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Molecular & Cellular Biomechanics 2024, 21(3), 372.
https://doi.org/10.62617/mcb372

Review

A systematic study of physical fitness assistance training for adolescents based on Kinect motion capture

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CITATION

Liao X, Lei X, Sun P. A systematic study of physical fitness assistance training for adolescents based on Kinect motion capture. Molecular & Cellular Biomechanics. 2024; 21(3): 372.
https://doi.org/10.62617/mcb372

ARTICLE INFO

Received: 14 September 2024
Accepted: 24 September 2024
Available online: 21 November 2024

Abstract: Kinect motion capture technology records body motions, allowing for accurate monitoring and analysis in a variety of fields. This study investigates the intelligent recognition of classroom teaching behaviours by physical fitness instructors through the combination of Kinect sensors and machine learning algorithms. We proposed a novel Crayfish Optimization-driven Adaptive-Weighted AdaBoost (CO-AWAdaBoost) approach for classifying physical fitness instructional behaviours based on body posture data recorded by Kinect sensors. Z-score normalization is utilized to pre-process the obtained raw data. In our proposed recognition model, the CO algorithm leverages the natural behaviours of crayfish to optimize the process of feature selection. AdaBoost iteratively trains weak classifiers, assigning higher weights to misclassified samples. Our model can assist with the quantitative assessment of physical fitness classroom instruction, instructive suggestions, and large-scale behavioural investigation. The proposed detection model has been implemented in a Python program. In the results assessment phase; we evaluate our proposed model's effectiveness in classifying physical fitness instructional behaviours using numerous evaluation metrics such as recall, $F1$-score, precision, and accuracy. During the finding evaluation phase, we thoroughly scrutinize the recognition effectiveness of the suggested model across various parameters, including precision (97.22%), accuracy (98.25%), specificity (97.85%), recall (97.86%), and $F1$-score (97.88%). We also carried out a comparison analysis with other traditional approaches. Our experimental findings demonstrate the reliability of the recommended framework.

Keywords: Kinect motion capture; Crayfish Optimization-driven Adaptive-Weighted AdaBoost (CO-AWAdaBoost); classification model

1. Introduction

Fitness trackers and smartwatches are examples of wearable technologies that offer teachers creative ways to teach and technological advancements have been used to enhance teaching and learning processes by tracking users' health, fitness, and environment [1]. Students' motivation and engagement in physical education (PE) settings have been linked to the teaching styles and PE teachers. As numerous academics have demonstrated, the way physical education teachers educate can significantly influence the supportive and motivating environment that appears to predict students' satisfaction of basic psychological needs, level of motivation, intentions and engagement in physical exercise [2]. For secondary PE teachers, the most concerning things are currently the understanding of cognitive pathways connected to students' academic achievement and discipline behaviors [3]. In the field of physical education and physical education teacher education (PETE), there has been extensive discussion of both content knowledge (CK) and pedagogical content knowledge (PCK). They identify two drawbacks with the way that physical education and PETE discuss CK and PCK-discourse [4]. A growing body of research indicates that physical activity (PA) has a key role in the prevention of numerous diseases. Furthermore, PA has a number of positive health effects on young people. Adolescents who engage in moderate-to-vigorous physical activity (MVPA) have numerous health benefits when compared to light PA [5]. Physical fitness is a very practical subject, and for students to fully understand the material taught in physical fitness classes, they must do repeated exercises. However, due to time constraints in the classroom, physical education teachers might find it difficult to provide each student in the class with comprehensive instruction, and students could find it difficult to completely understand the bodily motions they have learned [6]. Accurate recording and evaluation of the caliber of trainers' motions has grown in significance as sports training has become more specialized and popular. Motion capture is the process of gathering and storing athlete movement data for analysis and assessment using sensors or video equipment [7]. Children's physical and mental health advantages from PA are widely established. PA is also said to be essential for promoting active living from early childhood into adulthood. There are some accepted recommendations about young children's involvement in PA [8]. Adolescents who engage in regular physical activity have better health outcomes, such as a lower chance of obesity, enhanced cardio-metabolic health and physical fitness, stronger muscles and bones, and a lower risk of depression [9]. Teachers' methods for inspiring students in PE might vary, in line with the self-determination theory (SDT). When depending on need-supporting behaviors, educators make an effort to give students opportunities for initiative and choice, as well as useful information and feedback, in a helpful and affective setting [10]. Kinect motion capture technology, enhanced by the CO-AWAdaBoost technique, aims to improve adolescents' health and well-being by making physical fitness training more engaging and effective.

1.1. Study highlights

- Gather data on whole-body fitness movements.
- *Z*-score Normalization was used for pre-processing the data.
- Crayfish Optimization-driven Adaptive-Weighted AdaBoost (CO-AWAdaBoost) approach for classifying physical fitness instructional behaviours.
- This study examines how physical fitness instructors might use a combination of Kinect sensors to recognize teaching practices in the classroom intelligently.
- Compare the performance of CO-AWAdaBoost with the existing models based on the evaluation parameters.

1.2. User experience and acceptance of Kinect technology

The use of Kinect motion capture technology by physical fitness instructors to identify classroom teaching behaviors is an area where user experience and acceptability are critical to the effective use of the suggested CO-AWAdaBoost strategy. The system's teachers' feedback is crucial to understanding how simple and easy the technology is to use. User acceptability can be considerably increased by positive experiences including simplicity of use, accuracy of feedback, and the system's capacity to deliver useful insights. The methodology offers instructors quantitative assessments and instructional ideas that could improve their performance as teachers. But it's also critical to address consumers' worries about data security, privacy, and the learning curve involved in incorporating new technology into teaching methods. Gathering and analyzing user feedback will be vital to refine the system and ensure that it meets the needs and expectations of physical fitness instructors effectively.

The rest of the paper is organized as follows: Part 2 discusses about literature review. In part 3, the suggested Crayfish Optimization-driven Adaptive-Weighted AdaBoost (CO-AWAdaBoost) is thoroughly discussed. Part 4 discusses the experimental design, findings, and performance assessment of the CO-AWAdaBoost method. The conclusions are summarized in part 5 along with future scope.

2. Literature survey

Schools were putting more of an emphasis on encouraging PA before, during, and after classes to reduce the risks that come with being inactive. Understanding the relationship between PA attitudes and existing attitudes about PE, as well as PA intentions and actions, was crucial because attitudes influence decisions to engage in physical activity [11]. Physically active kids and teenagers typically had lower obesity rates, better cardio-metabolic health, and higher levels of fitness. In the world, less than thirty percent of kids and teenagers engage in the recommended 60 minutes a day of moderate to vigorous physical exercise [12]. In April and May of 2020, the study sought to investigate relationships between adult and adolescent users of digital platforms and compliance with physical activity recommendations [13]. PE teachers' perceived stresses at work have an impact on their motivation and behavior. The study was used to add to the body of knowledge already available on the subject. Using a structural equation modeling (SEM), was first determined how much the perception of pressures affects instructors' motivation and, consequently, their perceptions about how feasible it was to apply motivational techniques [14]. The Moti Train project sought to create an interactive fitness coach and a digital training process companion that, by utilizing cutting-edge techniques and tools, could greatly boost the user's motivation and success in fitness training [15]. Three-dimensional (3D) marker-based motion capture has been used historically in movement research and was considered the gold standard for biomechanical assessment. There were drawbacks, including immobility, lengthy setup times for data gathering, and training for marker placement, mistakes brought by marker movement, and potential skin irritation from marker adhesives [16]. The basic psychological needs theory (BPNT) has lately included the demand for novelty as a potential requirement. Research in PE has demonstrated that satisfying students' demand for novelty is frequently linked to improved student well-being. There was a negative correlation between frustrating students' novelty and attaining several favorable results in PE [17]. Alyce Healthcare, a digital healthcare startup, has created Weelo, an online fitness program accessible through the web. Weelo used machine learning to recognize the user's motion, suggest a workout regimen, and offer both visual and audio feedback [18]. Pupils who fit into the high quantity and quality profile showed reduced levels of boredom, better levels of enjoyment and intention for physical activity, and higher levels of autonomy support. Self-determined profiles were linked to male participants, younger pupils, and extracurricular activity participants. The cross-sectional and descriptive study's character made it impossible to establish cause-and-effect linkages. Some kids' responses might have been impacted by the teacher's presence [19]. Optimal prep indicates that children and teenagers might be particularly responsive to motor learning training methods that support injury-resistant movement mechanics. To reduce the risk of injury, recover from injury, perform better during exercise, and enjoy playing more [20]. In basketball, players engage in a great deal of physical contact, bumps, and struggles. The findings demonstrated that during high-intensity exercise, basketball players' maximum heart rate and 1-minute heart rate recovery were lower than during flat area training and that even slight hypoxia in the plateau significantly lowered their performance [21]. Markerless motion capture systems hold the potential for assessing movement in more practical, clinical and scientific settings. Although there is still work to be done for broader use, the analysis's data provides a helpful roadmap for this path and markerless motion capture technology is currently in an improved position [22]. To enhance the cognitive abilities and social skills of autistic youngsters, the article incorporated dual-task exercises with multiplayer gaming using augmented reality (AR) and a personal health record (PHR) system [23]. Graded age-related developmental motor activities were used in motor-sense to help solve the lack of accessible technology to facilitate motor development assessment. In addition, it might help with the tele-detection of deficits in motor development [24].

Problem statement

Due to a lack of drive and appropriate direction, adolescents frequently struggle to maintain physical fitness, which can result in unhealthy lives. The goal is to create an interactive, personalized, and motion capture-based training program using Kinect. Fitness will become more accessible and pleasurable with the help of this technology, which will provide real-time feedback, measure progress, and modify regimens to suit individual needs. The program attempts to improve motivation and commitment to regular exercise by utilizing gamification and immersive surroundings. The ultimate goals of this program are to create wholesome habits that will last a lifetime and enhance the physical health of teenagers.

3. Methodology

This section covers a systematic study using Kinect motion capture to support adolescents in their physical fitness training. **Figure 1** depicts the methodological framework.

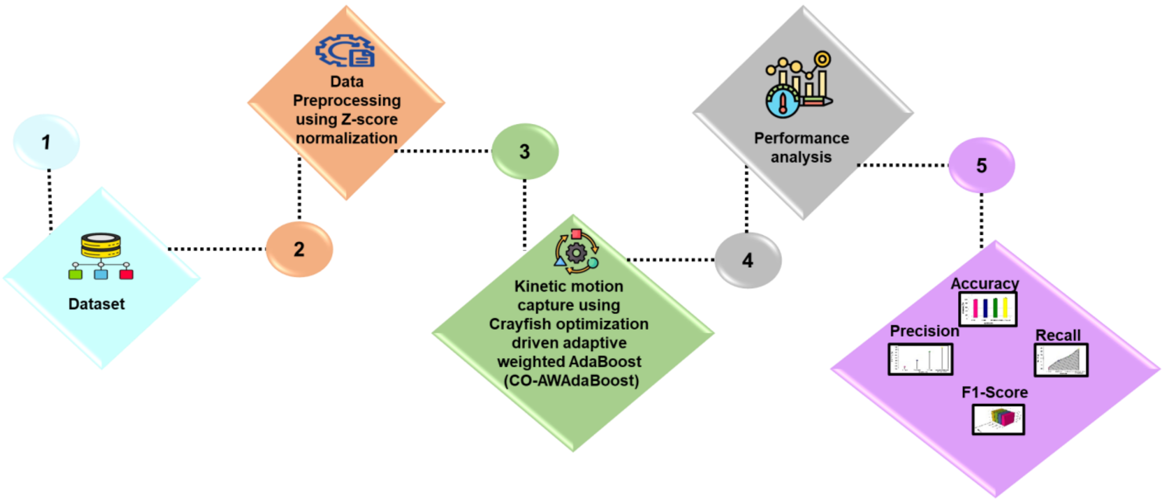


Figure 1. Methodological framework.

3.1. Dataset

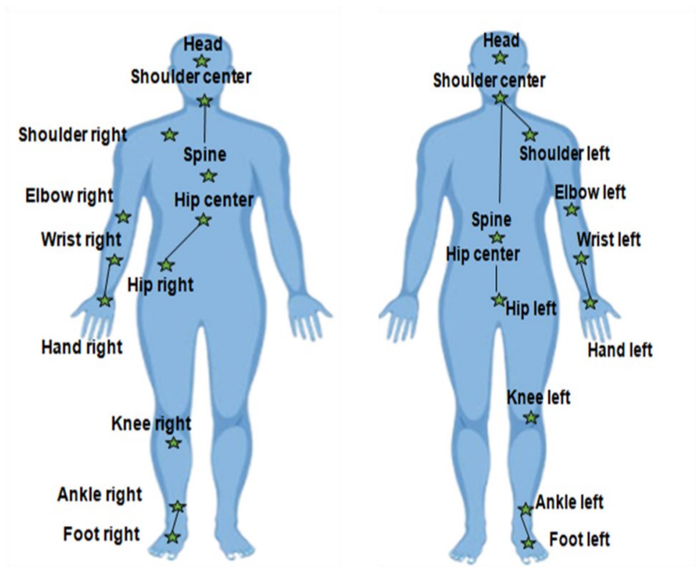


Figure 2. Body joint points.

The images in the video database had to be transformed into images for training. Every fitness exercise in the video database took an average of one to three seconds to perform. The entire exercise track can be properly recorded by using this approach of converting video to image. The database included images of every fitness exercise taken from several camera angles in addition to the full motion trajectories. Twenty people provided 15,260 fitness images in total. Personal activity data gathered with Kinect sensors, on the other hand, creates serious privacy concerns that must be properly handled. It is critical to secure participants' explicit authorization for the gathering and use of their data, including the conversion of video into photos. Anonymization procedures should be used to ensure that no persons can be recognized from the photos, and data should be maintained securely with restricted access. Clear data usage procedures should be implemented to ensure that the data is only used for the intended study goals, with participants retaining the ability to withdraw consent and request data deletion. Transparency in data handling processes is critical for fostering confidence and addressing privacy issues. **Figure 2** displays the chosen human body joint sites.

3.2. Data pre-processing using *Z*-score normalization

Z-score normalization is a statistical technique that sets the mean and standard deviation of a dataset to zero and one, correspondingly. It is often used in machine learning to prepare whole-body fitness movement data. The mean of each data point is deducted, and the resultant number is then divided by the standard deviation of the dataset. *Z*-score normalization may allow customers to assess how a specific rating would fit into a regular, usual set of facts. *Z*-Score is a method for controlling anomalies within a collective. This normalization method is widely used to compare and assess data that may have different sizes or distributions in several fields, including statistics, data analysis, and machine learning. Since all of the variables are on a similar scale and can be directly compared, they are better suited for certain statistical or modeling tasks.

$$\bar{z} = \frac{z - \tau}{\varsigma} \tag{1}$$

The numerical element is represented by Z. $\bar{z}$ is the recently presumed data point, τ represents the data point mean and ς the data point variance is indicated by ς.

3.3. Physical fitness instructional behaviours classification using Crayfish Optimization-driven Adaptive-Weighted AdaBoost (CO-AWAdaBoost)

The Crayfish Optimization-driven Adaptive-Weighted AdaBoost (CO-AWAdaBoost) method classifies physical fitness instructional behaviors based on body posture data recorded by Kinect sensors by combining an optimized algorithm modeled after crayfish behavior with an improved version of the AdaBoost algorithm.

3.4. Adaptive-Weighted Adaboost

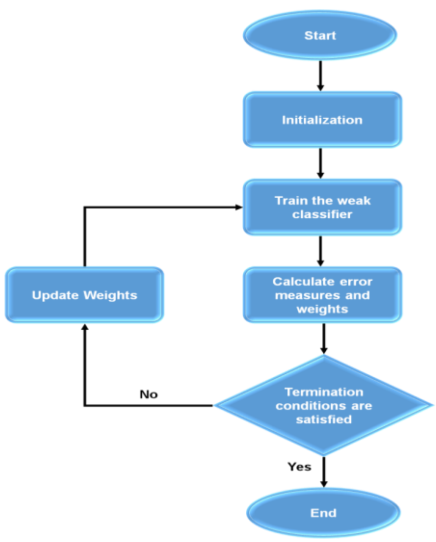


Figure 3. Work flow of adaptive-Weighted Adaboost.

AdaBoost trains weak classifiers iteratively, giving samples that are incorrectly categorized a higher weight. AdaBoost is a powerful ensemble learning algorithm that adjusts training example weights to maximize the utility of a restricted set of training instances. The number of samples taking part in the training is *N*. **Figure 3** shows the work flow of adaptive-Weighted Adaboost.

Step 1: Set the initial weight of each vector *D* (training data sample) in the data.

Step 2: Training was conducted using a weak learning algorithm. Following training, the error rate was computed using Equation (2). The number of samples inaccurately classified is denoted by M_{err}.

$$\varepsilon = \frac{M_{err}}{M} \tag{2}$$

Step 3: Determine the weak learning algorithm's weight. The error rate is used to calculate the weight of the weak learner method, which is represented by vector α, is shown in Equation (3).

$$\alpha = \frac{1}{2} In(\frac{1-\varepsilon}{\varepsilon}) \tag{3}$$

The weight and output of every weak classifier are acquired following *t*-round learning. The algorithm's final result is displayed in Equation (4).

$$G(W) = sign(\sum_{j=1}^{s} \alpha_j g_j(W)) \tag{4}$$

The CO-AWAdaBoost method seeks to achieve high accuracy and robustness in identifying and classifying different teaching postures and movements by optimizing the classifier weights and dynamically modifying them during the boosting process.

3.5. Crayfish optimization (CO)

A type of crab that inhabits freshwater, crayfish is also known as red crayfish or freshwater crayfish scientifically. Its food source, quick rate of growth, quick migration, great adaptation, and ability to form absolute advantages in the ecological environment all contribute to its unique characteristics. The behavior of crayfish is frequently affected by temperature fluctuations. The CO algorithm optimizes the feature selection procedure by taking advantage of crayfish's natural behaviors.

Crayfish are classified as ectotherms and exhibit behavioral variations in response to temperature fluctuations between 20 and 35 degrees Celsius. Here's how the temperature is computed, as shown in Equation (5):

$$temp = rand \times 15 + 20 \tag{5}$$

Population's initial state: Each crayfish in the d-dimensional COA optimization problem is a $1 \times d$ matrix that represents the problem's solution. Each crayfish's position (X) is in a collection of variables between the search space's upper (ub) and lower (lb) boundariesare shown in Equation (6).

$$W_{j,i} = ka_i + (ub_i - lb_i) \times rand \tag{6}$$

where the random number, rand, ranges from 0 to 1, the upper bound of the i^{th} dimension is displayed by ub_i, lb_i signifies the i-th dimension's lower bound and $W_{j,i}$ shows the location of the j-th crayfish in the i-th dimension.

Stage of exploration: A temperature of 30 °C serves as a threshold for determining whether the current living situation qualifies as excessive temperature. To protect itself from the damaging effects of high temperatures, crayfish will seek out a cool, moist cave and enter the summer when the temperature rises above 30 °C. This is the calculation for the caverns shown in Equation (7).

$$W_{shade} = (W_H + W_K)/2 \tag{7}$$

where W_K denotes the ideal position of the current population and W_H is the optimal position found thus far for this evaluation number. Random events govern the way that the Crayfish compete for the cave. The following is the formula used to calculate the Crayfish position update is shown in Equation (8).

$$W_{new} = W_{j,i} + D_2 \times rand \times (W_{shade} - W_{j,i}) \tag{8}$$

D_2 is a declining curve, and W_{new} is the position that comes after a location update. The equation for D_2 is shown in Equation (9).

$$D_2 = 2 - (\frac{FE_t}{MaxFE_s}) \tag{9}$$

The number of evaluations in this case is represented by FEs, while the maximum number of evaluations is represented by $MaxFE_s$.

Stage of competition: The two Crayfish will battle the cave, with Crayfish *Xi* shifting positions in response to Crayfish W_y's position. The Equation (10) is used to get the adjustment position.

$$W_{new} = W_{j,i} - W_{y,i} + W_{shade} \tag{10}$$

y stands for the crayfish random individual, and the formula for calculating random individuals is shown in Equation (11).

$$y = round(rand \times (M - 1)) + 1 \tag{11}$$

Stage of foraging: The crayfish will drill out of the cave when the temperature is less than or equal to 30 °C and will use the optimal position found during this evaluation to determine where the food is located to finish foraging. Equation (12) is used to determine the food's position.

$$W_{food} = W_H \tag{12}$$

Crayfish exhibit considerable foraging behavior in the 20–30 °C temperature range. At 25 °C, they find the most food and consume it to the maximum extent possible, as shown in Equation (13).

$$o = D_1 \times \frac{1}{\sqrt{2 \times \pi \times \sigma}} \times \exp\,(-\frac{(temp - \mu)^2}{2\sigma^2} \tag{13}$$

The crayfish cannot take food directly if it is too big. Before they can consume the meal, they must rip it up with their claws. The food's size is determined using the formula, which is shown in Equation (14).

$$R = D_3 \times rand(\frac{fitness_j}{fitness_{food}}) \tag{14}$$

Equation (15) illustrates that when $Q > (C3 + 1) \div 2$, the meal is too big for the crayfish to devour at one time, instead, it must tear it with its claws and eat with its second and third legs in turn.

$$W_{food} = \exp\left(-\frac{1}{R}\right) \times W_{food} \tag{15}$$

The mathematical models of the sine and cosine functions are utilized to imitate the act of feeding like a bipedal creature alternately. The following Equation (16) is the formula for crayfish alternate feeding.

$$W_{new} = W_{j,i} + W_{food} \times o \times (\cos(2 \times \pi \times rand) - \sin(2 \times \pi \times rand) \tag{16}$$

When $Q \leq (C3 + 1) \div 2$, the food size is appropriate for the crayfish to consume immediately at this moment, and it will proceed straight to the food location and begin eating. The Equation (17) is used for direct crush feeding.

$$W_{new} = \left(W_{j,i} - W_{food}\right) \times o + o \times rand \times W_{j,i} \tag{17}$$

The CO-AWAdaBoost method successfully classifies instructional actions in physical fitness based on Kinect sensor data by utilizing the advantages of both crayfish optimization and adaptive weighting in AdaBoost. Pseudo-code for CO-AWAdaBoost is as follows (Algorithm 1).

Algorithm 1 CO-AWAdaBoost algorithm pseudo-code

```
Function CO_AWAdaBoost (X, y, T):
    Initialize weights W to 1/N for each sample in X
    Initialize empty list of weak classifiers H
    Initialize empty list of alpha values
    for t = 1 to T:
        Train weak classifier h_t using weighted samples (X, y, W)
        Compute error rate e_t = sum w_i for misclassified samples i
          if e_t > 0.5:
          break
            Compute alpha_t = 0.5 × log((1 − e_t) ÷ e_t)
        Update weights W based on alpha_t and h_t predictions:
        for i = 1 to N:
          if h_t(x_i) = y_i:
w_i = w_i × exp(−alpha_t)
          else:
w_i= w_i × exp(alpha_t)
        Normalize weights W so they sum to 1
            Add h_t and alpha_t to H and alpha lists respectively
        return H, alphas
```

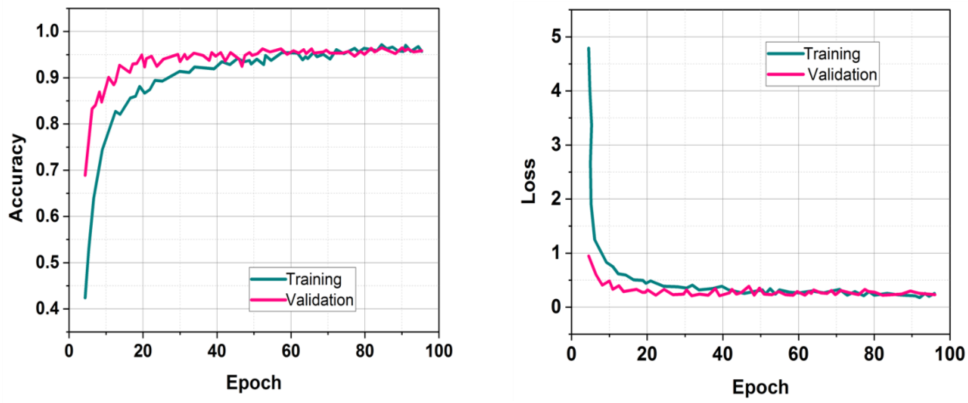
3.6. Implementing real-time feedback with Kinect technology

For Kinect motion capture technology to improve physical fitness education, real-time feedback is crucial because it enables instructors and students to modify their activities in response to instant performance data. The suggested CO-AWAdaBoost model rapidly detects deviations in body posture data and suggests corrections by continually analyzing the data. Tools for real-time visualization show performance metrics, which improves technique comprehension. *Z*-score normalization also standardizes data points so that they can be evaluated consistently and quickly against pre-established benchmarks. This instant response greatly enhances user experience and adoption of the technology, fostering a more engaging learning environment in addition to improving the instructional process.

4. Results and discussion

Python 3.6.14 was utilized extensively during the research process. This article offers an Intel Core i7 laptop running Windows 10 with a 64 GB solid-state drive. The Kinect sensor version 1.0, a 3D body camera, served as the test device for this investigation, the evaluation of the phase difference between the active infrared light's round-trip timings, and an RGB camera device to get human body depth image data. To demonstrate a suggested method's performance, its dependability and effectiveness are compared to those of more recognized techniques like Artificial Neural Network (ANN), Random Forest (RF), and IoT-based Physical Activity Recognition (IPAR) [25].

Figure 4a shows CO-AWAdaBoost's training and validation accuracy, whereas **Figure 4b** shows CO-AWAdaBoost's training and validation losses. The training dataset can be seen to gradually decrease as the model's complexity rises, suggesting that the model does not exhibit the over fitting issue throughout the training process.



(a) **(b)**

Figure 4. (a) Training accuracy and validation accuracy; **(b)** Training loss and validation loss curve.

The application of precisely calculating the total number of occurrences is known as accuracy. The accuracy of the CO-AWAdaBoost and the existing technique is shown in **Figure 5** and **Table 1**. The accuracy rate of the CO-AWAdaBoost is 98.25 %, while the accuracy rates of RF, ANN, and IPAR are

90.74 %, 91.74 %, and 95.82 % respectively. This depicts that the CO-AWAdaBoost method outperformed than the existing methods.

Table 1. Numerical results of accuracy.

Methods	Accuracy
RF [25]	90.74
ANN [25]	91.74
IPAR [25]	95.82
Co-AwAdaBoost [Proposed]	98.25

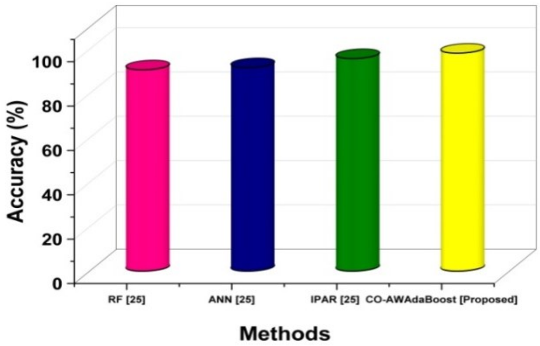


Figure 5. Comparative analysis of accuracy.

Precision is a metric used to assess a classification or prediction model's accuracy in the context of statistics and machine learning. The precision of the CO-AWAdaBoost and existing systems is displayed in **Figure 6** and **Table 2**. The precision of RF is 92.32% that of ANN is 95.42% that of IPAR is 96.95% and that of the CO-AWAdaBoost method is 97.22%. The precision of the CO-AWAdaBoost is higher than that of existing techniques.

Table 2. Numerical results of precision.

Methods	Precision
RF [25]	92.32
ANN [25]	95.42
IPAR [25]	96.95
Co-AwAdaBoost [Proposed]	97.22

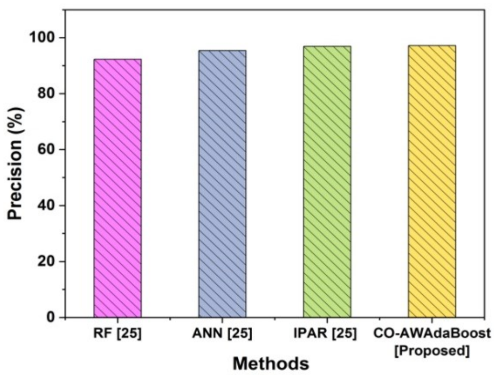


Figure 6. Comparative analysis of precision.

The $F1$-score evaluates the overall effectiveness of a classification model or system by combining accuracy and recall. **Figure 7** and **Table 3** displays the $F1$-score for both the existing and CO-AWAdaBoost methods. The CO-AWAdaBoost achieved 97.88% $F1$-score, when compared to RF (93.85%), ANN (94.83%), and IPAR (97.88%). This shows that the recommended technique F-score exceeds the existing methods.

Table 3. Numerical results of $F1$-score.

Methods	$F1$-score
RF [25]	93.85
ANN [25]	94.83
IPAR [25]	97.83
Co-AwAdaBoost [Proposed]	97.88

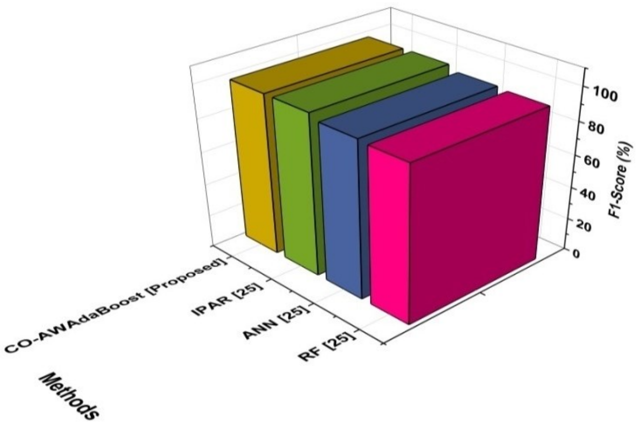


Figure 7. Comparative analysis of $F1$-score.

Specificity describes the property of being exact or precise. The CO-AWAdaBoost method achieved 97.85% specificity, surpassing RF (90.75%), ANN (93.12%), and IPAR (96.32%). This illustrates that the CO-AWAdaBoost exceeds the existing methods. The specificity of the CO-AWAdaBoost and existing systems is displayed in **Figure 8** and **Table 4**.

Table 4. Numerical outcomes of specificity.

Methods	Specificity
RF [25]	90.75
ANN [25]	93.12
IPAR [25]	96.32
Co-AwAdaBoost[Proposed]	97.85

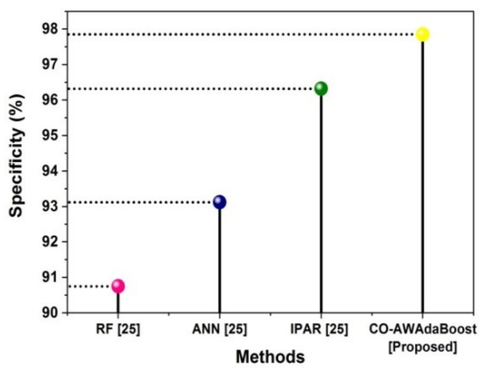


Figure 8. Comparative analysis of specificity.

The sum of true positives less false negatives is the mathematical formula used to calculate Recall. **Figure 9** and **Table 5** shows the recall of the CO-AWAdaBoost and the existing method. The CO-AWAdaBoost has a higher recall than the existing techniques. Whereas RF has a recall of 92.23%, ANN has a recall of 94.35%, IPAR has a recall of 95.63% and the CO-AWAdaBoost has a recall of 97.86%.

Table 5. Numerical outcomes of recall.

Methods	Recall
RF [25]	92.23
ANN [25]	94.35
IPAR [25]	95.63
Co-AwAdaBoost [Proposed]	97.86

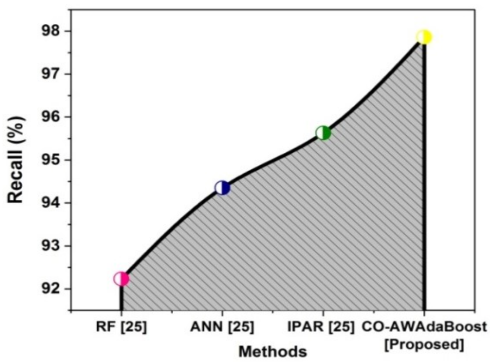


Figure 9. Comparative analysis of recall.

5. Discussion

Large-scale, well-labeled datasets are necessary for ANNs, but obtaining them in the context of teenage physical fitness might be difficult [25]. Additionally, they are prone to overfitting, which results in poor generalization, particularly with smaller or imbalanced datasets. The high dimensionality and noise in motion capture data could be too much for the RF algorithm to handle, which could result in inaccurate movement categorization [25]. Furthermore, RF models might not offer real-time feedback, which is essential for productive physical training sessions, and they might be computationally demanding. Reliance on constant internet access might cause latency problems in IPAR, impacting real-time feedback that is essential for training adolescents [25]. Furthermore, sending sensitive motion data raises privacy and security issues, and climatic conditions and sensor limitations might impair the accuracy of the system. To address these issues and increase activity detection accuracy, CO-AWAdaBoost, an adaptable boosting algorithm, can improve physical fitness training for teenagers using Kinect motion capture. Future research should focus on developing more robust data augmentation techniques to enhance dataset quality and quantity, improving the generalizability of models. Investigating alternative machine learning algorithms that can effectively manage high-dimensional data without overfitting is also recommended. Additionally, integrating edge computing solutions could reduce reliance on constant internet connectivity and improve response times for real-time feedback. Emphasizing privacy-preserving techniques in data handling will ensure user confidentiality, while refining sensor calibration processes can help mitigate the effects of environmental variables on system performance.

6. Conclusion

In a classroom, we utilized a Kinect sensor to obtain joint coordinates of the physical education teacher’s body positions. Changes in joint coordinates were used to classify a dataset of instructional activities. To investigate the techniques and means of intelligent recognition of PE classroom behavior, an intelligent recognition system was created, and the best classification assessment model was chosen through experimental comparison. The CO-AWAdaBoost technique’s accuracy, precision, recall, $F1$-score, and specificity are 98.25%, 97.22%, 97.86%, 97.88%, and 97.85%, respectively, according to the aforementioned statistics. Adolescents employing Kinect motion capture for physical fitness instruction encounter several obstacles when using CO-AWAdaBoost, including high computing demands, data requirements, and probable over-fitting. Furthermore, the expense of Kinect sensors and associated equipment could restrict the acceptance and use of this technology in educational settings. This costly barrier could prevent classrooms and fitness centers from investing in modern motion capture systems, limiting access to novel teaching tools. As a result, instructors may overlook chances to improve teaching quality and student engagement using technology. Addressing cost issues, whether through subsidies or other inexpensive alternatives, will be critical for increasing usage and boosting physical education programs. Future developments in wearable technology integration, data augmentation methods, and algorithm efficiency, however, may improve its usefulness. Using immersive technology like virtual reality in conjunction with customized training programs can increase effectiveness and engagement even more.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

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