages to overcome those disadvantages in several ways. Firstly, it raises the precision and optimality owing to the adaptive jellyfish search approach, which enhances the utilization of the search space. Second, it helps to prevent cases such as over fitting and the model will be optimized dynamically, whereby the generalization is enhanced. Third, due to the boosting mechanism, it will be shown that AJFSO-XGB performs better in comparing the results of an imbalanced dataset with the Random Forest model in recall and F1 score. Finally, AJFSO-XGB outperforms RF in terms of algorithms interpretability, as it can give extra information on feature rankings and decision rules. In conclusion, for the problem of predicting missing values of time series data, the proposed model AJFSO-XGB demonstrates higher availability, effectiveness, and non-identity compared to DeCoach, LSTM, and RF.

7. Conclusion

Study serves as a test to look at the implementation of the AI system. That is to improve the training schedule for badminton about shuttlecock velocity, muscle activation, and footwork pattern. To optimize extreme gradient boosting to adapt to specific characteristics of badminton training, the system uses the AJFSO-XGB technique that produces recommendations to improve training based on data acquired to help coaches and athletes achieve better performance and precisely inclined toward better practice in badminton training sessions. The author of this study applies the Adaptive Jellyfish Search Optimized Extreme Gradient Boosting (AJFSO-XGB) method to present an AI approach to optimizing badminton training plans. Compared to the previous models, including DeCoach, LSTM, and RF, the proposed AJFSO-XGB enhances the features of high accuracy (97.05%), high F1-score (97.23%) high precision (97.52%), and high recall (97.27%) while also exhibiting low computational consumption and a short training timeof350 (sec). It is an adaptive optimization algorithm, and unlike other optimization strategies, it increases the solution quality and makes it more effective in real-time applications. In conclusion, AJFSO-XGB can be revealed as appreciable and effectual for refining badminton training knowledge and resulting in higher efficiency for the coaches and athlete. One of the most significant limitations to this research is that it is an initial study, which does not encompass the inclusiveness of possible training paths or include sufficient participants for statistical analysis. Furthermore, the study used a single badminton skill as a test and it is substantiated that the real-world performance of badminton decreases in contrast to an increase in the AI-assisted system; therefore, there is a need to establish the accuracy of the method for the overall badminton skill and proficiency for different skill levels in other conditions. The direction for future work covers the extension of the developed AI-supported system, which considers various player types and abilities. It also affords the inclusion of personalized training optimization using enhanced data analytics and ML algorithm and feedback in real-time performance monitoring and control of injuries allied to badminton training.

Ethical approval: Not applicable.

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

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