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Article

Biomechanical analysis and teaching strategies of complex movements in physical education teaching

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Abstract: This study suggests a new method for evaluating students' ordinariness of movement in professional physical education by developing an assessment algorithm based on the biomechanical analysis of complex motions. The study aims to provide purposeful and data-driven techniques for assessing and optimizing movement ability in intricate physical tasks by utilizing higher motion capture and deep learning (DL) approaches, especially the Updated African Buffalo Optimization Based Deep Convolutional Neural Network (UABO-DCNN) categorization. The method includes collecting data utilizing high-precision movement capture equipment to research certain multifaceted movements, preprocessing trajectory data to extract kinematic, temporal, and spatial information, and increasing categorization algorithms with UABO-DCNN. The consequences specify that the algorithm can differentiate between normal and abnormal association patterns with outstanding accuracy. The UABO-DCNN model measures physical education teaching complex movements with accuracy (99.43%), precision (98.12%), recall (98.50%), F1-score (98.56%), and specificity (98.40%). Furthermore, the result is reliable, with a broader tendency toward instructive skill and individualized learning, which requires the development of physical education instruction actions by creating a culture of physical literacy and well-being. The implication of this employment includes an enhanced approach to promote optimal association skill increase in students, particularly for confronting complicated biomechanical measures.

Keywords: physical education; teaching strategies; complex movements; biomechanical analysis; updated African buffalo optimization-based deep convolutional neural network (UABO-DCNN); biomechanical actions

1. Introduction

Student development of their motor, cognitive, and social abilities is greatly aided by physical education. The comprehensive development and lifetime healthy behaviors and teaching complicated motions in physical education is a difficult endeavor that calls for a thorough grasp of biomechanics and efficient techniques for instruction [1]. The biomechanical assessment offers important insights into how complicated movements can potentially be optimized for better performance, injury avoidance, and learning effectiveness to technological improvements. The examined biomechanics can be included in physical education classes, emphasizing its advantages and the methods that improve the instruction of intricate motions [2]. Multiple joints are used in complex motions in physical education, which need balance, strength, adaptability, and concentration. These motions are essential to many physical activities and sports, such as soccer, basketball, athletics, and gymnastics [3]. **Figure 1** shows the movements in physical education.

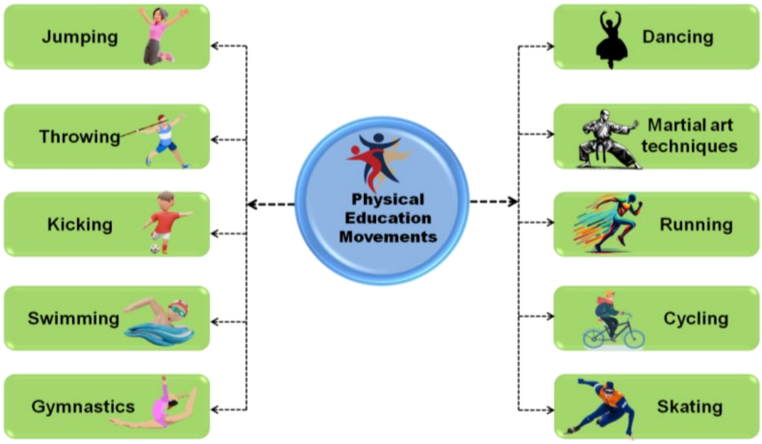

Figure 1. Movements in physical education.

These motions established the groundwork for improved physical performance and overall health; teaching them to learners in an efficient manner is crucial to their motor improvement. Students frequently struggle with complicated motions in traditional physical education training because of ineffective teaching strategies or a lack of knowledge of the inherent biomechanics [4]. The biomechanical strategy for teaching complicated motions improves student performance and the danger of injury while also improving student achievement and safety through scientifically supported motion that prevents incorrect movement patterns [5]. The source for finding how the human body functions and reacts to external influence is biomechanics, the physical actions of apparatus. With the classification of movements to their primary component, biomechanical assessment facilitates physical education instructor to evaluate the pattern of moves exposed by their students, spot incompetence, and maximize their performance [6]. Physical education teachers can assess elements together with body position, speed, force generation, and stimulation of muscles by utilizing movement recognition structures, wearable sensors, or video investigation software [7]. The majority of effectuation patterns can be established by utilizing, which enables teachers to provide students with tailored feedback and performance-improving changes. Excessive stress on certain joints, repeated strain, and deprived movement implementation are the main causes of injury continued in physical activity [8]. By examining stress areas during motions, biomechanical assessment supports the recognition of these hazards and enables educators to change their techniques to lessen the possibility of damage. By modifying landing tactics, one can lower the risk of knee injury by evaluating the forces practical to the knees throughout a leap. Because of biomechanics, educators can adapt their pedagogy to meet the necessities of every learner individually [9]. Biomechanical evaluation can streamline education by dividing intricate actions into smaller portions, therefore facilitating students' understanding of demanding ideas and enhancing the precision of tasks. When teaching complex activities in physical education, biomechanicals are a useful tool. The methods that teachers employ determine how well the training progresses. Growing development of skills helps students grasp the fundamentals before taking on more demanding behavior, raising their assurance and ability [10]. By breaking complicated motions down into simpler sections. With instruction based on biomechanical feedback, restricted mobility is accommodated, and advanced learners are challenged in physical education programs to meet the needs of students with different physical capacities, approaches to learning, and understanding levels [11]. While cognitive teaching helps with motor learning by offering biomechanical descriptions and separate signals, visual feedback and video investigation enhance learning by contrasting performance to optimal procedures. Which helps them internalize movement technicalities and strengthen biomechanical conception [12]. When fused, these strategies provide a physical education that is additionally productive and attractive. Greater performance, condensed risk of injury, and more effectual learning are attained when biomechanical investigation is included in the physical education curriculum while teaching complexmovements [13]. Physical education teachers can utilize extra focus and individualized training in addition to executing successful teaching techniques like severance, cognitive teaching, illustration feedback, and progressive growth of ability [14]. The investigation of the efficacy of biomechanical evaluation can be integrated into the instruction of complex movements in physical teaching, with an importance on the efficiency of diverse education procedures. Through feedback and modified teaching strategies to increase performance results, inferior the danger of injury, and get better students' growth of motor skills.

Key contributions

- The effort in attendance an assessment classification, the UABO-DCNN, that combinations of DL and innovative action capture techniques. For assessing and enhancing association capability in difficult physical activities, this program offers an unbiased, data-driven performance.
- Movement assessments are more reliable because of the algorithm's exceptional precision in differentiating between normal and abnormal patterns of movements. The result sustains more general trends in personalized learning and educational technology, which helps to create more dedicated physical education techniques.
- By highlighting the significance of optimum motion improvement in advanced professional physical education, the investigation promotes an atmosphere of physical awareness and wellness among students.
- Specifically in complicated biomechanical activities, the research findings have significance for improving instructional tactics to promote optimum movement improvement.

The rest of this study was organized into sections: Section 2 contained relevant works, and Section 3 had a comprehensive approach. Results were depicted in Section 4, Section 5 covers in discussion, and a conclusion was given in Section 6.

2. Related words

The improved efficiency and offered a framework for effective access to instructional techniques in physical education. The research suggested a multi-feature fuzzy assessment model based on artificial intelligence (AI). With fuzzy instructions and an improved cuckoo search optimization (CSO) technique, the model incorporated human communication [15]. The approach has demonstrated strong performance in several evaluation domains, such as typical abilities performances, learning progress, physical fitness, involvement rate, instructor satisfaction, and effectiveness in teaching. To provide students with real-time research and correction of their actions for a variety of sports, they suggested an online teaching assistance system that was based on the DL image identification algorithm ResNet34. The data collection can be enlarged to accommodate additional sports categories, and the feasibility of the system was clear [16]. Investigations reveal that the suggested system greatly enhanced student action correction in virtual sports education. To address problems such as poor data, the drawback of extensive models, and inadequate consideration of individual variations, the article provided a sports injury forecasting approach that makes use of medical images and biomechanical data [17]. The model provided tailored injury prevention suggestions by fusing and extracting features from suggested images and biomechanical data using Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). The approach was greater than conventional techniques in several aspects and also incorporated monitoring using wearable technology and sensors. Applications of AI in physical education as well as its prospective uses in personalized learning environments, information delivery, learner assessment, and coaching techniques [18]. To the level of proficiency needed for aspiring physical education teachers to utilize AI and its ramifications for other academic fields. Comprehending AI's development and potential in a variety of sectors by adding to the body of the investigation and sharing possibilities about AI applications in sports and education. It presented a voice-activated hybrid instruction mode with an educational robot. The system combined intelligent information technology with conventional teaching techniques to increase recognition accuracy. The incorporation of the robot also improved students' disposition towards research. The students discussed the way of learning increased by points when the robot was introduced [19]. The advancement of AI education can benefit from the reference provided by the investigation.

To encourage active engagement and a hunger for information in the acquisition of physical abilities, researchers have included flipped learning in their courses. However, traditional approaches lack direction frequently. The Identification, Communication, Reflection, and Analysis (ICRA) instructional method was presented in the research and was utilized for the development of badminton skills [20]. Students serve precision, quality, and self-reflection showed a substantial improvement with the ICRA-based mobile flipped learning (ICRA-MFL) method. Peer engagement, concept identification, and research were instances of instructional strategies that promote self-reflection and enhance learning outcomes. Through affordable hardware and mobile applications, the Internet of Things (IoT) has enabled linked settings that have revolutionized physical education. To gather data from the IoT and to communicate with handheld devices, they investigated the IoT-driven Physical Activity Recognition System (IoT-DPARS) for educational institutions [21]. To encourage students to increase their based-on performance, IoT understanding as well as accuracy, reliability, and error rate, the system employed a structured architectural platform to track physical activity. Multimedia and computer technology were required to improve college physical education lessons. To improve the efficacy of teaching college sports, a multimedia supplementary teaching impact evaluation model built on the random number forest method was suggested. The methodology assessed the multimedia teaching impact of physical education courses and examined the auxiliary teaching level of the college physical education network [22]. The user satisfaction rating validated the effectiveness of the approach, which encourages scientific, standardization, and specialization in the administration of physical education instruction. Although additional empirical evidence was required, the teaching games for understanding (TGfU) paradigm highlighted the cognitive development of athletic competence. A TGfU football unit enhanced students' tactical knowledge at all three levels: conceptual substance, complexity, and structure, according to research looking at how the unit affected middle school physical education students' tactical knowledge growth [23]. The findings highlight the necessity of implementing instructional models such as TGfU to build students' tactical thought and enhance their ability to analyze physical education. Although physical education in elementary schools has been the focus of scholarly discussion, its components, and practices have not been sufficiently acknowledged in contemporary regulations. To create a model for the core curriculum of sport and exercise sciences degrees, as well as fundamental didactic-methodological components, for the investigation of teaching physical education in schools, sports associations, and leisure activities [24]. The basic instructional components of physical education in primary schools were determined by the research through ministerial, focus groups, and targeted initiatives involving physical education investigators.

3. Methodology

The approach uses motion capture technology to gather biomechanical data from students enrolled in physical education classes, enabling an unbiased evaluation of their ability to move during challenging tasks. To evaluate movement patterns and improve teaching tactics, a UABO-DCNN model combines advanced optimization techniques. By conducting a thorough assessment of biomechanical traits, the technique seeks to enhance motor skills, personalize training regimens, and optimize physical education teaching strategies. **Figure 2** shows the flow of the recommended methodology.

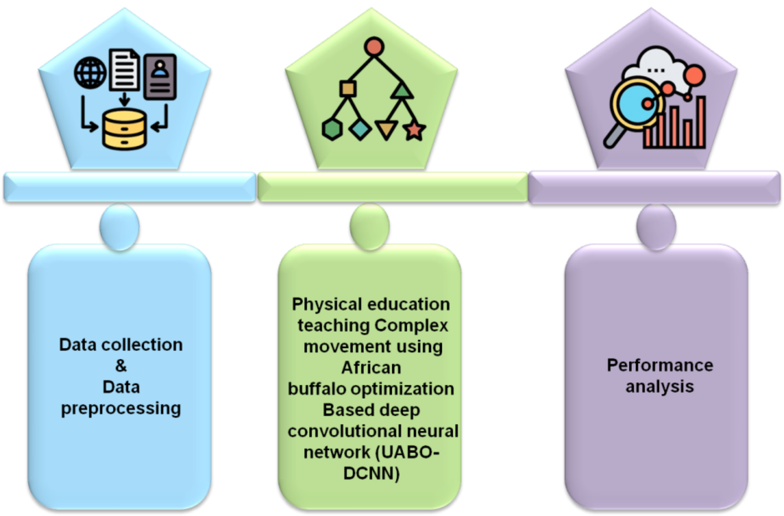

Figure 2. Flow of the recommended methodology.

3.1. Data collection

The dataset for analysis in this biomechanical study is data collected from 50 physical education students. This study employs biomechanical examination to objectively assess and exploit students' movement skills while focusing on the forces and dynamics established in physical activities. It evaluates and improves movement performance, safety, and competence through demanding physical tasks using quantitative approaches. With the use of sophisticated motion capture equipment, participants were able to do a selection of intricate moves in a safe setting, such as roundhouse kicks, pirouettes, and cartwheels. This device records intricate movement data, giving information on each student's coordination and physical performance. The study highlights significant facets of movement expertise to enhance physical education teaching methods. It encourages better safety procedures during physical activities and a superior comprehension of biomechanics. The results give to a more successful curriculum by assisting educators in creating training programs that recover students' physical abilities. Biomechanical analysis is necessary for optimizing mobility.

3.2. Data preprocessing using Min-Max normalization

After collecting the data, applying Min-Max normalization ensures consistent scaling across characteristics and standardizes the data inputs in a physical education teaching technique. This preprocessing phase improves performance and resiliency in real-time applications for analysis and interacting physical education technology advancement by improving the model's capacity to precisely categorize and interpret different teaching movements. The maximum and minimum values that containmax (W) and min (W) value and their comparisons among the pre- and post-process data in W_{new} depicts normalized in Equation (1).

$$W_{new} = \frac{W - \min(W)}{\max(W) - \min(W)} \tag{1}$$

3.3. Updated African buffalo optimization-based deep convolutional neural network (UABO-DCNN) using physical education teaching in complex movements

The UABO-DCNN enhances biomechanical evaluations in physical education by integrating with advanced optimization approaches. In the examination of difficult movement patterns, the model determines significant features that guide efficient training methods. Students' motor skills and output of intricate motions are enhanced by UABO's ability to facilitate customized educational techniques. By encouraging collaborative dynamics and personalizing training regimens, the algorithm maximizes learning performance. Enhancing the effectiveness and flexibility of physical education techniques is the fused UABO-DCNN technique.

3.3.1. Deep convolutional neural network (DCNN)

The DCNN model for examining the biomechanical characteristics of intricate motions in physical education is presented to help with the creation of successful teaching methods. The consideration of a movement sequence with n critical places.

By consulting a feature matrix $K \in Q^{m \times |u|}$ created by biomechanical analysis, where u is the collection of features, each point in the movement is mapped to the appropriate biomechanical features. Every point o is transferred to a feature vector $x_j \in Q^m$. Following Equation (2) the movement sequence is expressed as a vector of concatenation biomechanical assessments. Performance metrics, the dynamic characteristics vector, and the kinematic features field the feature vector u of the movement sequence s can be formed by concatenating the vector with the biomechanical insertions vector.

$$u = x_1 \oplus x_2 \oplus x_3 \oplus \dots \oplus x_n \oplus x_{n+1} \oplus x_{n+2} \oplus x_{n+3} \tag{2}$$

where the concatenation operator is represented by the symbol $\oplus$, the performance metrics vector of the movement sequence $x_n + 1 \in S$, the kinematic features vector of the movement sequence s is represented by the symbol $w_{m+3} \in Q^{k'}$, and $x_{n+2} \in \{0,1\}^k$.

It's the vector of dynamic characteristics for the movement sequence s. Local biomechanical feature vectors w_j are generated for every conceivable position in physical education teaching in the first convolution layer by the use of a lot of varied dimensions g. The bias term, $A \in Q$, and a transition matrix, $X \in Q^{g_v \times g_m}$, are several hidden units in the convolution layer represented by the symbol g_v. A fresh local feature vector w_j in a location window g is created by each convolution operation using Equation (3):

$$w_j = e(X.u_{1:j+g-1} + a) \tag{3}$$

where g is a non-linear activation function and $u_{j:j+g-1}$ represents the local feature vector from location to position $j + g - 1$ in the vector u. After completing the convolution process, the convolution filter creates a new vector that can be a physical education teaching procedure as follows for each potential location in the physical movement sequence using Equation (4):

$$w = [w_1, w_2, \dots, w_{m-g+1}] \tag{4}$$

Finding important movement patterns or approaches is typically crucial in biomechanical assessment these distinguishing characteristics are not dispersed evenly throughout the physical education teaching movement. To preserve important data about intricate movement patterns, the efficiently most important biomechanical components, choosing the l characteristics that correlate to different hidden layers. The limitations of previous approaches that could ignore important facets of movement analysis, such as the effect of unfavorable movements on overall performance in physical education, are addressed by this methodology, which additionally takes into account the movement and contextual details of every phase followed by Equation (5).

$$v' = \max\{w_1, w_2, \dots, w_{m-g+1}\} \tag{5}$$

Used k-max pooling to build fixed-length vectors, which were then convolution layer to get a refined feature vector. This resulted in improved feature information for analyzing complicated movements in physical education. To correctly signify every feature of biomechanical motions, the model is constructed with three convolution layers and three k-max pooling layers. A softmax layer in the output layer generates probabilities for different physical movement classifications. Using a completely linked mechanism, the output layer modifies the movement characteristics obtained from the input layer, producing a possibility distribution for different movement classifications using Equation (6).

$$z^{(i)} = X^{(i)} z^{(i-1)} + a^{(i)} \tag{6}$$

where the layer's output vector is denoted by $z^{(i)}$, the pooling layer's output vector is denoted by $z^{(i-l)}$, the transition matrix is represented by $X^{(i)}$, and the bias factor is represented by $a^{(i)}$. The following provides the probability distribution across the physical education teaching movement classifications followed by Equation (7):

$$O(j \setminus s, \theta) = \frac{\exp\left(z_j^{(i)}\right)}{\sum_{l=1}^{m} \exp\left(z_l^{(i)}\right)} \tag{7}$$

The DCNN model improves the assessment of biomechanical properties in complex motions used in physical education, which makes it easier to create instructional plans that work. During the mapping of movement sequences to biomechanical properties, instructional methods are significantly improved by identifying important patterns and performance measures. Movement features are extracted and refined using the model's structural design, which consists of various convolutions and layers, producing a strong classification system. This method enables teachers to exploit their instructional strategies and develop the physical education performance of their students.

3.3.2. Updated African buffalo optimization (UABO)

The UABO method is an improved algorithm that draws inspiration from social interactions and gait movements. This optimization technique improves the procedure of finding a variety of demanding issues, such as biomechanical assessments in physical education. Through the combination of UABO and biomechanical analysis, instructors can assess and improve their methods for teaching intricate motions in physical education. This method makes it probable to thoroughly analyze the movement patterns of athletes, which aids in locating areas that require optimization and growth. To get better learning results and movement efficiency, UABO can help customize instructional strategies to meet the needs of specific students. Teachers can build focused training programs that improve motor abilities and foster a better comprehension of movement mechanics by implementing biomechanical concepts. The combination of biomechanical analysis and UABO techniques can transform physical education, increasing its effectiveness and flexibility to the diverse needs of students. The democratic equation expressed mathematically, governs the buffalos' movement and replicates their cooperative interactions.

$$n_l' = n_l + k_p 1(a_h - x_l) + k_p 2(a_o . l - x_l) \tag{8}$$

There are three key components to Equation (8). The first is the physical education teaching complexes (n_l'), indicating that the UABO is aware that they have moved from their previous platforms (n_l) particularly biomechanical assessments. This feature highlights the need for memory and attentiveness when learning complex physical abilities. In physical education, the second component embodies the cooperative learning dynamics in which students successfully interact and communicate, using the talents of other students to augment their learning experience. Evaluation of physical skills by having them compare their present performance to past performances, which promotes continued growth for development. Therefore, incorporating critical analysis, cooperative learning, and cognitive awareness into teaching methodologies for complicated motions in physical education.

To decide if the teaching method has to be modified to incorporate a new strategy x_l', it can be important to stress that the new strategy for teaching complicated motions, indicated as x_l, is dependent upon the teaching strategy that was previously used. The modification also takes into account the based-on information metrics k_o1 and k_o2, which let teachers determine if changes are necessary after comparing the efficacy of the present teaching approach x_l to both personal best practices $a_o.l$ and general best practices a_h. Additionally, take note of the fact that a_h is determined by Equation (9):

$$a_h = x \times (s) \tag{9}$$

where s denotes the iteration and the physical instruction. Likewise, $a_o.l$ can be acquired through:

$$a_o.l = x_l\,(s) \tag{10}$$

In Equation (10), buffalo l indicates the ideal exploration site, while $a_o.l$, with s signifying the iteration, represents the buffalo l in concern. That UABO method takes the dimensional element X_a and subtracts it from the two maximal vectors a_h and $a_o.l$. Subsequently, the outcome is multiplied by the learning parameters k_o1 and k_o2. This physical education is in the determination of the UABO's corresponding fitness dimensions. Used to direct the UABO to a different location, including biomechanical analysis to enhance the methods of instructing intricate motions in physical education.

$$x_l' = \frac{(x_l + n_l)}{\lambda} \tag{11}$$

As followed by Equation (11), x_l' denotes the transition to physical training, x_l stands for current exploration values, and m_l for current exploitation values. The exploitation driver is represented by a random number between $0\ and\ 1$. **Figure 3** shows the flowchart of UABO.

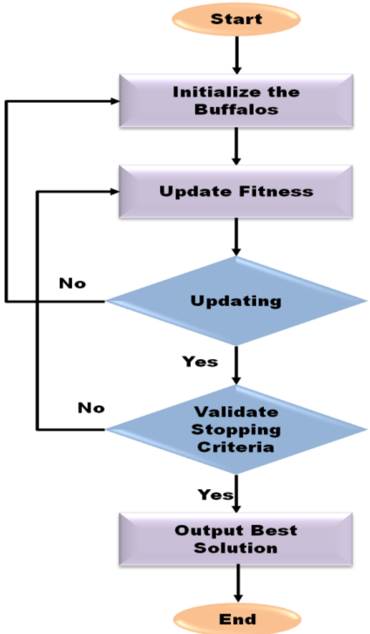

Figure 3. Flowchart of UABO.

The flowchart describes an optimization procedure that can improve biomedical analysis and instructional methods for indicating actions in physical education by utilizing the UABO-DCNN. Buffalo agents, which stand for various movement parameters, are initialized at the start of the algorithm. Fitness update monitors how well these characteristics work to achieve ideal biomechanics. The moves or tactics are improved by iterative updates. To ensure convergence towards better teaching solutions, the method keeps going until a stopping requirement is satisfied. The optimal solution is subsequently identified and produced, giving teachers the knowledge they need to maximize intricate movement instruction methods based on biomechanical data and analysis.

- UABO process:

The UABO randomly initializes an assortment of simulated agents that represent different approaches to teaching complicated motions in physical education. Each strategy's initialization entails allocating random locations inside the specified parameter space. The algorithm then modifies each strategy's utilization and investigation fitness concerning the specified learning objectives, determining each strategy's personal best as well as the greatest performance in the physical education training strategy. For every iteration, every agent keeps track of where it is in the learning framework. The optimization keeps that position vector for that strategy if its current performance exceeds its highest recorded fitness. The system then uses this information to readjust the agents' locations. It then assesses how well the optimal method has improved. The algorithm reinitializes all of the strategies in the population if the best strategy's performance does not improve after a certain number of iterations. The optimal approach has proven to be more effective; the algorithm evaluates whether the predetermined stopping conditions. The procedure is finished, and the associated approach is offered as the best way to teach difficult motions if its physical education satisfies the exit requirements.

- Convergence analysis of UABO:

The physical education teaching exploitation and the algorithm's convergence are related. In physical education, the population's fitness is defined in terms, where λ is the exploitation driver and a key factor in determining how efficiently students move. Better performance can be achieved by using acquired skills and tactics more frequently, as indicated by a higher value conversely, a lower value emphasizes skill learning and exploration using Equation (12).

$$\lambda = \frac{1}{M}\sum_{k=1}^{M}\left(\frac{x_l - x_{avg}}{x_i}\right) \tag{12}$$

The population of students is denoted by M, the fitness of student l in terms of biomechanical performance is $l = 1, 2, 3, \ldots., m$ the current average performance fitness of the group is x_{avg}, and the normalized calibration factor of the exploitation driver is x_i. It can derive the value of $x$by using Equation (13):

$$x = \max\left(\left(\left|x_l - x_{avg}\right| l, max\right)\right) l \in [1, M] \tag{13}$$

The definition suggests that it is an exploitation driver that represents the degree of convergence of all students in the cohorts. Thus, in complicated motions, a bigger λ indicates stronger convergence around optimal movement approaches and tactics. Students continue to explore at random, concentrating more on physical education teaching abilities than perfecting intricate motions. Another way to look at students' convergence is as follows Equation (14).

$$\lim \genfrac{}{}{0pt}{}{l(s)}{m \to \infty} = i \tag{14}$$

The buffalo's l values at iteration s and the search space are represented by the equation $l(s)$. This demonstrates that the buffalos congregate in the space at a predetermined location. In terms of math, this is expressed as Equation (15):

$$\lim \genfrac{}{}{0pt}{}{l(s)}{m \to \infty} = \theta \times a_o + (1 - \theta) \times a_h \tag{15}$$

By combining social interactions with biomechanical research, the UABO system provides a revolutionary method for optimizing physical education. With the help of this advanced algorithm, trainers can enhance the way of teaching, which benefits the outcomes of learning and movement efficiency. Through the utilization of cooperative learning dynamics, UABO facilitates customized training plans that address individual requirements and encourage improvement. By increasing motor skills and accommodating a variety of learning styles, the UABO technique dramatically improves the efficacy of physical education training. Algorithm 1 shows the pseudocode in UABO-DCNN.

Algorithm 1 UABO-DCNN

```
Initialize DCNN model parameters
Initialize UABO parameters
For each student in training_set:
Get movement_sequence from the student
Perform biomechanical analysis
biomechanical_features = extract_biomechanical_features(movement_sequence)
DCNN processing
feature_vector = DCNN (biomechanical_features)
UABO Optimization
```

Algorithm 1 (*Continued*)

For each iteration in max_iterations:
For each strategy in strategies:
Evaluate the fitness of strategy using feature_vector
If fitness >personal_best[strategy]:
personal_best[strategy] = fitness
if fitness >global_best:
global_best = fitness
best_strategy = strategy
Update strategies based on UABO rules
for each strategy in strategies:
If strategy is best_strategy:
$x^{1'}$ = update_exploration(strategy)
Else:
Check for convergence
if converged:
break
Implement the best strategy in teaching.
End For

The UABO-DCNN utilizes sophisticated optimization approaches to improve biomechanical evaluation in physical education and enable modified teaching for enhanced motor ability and understanding of multifaceted activities. The UABO-DCNN technique improves student accomplishment and flexibility in physical education by promoting shared dynamics and personalizing instruction approaches. It utilizes social communications and gait motions to recognize improvement areas and cater to diverse learning preferences.

4. Performance analysis

A lot of Python 3.6.16 was used in the study process. An Intel Core i8 laptop with a 66GB solid-state drive and Windows 10 operating system is available in this article. The test tool used in this study was a 3D body camera called the Kinect sensor version 1.2. In evaluating the efficacy of the proposed system, assessment parameters like recall, accuracy, F1-score, precision, and specificity are used. The proposed method UABO-DCNN was compared to Artificial Neural Network (ANN) [25], Random Forest (RF) [25], and IoT-based Physical Activity Recognition (IPAR) [25], and Crayfish Optimization-driven Adaptive-Weighted AdaBoost (CO-AWAdaBoost) [26].

4.1. Accuracy

Accurate biomechanical examination and complicated movement teaching in physical education center on improving students' presentation with assessment of their physical activities. Educators can get better ability attainment by recognizing and correcting association inefficiencies with the utilization of biomechanical concepts. Teaching techniques for intricate motions, including higher sports tactics, provides a greater outcome of biomechanics and helps students develop their ability. The UABO-DCNN algorithm is a leading technique in its category because of its outstanding performance, which includes the greatest accuracy of 99.43%. Other well-known methods are not successful; the ANN reports an accuracy of 91.74% and the RF records 90.4%. The accuracy of Co-AW AdaBoost is 98.25%, whereas the IPAR performs almost better at 95.82%. These outcomes unequivocally show how successful the UABO-DCNN algorithm is in comparison to its competitors. To demonstrate the algorithm's superiority, detailed accuracy results are methodically displayed in **Table 1** and graphically depicted in **Figure 4**.

Table 1. Numerical result of accuracy.

Techniques	Accuracy (%)
ANN [25]	91.74
RF [25]	90.4
IPAR [25]	95.82
Co-AWAdaBoost [26]	98.25
UABO-DCNN [Proposed]	99.43

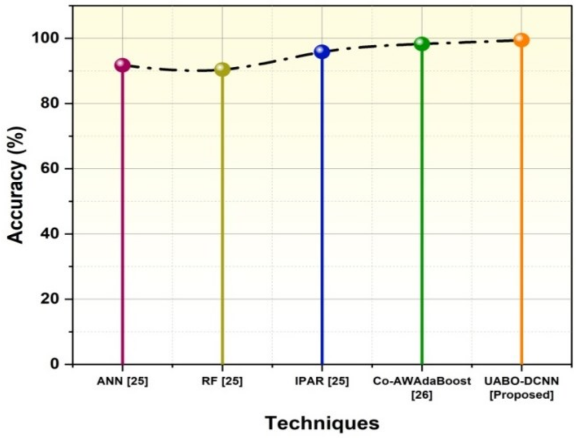

Figure 4. The outcome of accuracy.

4.2. Precision

Difficult movement instruction is enhanced in physical education when precision, biomechanical evaluation, and successful teaching approaches are combined. Teachers can identify movement patterns, evaluate performance efficiency, and customize feedback for every student by utilizing biomechanical estimates. It is essential to perform these motions precisely to enhance ability, prevent injuries, and promote general physical education. Utilizing focused teaching approaches helps students get a deeper comprehension of biomechanics, which improves their ability to perform and allows them to participate more actively in physical activities. The suggested UABO-DCNN algorithm achieves an outstanding score of 98.12%, indicating superior precision performance. The precision scores of popular methods like ANN, RF, IPAR, and Co-AW AdaBoost, which are 95.42%, 92.32%, 96.95%, and 97.22% respectively, are comparatively low. These findings demonstrate that the UABO-DCNN is not only more efficient than its rivals but also effective in the particular application for investigation. These precision results are shown graphically in **Table 2** and **Figure 5**, which allows for clear comparison and emphasizes the benefits of the algorithm in terms of increased prediction accuracy.

Table 2. Numerical result of precision.

Techniques	Precision (%)
ANN [25]	95.42
RF [25]	92.32
IPAR [25]	96.95
Co-AWAdaBoost [26]	97.22
UABO-DCNN [Proposed]	98.12

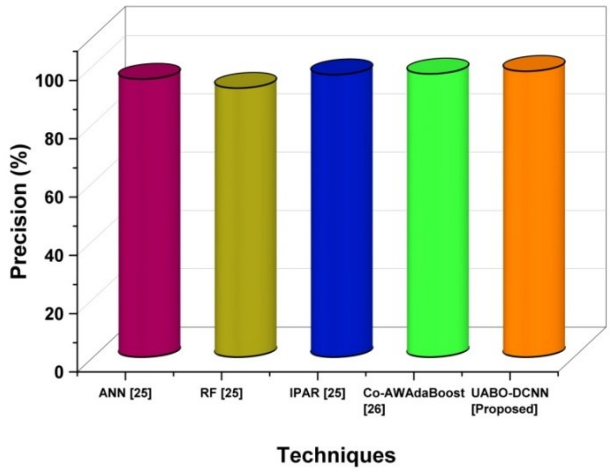

Figure 5. The outcome of precision.

4.3. Recall

Recall combined with biomechanical analysis improves comprehension and instruction of intricate actions in physical education. Teachers can recognize important elements that affect student performance and learning results by looking at the mechanics of the motions. By addressing each student's unique demands, this technique enables customized teaching tactics that promote better skill development. A more thorough and productive physical education program is eventually fostered by integrating recall techniques, which also reinforce learning by helping students recall and implement biomechanical concepts. At an excellent 98.50%, the recommended UABO-DCNN algorithm outperforms other existing methods in terms of recall performance. Recall was 94.35% for the ANN, 92.23% for the RF approach, 95.63% for the IPAR approach, and 97.86% for the Co-AW AdaBoost. The UABO-DCNN's capacity to accurately recognize relevant instances within the dataset is verified by this distinguished recall improvement. A clear comparison of the recall rates for the various algorithms is provided by the data, which are graphically displayed in **Table 3** and **Figure 6**.

Table 3. Numerical result of recall.

Techniques	Recall (%)
ANN [25]	94.35
RF [25]	92.23
IPAR [25]	95.63
Co-AWAdaBoost [26]	97.86
UABO-DCNN [Proposed]	98.50

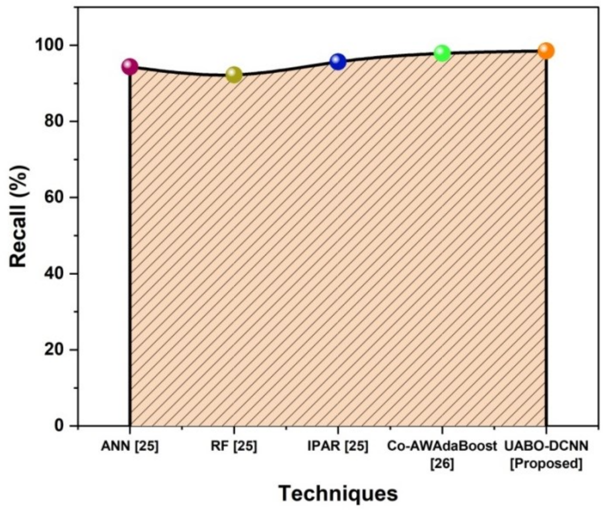

Figure 6. Outcome of recall.

4.4. F1-score

Table 4. Numerical result of F1-score.

Techniques	F1-score (%)
ANN [25]	94.83
RF [25]	93.85
IPAR [25]	97.83
Co-AWAdaBoost [26]	97.88
UABO-DCNN [Proposed]	98.56

The performance indicator for classifying models that balances recall and accuracy is the F1-score. The F1 score measures the degree to which these models can classify and categorize diverse movement patterns in the framework of biomechanical investigation and instructional methods for complex motions in physical education. Through the integration of biomechanical insights, educators can generate focused instructional techniques that improve students' comprehension and performance of complicated motions, leading to improved performance results in physical education. This methodology cultivates a deeper communication with those under deliberation. With a better F1-score of 98.56%, the UABO-DCNN algorithm performs estimably in classification tests. This result surpasses several current approaches, such as RF, which achieved 93.85%, and ANN, which achieved an F1-score of 94.83%. Moreover, the

UABO-DCNN outperforms the Co-AW AdaBoost algorithm (97.88%) and the IPAR approach (97.83%) with its F1-score. As exposed in **Table 4** and **Figure 7**, these findings demonstrate the UABO-DCNN algorithm's effectiveness in improving prediction accuracy, underscoring its potential as an outstanding solution in its field.

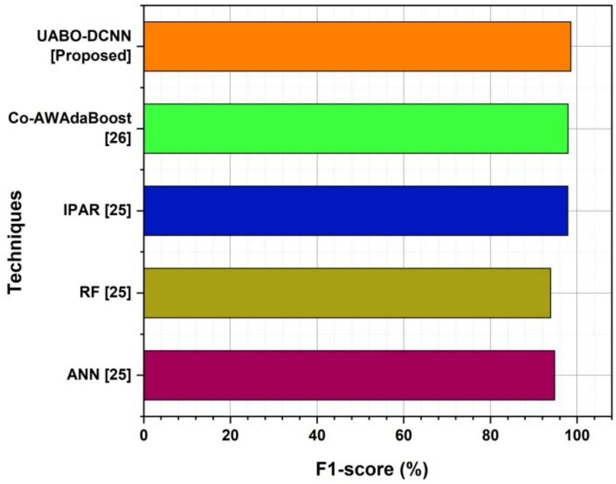

Figure 7. The outcome of F1-score.

4.5. Specificity

Through biomechanical study and proficient teaching techniques for intricate actions, this research investigates how specificity might be integrated into physical education. Teachers can alter their instruction to develop students' motor abilities and comprehension of movement patterns by dissecting the mechanics of positive physical activities. This highlights the need to customize instruction to meet the requirements of each student to improve performance and lower the chance of damage. The results are intended to help students have more successful and interesting physical education knowledge. The UABO-DCNN algorithm achieves an impressive 98.40% specificity, indicating extraordinary performance. This outperforms several present techniques, such as RF with 90.75% certainty and ANN with 93.12% specificity. Other algorithms, like Co-AW AdaBoost and IPAR, also demonstrated strong performance, achieving specificity values of 97.85% and 96.32% respectively. A useful tool for applications requiring high accuracy, the UABO-DCNN algorithm's notable improvement in specificity demonstrates how well it can recognize genuine negatives in the dataset. **Table 5** and **Figure 8** provide detailed comparisons of these outcomes, showing the performance measures of each approach.

Table 5. Numerical result of specificity.

Techniques	Specificity (%)
ANN [25]	93.12
RF [25]	90.75
IPAR [25]	96.32
Co-AWAdaBoost [26]	97.85
UABO-DCNN [Proposed]	98.40

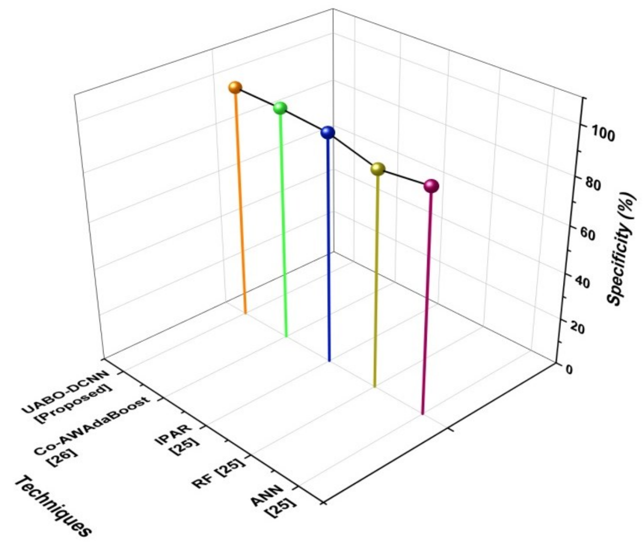

Figure 8. The outcome of specificity.

5. Discussion

The ANN [25] model's complexity and computational demands can hinder its combination with physical education, potentially involve significant training data and resources, and potentially deflation of traditional instruction approaches. RF models struggle to exactly imprison temporal dynamics in movement data, and hinder integration with biomechanical assessment and teaching techniques for difficult movements in physical teaching. Integrating IPAR with biomechanical investigation and movement teaching in physical education can lead to data overload, making real-time assessments demanding and potentially cooperation precision and pedagogical techniques. The intricacy of utilizing CO-AWAdaBoost [26] in combination with biomechanical data and teaching methods is a main drawback. General data collecting and processing are essential for this approach, which can be time and resource-consuming. In evaluating difficult motions, the recommended UABO-DCNN model performs better than other models like ANN, RF, IPAR, and Co-AW AdaBoost. This allows for more correct assessment and optimization of student performance in physical education. The structure of well-organized teaching methods that raise movement ability and security during physical activities is made easier by this better capacity. The proposed UABO-DCNN method is an influential tool for addressing the complexity related to integrating complex movement teaching and biomechanical valuation in physical education, reducing computing burden, improving modeling precision, streamlining data processing, and enhancing interpretability through easy-to-use data visualization interfaces.

6. Conclusion

In physical education, biomechanical assessment examines the mechanics of intricate movements to improve performance and decrease injury risk. Body mechanics, movement patterns, and the forces as a consequence during an activity were all examined in this study. To assist students in understanding and doing complicated physical activities, the teaching strategy emphasizes transmitting this information to them through the use of modeling, feedback, and skill development. The proposed method had the greatest performance recall (98.50%), precision (98.12%), F1-score (98.56%), accuracy (99.43%), and specificity (98.40%). A drawback of this research is the range of physical abilities and learning preferences among the students, which might impact the efficacy of the instructional approaches utilized. Also, other variables that might affect students' performance and comprehension of difficult motions in physical education, such as the classroom setting and examination pressure couldn't have been taken into consideration by the examination. Future research in physical education can examine how to integrate innovative technology, such as wearable sensors and machine learning (ML) algorithms, to improve movement analysis in biomechanical analysis and teaching techniques of complicated motions. Furthermore, research endeavors can explore customized instructional techniques for heterogeneous student cohorts, cultivating proficiency and perpetual physical activity participation among students with disparate aptitudes and experiences.

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