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Article

Pattern recognition and classification of physical education teaching movements based on biomechanics

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Abstract: In physical education teaching, motion analysis techniques are very crucial in teaching, standardizing the methods of teaching, and improving student performance. This study examines biomechanics and its application on how deep learning (DL) techniques together with motion capture data can be used for classifying and recognizing the different movements in teaching PE. Using stationary cameras, the collection includes high-quality motion capture recordings of various PE activities, such as running, passing, jumping, crossing, and dribbling. Normalization and noise reduction are preprocessing processes that help to improve the quality and integrity of the data. Biomechanical characteristics are gathered to depict movement dynamics that incorporate significant elements, such as the angle of joints, angular velocity, angular acceleration, and joint displacement. The Intelligent Tunicate Swarm Search deep convolutional recurrent neural network (ITS-DCRNN) technique uses these characteristics as inputs for classification models. The proposed model is assessed on various types of metrics, including accuracy (98.58%), precision (98.23%), recall (98.87%), and F1-score (98.89%). The results show that the suggested system of teaching assessments is effective. According to the findings, biomechanics-based pattern recognition can improve PE teaching methods by providing educators with data-driven insights on movement performance and areas for improvement. This strategy can result in more efficient teaching techniques, improving student learning results while lowering the chance of harm.

Keywords: physical education; pattern recognition; teaching movements; biomechanics; motion capture

1. Introduction

Physical education (PE) is crucial in the development of physical capacities, embracing healthy habits, and teaching and practicing bodily skill procedures. It seems like an indispensable part of educational systems worldwide, striving not only to enhance the overall skills but also cognitive skills and emotional and social development [1]. The teaching of PE is a complex process that requires a high level of precision in teaching methods and optimizing movements involved in intricate sports activities [2].

Biomechanics provides relevant techniques for enhancing the pedagogy of PE motor tasks, such as mechanical principles, which provide a rational basis for estimating and enhancing physical activities [3]. Teachers use biomechanics principles to establish ways of performing movements in efficient ways, prevent injuries, and enhance learning. Teachers can create efficient research-based teaching strategies that correspond to the physiological and psychological specifications of their students through the integration of biomechanics into PE [4]. **Figure 1** describes the physical movement activities.

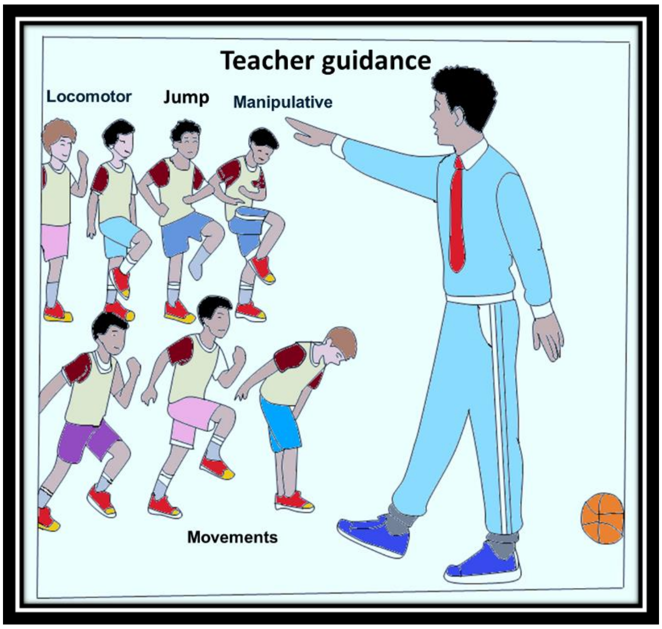

Figure 1. Examining the function of physical activity in the identification and categorization of biomechanical patterns.

1.1. The evolution of PE

The philosophy of PE has evolved to encompass a wide range of benefits, beyond simply providing regular physical activity for children [5]. In PE, difficult actions involving several joints require balance, strength, flexibility, and focus. These movements are necessary for various physical sports and activities like gymnastics, basketball, soccer, and athletics [6]. Each student has distinct anatomical and physiological traits, and sprinting mechanics highlight the significance of stride length and arm motion in reaching maximal speed with a low amount of energy consumption [7]. By evaluating these variations and developing customized training programs, biomechanics assists the teachers in making sure that children of all skill levels can engage in physical activities safely and efficiently. By examining variables including velocity, acceleration, and trajectory, kinematics focuses on the study of motion. This idea is highly beneficial for teaching sports like throwing, sprinting, and jumping [8]. Kinetics is the motion of factors such as gravity, friction, and muscle power; these factors enable the teacher to direct the students towards movements, which are performed in the most efficient method with less strain on the body. Biomechanics teaches students to control their center of mass relative to their base of support, improving stability in activities like gymnastics and martial arts [9]. High-quality biomechanical tools, such as motion capture systems and force plates, can be expensive, limiting their availability in schools [10]. Younger students find it challenging to understand biomechanical concepts, so educators need to adapt these ideas into relatable and engaging activities. The objective is to develop a pattern classification system for PE teaching movements using biomechanics, leveraging DL algorithms and motion capture data to enhance teaching effectiveness and student performance while minimizing injury risks.

1.1.1. Key contribution

The main contributions are as follows:

- This research investigates the use of biomechanics in the classification and pattern recognition of PE teaching movements by utilizing DL algorithms and motion capture data.
- Initially, physical education activity motion data gathered include high-quality motion capture recordings of a variety of PE activities, such as running, passing, jumping, crossing, and dribbling.
- After that, data preprocessing is performed using a robust scaler for normalization and a Savitzky-Golay filter for smoothing the data. Feature extraction using the Fast Fourier transform (FFT) illustrates significant components of movement dynamics, and biomechanical features are collected, including joint angles, velocities, accelerations, and angular displacements. Intelligent Tunicate Swarm Search deep convolutional recurrent neural network (ITS-DCRNN) technique uses these characteristics as inputs for classification models.
- The outcomes display that ITS-DCRNN performs better than existing algorithms in the classification of PE movements.

1.1.2. The work organization is as follows:

The work is planned as follows: Section 2 defines related work, section 3 demonstrates methods, section 4 evaluates the result, section 5 explains the discussion, and section 6 concludes the article.

2. Related work

The article addressed issues such as inadequate data by combining biomechanical data and medical images to create a sports injury prediction model for calisthenics, lack of comprehensive models, and insufficient real-time monitoring [11]. Machine learning (ML) methods to classify features were joint angles, muscle strength, and motion data. Real-time monitoring achieved high accuracy, enhancing injury prevention and athlete safety. The study explained the leverage of sports biomechanics and ML methods to predict and address joint injuries in basketball training, with a focus on athletes in collegiate leagues, such as the Basketball Super League [12]. The improved Extreme Learning Machine (ELM) regression model enhances injury prediction accuracy, supports advanced athlete health monitoring, and optimizes training programs. The biomechanical properties of taekwondo practitioners' horizontal kicks were examined through the use of ML [13]. It offered insights into the biomechanics of athletes' kicking technique by fusing ML algorithms with the examination of technical martial arts motions. It provided insightful findings on performance optimization and demonstrated how well neural networks (NN) differentiate between different kick phases. Research developed models that accurately predict and examine the dynamics of human mobility. Pre-processing was used to extract important characteristics from the skeletal structure following computer vision was used for skeleton recognition and tracking [14]. To identify motion patterns, these characteristics are input into a variety of ML models, such as support vector machine (SVM). It highlighted the practicality of multiple algorithms in a variety of scenarios, such as robots, and security systems, while addressing their benefits and drawbacks. The article explained comprehensive data collected through an exhaustion procedure connecting shoulder internal and external rotation movements. It focused on evaluating physical fatigue and biomechanical characteristics by capturing demographic, anthropometric, sensor-based data electromyography, inertial measurement unit, and photoplethysmography [15]. It supports the growth of exhaustion recognition processes and enhanced understanding of shoulder biomechanics under fatigue. A study proposed an intelligent student movements assessment organization using the DL [16] technique for operative student monitoring in PE. This system utilized deep convolutional neural networks (DCNN) to classify risky actions, assess learners' progress, retention, and achievements, and provide targeted improvements while comparing the performance of the proposed model to traditional teaching methods. **Table 1** displays the summary of the literature review.

Table 1. Summary of literature review.

Reference	Objective	Results	Limitations
[17]	The research combined musculoskeletal modeling and advanced ML methodologies for spine analysis using a single camera.	The result showed potential in performance optimization and risk evaluations.	Limitations in prediction accuracy, complex interactions, and external load estimation.
[18]	The article described a new physics-based DL technique for determining customized muscle-tendon characteristics and forecasting muscle forces without the need for labeled training data.	The approach accurately identifies muscle-tendon parameters and obtains a greater coefficient of determination and a smaller root mean square error (RMSE) than baseline methods.	Despite its advantages, the method requires extensive experimental validation and faces challenges in scalability to other joints or populations.
[19]	The study described the comprehensive fitness monitoring solution using service robots, leveraging cloud computing, big data, and AI for enhanced physiological parameter tracking.	The Service Robot-based system improved user experience by 4.68%, offering richer application scenarios and more significant effects in fitness monitoring and disease risk reduction.	Existing methods were simple and unstable, and the new system's practicality and scalability in diverse real-world environments require further evaluation and optimization.
[20]	Investigated event identification and recognition in sequential images through key point estimation, utilizing body part size, location, and contextual parameters. ML is employed for classification.	The results demonstrated strong performance with high accuracy, precision, and recall on the UCF-101 dataset, highlighting the effectiveness of recognizing actions within the dataset.	The method's performance on diverse datasets and its applicability to real-world, dynamic environments require further exploration.
[21]	The study offered a data analysis model based on physiological variables for performance forecast and fitness calculations in recreational sports.	The combined Lasso and regression models within a Stacking framework achieved a coefficient of determination of 0.9832, outperforming individual models in accuracy and stability.	The study's reliance on physiological data limits the generalizability to diverse populations, and future research should address real-world application challenges, such as sensor accuracy and data diversity.
[22]	The article explained the physical workout monitoring process by utilizing ML to identify exercises from live video streams.	The proposed framework classifies physical exercises with 89% precision, recall, and F1-score using the ML technique.	The system struggles with occlusions or low-quality video streams, limiting its applicability in real-world scenarios.
[23]	A study optimized the energy efficiency of wearable biomechanical data analytics by exploring sensor locations and channels for minimizing data processes.	The upper arm location with the Y-axis of the accelerometer emerged as the optimal configuration, reducing energy consumption for continuous precision medicine.	The study focuses on specific sensor configurations, limiting generalizability to other body parts or sensor types.

3. Methodology

This study's objective is to establish a pattern recognition and classification system for PE teaching movements using biomechanics. Initially, PE activity motion data is gathered from stationary cameras, the collection includes high-quality motion capture recordings of a variety of PE activities, such as running, passing, jumping, crossing, and dribbling. Data preprocessing using a robust scaler standardizes data by reducing the impact of outliers, and scaling features, and improving pattern classification performance analyses movement patterns in PE and Savitzky-Golay filter smoothing assistances eliminates noise, ensuring data accuracy and consistency. Feature extraction using FFT illustrates significant components of movement dynamics, and biomechanical features are collected, including joint angles, velocities, accelerations, and angular displacements. ITS-DCRNN technique uses these characteristics as inputs for classification models. **Figure 2** shows the proposed framework.

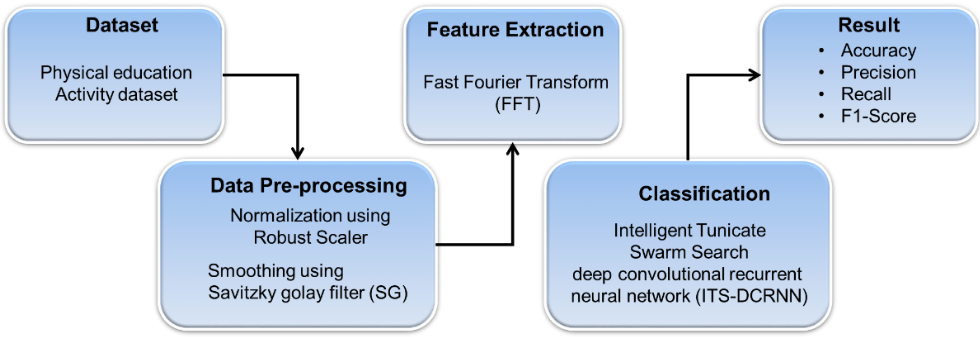

Figure 2. Proposed framework for physical education teaching movements.

3.1. Dataset

The UCF101 Action Recognition Dataset is a comprehensive video dataset that includes 101 distinct human action classes, including "knitting,""surfing," and "playing guitar." A unique action class is assigned to each of the 13,320 video clips that were gathered from YouTube. The dataset is difficult for action identification tasks since it contains a variety of perspectives, sizes, camera movements, and lighting conditions. Human-object interaction, Body-Motion Only, Human-Human Interaction, Playing Musical Instruments, and Sports are the five categories of action classes. In computer vision, it is frequently used as a benchmark dataset for action recognition model evaluation and training. There are 13,320 video clips in the collection. Three sets of the dataset are separated: test, validation, and train.75% of each action class is included in the train set. The test and validation set each received an equal portion of the remaining 25% of the dataset.

The action class label given to the video clips within a subfolder determines the subfolder's name.

A CSV file containing the names, locations, and labels of the clips in each set directory is linked to the set.

The goal is to develop a pattern classification system for PE teaching movements using biomechanics. The data features high-quality motion capture recordings of diverse PE activities, including running, passing, jumping, crossing, and dribbling, captured using stationary cameras. Each activity is documented in full HD with a frame rate of at least 30 fps. It enables detailed biomechanical analysis and performance evaluation, supporting studies on movement optimization and injury prevention in sports and education.

3.2. Data preprocessing

After collecting the data, preprocessing is performed using the robust scaler to standardize the data by reducing the impact of outlines scaling features and improving patterns classification performance. Savitzky-Golay filter is used for smoothing in to eliminate noise, which ensures that the data obtained is accurate and consistent.

3.2.1. Robust scaler

Robust scalers are applied to data normalization to scale features. They make the model resilient to outliers. The features are scaled using the IQR, and the median is excluded in such scaling. This is how one can scale features by decreasing their sensitivity to outliers compared with ordinary techniques such as *z*-score normalization or min-max scaling. It is very useful in recognition and classification of patterns, especially in teaching movements in PE on the basis of biomechanics because it makes the model stable even when values in the data are extreme. The IQR is the interval between the first quartile, that is, (25_{th} quantile), and third quartile, that is, (25_{th} quantile) as shown in Equation (1).

$$RS(Y_j) = \frac{(Y_j - median\ (y))}{IQR_{1,3}\ (Y)} \tag{1}$$

where Y stands for the data point and plus signs are represented with the notation$RS(Y_j)IQR_{1,3}\ (Y)$. The IQR represents a real number that is defined by difference of the first and the third-quartile of data. The IQR being an excellent measure of spread determines a distribution of middle 50% of data. This, $Y_j - median\ (y)$ refers to a metric of a measure for a central propensity to which random fluctuations don't apply significantly$RS(Y_j)IQR_{1,3}\ (Y)$.

3.2.2. Savitzky-Golay filter (SG)

The SG filter is a smoothing technique that reduces noise in biomechanical data, such as motion capture recordings. This method also called a digital filter, is used to smooth data while preserving important features like trends and peaks. It applies a polynomial smoothing technique to a set of data points, which helps reduce noise and outliers, making the data more suitable for analysis. Local least-squares and polynomials approximations of the processed data filter function, an SG filter lowers the noise and locates the noisy input signal's trend line and the moving window method is SG filtering. The main factor influencing SG's improved smoothing capabilities is the polynomial function's order, filter coefficients require computed, and smoothing performance improves with window size. By solving the Equation (2), the method determines a local polynomial regression on the input data.Z is the dependent variable and $b_0 + b_1y + b_2y^2 + \cdots + b_ly^l$ is the polynomial coefficient considering the coefficients of the smoothing procedure remain consistent across all

H values, Savitzky and Golay's initial investigation demonstrated that a moving polynomial fit is $(T^S - T)^{-1} = [h_0, h_1, \dots, h_m]$mathematically managed in the same method as a weighted moving average using Equation (3).

$$Z = b_0 + b_1 y + b_2 y^2 + \dots + b_l y^l \quad (2)$$

$$H = T(T^S - T)^{-1} = [h_0, h_1, \dots, h_m] \quad (3)$$

$e_m(s)$is the result of the weighted sum conceivably an error or a signal at state s coefficients weights for the terms in the summation, indexed$\sum_{j=-n+1}^{n} g_{m,0,s,n,j} w_j$ using Equation (4). Where $e_m^{(t)}(s)$ weighted sum of specific time state t which is the point of symmetry midway, determined by the distinction and smoothing using Equation (5).

$$e_m(s) = \sum_{j=-n+1}^{n} g_{m,0,s,n,j} w_j \quad (4)$$

$$e_m^{(t)}(s) = \sum_{j=-n+1}^{n} g_{m,t,s,n,j} w_j \quad (5)$$

The SG filter smooths biomechanical data, including joint angles, velocities, and accelerations. It reduces noise and preserves movement trends, improving the precision of pattern recognition, classification, and biomechanical analysis for movement optimization and injury prevention.

3.3. Feature extraction using FFT

FFT is used for feature extraction from motion capture data of PE activities, enabling the identification of key movement patterns, frequencies, and intensities. This kind of analysis is essential for evaluating and carrying out actions such as running, passing, jumping, crossing, and dribbling. FFT is an advanced mathematical device that converts time signals into frequency for easy analysis. Motion capture recordings are initially captured in the time domain wherein each measurement vector is a movement measurement taken at a certain instant in time. Signals could be the joint angles, velocities, or positions of different parts of the body in the event of physical activity involving sprinting, leaping, or even dribbling. FFT is a technique that differentiates a time signal, from a frequency signal, and the end product is referred to as the frequency spectrum and it shows the distribution of signal energy across its frequency components. It highlights recurring or periodic patterns in the data and assists in comprehending how the signal reacts at different frequencies. W_l is the frequency component of the transformed signal. $\sum_{m=0}^{M-1} w_m f^{-j2\pi lm/M} + l = 0, \dots, M-1$ denotes comprises information amplitude and the signal is converted into the frequency domain using an elaborate exponential kernel using Equation (6).

$$W_l = \sum_{m=0}^{M-1} w_m f^{-j2\pi lm/M} + l = 0, \dots, M-1 \quad (6)$$

FFT consists of several frequency components, which provide amplitude that indicates the power and strength at that specific frequency. Higher harmonics extracted from deviations from ideal periodicity often indicate inefficiencies and irregularities in the movement.

3.4. Classification using intelligent tunicate swarm search deep convolutional recurrent neural network (ITS-DCRNN)

ITS-DCRNN techniques to enhance biomechanical assessment in PE and modify instructional methods. This approach enhances student performance and flexibility in physical activities. PE by encouraging collaborative dynamics and tailoring educational methods. This approach uses social interactions and gait movements to identify areas for development and accommodate different learning styles.

3.4.1. Deep convolutional recurrent neural network (DCRNN)

The DCRNN model plays different roles in the PE teaching movement categorization. It offered to develop efficient ways of teaching by analyzing the biomechanical properties of complex movements in PE. DCRNN is able to learn complex behaviors by incorporating the recurrent layers used in learning the temporal sequence of the data as well as the convolutional layers, which are utilized in learning the spatial features of the data. It captures fine movement dynamics by applying biomechanical parameters, such as joint angles and motion trajectories. This improves reliability in movement categorization. Such reliability allows teachers to assess and fine-tune their methods. Other features of DCRNN aside from these are that it supports the enhancement of physical education activities. Equation (7) indicates the input categorization vector t_s and the hidden state is $X_{wt}w_s$ is the feature matrix of $X_{tt}t_{s-1} + a_t$ fitting biomechanical features.

$$t_s = (X_{wt}w_s + X_{tt}t_{s-1} + a_t) \tag{7}$$

DCRNN is an effective structure for identifying and categorizing PE instructional motions.$X_{tp}t_s$ feature matrix derived from the input biomechanical data t_s temporal step of the movement sequence. p is a nonlinear activation function using Equation (8).

$$z_s = p(X_{tp}t_s + a_z) \tag{8}$$

Equation (9) denotes the transformations of the time-domain signal $\{y(s)\}(\tau, \omega) \equiv S(\tau, \omega)$ into the frequency domain. $\int_{-\infty}^{+\infty} y(s)\omega(s-\tau)f^{-e\omega s}cd$is the frequency function and time index of $f^{-e\omega s}\, cd$ window function localized analysis. The movement signals for frequency patterns relevant to physical movements using Equation (9).

$$STFT\, \{y(s)\}(\tau, \omega) \equiv S(\tau, \omega) = \int_{-\infty}^{+\infty} y(s)\omega(s-\tau)f^{-e\omega s}\, cd \tag{9}$$

where $X_{ST} \times S_s + X_{tt}$ and $X_{tt} \times T_{s-1} + A_t$ indicate transform point of the hidden layer X_{ST} to input layerS_s. The activation function is $T_s = \sigma$ using Equation (10).

$$T_s = \sigma(X_{ST} \times S_s + X_{tt} \times T_{s-1} + A_t) \tag{10}$$

The transformation function of Z_s links biomechanical features to movement classification $p(X_{zt} \times T_s + A_z)$ using Equation (11). The movement classification is expressed as a vector of concatenation biomechanical valuations of the current layer of $\hat{q} = \sigma(X_g \times g + a_g)$. The process of convolution occurs during the input transition to the hidden layers and operates among weights and inputs using Equation (12).

$$Z_s = p(X_{zt} \times T_s + A_z) \tag{11}$$

$$\hat{q} = \sigma(X_g \times g + a_g) \tag{12}$$

Gradient loss function that $K(q, \hat{q})$ it enabling backpropagation of $\frac{1}{2}||q - \hat{q}||_2^2$. Convolutional layers are used to obtain spatial characteristics, and temporal relationships of motions are adequately modeled using Equation (13).

$$K(q, \hat{q}) = \frac{1}{2}||q - \hat{q}||_2^2 \tag{13}$$

To discover parameters for optimization, gradient descent is used $(q - \hat{q})\sigma'(.)g$ and computes the grade loss function with deference to parameters $\frac{\partial K}{\partial X_g}$ using Equation (14).

$$\frac{\partial K}{\partial X_g} = -(q - \hat{q})\sigma'(.)g \tag{14}$$

In biomechanical evaluation, identifying significant movement patterns or approaches is usually essential, since these distinctive traits are not distributed uniformly across the PE teaching movement. $\sum_{i=1}^{m}\left(\Phi w_{ji}(0) - \Phi w_{ji}\right)^2$ identifies the complex movement patterns, and crucial biomechanical elements, and selects the T_{w_j} traits that correspond to various hidden levels using Equation (15).

$$T_{w_j} = \sum_{i=1}^{m}\left(\Phi w_{ji}(0) - \Phi w_{ji}\right)^2 \tag{15}$$

These equations are combined to determine and categorize actions by improving performance and reducing injuries in PE. Finding significant patterns and performance metrics during the mapping of movement sequences to biomechanical parameters significantly improves instructional techniques. The model's structural architecture includes several convolutions and layers to extract and enhance movement characteristics, creating a powerful classification system. Teachers use this strategy to improve their students' performance in PE while utilizing their teaching skills.

3.4.2. Intelligent tunicate swarm search (ITS)

The ITS algorithm is influenced by social interactions and movement actions. This optimization approach helps the process of identifying complex difficulties, such as biomechanical evaluations in PE. In biomechanical analysis, teachers enhance their approaches to teaching complex motions in PE. It effectively simplifies model parameters by establishing a balance between local exploitation and global exploration, adopting influence through the swarm intelligence of tunicates. The search agents' assignments are determined to force them to perform enough local exploration close to the ideal individual to locate the best solution of the current iteration. ITS uses motion capture data to improve the reliability of biomechanics-based movement analysis

$W(s)$ is vector that determines every agent's new location; $W_{best} - \vec{B}\,.\overrightarrow{OC}\,, if\ q_{rand} < 0.5$ assigns the agent investigates the area close to the ideal individual positive stage of $W_{best} + \vec{B}\,.\overrightarrow{OC}\,, if\ q_{rand} \geq 0.5$ is updated the position of Tunicate using Equation (16).

$$W(s) = \begin{cases} W_{best} - \vec{B}\,.\overrightarrow{OC}\,, if\ q_{rand} < 0.5 \\ W_{best} + \vec{B}\,.\overrightarrow{OC}\,, if\ q_{rand} \geq 0.5 \end{cases} \tag{16}$$

Swarm Behavior:

The search agents interchange position information based on the tunicate's swarm behavior. The technique is based on the current search agent's updated location and is impacted by its placement in the next iteration. This is accomplished by using swarm behavior to update the position of the preceding person and the ideal individual. The mathematical function is the following, where $\overrightarrow{W_J(s+1)}$ size of tunicate function population is $\frac{\overrightarrow{W_J(s)}+\overrightarrow{W_{J-1}(s+1)}}{2+d_2}$the location of the current exploration agent in the next iteration of $\overrightarrow{W_J(s)}$ computed by Equation (17).

$$\overrightarrow{W_J(s+1)} = \begin{cases} \dfrac{\overrightarrow{W_J(s)} + \overrightarrow{W_{J-I}(s+1)}}{2+d_2}\ if\ j > 1 \\ \overrightarrow{W_J(s)}\ if\ j = 1 \end{cases} \tag{17}$$

Update Swarming Behavior:

Utilize the biological foraging strategies of the tunicate to modify their locations. The leader attracts the attention of other tunicates, which imitate the group's progress towards potential solutions. Tunicates interact with their neighbors to strike a balance between exploitation and improving on known excellent regions) and exploration, exploring new areas. $K(t)$describes the asymptotic behavior of a probability density function of $\frac{\alpha\beta\Gamma(\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\pi|t|^{1+\beta}}$ which typically represents a Lévy distribution for large $t \to \infty$ using Equation (18).

$$K(t) \to \frac{\alpha\beta\Gamma(\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\pi|t|^{1+\beta}}, t \to \infty \tag{18}$$

Substantiate the termination conditions, such as the convergence of fitness values or the maximum number of iterations function T. The probability distribution function of $\frac{v}{|u|^{\frac{1}{\alpha}}}$ creates a novel population-based metaheuristic algorithm to tackle several issues that are challenging to resolve using current optimizing methods using Equation (19).

$$T = \frac{v}{|u|^{\frac{1}{\alpha}}} \tag{19}$$

The ITS draws inspiration from two key behaviors of tunicates: jet propulsion and swarm intelligence.

- The jet propulsion process involves the backward ejection of high-speed liquid or gas, enabling tunicates to move efficiently and rapidly adapt to their environment.
- Swarm intelligence (SI) denotes the cooperative performance of regionalized, self-organized groups, whether natural or artificial. Tunicates exhibit SI by coordinating as a group to locate and exploit food sources effectively. **Figure 3** illustrates how swarm intelligence relates to tunicates' jet propulsion. Water enters and exits the tunicate during jet propulsion, creating motion. This motion's direction depends on the leader tunicate being followed by other tunicates. This is a concept that is very similar to swarm intelligence, which states that one entity in this example, several entities follow a certain action to accomplish a goal, so to speak. To improve learning and decision-making abilities, this may be utilized to maximize pattern recognition and categorization, which are motivated by natural behaviors and implemented in physical education motions.

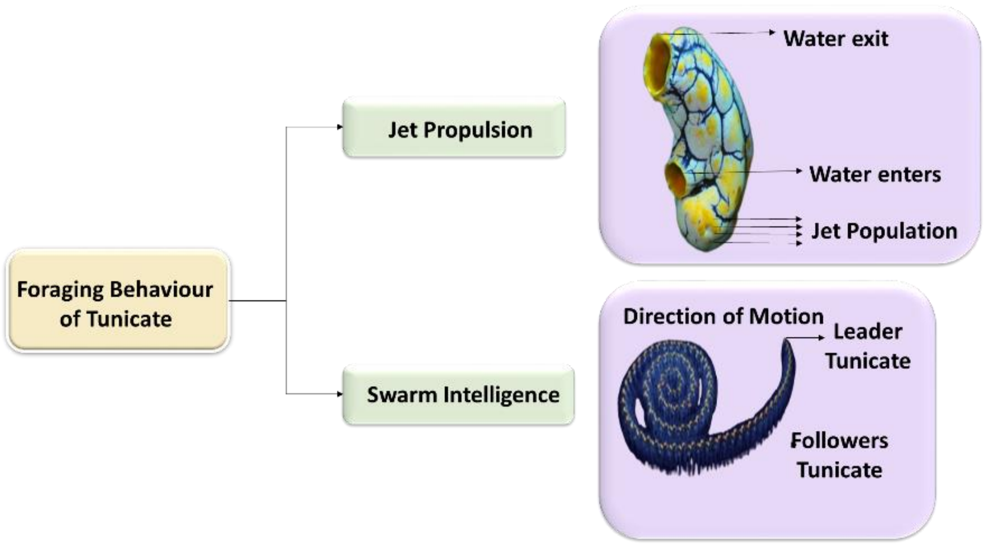

Figure 3. Foraging behavior of intelligent tunicate swarm search.

This model mechanism balances exploration through jet propulsion-inspired moves and exploitation through swarm coordination. Algorithm 1 shows the ITS-DCRNN method.

Algorithm 1 Intelligent Tunicate Swarm Search deep convolutional recurrent neural network (ITS-DCRNN)

```
1. Initialize:
  a. Load data and preprocess.
  b. Define categories for classification.
  c. Initialize Intelligent Tunicate Swarm (ITS) with:
    - Population size (N).
    - Randomly initialize individuals (weights and biases for DCRNN).
2. Fitness Evaluation:
  a. Define fitness function ( F ):
    - Train DCRNN on a subset of ( D ).
    - Compute accuracy as fitness.
3. ITS Optimization:
  Repeat for \(max\_iterations \) or until convergence:
  a. Update tunicate positions (N):
    - Current best position ( X_{best} ).
    - Attraction towards food and swarm dynamics.
  b. Evaluate for all positions.
  c. Update ( X_{best}) based on highest fitness.
4. DCRNN Training:
  a. Use optimized weights and biases from ITS to initialize DCRNN.
  b. Train DCRNN on the full dataset ( D ):
    - Use convolutional layers for spatial feature extraction.
    - Use recurrent layers (e.g., LSTM/GRU) for temporal dependency modeling.
5. Classification:
  a. Perform forward propagation for test data using trained DCRNN.
  b. Predict movement category based on output probabilities.
6. Output Results:
  a. Evaluate performance metrics (accuracy, precision, recall, F1-score).
  b. Display classified movement categories.
```

The benefits of ITS-DCRNN improve biomechanical assessments in PE by incorporating modern optimization techniques. The model analyses complex movement patterns and identifies key aspects to guide effective training techniques. Improved motor skills and knowledge of varied tasks. ITS customizable instructional strategies improve students' motor skills and ability to perform complex actions. DCRNN algorithm optimizes learning performance by promoting collaboration and personalized training plans and improves the efficacy and adaptability of PE techniques.

4. Result analysis

The purpose of the study is to develop a pattern recognition and classification system for PE teaching movements using biomechanics. Experimental setup: The system with an Intel core i7 10th Gen CPU, 16GB RAM, and a GPU such as an NVIDIA GTX 1660 for DL tasks. The software includes Python with libraries like tensor flow, and NumPy for data processing, extraction, and classification. Data is gathered through motion capture systems like Kinect or cameras, and the development environment utilizes tools like Jupiter Notebook or PyCharm for coding and testing the algorithms. The proposed approach outcomes of accuracy, precision, recall, and f1-score performance indicators for the physical movement category are displayed in **Table 2** and **Figure 4**.

Table 2. Numerical values of movement category.

Movement category	Accuracy	Precision	Recall	F1-score
Running	95.2	94.5	96.1	95.3
Passing	93.8	94.7	93.6	93.8
Jumping	97.4	93.1	93.9	94.2
Dribbling	97.9	97.2	94.1	93.1
Crossing	91.4	95.2	91.3	97.3

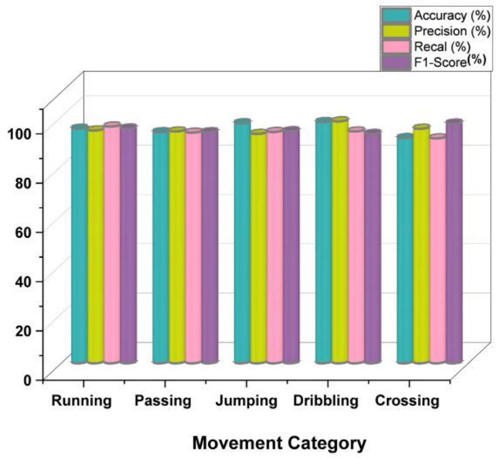

Figure 4. Performance measures for classifying movements in physical education instructional activities.

In the context of pattern identification and classification of instructional motions in physical education concerning biomechanics, the table summarizes the performance metrics Accuracy, Precision, Recall, and F1-score for various movement categories. A high degree of performance in differentiating running is shown by the running category's accuracy of 95.2%, precision of 94.5%, recall of 96.1%, and F1-score of 95.3. High categorization accuracy is also attained by passing and jumping motions. Compared to other actions, the jumping movement has the highest accuracy (97.4%), but it also has the lowest precision and recall. The best precision (97.2%) is attained by dribbling, but the recall and F1 scores are somewhat lower. Despite having the lowest accuracy (91.4%), the Crossing movement has very high precision and F1-score (95.2% and 97.3%), suggesting that its detection is comparatively low. Although it is somewhat less common, when it is found, it is quite accurate. These findings demonstrate that by using biomechanics data, the model could identify various PE movements quite accurately.

4.1. Confusion matrix

Confusion matrices offer a common performance measure for comparing the actual classification of each movement type to that predicted by the model to assess the model's performance in the context of pattern recognition and classification of physical education (PE) teaching movements based on biomechanics. The model's ability to distinguish between distinct movement types, such as running, passing, jumping, dribbling, and crossing, is effectively highlighted by a confusion matrix. This makes it possible to monitor the model's strong points and places in need of development to achieve greater accuracy in practical applications.

A confusion matrix for action types, such as running, passing, jumping, dribbling, and crossing is defined as a table that consists of true and predicted action types in which proper identification is represented as diagonal elements whereas all others are represented as non-diagonal elements, which are used in performance evaluation of a model. The best performance is exhibited by the crossing movement type, which is consistently properly predicted (2). With no misclassifications and two accurate predictions, the passing category is also well-predicted. **Figure 5** shows the confusion matrix.

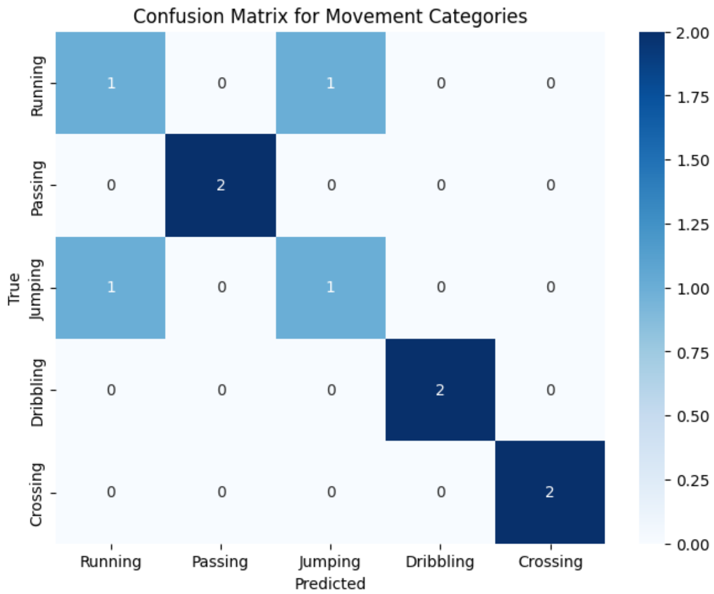

Figure 5. Confusion matrix for movement categories.

4.2. Comparative analysis

The effectiveness of the ITS-DCRNN method and existing methods is evaluated using F1-score, recall, accuracy, and precision. ITS-DCRNN method is associated with the existing approaches, including Co-AwAdaBoost [24], and CNN-LSTM [25]. **Table 3** depicts the numerical values of metrics. In terms of biomechanics-based PE movement categorization and identification, the suggested ITS-DCRNN model performs better than the current approaches, specifically CNN-LSTM and Co-AwAdaBoost. Because Co-AwAdaBoost requires data gathering and processing, which consumes a lot of resources, it is a difficult approach. Additionally, CNN-LSTM is computationally limited, converges slowly, and requires appropriate tuning of both its components. These problems are resolved by the ITS-DCRNN model, which improves accuracy at 98.52 precision at 98.23, and recalls at 98.87, score 98.89. With lowers the computing burden, and simplifies data display. It effectively incorporates biomechanical data to enhance categorization and movement analysis.

Compared to current techniques, it is therefore highly adapted for identifying PE motions with higher accuracy, recall, and overall performance.

Table 3. Numerical values of metrics.

Methods	Accuracy	Precision	Recall	F1-score
Co-AwAdaBoost [24]	98.25	97.22	97.86	97.88
CNN-LSTM [25]	92.4	90.2	91.7	90.9
ITS-DCRNN [proposed]	98.58	98.23	98.87	98.89

4.2.1. Accuracy

The accuracy aids in assessing how effectively the model distinguishes between various movement types when it comes to pattern identification and categorization of biomechanics-based physical education instructional movements. To enhance physical education training and instructional tactics, the model's accuracy increases when its score accurately identifies movement types, such as running, passing, jumping, dribbling, and crossing. The efficacy of movement analysis is precisely impacted by direct categorization, enabling improved teaching strategies and feedback. Accuracy is the degree to which a measurement or computation reflects the nearness of observations to true value and relates to an accurate value or standard represented in Equation (20). It calculates the total percentage of accurate classifications for each movement category. It provides a general indication of the model's performance in categorizing every movement. High accuracy indicates that the model could often discriminate between various movement types. **Figure 6** shows the result of accuracy.

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

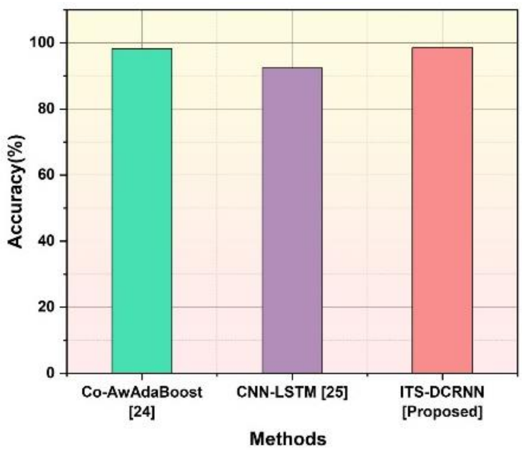

Figure 6. Comparison of accuracy with ITS-DCRNN and other methods.

When comparing with other existing methods, the proposed method attained an accuracy of 98.58% while the existing methods attained values, such as Co-AwAdaBoost attained (98.25%) and CNN-LSTM attained (92.4%). It displays that the proposed method is more effective than other existing methods.

4.2.2. Precision

When it comes to identifying and categorizing biomechanics-based physical education teaching activities, accuracy will be essential in determining how well the model classifies different types of movements. To make sure the model is focused on reducing false positives, precision is calculated as the ratio of accurately predicted positive cases and overall projected positive instances. High accuracy at recognizing certain motions, such as dribbling, passing, and sprinting, without mistakenly classifying them as other activities.

The degree of accuracy in calculating the promise between measurements of the same item is referred to as precision. The biomechanical assessment and effective teaching methods improve instruction in physical education and teachers recognize movement patterns and assess performance efficiency using Equation (21). **Figure 7** depicts the result of precision.

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{21}$$

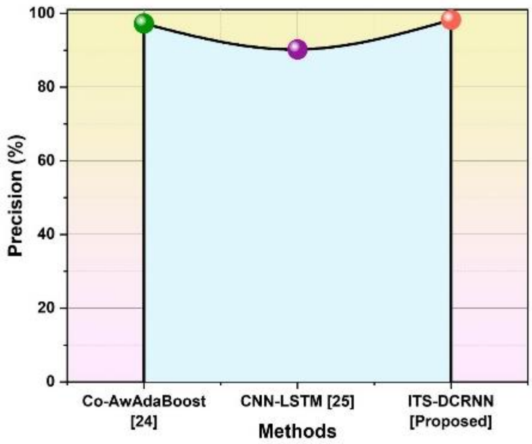

Figure 7. Result of precision with ITS-DCRNN and other methods.

When comparing with other existing methods, such as Co-AwAdaBoost of 97.22% and CNN-LSTM of 90.2%, the proposed method attained a precision of 98.23%. Compared to other existing methods, the proposed method has greater precision. This enhancement demonstrates how well our suggested model classifies physical education motions, making it a useful tool for teachers to improve their lessons and evaluate student performance.

4.2.3. Recall

The capacity of a model to identify each significant incident in a specific collection of data is known as recall. It assesses the model's ability to identify and evaluates the model's ability to correctly identify all instances of a specific movement category. High recall ensures that the model identifies any instances of a movement. Its sensitivity and the importance of capturing true positive instances using Equation (22). Recall is crucial for our task, which is to recognize patterns and classify physical education teaching movements using biomechanics. This is because every example of each movement needs to be correctly identified, which is particularly challenging when there are numerous physical activity types, like running, jumping, or dribbling. **Figure 8** shows the result of the recall.

$$\text{Recall} = \frac{\text{FN}}{\text{FN} + \text{TP}} \tag{22}$$

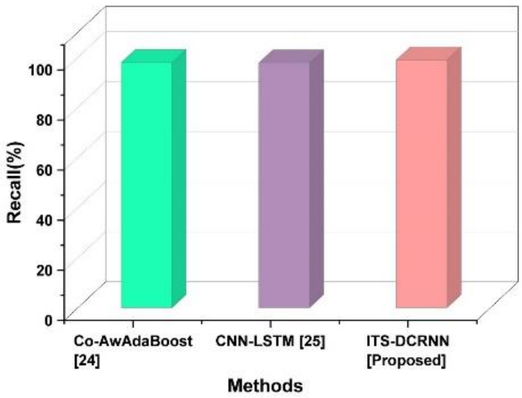

Figure 8. Result of recall ITS-DCRNN and other methods.

When comparing with other existing methods, the proposed method achieved a recall of 98.87% while the existing methods achieved values, such as Co-AwAdaBoost of 97.86% and CNN-LSTM of 91.7%. The suggested method is more accurate than other existing approaches. In real-time applications, where precise movement identification is essential for training and instruction, this is extremely important.

4.2.4. F1-score

When accuracy and recall are combined into a single metric, the F1-score is a crucial performance statistic for assessing model performance, particularly on imbalanced data. The identification and categorization of movement are especially crucial for biomechanical study and instruction in physical education.

When accuracy and recall are combined into a single metric, the F1-score is a crucial performance statistic for assessing model performance, particularly on imbalanced data. The identification and categorization of movement are especially crucial for biomechanical study and instruction in physical education.

The balanced indicator of a model's performance, particularly when dealing with unbalanced data, is the harmonic mean of accuracy and recall. The ability of these models to identify and group various movement patterns in the context of biomechanical research and teaching strategies for intricate movement in physical education is assessed by the F1 score. Equation (23) illustrates how the F1 score is useful for precision and recall. **Figure 9** shows the result of the F1-score.

$$\text{F1} - \text{score} = \frac{(\text{precision}) \times (\text{recall}) \times 2}{\text{precision} + \text{recall}} \tag{23}$$

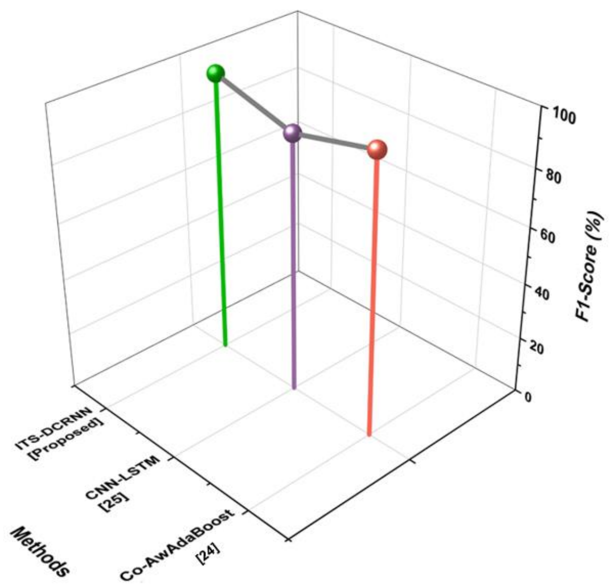

Figure 9. Result of F1-score ITS-DCRNN and other methods.

When comparing with other existing methods, the proposed method achieved an F1-score of 98.89% while the existing methods obtained values, such as Co-AwAdaBoost obtained (97.88%) and CNN-LSTM obtained (90.9%). The suggested method is more accurate than other existing approaches. Such as sprinting, passing, and leaping. The model is more reliable when biomechanical data is incorporated into the categorization process, which makes it especially appropriate for physical education performance evaluation and instructional tactics. This outcome highlights how well the suggested method may enhance movement analysis and maximize physical education training.

5. Discussion

The research discussed the application of biomechanics in the classification and pattern recognition of PE teaching movements through DL algorithms and motion capture data. Co-AwAdaBoost [24], and CNN-LSTM [25] are instances of the available algorithms that have significant drawbacks. The Co-AwAdaBoost model [24] combination with biomechanical data and instructional strategies is cumbersome. This method demands general data collection and processing, which could require an over-abundance of time and resources. Applied to large data sets or real-time applications, CNN LSTM [25] faces several computational limitations. Its functioning is hampered since, it optimal tuning of the two components of the CNN LSTM is a requirement, which leads to overfitting or very slow convergence. The proposed ITS-DCRNN approach is an effective method in dealing with the challenges related to combining biomechanical evaluation and complex movement instruction in PE. It enhances interpretability through simple-to-use data visualization interfaces, reduces computing load, improves modeling accuracy, and streamlines data processing. The proposed method enhances movement analysis by integrating biomechanical data, optimizing instructional strategies, and improving the accuracy of movement identification in PE.

6. Conclusion

A biomechanical evaluation in physical education assists in improving performance and reducing injury risk by analyzing the mechanics of complex actions. Overall body mechanics, movement patterns, and resulting forces during activities presented in the study. To help students comprehend and perform complex physical actions, the instructional technique concentrates on transmission. ITS-DCRNN outperformed traditional algorithms in classification accuracy (98.58%), precision (98.23%), recall (98.87%) and F1-score (98.89%), offering a more effective and data-driven approach to movement analysis. The improvement of teaching methods works to improve safety and prevent injuries, enhancing the quality and safety of PE for students. The limitations include challenges with real-time data processing, as some data would require more optimization due to their size and diversity. Future work will focus on deepening the sensor integration, enhancing the power of computation, and tackling the use of the model in the diversity of PE activities.

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