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Article

Optimization design of biomechanical parameters based on advanced mathematical modelling

Yuan Wen

Yunnan Communications Vocational and Technical College, KunMing 650000, China; megotion@163.com

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Abstract: In recent years the use of biomechanics in athletic training and performance has received a lot of attention, especially in university sports programs. Biomechanics is the study of the mechanical principles that control how biological things move or are constructed. It is critical for understanding the intricate relationships between physical performance, body mechanics, and injury prevention. The objective of this study is to establish how biomechanical variables can be designed and optimized in universities using mathematical modeling. In this study, a novel Emperor Penguin Search-driven Dynamic Feedforward Neural Network (EPSO-DFNN) is proposed to optimize the biomechanical parameters of athletes. Various biomechanical data are utilized from athletes participating in different sports. Biomechanical parameters include muscle activation patterns, joint angles, forces, and movement. The data was preprocessed using Z-score normalization from the obtained data. The Fast Fourier Transform (FFT) using features is extracted from preprocessed data. The proposed method is to identify the optimal configurations for athlete's movements tailored to their sports and individual biomechanical profiles. The proposed method is the performance of various evaluation metrics such as F1-score (92.76%), precision (91.42%), accuracy (90.02%), and recall (89.69%). The result demonstrated that the proposed method effectively improved the performance in athletic capabilities compared to other traditional algorithms. This study demonstrates how mathematical modeling may be used to optimize biomechanical characteristics, providing insightful information that can be used to improve athletic performance and encourage safer behaviors in athletic settings.

Keywords: biomechanical parameters; athlete; Emperor Penguin Search Driven Dynamic Feedforward Neural Networks (EPSO-DFNN); Fast Fourier Transform (FFT)

1. Introduction

In recent times the interface between biomechanics and sports performance has become very popular, particularly in the university sports system [1]. Indeed when athletes seek to excel finding out the mechanical principles underlying human movement becomes essential [2]. Biomechanics can be defined as that branch of knowledge that deals with the mechanical aspects of living organisms bringing out precious elements of how physical performance, body mechanics, and injury prevention are integrated [3].

Through the application of biomechanics in contemporary sports science performance is evaluated for athletes and training programs are developed for an athlete [4]. Today, as viewed differently [5], different physical demands are realized in different sports disciplines, and movement is characterized by complex interaction at the levels of joint angles, muscle activation patterns, and the forces applied [6]. These interactions heavily influence how performances may be optimized and proper analysis and optimization of biomechanical parameters may make a difference between winning and losing [7].

Optimizing biomechanical parameters is particularly important. Poor movement patterns or ineffective force application can result in poor performance and, more importantly, injuries [8]. The knowledge of such parameters can help coaches design training programs in which the appropriate movement mechanics are practiced thus there may be a reduction in injury [9]. For example, an analysis of inefficiency can be shown in an analysis of the gait cycle when corrected, it may lead to increased speed and endurance. In addition, muscle activation regarding sports-specific movement is also important in determining the strength and conditioning needs unique to each athlete's profile [10].

Advanced mathematical modeling to optimize biomechanical parameters has strong limitations. First, it becomes extremely demanding to require accurate and detailed data errant data or noise results in wrong predictions. Intrinsic human biomechanics complexity creates great demands for universally applicable models. At a minimum, mathematical assumptions could severely understate the dynamical complexity existing in reality, creating poor results. There is a danger of overfitting, models may fit well to the training data but fail with any other input. Moreover, the computational requirements of these models limit their applicability in real-time and, therefore make such use to coaches and athletes limited. The purpose of this study is to determine how biomechanical aspects can be established and optimized in universities utilizing mathematical modeling.

Motivation and contribution of the study

The motivation for this study is derived from the growing need for specificity in enhancing the biomechanical potential of athletes concerning training effectiveness and minimizing risks of injury. Indeed, in the great majority of cases, traditional approaches are not well adapted to capture the dynamics of human motion. Incorporating a novel search model known as Emperor Penguin Search-driven Dynamic Feedforward Neural Network (EPSO-DFNN) improving the optimization tools efficiency, flexibility, and precision as a parameter tuning are anticipated. Such a combination could alter the traditional way of exercising with the individualized insight of an athletic performer based on analyzed data. Therefore, the following is a summary of this work's contributions:

- Data collection: Initially a CMU Mocap motion capture dataset is collected from the Kaggle website;
- Data preprocessing: The data was pre-processed using Z-score normalization from the obtained data;
- Feature extraction: The FFT using features is extracted from preprocessed data;
- Model classification: A novel Emperor Penguin Search-driven Dynamic Feedforward Neural Network (EPSO-DFNN) is proposed to optimize the biomechanical parameters of athletes;
- Model evaluation: F1-score, Precision, Accuracy, and recall parameters are used to assess the simulation outcomes.

This work is organized as follows: Part 2 reveals the related work. The methods and materials are explained in Part 3. Part 4 offers the results and Part 5 concludes the study.

2. Related work

A computational framework for optimizing the cross-sectional size and shape of Transcatheter Aortic Valve (TAV) frames was presented [11]. Idealized aortic root models were subjected to finite element analyses with an emphasis on contact pressure, peak maximum principal stress, and pullout force magnitude. The optimization problem was defined by surrogate modeling. Through multi-objective design optimization, the best TAV frame geometries for various aortic root anatomies were found. The framework reduced costs and improved procedural outcomes by improving mechanical efficiency.

The biomechanics of martial arts development with a particular emphasis on Wushu a traditional Chinese sport were looked [12]. It made use of bibliometric analysis to examine doctoral dissertations and core journals to comprehend the most recent advances in biomechanical research concerning martial arts routines. The findings demonstrated a significant improvement in test classification accuracy, recall, and F value when using the Backpropagation (BP) neural system model. The study highlighted Wushu’s need for innovative forward-thinking and modern biomechanical research.

To enhance the computational simulation of dental prosthetics by applying the vibroacoustic Resonance Frequency Analysis (RFA) technique was aimed [13]. The implantation was stimulated with a sinusoidal force in the study, and the displacement that resulted was recorded. With values ranging from 8975 to 8995 Hz, MATLAB was used to plot a resonance frequency that was equivalent to the maximum micro-motion. With less micromotion a higher resonance frequency denoted improved integration. To develop systems with several degrees of freedom to replicate dental implant models more research was required.

Finite element modeling proved to be an effective technique for studying the biomechanics of the musculoskeletal system. The development of precise models required medical imaging. Segmentation, meshing, and assigning material properties to the various model components were steps in the workflow. Quantitative computerized tomography was employed for bone tissue and elastography, T1 rho, and T2 imaging for soft tissues. In their 2020 study, [14] concentrated on computational models of the musculoskeletal system and provided an overview of techniques for meshing, image segmentation, and assessing the mechanical characteristics of biological tissues. They also addressed current advancements in Artificial intelligence (AI).

A 2D biomechanical model for bone remodeling a multifaceted process to involves the interaction and regulation of apparent density by bone cells was presented [15]. Automatic boundary recognition, mechanical transduction, and mathematical parameters were all included in the model. To create boundary maps it was coupled with the Radial Point Interpolation Method (RPIM). The model also examined bone resorbs and strain energy density (SED) changes in response to different loading regimes.

To describe force generation in cardiac muscle tissue, [16] offered four mathematical models. Applying those highly computationally efficient models to multiscale 3D numerical simulations could accurately predict features related to force generation thereby obviating the need for the Monte Carlo (MC) method. The algorithms were based on biophysically precise depictions of regulating and contractual proteins in sarcomeres.

In simulating the circumstances of specialized motions and collaborating by employing joint angles calculated from inertial measurements [17] sought to improve ergonomic analysis. The Gesture Operational Model (GOM) forecasted workers' postures and identified contributing joints for ergonomic risk prevention by using autoregressive models to learn joint dynamics. To prevent mistakes such as bone stretching and improper skeleton configurations Euler angles were employed. The most involved joints in movements were identified by computing the statistical significance of each model. High gesture recognition performance validated the selection of joints, and the models' forecasting performance was assessed.

A semi-implicit hybrid boundary element method (HBEM) was created by [18] to describe unpredictable partial biomechanical connections in asymmetrical soft tissue structures with functioning grades. The irregular fractional dual-phase-lag bioheat (DPLB) regulating calculation was solved using the universal Boundary Element (BE) method and the regional base function radial association technique. For BE separation calculations an effective separated semi-implicit connecting algorithm was employed. It established the reliability, efficiency, and efficacy of the method used to graphically illustrate the effects of evaluated factors limited variables, and asymmetrical assets on bio-thermal anxiety.

The purpose of [19] was to determine that female athletes' drop vertical jump (DVJ) biomechanical characteristics varied depending on the sport they played. 42 female athletes, 25 played basketballs, 8 played soccer, and 9 played volleyball. The findings demonstrated that, in comparison to basketball players, soccer players had fewer scores, larger peak knee flexion angles, and smaller knee abduction angles at initial contact. The study found that while performing the jump-landing task, female basketball and volleyball players might be more susceptible to non-contact anterior cruciate ligament (ACL) injuries.

The purpose of the [20], which involved eight competitors from the 2017 World Championship, was to ascertain the connections between the techniques of elite hammer throwers. The Dartfish program was used to determine the biomechanical parameters. The angle left knee, the angle incline torso, and the time of the second pre-swing were found to be strongly correlated with each other. The second preliminary swing technique was not considerably affected by the parameters of the first preliminary swing. For pre-swing implementation to be effective it emphasized the significance of time parameters, angular parameters, and hammer height during pre-swing.

The body adjusts to training and maintains homeostasis when it experiences acute fatigue from running were examined [21]. A combination global navigation satellite system—inertial measurement units (GNSS-IMU)-electrocardiogram sensor and an Android smartphone were given to 13 runners. The study discovered that during the race, heart rate gradually increased along with contact time, duty factor, and trunk anteroposterior acceleration. The results emphasized how crucial it was to research the biomechanical, physiological, and psychological aspects of running in actual environments.

A surrogate model-based, effective method for correlated global sensitivity evaluation was presented [22]. Although the correlation structure was unknown, the method could yet serve as an orientation for modelers during the model expansion and personalization process. When the technique was applied to a model of pulsed wave propagation it produced precise results at a computational cost 27,000 times less than that of the correlated SA approach in the absence of a substituting model. It enabled modelers to concentrate on input prioritization fixing, and reduction while highlighting the significance of looking into input correlations during model development.

The effects of backseat support, inclination angles, frequency, and magnitude of vibrations on Seat to Head Transmissibility (STHT) in a biodynamic individual's model were examined in [23]. Based on anthropometric data the model parameters (mass, stiffness, and damping) were calculated. For every scenario, the STHT was calculated with MATLAB software and the implications of vibration and excitation frequencies were examined. When the outcomes were compared to mean STHT characteristics from prior research, they showed good agreement with those findings.

An integrative finite element framework for the pelvis including the surrounding soft tissues and bone has been created by [24] and verified experimentally. According to the model adding soft tissue decreased the amount of stress and strain on the pelvis and improved the accuracy of strain and stress dispersion under pelvis stimulation. The results showed that the combined model had the potential to improve clinical interventions and treatments for pelvic injuries as well as an understanding of the complex biomechanics of the pelvis. It would increase the probability of success of pelvic bone repair using surgical navigation systems and robotics.

3. Methods

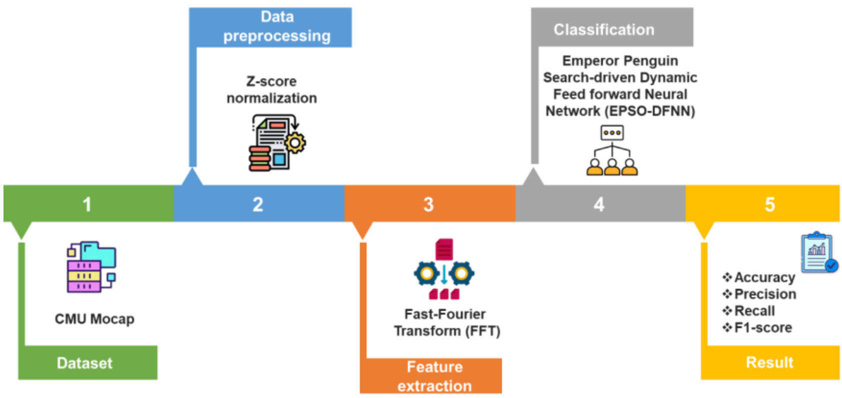

Figure 1. Overall flow for EPSO-DFNN.

Source: https://www.kaggle.com/datasets/kmader/cmu-mocap.

In this study, the CMU Mocap dataset is gathered on Kaggle websites. Next preprocessing was done using Z-score normalization techniques. Normalize the raw biomechanical data to ensure uniform scaling across different parameters. Feature extraction is done using FFT. Extract relevant features from the normalized data, focusing on frequency components of movement. For classification, a novel Emperor Penguin Search-driven Dynamic Feedforward Neural Network (EPSO-DFNN) is proposed to optimize the biomechanical parameters of athletes. **Figure 1** depicts the overall flow for EPSO-DFNN.

3.1. Dataset

The CMU Motion Capture (Mocap) dataset available on Kaggle features comprehensive movement capture data collected from the Carnegie Mellon University Motion Capture Lab. This dataset comprises recordings of human movements in three-dimensional space, captured using a variety of sensors and recording systems. The biomechanical data includes joint angles, limb velocities, and accelerations, providing detailed insights into human motion dynamics. The sensor data collection process involves multiple high-fidelity cameras and inertial measurement units (IMUs) to accurately track and record movements from various perspectives. This dataset consists of recordings of human movement in 3-D accrued by the usage of several sensors and systems. The dataset consists of c3d files, mpg documents, h5 files, and ASF + AMC files, which may be accessed through repositories like AMC Parser. The data is often used for responsibilities like human pose estimation, animation, biomechanics, and more. The dataset is prepared by different types of movements and can be useful for researchers and developers working in fields associated with motion analysis and system machine learning.

3.2. Data preprocessing using Z-score normalization

The resultant raw biomechanical data had vastly disparate scales because of the various units, ranges, and techniques used for measurement. For consistent scaling of all the parameters to be comparable Z-score normalization was applied. This is a feature normalizing procedure that scales the data to a universal scale, provided the mean value is zero, and the standard deviation is one, which can help in achieving better integration of features and prevent machine learning biases.

The number of standard deviations is represented by the Z-score, a traditional standardization and normalization technique that indicates whether the original data point was higher or lower than the population mean. The ideal range is between −3 and +3. To apply the default scale to all the data with different scales it normalized the dataset to the previously mentioned scale.

Equation (1), where w denotes the value of a specific sample, μ denotes the mean, and σ denotes the standard deviation, can be utilized to calculate the Z-score, which normalizes the data by subtracting the population mean from a raw data point and dividing the result by the standard deviation. This yields a score that ideally varies between −3 and +3.

$$z\_score = \frac{(w - \mu)}{\sigma} \tag{1}$$

3.3. Feature extraction FFT

The FFT is a method that transforms time-domain signals into the frequency domain where such periodic functions can be very powerfully used to transform time-domain signals into the frequency domain. For biomechanics, the FFT was applied in extracting frequency-based features from time-series data, giving valuable insights into movement rhythmic and repetitive components.

The process of splitting a function over some time into its component frequency is known as the FFT. The Fourier transform holds significant importance in signal processing speech and communication image processing, and other fields where it finds numerous uses. Here is the Equation (2) for the Fourier transform,

$$W(\zeta) = \int_{-\infty}^{\infty} w(s) e^{-2\pi j \zeta s} ds \tag{2}$$

where time is represented by s, frequency by ζ, and $w(s) \in \mathbb{D}$is Lebesgue integral feasible.

FFT can be used to employ it quickly for practical use. The most significant distinction is that a Discrete Fourier Transform (DFT) is much quicker and more reliable in the presence of round-of-error. The DFT is determined by FFT which produces an identical outcome when immediately assessing the DFT explanation. The DFT is defined as Equation (3).

$$W_l = \sum_{m=0}^{M-1} w_m e^{-\frac{j2\pi m}{M}},\ (l = 0, \ldots\ldots, M-1) \tag{3}$$

$w_0, \ldots\ldots, w_{M-1}$ represent complex numbers. FFT is widely used in science, engineering, and mathematics for a variety of purposes. The revolving machine signal was transformed into the frequency domain from numerous studies and examined using this FFT.

3.4. Emperor Penguin Search-driven Dynamic Feedforward Neural Network (EPSO-DFNN)

The Emperor Penguin Search-driven Dynamic Feedforward Neural Network is used to optimize the biomechanical parameters of athletes because this approach combines both of them to achieve precise, customized enhancements of their performances. For instance, if more complex non-linear relationships exist between different biomechanical parameters such as joint angles, muscle activation, and forces, then use the Dynamic Feedforward Neural Network that will model behavior and handle variability in movement for athletes across different sports because this DFNN has the capability of adapting uniquely to the individual profile of each athlete. This is enhanced by the EPSO algorithm because it efficiently tunes hyperparameters in the network and, therefore, determines optimal configurations. A better balance between exploration and exploitation is offered with the EPSO. Allowing it to quickly find global optima while avoiding local traps. This hybrid approach enables the system to optimize biomechanical parameters more effectively, leading to enhanced athletic performance, injury prevention, and personalized movement recommendations tailored to each athlete's specific needs and sport.

3.4.1. Dynamic feedforward neural network (DFNN)

A DFNN approach is applied in the biomechanical parameters of athletes since it models rich, complex, nonlinear relationships between parameters like joint angles, muscle activation, and forces. It is adaptable; hence, it can handle variation among individuals and provide an accurate optimization that improves athletic performance and decreases injury risk based on biomechanically distinct profiles.

In every adjacent layer, there exists only one connection between any two neurons. The initial input level, output level, initial hidden level, and the final hidden layer, accordingly, are accessions for the delay dynamic operators $y^{-\tau_{ij}^{(1)}}$ and $y^{-\tau_{or}^{(2)}}$. In addition to the threshold a and weights of connections ω, Adaptive adjustments are made for those two flexible variables. The connections between the input and output, which are implied in the hidden layers, can be expressed as Equations (4) and (5),

$$net_i^{(k)}(l) = \sum_{j=1}^{M^{(k-1)}} \omega_{ij}^{(k-1)} P_j^{(k-1)}(l) + a_{ki} \tag{4}$$

$$P_i^{(k)}(l) = e\left[net_i^{(k)}(l)\right] \tag{5}$$

where the output and input of the i^{th} neuron in the k^{th}level at time l are indicated by $net_i^{(k)}(l)$and $P_i^{(k)}(l)$, respectively.

The limit value parameter of the i^{th}neural in the k^{th} layer is indicated bya_{ki} and the quantity of mass concerning the i^{th} neural in the k^{th} layer to the i^{th} neural in the $(k-1)^{\text{th}}$ layers is characterized by$\omega_{ij}^{(k-1)}$. It has been observed that modifications from 1 to M^k when j variations from 1 to M^k. The bipolar sigmoid activation function, $e[.]$, is described as Equation (6).

$$e(w) = L\frac{1-e^{-dw}}{1+e^{-dw}} \tag{6}$$

Particle structure data is represented using the DFNN variables, as shown in Equation (7).

$$w_i(l)\omega_{11}^{(1)}(l), \dots\dots, \omega_{1j}^{(N-1)}(l)a_{21}(l), \dots\dots, a_{N1}(l)\tau_{11}^{(1)}(l), \dots\dots, \tau_{11}^{(1)}(l), \dots\dots, \tau_{1j}^{(2)}(l) \tag{7}$$

Consequently, the intersection of the flexible interruption operators between the relationships can be used to describe the original hidden neurons and their output neurons are described in Equations (8) and (9),

$$net_i^{(2)}(l) = \sum_{j=1}^{M^{(1)}} \omega_{ij}^{(1)} P_j^{(1)}\left(l-\tau_{ij}^{(1)}\right) + a_{2i} \tag{8}$$

$$net_o^{(N)}(l) = \sum_{r=1}^{M^{(N-1)}} \omega_{or}^{(N-1)} P_r^{(N-1)}\left(l-\tau_{or}^{(2)}\right) + a_{Nr} \tag{9}$$

where $\tau_{ij}^{(1)}$ and $\tau_{or}^{(2)}$ represent the corresponding delay time between the input and output layers and the layers that are concealed, accordingly. Examine the impact of the inputs $v_1(l-1)$on output $z(l)$asEquation (10).

$$(l) = e[\sum_{1}^{M^{(N-1)}} \omega_{or}^{(N-1)}.\left(e \ldots \left(e\left(\omega_{ij}^{(1)} v_1 \left(l - 1 - \tau_{ij}^{(1)} - \tau_{or}^{(2)}\right) \vdots + a_{2i}\right) \ldots\right) + a_{N1}\right] \quad (10)$$

After achieving the fitness function's lowest value, the algorithm adaptively modifies the parameters $\tau_{ij}^{(1)}$and $\tau_{or}^{(2)}$, which vary from 0 to τ_{max}. An input vector that combines the most recent output with supplementary input vectors represents the complete input-output connecting with a delay of the DFNN.

$$z_n(s) = h_n\left(z_n\left(l - \tau_{11}^{(1)} - \tau_{1r}^{(2)}\right), \ldots., z_n\left(l - \tau_{M^1M^2}^{(1)} - \tau_{1M^{(M-1)}}^{(2)}\right), v\left(l - \tau_{11}^{(1)} - \tau_{1r}^{(2)}\right), \ldots\ldots, v\left(l - \tau_{M^1M^2}^{(1)} - \tau_{1M^{(N-1)}}^{(2)}\right)\right) \quad (11)$$

where h_n denotes the DFNN's nonlinear mapping. Due to the arbitrary time delay on each neuron relationship, the system thus possesses the time sequence $\tau_{ij}^{(1)}$. Connecting the present period output to some input instances increases the adaptability of the DFNN. Particularly emphasizing unpredictable characters, the fluctuating delays between the input layer and the initial hidden layer completely convey the fundamental connection between the output and the input. In contrast, a controlled long-delay mechanism is identified by the delay operatives across the concealed and output layers, yielding unregulated time delays $\tau_{or}^{(2)}$.

As a result, the suggested DFNN could effectively capture the delay and nonlinear aspects of the system using a small number of parameters. After training, the precisely regulated plant is obtained without any delays if the delay operators $\tau_{or}^{(2)}$are eliminated. At that point, a satisfactory regulation effect can be obtained with the common predictive control strategy.

3.4.2. Emperor penguin search optimization (EPSO)

EPSO is deployed for the biomechanical parameters of the athlete because it very efficiently explores the search space to find optimal configurations for complex, multi-variable problems. It therefore represents exploration and exploitation to concentrate on convergence whilst ensuring appropriate global optimization of parameters such as muscle activation and angles of joints, leading to improved performance and injury prevention across various profiles of athletes.

An innovative meta-heuristic algorithm is the EPO. The socially awkward behavior of emperor penguins served as the model for the EPO algorithm. Because the Antarctic continent is the emperor penguin's natural habitat it can get extremely cold there in the winter, making it extremely difficult for the species to survive. Because of this, the emperor penguins flock huddles together in an arrangement that keeps everyone's body temperature within an appropriate range for survival.

The only animals that cuddle are emperor penguins. It depends on several variables including the huddle's effective movers, distance, and temperature. All of these elements and more form the foundation of the EPO algorithm, where the observer and update equations, respectively, replicate the temperature and distance. The efficacy of the EPO algorithm has been demonstrated through testing on multiple optimization problems. The emperor penguins' primary goals when they huddle are to preserve energy and increase the interior temperature. As a result, the following relationship exists between the temperature S and the huddle polygon's radius Q as Equation (12).

$$S = \begin{cases} 0, if\ Q > 1 \\ 1, if\ Q < 1 \end{cases} \tag{12}$$

Exploration and exploitation are processes that are driven by the temperature profile S_0. This is how it's computed as Equation (13),

$$S_0 = S - \frac{MI}{CI - MI} \tag{13}$$

where S_0 is the temperature profile surrounding the gathering area, $and\ MI$ stands for maximum iteration count. Iteration CIrefers to the current iteration.

The distance between the emperor penguin and the optimal solution C is calculated as follows after the huddle boundaries have been established in Equation (14),

$$C = T(B).O_{ep}(w) - C.P(w) \tag{14}$$

where $T(B)$ refers to the emperor penguins' social forces. $O(w)$ is the emperor penguin's current position vector. Anti-collision factors (B, D) separate neighbors. The vector containing the best possible solutions is called $O_{ep}(w)$.

The distance C is tuned by B and D, which can be determined using the following Equations (15)–(17),

$$D = rand_1 \tag{15}$$

$$B = N \times \left(S_0 + O_h(ac)\right) \times rand_2 - S_0 \tag{16}$$

$$O_h(ac) = O_{ep}(w) - O(w) \tag{17}$$

where N is the movement parameter that keeps search agents apart to prevent collisions. By assessing the variations amongst emperor penguins, $Oh(ac)$defines the polygon grid accuracy. Equation (18) can be used to calculate $T(B)$, which is in charge of moving in the direction of the best optimal search agent, whereas Equation (19) updates the position.

$$T(B) = \left(\sqrt{e.f^{-\frac{w}{l}} - e^{-w}}\right)^2 \tag{18}$$

$$O(w+1) = O_{ep}(w) - B \times C \tag{19}$$

Here $e\&\ l$ are control variables for improved exploration and utilization. The emperor penguin's next updated position is denoted by $O(w + 1)$. The following are the key procedures for executing EPO:

Step 1: Set the starting values for $Q, (\quad) S, S0, B, D, TB, N, e,$ and $rand1$, $rand2$.

Step 2: Determine the starting values for the important parameters $O(w)$ and the matching fit values.

Step 3: Using the computed fitness, identify the first best optimal solution.

Step 4: Determine the new values for $S0, T(B), Oh(ac), and\ B$ to begin the first iteration.

Step 5: Determine the values of C and employ them to compute the new, updated solution $O(w+1)$ using the best solution $Pep(w)$.

Step 6: preserve the newly found best optimal solution in $Pep(w)$. Additionally, keep the matching best capability.

Step 7: Ascertain that the repetitions have concluded; if otherwise, proceed again to Step 4 and continue to reach the required number of repetitions.

Step 8: To regulate the ideal capability and demonstrate the corresponding response, appear over the fitness array.

Algorithm 1 demonstrates the pseudocode for Emperor Penguin Search-driven Dynamic Feedforward Neural Network (EPSO-DFNN).

Algorithm 1 EPSO-DFNN

```
import numpy as np
MAX_ITERATIONS = 1000
NUM_PENGUINS = 30 # Number of penguins in the population
TAU_MAX = 5 # Maximum delay parameter
M = ... # Number of neurons in each layer (to be defined based on the specific problem)
N = ... # Number of layers (to be defined based on the specific problem)
L = ... # Length of input data (to be defined based on the specific problem)
def initialize_df_nn_params():
    weights = np.Random.rand(NUM_PENGUINS, M, N)
    thresholds = np.random.rand(NUM_PENGUINS, N)
    delays = np.random.rand(NUM_PENGUINS, M, 2) * TAU_MAX
    return weights, thresholds, delays
def bipolar_sigmoid(x):
    return (1 - np.exp(-x)) / (1 + np.exp(-x))
def df_nn_forward_propagation(input_data, weights, thresholds, delays):
    for k in range(N):
        net_input = np.zeros(M)
        for i in range(M):
            delayed_input = input_data[-delays[i][0]] if len(input_data) > delays[i][0] else 0
            net_input[i] = np.sum(weights[:, i, k] * delayed_input) + thresholds[:, k]
        input_data = bipolar_sigmoid(net_input)
    return input_data
def emperor_penguin_search(weights, thresholds, delays):
    for iteration in range(MAX_ITERATIONS):
        fitness = np.zeros(NUM_PENGUINS)
        for i in range(NUM_PENGUINS):
            fitness[i] = calculate_fitness(df_nn_forward_propagation(input_data, weights[i], thresholds[i], delays[i]))
        best_index = np.argmin(fitness)
        best_solution = (weights[best_index], thresholds[best_index], delays[best_index])
        for i in range(NUM_PENGUINS):
            if i != best_index:
                C = calculate_distance(weights[i], best_solution[0], thresholds[i], best_solution[1])
                weights[i], thresholds[i], delays[i] = update_position(weights[i], best_solution, C)
    return best_solution # Return the best DFNN parameters
def calculate_distance(current_solution, best_solution, current_threshold, best_threshold):
    return np.linalg.norm(current_solution - best_solution) + np.linalg.norm(current_threshold - best_threshold)
def update_position(current_weights, best_solution, distance):
```

Algorithm 1 (*Continued*)

```
    new_weights = current_weights − distance
    new_thresholds = best_solution[1] − distance
    new_delays = best_solution[2] # Use best delay as a placeholder
    return new_weights, new_thresholds, new_delays
def main():
    weights, thresholds, delays = initialize_df_nn_params()
    input_data = ...
    best_weights, best_thresholds, best_delays = emperor_penguin_search(weights, thresholds, delays)
    final_output = df_nn_forward_propagation(input_data, best_weights, best_thresholds, best_delays)
    return final_output
if _name_ == "_main_":
    output = main()
    print("Final output from DFNN: ", output)
```

4. Results and discussion

4.1. Simulation setup

The simulation setup for the EPSO-DFNN model involved simulating and optimizing athletes' biomechanical parameters using a Python-based environment on a system with an Intel Core i7 processor, 16GB RAM, and a 64-bit operating system. The neural network was implemented using TensorFlow (version 2.8) and Keras, while the Emperor Penguin search algorithm was coded using Python (version 3.9). The dataset for athlete biomechanics was processed using NumPy and pandas libraries.

For the EPSO-DFNN model for optimization of the biomechanical parameters of athletes, accuracy means that the percentage of correct prediction of the optimal output for biomechanics is achieved in 100 epochs. The loss represents a measure of the amount of error or the difference between the values of the biomechanics to be considered during training. Greater than 100 epochs over, graphs of accuracy display the model's improvements in prediction capability while the loss keeps track of the errors. **Figure 2** provides a way to monitor the performance of models, including whether they are learning and improving at the progressive stages with each epoch.

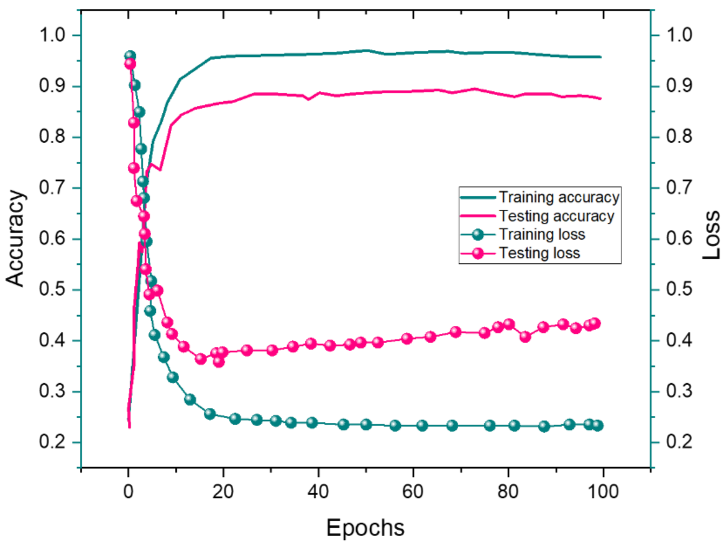

Figure 2. Accuracy and loss.

The output frames display the processed samples with key points marked, which represent various classes relevant to the study. Each key point highlights specific biomechanical parameters, facilitating a visual understanding of the model's predictions. As illustrated in **Figure 3**, these marked key points serve as critical indicators for evaluating the performance and accuracy of the optimization process.

Figure 3. Specific points of biomechanical parameters.

Accuracy measures the number of correct predictions of the model with all predictions. In this case, it shows how well it can optimize the biomechanical parameters, thus showing the efficiency of the training and the performance of the model regarding prediction for the desired outcomes in athletes.

The accuracy attained by the suggested methodology is shown in **Figure 4**. The suggested model achieves an accuracy of 90.02% when compared to alternative approaches. By contrast, the accuracy rates for Random Forest (RF), Multi-layer perception (MLP), and Support Vector Classifier (SVC) were 85.03%, 71.42%, and 63.26%, respectively. When compared to other methods currently in use, EPSO-DFNN produces better results for optimizing the biomechanical parameters of athletes.

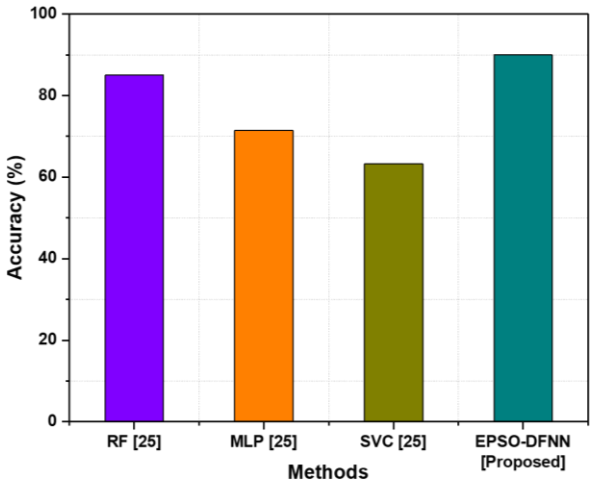

Figure 4. Results of accuracy

The precision of a model is calculated as the ratio of true positive predictions to all positive predictions. When optimizing biomechanical parameters, the algorithm's beneficial outcomes are consistent, demonstrating its capacity to prevent false positives in forecasting successful athlete biomechanics. Precision in the improving biomechanical parameters refers to the level of efficiency and consistency in measurements and forecasts based on advanced mathematical models. It demonstrates the model's capacity to minimize parameter estimation errors, ensuring that the improved biomechanical outputs precision meet the predicted goals. High precision is essential to increase the dependability and efficacy of biomechanical designs, resulting in better performance, safety, and capability in applications such as sports and rehabilitation.

Figure 5 illustrates the precision that the suggested methodology achieved. When the suggested model is compared to other methods its precision is 91.42%. In comparison, RF, MLP, and SVC had precision rates of 85.10%, 73.76%, and 66.57%, respectively. In terms of optimizing the biomechanical parameters of athletes, EPSO-DFNN yields superior results than other currently used methods.

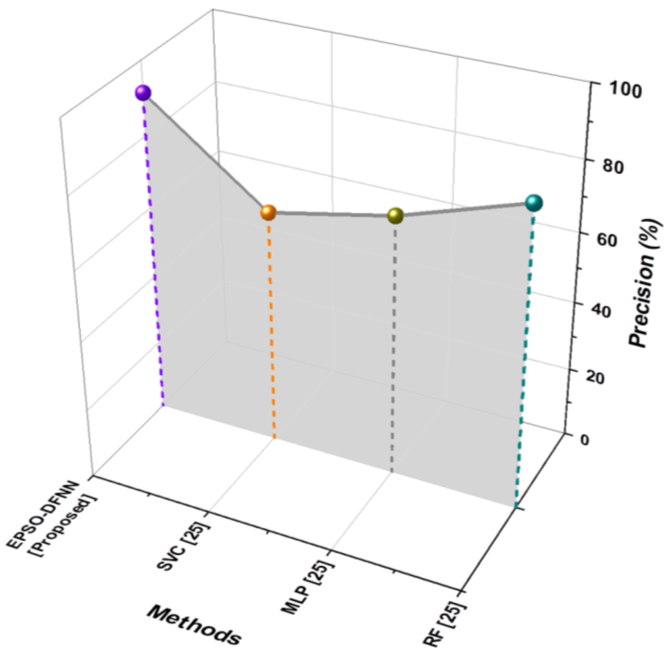

Figure 5. Results of precision

Recall is a task performance metric that measures a model's ability to recognize relevant occurrences. Recall, also known as sensitivity, evaluates the number of actual positive occurrences correctly predicted by the proportion of genuine positive predictions, evaluating the model's ability to catch all important samples. In the context of improving biomechanical parameters using advanced mathematical modelling, recall access how well the model detects the correct biomechanical configurations, ensuring accurate predictions that could increase performance and injury prevention in physical sports.

The recall that was attained with the suggested methodology is shown in **Figure 6**. The recall of the suggested model is 89.69% when compared to alternative techniques. The recall rates of RF, MLP, and SVC were 85.03%, 71.42%, and 63.26%, respectively. Compared to other existing methods, EPSO-DFNN generates superior outcomes when it is used for optimizing the biomechanical parameters of athletes.

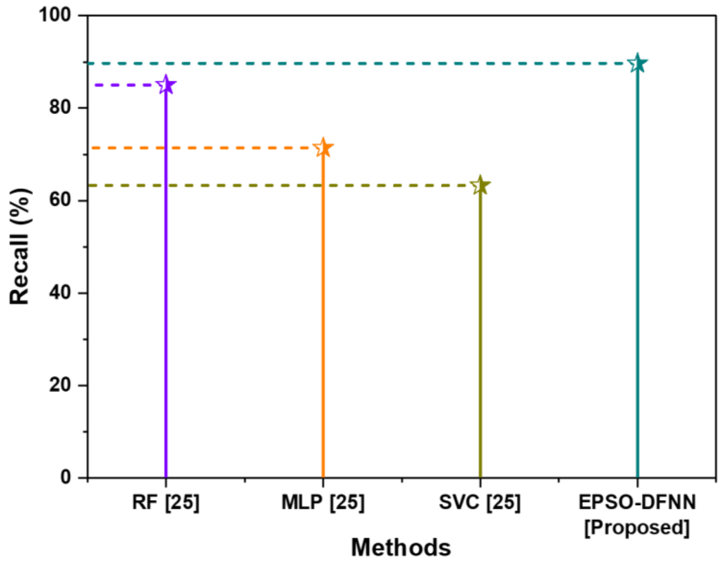

Figure 6. Results of recall

The F1-score is an important evaluation statistic it expresses the harmonic relationship between precision and recall. When improving biomechanical parameters using advanced mathematical modelling, the F1-score is used to measure the model's accuracy in forecasting relevant results. Recall evaluates the correctness of positive predictions, whereas recall examines the ability to recognize all relevant occurrences. A high F1-score indicates balanced overall performance, reducing both false positives and false negatives in biomechanics.

The F1-score that was attained with the suggested methodology is shown in **Figure 7**. This model's F1-score is 92.76% when compared to alternative approaches. In contrast, the F1-score rates for RF, MLP, and SVC are 84.99%, 71.57%, and 61.80%, respectively. EPSO-DFNN outperforms other existing techniques in terms of optimizing athletes' biomechanical parameters. **Table 1** shows the values of suggested and existing methods.

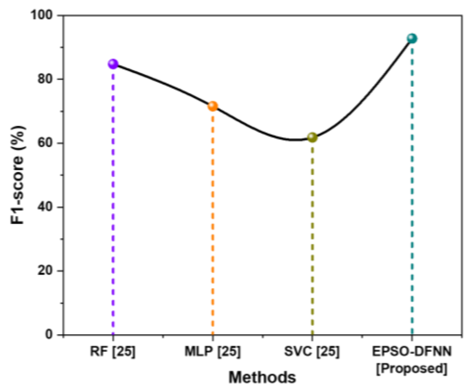

Figure 7. Results of F1-score.

Table 1. Values of suggested and existing methods.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
RF [25]	85.03%	85.10%	85.03%	84.99%
MLP [25]	71.42%	73.76%	71.42%	71.57%
SVC [25]	63.26%	66.57%	63.26%	61.80%
EPSO-DFNN (Proposed)	90.02%	91.42%	89.69%	92.76%

4.2. Discussions

The most commonly used algorithms in optimizing the biomechanical parameters are RF, MLP, and SVC, but each has critical limitations. While suffering from overfitting, especially with high-dimensional data, the random forest fails to capture many intricate relations within biomechanical parameters. MLP is very powerful, but a tremendous number of hyperparameter tuning is required, and it usually fails to converge in non-linear problems, hence obtaining a rather suboptimal performance. SVCs suffer from outliers but also do not scale well with big data sets, which is common in biomechanical analysis. To overcome these limitations, it proposes EPSO-DFNN as a novel algorithm by combining the optimization abilities of the Emperor Penguin Search with the adaptive learning capabilities of dynamic feedforward networks. This hybrid approach improves exploration and exploitation at the solution space by overcoming overfitting, convergence, and scalability. EPSO makes use of its global search to effectively fine-tune biomechanical parameters within an EPSO-DFNN environment so the performance improves and the insights will be more reliable when optimizing athletic performance. This work builds on prior research by introducing the EPSO-DFNN hybrid algorithm, which combines emperor penguin search optimization’s global search capabilities with dynamic feedforward networks’ adaptive learning qualities. This unique technique efficiently addresses the concerns of overfitting, convergence, and scalability that plague standard algorithms such as RF, MLP, and SVC. EPSO-DFNN improves performance and reliability in optimizing biomechanical parameters by increasing exploration and exploitation within the solution space, making it particularly well-suited for high-dimensional data in athletic performance analysis.

5. Conclusions

The study successfully developed a framework for the design and optimization of parameters in biomechanics at universities based on mathematical modeling. The novel Emperor Penguin Search-driven Dynamic Feedforward Neural Network (EPSO-DFNN) was introduced for the improvement of the optimization of athletes’ biomechanical parameters. All critical biomechanical parameters from a comprehensive dataset for athletes across different sports were considered, including muscle activation patterns, joint angles, forces, and movements. The Z-score normalization was used for data preprocessing, and FFT-based feature extraction was utilized in the empirical tuning of athletic movement optimization concerning individual biomechanical parameters. The EPSO-DFNN outperformed various evaluation criteria, achieving an F1-score of 92.76%, precision of 91.42%, accuracy of 90.02%, and recall of 89.69%. These findings indicate that the proposed method has an intriguing potential for increasing athletic capabilities when compared to standard methods. It emphasizes the potential for mathematical modeling to optimize biomechanical aspects and provides vital information that may help to significantly improve athletic performance and safer practicing settings. The EPSO-DFNN may require significant computational resources to train big data sets, and it is likely to be very sensitive to both hyperparameter selection and initialization. Further study can help lead efforts to improve the efficiency of the EPSO-DFNN by hybrid approaches that connect it to other types of optimizations. Finally, using portable detectors to feed real-time data can help athletes better monitor their performance. It would extend the analysis and application of biomechanical optimization by incorporating numerous sports, psychological aspects, and so on, with results that would allow for more tailored therapies for athletes.

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

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