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Article

Wearable sensor-based real time monitoring system for physical education teaching and training

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Abstract: The comprehensive progress of mental and physical quality is majorly influenced by the college physical education, which is considered a part of the educational system. Developing a scientific and efficient evaluation index is significant to compute physical education teaching quality. The traditional methods of assessing performance in physical education often rely on subjective evaluations or delayed feedback from manual data collection. To overcome these challenges, a design based on a real-time monitoring system is introduced that leverages wearable biosensor technology to improve physical education teaching and training. Initially, some physiological indicators, namely heart rate, respiration rate, body temperature, and motion activity, were recorded and analysed to provide individualized insights into physical performance. Data pre-processing is performed using a median filter to reduce noise and Z-score normalization to standardize the input dataset. Key features are extracted using Fast Fourier Transform (FFT), enabling the identification of critical performance metrics. A Rat Swarm Optimized Efficient Random Forest (RSO-ERF) algorithm was introduced to enhance classification accuracy and optimize system performance. Experimental results demonstrate the proposed system's effectiveness in providing real-time feedback, identifying individual fitness levels, and supporting adaptive teaching strategies. The increased system's analysis tendency allows for customized training regimens, ongoing feedback, and improved physical health metrics monitoring. It also gives educators the ability to make data-driven decisions, encourage safety, and improve the educational experience for athletes and students. The findings underscore the potential of wearable biosensor technology combined with advanced algorithms in transforming physical education methodologies for improved engagement and performance outcomes.

Keywords: physical activity monitoring; wearable biosensor; physical education teaching; rat swarm optimized efficient random forest (RSO-ERF); college

1. Introduction

Particularly at higher education organizations, physical education is an essential component of the educational program and it is essential to deliver high-quality teaching. It helps the student to develop intellectually and physically. To satisfy the demands of economic development, young people should improve their health, gain knowledge, learn new skills, cultivate empathy, and boost their spirits [1]. All physical education teacher education (PETE) programs are expected to produce highly qualified graduates who are considered successful educators. Thus, to achieve this goal, physical education departments have historically determined what is necessary to be covered in each student's coursework in compliance with the mandates of state offices of public teaching (SOPI) [2]. Programs for physical education are often to raise awareness of both the requirements of students and instructors. Pre-service teacher education programs are essential to ensuring that teachers are equipped to deliver effective physical education training and fundamental movement skill (FMS) programs [3]. Self-determination theory (SDT) has gained recognition as a theoretical framework that has been proven to be effective over the past forty years for the conceptualization and research of motivation in a variety of real-world scenarios, including classroom environments like physical education programs [4]. A student's development with memory, growth ability, reasoning, brain function, and attention is crucial to encouraging the best possible motivation, learning engagement, and tenacity. Various AI-based methods have recently shown successful in teaching physical education innovations, particularly in increasing students' involvement in sports [5]. **Figure 1** represents the student conditions in sports using wearable biosensors.

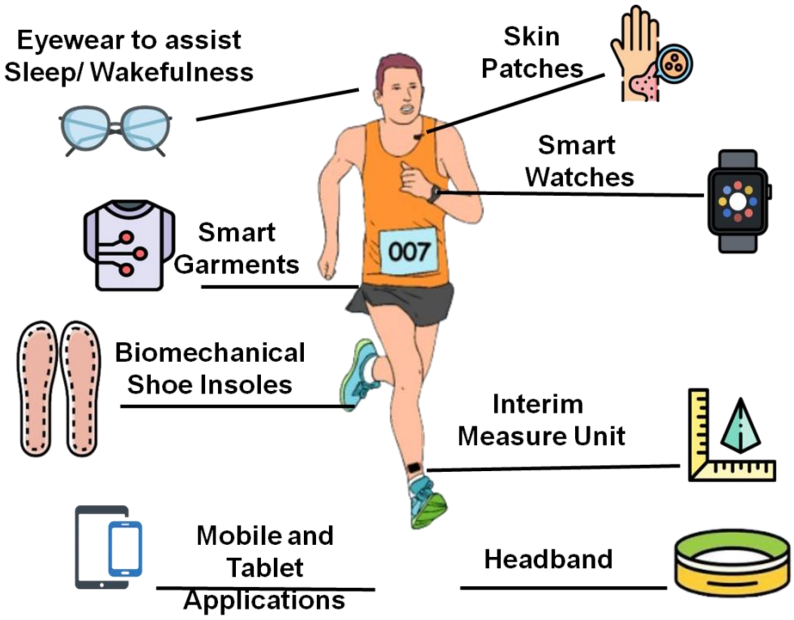

Figure 1. Student conditions in sports using wearable biosensors.

Physical education needs to provide a high level of teaching to produce top-notch athletes. At the same time, effective assistance in the enhancement of academic physical involvement teaching is essential [6]. Several athletic and fitness-related fields have incorporated persistent or ubiquitous technology by integrating sensor data, processing, and communication technologies. The developments in wearable intelligent monitoring systems' sensor integration will be discussed in general terms. Sports and health monitoring specifically employ sensor fusion to measure workouts, categorize activities and metrics, estimate energy consumption, analyze movement patterns, track body response, and assess sleeping patterns [7]. The development of wearable technology predates popular belief. Smart bracelets, smart tattoos, smart contact lenses, and smartwatches are examples of wearable electronics that are commonly referred to as wearable gadgets. Flexible wearable technology has incorporated microfluidic chips into its design and development in recognition of the potential for improved monitoring accuracy. These chips specifically enable wearable devices to monitor biochemical, physiological, and bioelectrical signals with greater accuracy in a smaller volume [8]. A strong basis for evaluating athletes' training state, tracking exhaustion, and identifying and treating sports-related injuries is provided by this technical development. In addition, the portable and adaptable nature of microvascular chips allows flexible wearable gadgets to easily fit a person's body. These wearable devices have improved the training and learning capabilities of college physical education systems when combined with athlete performance data and feedback from sports trainers [9]. These observations may be influenced by students' emotional state with physical education, but more detailed research is required to comprehend how physical education affects students' responsiveness throughout the college day and how variables like student involvement can alter during physical education. Different pedagogical approaches are implemented in physical education training. Wearable technology is growing in popularity in a variety of fields, such as gaming, fashion, entertainment, health monitoring, and gesture recognition. Wearable technology has been applied to teaching in more recent years. Because of its visibility and direct contact with the human body, wearable technology has the potential to have a big impact on physical education teaching and training [10]. Six of these documents, however, are primarily concerned with the experiences of learners before attending college. Physical education aims to further investigate the rapid progress in wearable learning technologies, with a intend on potential application for training and teaching in physical education. Strength training is mostly provided to college students as a way to enhance their physical activity, mental well-being, sports performance, muscle strength, and even the prevention and treatment of injuries. Health and injury management for physical education training can be greatly optimized by technological advancements like cloud computing, the Internet of Things (IoT), as well as clever AI methods. Real-time data processing and improved decision-making are made possible by these advancements, which lead to more efficient training management [11].

1.1. Objective

The main goal is to put in place a real-time monitoring system that makes use of physical education instruction and training. To improve classification accuracy and optimize system performance, a Rat Swarm Optimized Efficient Random Forest (RSO-ERF) algorithm was suggested for analysing physical education training. This approach aids in providing improved training and teaching as well as improved athletic performance through the use of wearable biosensors. Additionally, teachers learn how to use the best teaching techniques to maintain students' interest and engagement in the physical education system.

1.2. Key contributions

The following are the key findings of the current research.

- To collect input data based on wearable biosensors, including heart rate, respiration rate, body temperature, and motion activity.
- To apply a pre-processing method that standardizes the dataset by using Z-score normalization and a median filter to eliminate noise.
- To determine the important features from the input data, the Fast Fourier Transform Algorithm (FFT) for the feature extraction technique is introduced.

- To implement RSO-ERF to effectively monitor and analyse the performance of physical education teaching and training.

1.3. Paper organization

Section 2 explains relevant studies based on analysing physical education training. The implemented methods are thoroughly explained in Section 3. Also, in Section 4, the outcomes obtained from applying the suggested RSO-ERF model are discussed. Then, a brief summary of the results produced is covered in Section 5, and Section 6 provides a conclusion with the constraints and upcoming work of the research.

2. Related works

The intelligent sports program suggestion function was executed by using the artificial intelligence recommendation (AIR) algorithm [12]. It analysed the individual’s body mass index (BMI), physical condition, and age for the student’s athletic practices. The result of the functional tests showed that the colleges’ teaching needs were satisfied by the sports training environment teaching system, which also increased college students’ participation in sports and advanced psychological education. The design of a deadly control and prevention system was developed [13] by implementing a convolutional neural network (CNN) algorithm. CNN was developed to illustrate the dynamic changes between joints by taking advantage of the joint action trajectory within the time interval. Results from experiments proved that, when compared to other algorithms, the CNN model exhibited improved accuracy in action recognition.

A synthetic neural community expert system was the main framework of a junior assessment system for excessive college students’ outstanding mastery of their body education [14]. The reduced number of participants in the comparing process increased the assessment’s credibility and produced significantly improved and accurate comparisons. Research [15] created a one-dimensional CNN (1D-CNN) using an LSTM model to classify teenagers’ levels of physical fitness into four categories: outstanding, good, medium, and low. For physical fitness, the prediction accuracy was 99.26% for females and 98.27% for boys. The experimental findings demonstrated that it was possible to use running photoplethysmography (PPG) recordings of teens to estimate their degrees of physical fitness. Research [16] examined the viability of a generic estimating approach for evaluating human activity that uses a single back-mounted sensor. When bearing varying weights, the approach takes into account the smallest variability in human body motions. A deep learning (DL) structure with comprehensive environment for monitoring behaviours of human beings was proposed.

A deep learning-CNN (DL-CNN) and a long short-term memory (LSTM) technique were used [17] to forecast the students’ physical fitness at four different accuracy levels: low, medium, good, and outstanding. The results of the study showed that running photoplethysmography (PPG) data were used to assess the physical fitness of adolescents. Biosensor-based deep neural network-based college student mental health prediction model (BDNN-CSMHPM) concept of university learners throughout the tracking period consuming biological knowledge comprising biomechanical electroencephalogram (EEG) stress levels were predicted [18]. It divided mental health into three categories: good, bad and normal. Compared with other methods, the model exhibited better accuracy, emotion recognition, Pearson correlation, and psychometric analysis.

The wireless body area sensor network (WBASN), classification of machine learning (ML) algorithms, and intelligent wearable sensors were employed in sports and health monitoring [19]. It provided practical answers to the ongoing advancement of smart wear materials, identifying potential barriers, future growth prospects that may affect them and insightful descriptions of interesting possibilities, presenting smart wear technology that is sporty and it happens. It will change health care. The analysis of how algorithms were merged with the rise of digitized health and physical education (eHPE) through the implementation of new biophysical data and health-tracking technology was performed in educational environments [20]. The difficulties and advancements pointed to the need for further focus on the integration of algorithmic systems into new eHPE pedagogies and technology.

A multi-attribute fuzzy evaluation model (MAFEM) was developed to assess student health based on sensor data [21]. The MAFEM method used fuzzy logic and fuzzy sets to identify relationships between objects. By using data from the input dataset, the effectiveness of the technique was improved, maintaining the minimum level of operational complexity and delay potential. DL architecture was presented to predict the level of restlessness experienced by sporty students while engaging in physical activity [22]. The ML models properly evaluated a person’s training session and presented individuals with performance feedback. Decision trees (DT), weighted K-Nearest Neighbour (KNN), fine-grained support vector machines (FGSVM), and bagged trees (BT) were among the ML techniques applied to the dataset. The testing results showed that the weighted KNN model provided increased accuracy. It applied fivefold cross-validation on the training and testing datasets. Better precision and acceptable classification were achieved by the model based on the testing dataset [23]. The gathered data was categorized using machine learning-based classification techniques.

Research gaps

In researching DL-based models of exercise training and instruction, separation and search improved significantly. Even if the research warrants it, there are limitations. Although the AIR algorithm is effective in proposing game plans based on physical conditions and objects, it still needs further investigation. Future research can be more accurate if behavioural, lifestyle, and psychological factors are considered and adjusted in real time based on user feedback, functional dynamics, and environmental factors. A more integrated strategy that incorporates data from movement devices may provide an improved understanding of student health. The wearable biosensors and other AI models commonly depend on individual physiological parameters to predict health outcomes. Moreover, environmental difficulty appears to be a problem for wearable sensor reliability, especially for wrist-worn machines. The integration of wearable technology and biosensors in multiple disciplines ensures that AI-powered solutions in educational settings address every element of students' well-being. To address the issues related to conventional techniques, the present research implements the RSO-ERF algorithm to enhance classification accuracy and optimize system performance in physical education systems. This approach emphasizes the potential of combining wearable biosensors and advanced algorithms to transform physical education methodologies, promoting better health and fitness outcomes for students.

3. Proposed methodology

This section presents the important techniques used in physical education training and teaching. Analysis and forecasting of physical education using the proposed methodology represents one of the techniques. Initially, data collection, and data pre-processing using two methods such as the median filter algorithm, Z-score normalization, feature extraction using Fast Fourier transform (FFT), classification technique utilizing the Rat swarm optimized efficient random forest algorithm (RSO-ERF), and finally performance analysis. **Figure 2** shows the suggested approach for physical education teaching and training.

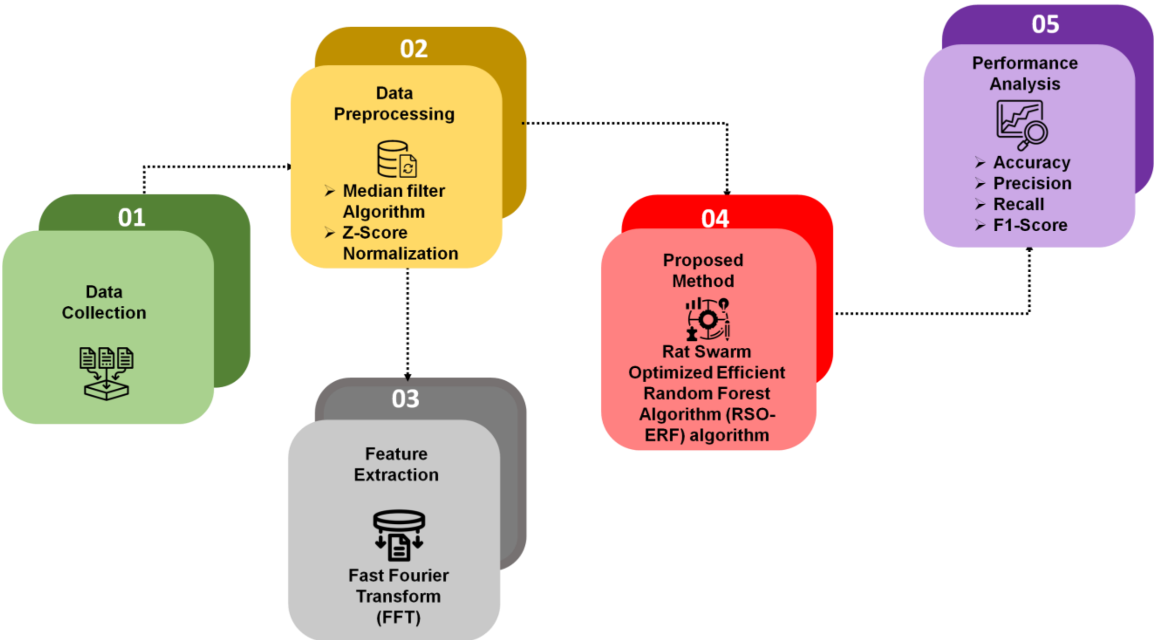

Figure 2. Overall suggested approach for physical education teaching and training.

3.1. Dataset description

The Collective Sports [Sensor] DB of Practice Sessions dataset is used in this research, which is a collection of data mainly intended for the analysis of collective sports using wearable sensors. Information was collected during practice sessions from 130 participants when athletes wore sensors to record various performance indicators. Height, alcohol use, weekly training rate, smoking, the existence of illnesses, heart-rate series, weight, R-R interval (the interval between two successive RR waves), and/or breathing-rate series are all included in this dataset. This dataset is gathered from a publicly available resource platform and is accessed using https://www.kaggle.com/datasets/sujaykapadnis/comprehensive-sports-database.

3.2. Data pre-processing

The preprocessing method refers to the steps taken to clean, normalize, and transform the raw data from sensors or wearables before it is used for analysis or model training. The following pre-processing techniques are used in this research.

3.2.1. Median filter

The non-linear median filter is primarily employed to reduce noise in the input raw data which interferes with accurate analysis and may distort the true signals. It is also known as a signal processing method that aids in removing noise and other outliers effectively. This helps to ensure that the data better represents the actual physiological or motion signals from the athletes with reduced irregularities. The median filter is illustrated by Equation (1).

$$\hat{g}_{(y,x)} = \frac{1}{nm} \sum_{(r,p)\in R_{yx}} f(r,p) \tag{1}$$

where, R_{yx} is the set of coordinates in a window (kernel size) of $n \times m$ centered at any position (y, x) in the original image, p and r are the column and row coordinate whose coordinates are members of the set. By substituting the median of each surrounding data point for each data point, this filter helps to smooth out sudden noise-induced shifts.

3.2.2. Z-Score normalization

Z-Score normalization is a method employed for normalizing a dataset, transforming it to have a mean of 0 and a standard deviation (SE) of 1. Standardizing the data guarantees that every feature is on a comparable scale, preventing any variable from unduly impacting the analysis or the proposed physical education training model because of its scale. It is indicated by Equation (2).

$$Z = \frac{X - X}{SD_x} \tag{2}$$

where SD denotes standard deviation, x is the quantity to be normalized, $\bar{X}$ is the average value, and Z is the normalization outcomes.

3.3. Feature extraction

Key patterns in physical education are detected by feature extraction using the FFT.

Fast fourier transform algorithm (FFT)

The FFT approach provides the ability to preserve more processing resources as the number of sampling points increases. First, the original signal's consecutive time-domain data is obtained by using a sliding window. Then, using the FFT approach, which is explained by Equation (3), all window data are converted to frequency information.

$$Z_l = \sum_{m=0}^{M-1} z_m d^{-j2\pi lm/M} \; l = 0, \ldots., M - 1 \tag{3}$$

where Z_l is time-domain data, and $l = 0, \ldots.$, M − 1 is a complex number. The number of sampling points is denoted by. Critical performance indicators are significantly identified by applying the FFT algorithm to extract key features.

3.4. Classification using rat swarm optimized efficient random forest (RSO-ERF) algorithm

The RSO-ERF program is an excellent comprehensive tool that combines the ERF approach with a naturally stimulated RSO-efficient algorithm to accurately predict college students' physical and cognitive development Educators to make data-driven decisions, promote safety encourage, and improve the academic experience for student athletes, 1999. The RSO and ERF concepts are used to enhance the performance quality function through the benefits of monitoring physiological and health parameters.

3.5. Efficient random forest algorithm (ERF)

Several decision trees are used in the RF algorithm, an ensemble technique that increases classification accuracy. By adding a feature weighting mechanism and a tree selection approach, the ERF improves RF for improved multi-class categorization. The association between input features and class labels is used to calculate feature weights. The ERF model's classification accuracy is further improved by normalized weights.

3.5.1. Random forest (RF) algorithm

The RF is known as an ensemble technique, which comprises a group of classifiers in a tree-like structure. It uses bagging, averaging, and bootstrapping concepts to continuously train multiple decision trees (DTs). It is possible to use specific groups of available characteristics to build multiple independent DTs simultaneously on different training sample segments. Without the problems of imbalanced datasets or overfitting, the RF classifier aims to continuously outperform all other existing classifier algorithms in terms of precision.

3.5.2. Efficient random forest (ERF) algorithm

The ERF classification strategy employs an instance filter method, an attribute evaluator method, and the RF algorithm. This classification approach is currently used to classify text documents by combining the tree selection method with a special feature weighting mechanism. Amaratunga's t-test approach can be modified with the chi-square statistic as characteristics measurement for weighting randomized subdomain selection, which may result in ERF classification, helping to address the multi-class text classification problem. The method's objective is to increase the ERF's prediction accuracy for the physical education training system. In this part, a feature weighting mechanism for subspace sampling is introduced, followed by a tree selection strategy. **Figure 3** represents the working model of the ERF algorithm involved in analyzing the accurate classification.

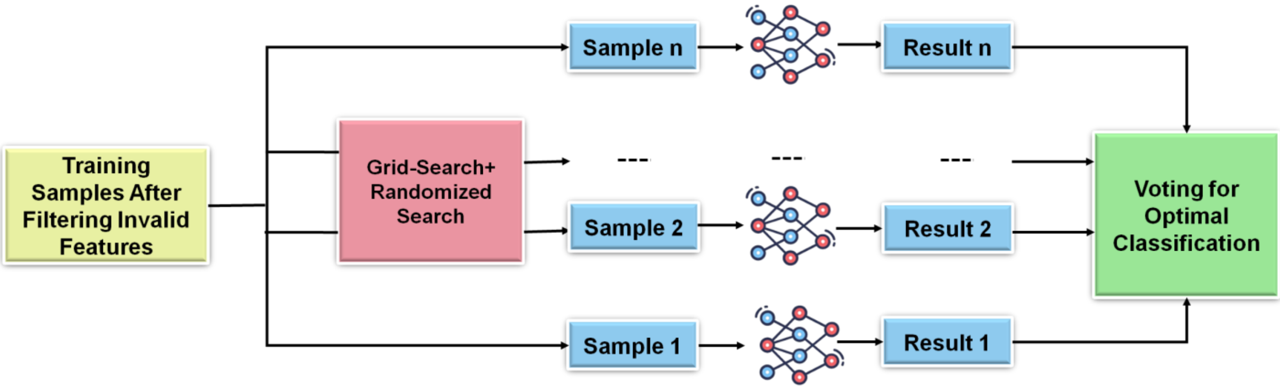

Figure 3. Efficient random forest classification model.

1) Feature Weighting Method

The feature weighting technique for subspace sampling in ERF aids in improving the classification accuracy. Let $\{B1, B2, \ldots, bN\}$ be an N-dimensional feature space. The computation of the weights $\{v1, v2, \ldots, vN\}$ for each feature in the space is presented. Each DT in RF is then grown using these weights. Normalized weights and feature weight computation are the only focus of the feature weighting approach.

The information of each input feature b_J's is determined by its correlation to the class feature Z, which is then used to calculate the feature weight. When the weight is high, the feature's values correspond to the class labels of the training set's objects. The class feature B, represented as $z_i(for\ i = 1, \ldots, s)$, can accept r values, represented by $b_j\ (forj = 1, \ldots, r)$, given that it contains s distinct values or classes.

Given a dataset of class feature Z and input feature B, the correlation based on the chi-square statistic is calculated by using Equation (4).

$$corr(B, X) = \sum\nolimits_{j=1}^{r} \sum_{i=1}^{s} \frac{(\lambda_{ji} - r_{ji})^2}{r_{ji}} \tag{4}$$

Here, the data samples are denoted by$\sum_{j=1}^{r} \sum_{i=1}^{s} \lambda_{ji}$, where r_{ji} is the anticipated frequency andλ_{ji} is the observed frequency.

2) Normalized Weights

Feature weights are normalized for feature subspace sampling. Assume that a feature b_J and its class label feature z have a relationship for $J = 1, \ldots, N$. It is expressed by Equation (5).

$$v_j = \frac{\sqrt{corr(B_j, Z)}}{\sum_{j-1}^{N} \sqrt{corr(B_j, Z)}} J = 1, \ldots, N \tag{5}$$

The extraction of the correlation's square root is a popular smoothing method. It is visible that the normalized weight v_j calculates feature b_J's. One popular method for smoothing is to obtain the correlation's square root. Feature B_j's relative informativeness is measured by the normalized weight v_j. Thus, the algorithm is designed using this weight information for feature subspace sampling.

3) Tree Selection Method

Determining each tree's accuracy is the primary problem in the tree selection procedure. To assess the significance of a tree, the research employs out-of-bag accuracy. Using the bagging method, several training data subsets are created for the ERF construction model. These training subsets are subsequently employed to build trees. Each tree has two types of data: out-of-bag (OOB) data, which is the subset of data composed of the remaining data, and in-bag (IOB) data, which is the subset of training information is applied to build the tree.

Given a tree classifier $g_l(IOB_l)$ constructed from the l^{th} subset of training data IOB_l. The OOB correctness of the tree $g_l(IOB_l)$is defined by Equation (6).

$$OOBAcc_l = \frac{\sum_{j=1}^{m} J(g_l(e_j) = z_j; e_{j \notin} IOB_l)}{\sum_{j=1}^{m} J\,(e_j \notin IOB_l)} \tag{6}$$

where $J$is is an indicator function, all the trees are sorted according to their OOB accuracy in descending order, and the top-ranked trees are chosen to construct the ERF. A good tree population is produced by such a tree selection technique.

3.6. Rat swarm optimized (RSO) algorithm

Rats are long-tailed, medium-sized animals that differ in size and weight. They groom one another and engage in a variety of sports like boxing, tumbling, chasing, and jumping. Rats live in groups of both men and females and are territorial creatures. They frequently exhibit extremely aggressive behavior, which can cause some animals to die. The primary driving force behind this effort is aggressive conduct and engaging in combat with prey. Rats' chasing and fighting activities are mathematically represented to create an RSO algorithm and carry out optimization.

3.6.1. Catching the prey (Exploration)

Rats are generally expressive animals that exhibit social agonistic behaviour when hunting in groups. It is assumed that the ideal search agent knows the position of the prey to quantitatively explain this behaviour. In Equation (7), the process is presented clearly.

$$\vec{Q} = B.\vec{Q}_j(y) + D.(\vec{Q}_s(y) - \vec{Q}_j(y)) \tag{7}$$

where, the best optimal solution is $\vec{Q}_s(y)$, and the rat positions are defined by $\vec{Q}_j(y)$. While Equation (8) is used to derive the B and D parameters.

$$B = S - y \times \left(\frac{S}{Max_{Iteration}}\right) \tag{8}$$

$$D = 2 \cdot rand() \tag{9}$$

$S\ and\ D$ are random numbers in the present scenario. B and Dlead to better exploration and exploitation during iterations.

3.6.2. Fighting with prey (Exploitation)

Rats' fighting behavior with prey has been quantitatively defined by the Equation (10).

$$\vec{Q}_j(y+1) = |\vec{Q}_s(y) - \vec{Q}| \tag{10}$$

where the rat's updated future position is defined by $\vec{Q}_j(y+1)$. As demonstrated by Equations (9) and (10), the parameters can be changed to attain a different number of places relative to the current position. However, this idea can also be expanded in an environment with n dimensions. **Figure 4** represents the entire process involved in the RSO algorithm in effectively providing real-time feedback for physical education training.

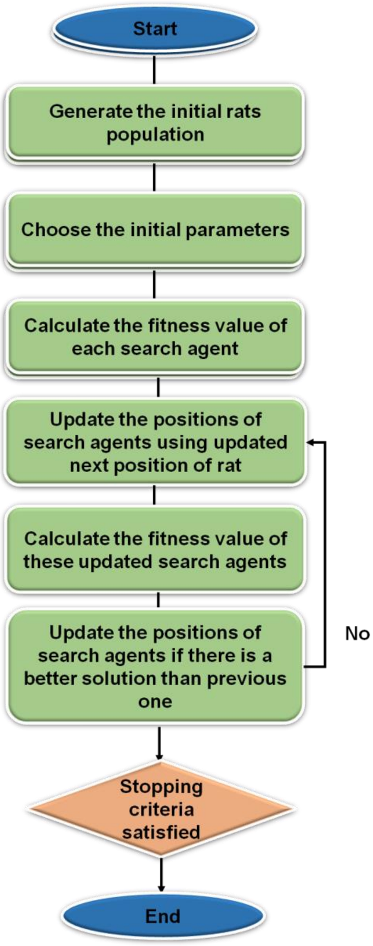

Figure 4. Flowchart of rat swarm optimized (RSO) algorithm.

Thus, the RSO-ERF is considered a powerful optimization technique that combines the strengths of both the metaheuristic approach of RSO with the relational learning capability of ERFs. The RSO-ERF model creates a very successful optimization framework for intricate data analysis tasks by skilfully fusing the relational learning capabilities of ERFs with the metaheuristic approach of the RSO technique. RSO uses the benefits of both methods in this hybrid technique to enhance classification performance by optimizing the hyperparameters of the ERF algorithm. To improve model accuracy, especially in classification problems, two crucial factors must be changed throughout the optimization process: feature weighting and tree selection. By optimizing these hyperparameters, the RSO-ERF can navigate high-dimensional data fields efficiently, ensuring that relevant features are prioritized while lowering the risk of overfitting. **Table 1** illustrates the hyperparameters used to increase the accuracy of the analysis process. The extent of the search space is probably indicated by the suggested range (10 to 30). The algorithm exploration parameter (1–5) determines how much it looks for new solutions, and its exploitation parameter (0–2) determines how much it concentrates on improving existing ones. The number of algorithm runs is defined by max iterations (50 to 200), and fixing a random seed, a common setting of 42 guarantees repeatability across tests.

Table 1. Details of hyperparameter for RSO-ERF.

Hyperparameter	**Values**
Suggested Range	10 to 30
Exploration Parameter	Between 1 and 5
Exploitation Parameter	Between 0 and 2
Max Iterations	50 to 200
Common Setting	42 (for reproducibility)

Algorithm 1 reveals the methods and strategies employed in the proposed RSO-ERF for physical education instruction and training.

Algorithm 1 RSO-ERF used in training and teaching physical education

```
Step 1: ERF Training
deftrain_optimized_erf(features, class_labels, feature_weights, max_trees=100):
    subsets = create_training_subsets(features, class_labels)
    trees = []
    for subset in subsets:
tree = train_tree_with_weights(subset, feature_weights)
trees.append(tree)
oob_accuracies = evaluate_oob_accuracy(trees)
selected_trees = select_best_trees(trees, oob_accuracies)
random_forest = build_random_forest(selected_trees)
   return random_forest
Step 2: RSO Optimization
defoptimize_hyperparameters_using_RSO(features, class_labels, max_iterations, population_size, exploration_param,
exploitation_param):
    population = initialize_population(population_size)
    for iteration in range(max_iterations):
 for rat in population:
update_position_chasing(rat, exploration_param, exploitation_param)
update_position_fighting(rat)
evaluate_population_fitness(population, features, class_labels)
best_solution = get_best_solution(population)
    return best_solution
Step 4: Execute the RSO-ERF Algorithm
defRSO_ERF_algorithm(dataset, class_labels, max_iterations=100, population_size=20, exploration_param=3,
exploitation_param=1, max_trees=100):
    features = preprocess_data(dataset)
feature_weights = compute_feature_weights(features, class_labels)
best_hyperparameters = optimize_hyperparameters_using_RSO(features, class_labels, max_iterations, population_size,
exploration_param, exploitation_param)
random_forest = train_optimized_erf(features, class_labels, feature_weights, max_trees)
    predictions, evaluation_metrics = classify_with_erf(random_forest, dataset)
    return predictions, evaluation_metrics
End
```

4. Results and discussion

The RSO-ERF method aims to improve classification accuracy by providing more accurate information on student activities, which can significantly enhance physical education instruction. This section presents the results obtained by the proposed RSO-ERF method based on a few performance parameters. Furthermore, comparative studies with the proposed model as well as existing studies have been adopted to determine the reliability of the study.

4.1. Experimental setup

The RSO-ERF method is implemented in a setting with Windows 10 (64-bit), TensorFlow 2.4.1, and Python version 3.6. RAM of 8 GB, an Intel Core i7 multi-core processor, CUDA 11.1, and an NVIDIA GeForce GTX 1650 graphics card, comprising the software environments for the experiment.

4.2. Performance analysis

The performance of the exercise training and instruction is verified through the comparison of the proposed RSO-ERF method with traditional methods. Existing studies used for comparison include recurrent neural networks (RNN) [24] and LSTM and generative adversarial networks (LSTM-GAN) [25] Thus, results are stated with each method depending effects on research variables are discussed below. The experimental results are analysed in this research incorporating multiple evaluation metrics comprises accuracy, F1-score, precision and recall. The outcomes procured by implementing the RSO-ERF method are displayed in **Table 2**. The model properly diagnoses the majority of cases with an accuracy of 99.3%. With an accuracy of 93.8%, 93.8% of the anticipated positive cases turn in to be true. The 92% recall indicates that 92% of real positive events are properly identified by the technique. The model's capability in handling inaccurate result is demonstrated by its F1-score of 95.3%, which strikes a compromise between accuracy and recall.

Table 2. Evaluation matrices of the RSO-ERF outcomes.

Evaluation Metrics	RSO-ERF [Proposed]
Accuracy	99.3%
Precision	93.8%
Recall	92%
F1-Score	95.3%

4.2.1. Accuracy

Accuracy is used to evaluate how frequently the students complete tasks correctly, such as performing a movement with the right form or technique. It indicates how frequently students perform a particular physical movement correctly versus poorly (true positive vs. false negative) when learning physical exercises. Accuracy is used to evaluate the effectiveness of the system in providing real-time feedback or assessing the students' performance. It is expressed in Equation (11).

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \tag{11}$$

where tn stands for true negative, fp indicates false positive, fn means false negative, and tp represents true positive.

4.2.2. Precision

Precision ensures accurate and helpful feedback for skill development in physical education by accurately detecting performance. This enables teachers to customize interventions according to the needs of individual students by customizing activities based on the data. Achieving this improves the quality of education, facilitates successful learning, and stops the reinforcement of inappropriate or unwanted actions, which leads to better performance and behavior. Equation (12) denotes the representation of precision.

$$Precision = \frac{tp}{tp + fp} \tag{12}$$

Improved precision values help in improving athlete feedback, customizing training plans, and assisting coaches in making more informed, data-driven decisions to enhance sports performance by reducing false positives, or inaccurate predictions. **Table 3** provides the outcomes based on precision and accuracy procured by the existing and the suggested model. The suggested RSO-ERF approach outperforms the other models in both measures, with 99.3% accuracy and 93.8% precision, and the LSTM-GAN model has 95% accuracy and 92.1% precision, while the RNN model obtains 99% accuracy with 88% precision.

Table 3. Results determined by accuracy and precision.

Methods	Accuracy	Precision
RNN [24]	99%	88%
LSTM-GAN [25]	95%	92.1%
RSO-ERF [Proposed]	99.3%	93.8%

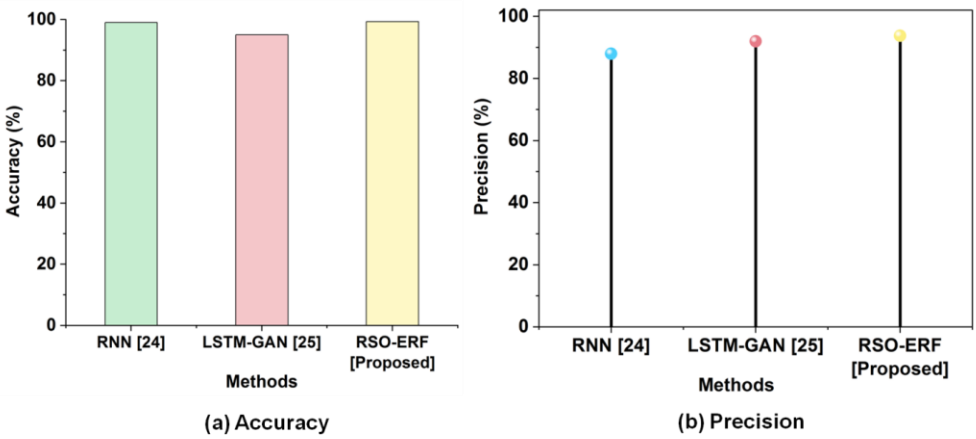

Figure 5. Outcomes of **(a)** Accuracy; **(b)** Precision.

Figure 5 shows the comparison of existing and proposed methods in **(a)** accuracy, as well as **(b)** precision. The accuracy and precision results for the three approaches LSTM-GAN, RNN, and the suggested RSO-ERF. (**a**) Accuracy of the suggested RSO-ERF was obtained 99.3%, LSTM-GAN 95%, and RNN 99%. (**b**) Precision was attained by RNN at 88%, LSTM-GAN at 92.1%, and RSO-ERF at 93.8%. Outperforming both RNN and LSTM-GAN, the suggested RSO-ERF approach exhibits the best accuracy and precision.

4.2.3. Recall

Recall refers to the model's capacity to accurately pick out positive examples among all real positive examples, such as when pupils reach a particular performance threshold or participate in particular physical activities. It measures how successfully the system uses information gathered from wearable sensors to determine each student's accurate performance or fitness level. Recall helps successful teaching by acknowledging achievement in skills and recording positive behaviours to reinforce growth in physical education.

$$Recall = \frac{tp}{tp + fn} \tag{13}$$

4.2.4. F1-score

The F1 score tracks the trade-off between false positives (FN) and false negatives (FP), combining accuracy and recall to offer an improved assessment of model performance. Since precision and recall are reconciliation tools, it ensures that they are given equal weight in the analysis. The sample determines the percentage of true positives, while the accuracy is the percentage of true positives and negatives. The two criteria are balanced by the F1-score, where a higher F1-score indicates the need for more accurate and detailed modelling.

Accuracy and recall are combined in the F1 score to provide a reliable evaluation of physical education proficiency. It helps to assess both the identification of appropriate behavior and the ability to record any positive incidents. Improved assessment, more accurate feedback, and enhanced student skill assessment are all indicated by higher F1-scores.

$$\mathrm{F1} - \mathrm{score}\ 2 \times \frac{(\mathrm{Precision}) \times (\mathrm{Recall})}{(\mathrm{Precision}) + (\mathrm{Recall})} \tag{14}$$

The results produced by the proposed and existing models based on recall and F1-score are shown in **Table 4**. The LSTM-GAN advances to 91.2% recall and 94.5% F1-score, whilst the RNN attains 89% recall. A recall of 92.7% and an F1-score of 95.3% are both superior to those of the suggested RSO-ERF approach. These findings imply that RSO-ERF outperforms earlier techniques like RNN and LSTM-GAN in terms of recall and F1 score, suggesting its potential efficacy for the position.

Table 4. Results based on Recall and F1-Score.

Methods	**Recall**	**F1-Score**
RNN [24]	89%	-
LSTM-GAN [25]	91.2%	94.5%
RSO-ERF [Proposed]	92.7%	95.3%

Figure 6a,**b** shows the F1-score and recall metrics outcomes. With considering **(a)** recall, the proposed RSO-ERF approach attains the greatest value at 92.7%, followed by LSTM-GAN at 91.2%, and RNN at 89%. In terms of **(b)** F1-Score, which the suggested RSO-ERF approach achieves at a high level of 95.3%, LSTM-GAN outperforms RNN with 94.5%, suggesting that both approaches perform well overall.

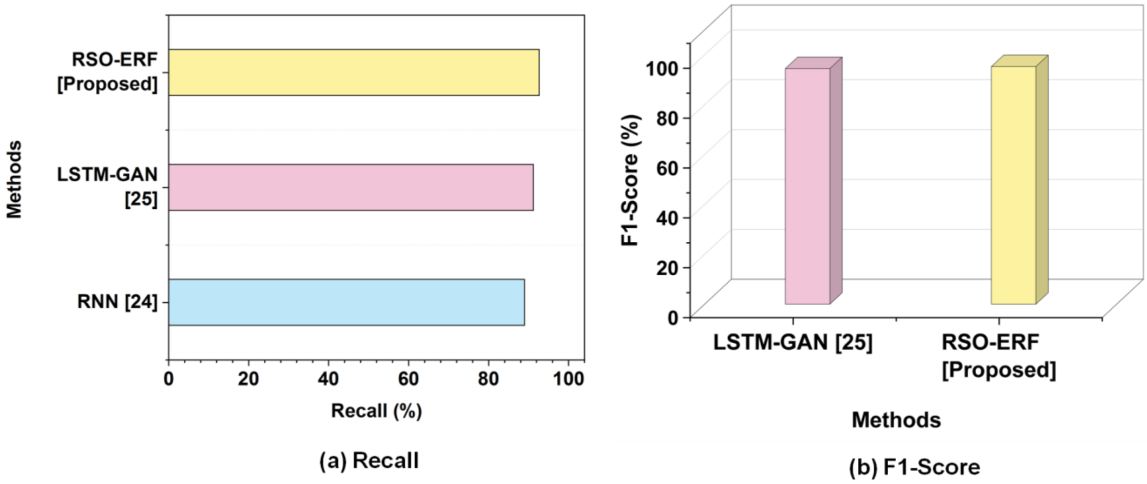

Figure 6. Results of **(a)** Recall; **(b)** F1-Score.

5. Discussion

The results highlight the effectiveness of the RSO-ERF method in assessing exercise training and learning, and show that it is better able to produce and test exercise effects than traditional methods. Despite their efficiency, the RNN and LSTM models are far inferior to the RSO-ERF method, especially for classification tasks such as performance evaluation in exercise. The RNN model has the disadvantage of relying on sequential input, which makes it difficult to deal with missing paths and long dependence times. While RNNs can recognize patterns over time, they may have problems processing data with complex layers or long associations. In addition, RNN models have limited scalability and fitness in practical applications, are computationally expensive, and involve large amounts of training data to achieve high accuracy The perfect generalization LSTM-GAN model for unusual complex motion sequences Capacity is hampered by data scarcity. Additionally, motion blurring during prediction is still an issue even after dilated RNN and CNN were included for improved spatiotemporal feature modelling. Although the model performs strongly in action identification and prediction, real-time motion difficulties may not be adequately addressed by its reliance on accurate feature extraction and prediction modules, particularly in dynamic, unexpected circumstances. The RSO-ERF algorithm reduces false positives and false negatives and provides more reliable results for exercise training and instructional evaluation. Because of its robustness and accuracy, the RSO-ERF is a highly reliable resource for accurate, real-time feedback in exercise situations.

6. Conclusion

To develop improved exercise teaching and training strategies, the present study uses a DL-based RSO-ERF model. The study includes data preprocessing techniques to reduce noise and standardize input data, such as mean filtering and Z-normalization using fast Fourier transform (FFT) algorithms for feature extraction to carefully measure physical activity parameters. These techniques improve the ability of the models to detect abnormal behaviour in the training data and can capture significant improvements in fitness. By optimizing the parameters of the ERF model, the RSO method provides more accurate forecasting and classification. The results show that the model bought F1-score (95.3%), accuracy (99.3%), precision (93.8%), and recall (92.7%). This confirms that the model consistently predicts positive and negative aspects of training and exercise. It demonstrated the potential of the model to provide useful insights that could improve academic achievement and increase student engagement in physical activity programs. Despite these positive results, there is still room for improvement. If a model does not adapt well to different learning environments or performs poorly with variables and complex data, it may restrict its generalizability to different situations Future research can focus on addressing these issues, for its flexibility has increased, and it has expanded its scope to include ever-changing doctrinal formats.

Ethical approval: Not applicable.

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

References

1. Li, J., 2021. Application of mobile information system based on internet in college physical education classroom teaching. Mobile Information Systems, 2021(1), p.1481070.
2. Zhong, F., 2021. Experiment of biological pulse sensor and its application in physical education. Microprocessors and Microsystems, 81, p.103781.
3. Salters, D. and Scharoun Benson, S.M., 2022. Perceptions and use of teaching strategies for fundamental movement skills in primary school physical education programs. Children, 9(2), p.226.
4. Wang, Y., Muthu, B. and Sivaparthipan, C.B., 2021. Internet of Things driven physical activity recognition system for physical education. Microprocessors and Microsystems, 81, p.103723.
5. Cong, C. and Fu, D., 2021. An AI based research on optimization of university sports information service. Journal of Intelligent & Fuzzy Systems, 40(2), pp.3313-3324.
6. Zhao, X. and Zheng, C., 2021. Fuzzy evaluation of physical education teaching quality in colleges based on analytic hierarchy process. International Journal of Emerging Technologies in Learning (iJET), 16(6), pp.217-230.
7. Baca, A., Dabnichki, P., Hu, C.W., Kornfeind, P. and Exel, J., 2022. Ubiquitous computing in sports and physical activity—recent trends and developments. Sensors, 22(21), p.8370.
8. Wu, J.Y., Ching, C.T.S., Wang, H.M.D. and Liao, L.D., 2022. Emerging wearable biosensor technologies for stress monitoring and their real-world applications. Biosensors, 12(12), p.1097.
9. Fogarty, J.S., Goodwill, A.M., Tan, A.L. and Tan, S.J., 2023. Student arousal, engagement, and emotion relative to Physical Education periods in school. Trends in Neuroscience and Education, p.100215.
10. Khosravi, S., Bailey, S.G., Parvizi, H. and Ghannam, R., 2021. Learning enhancement in higher education with wearable technology. arXiv preprint arXiv:2111.07365.
11. Hou, Y., 2024. Optical wearable sensor-based dance motion detection in health monitoring system using quantum machine learning model. Optical and Quantum Electronics, 56(4), p.686.
12. Wang, T. and Park, J., 2021. Design and implementation of intelligent sports training system for college students' mental health education. Frontiers in Psychology, 12, p.634978.

13. Weng, Y., Chen, Z., Weng, S. and Yin, Z., 2024. Design of an epidemic prevention and control bracelet system integrated with convolutional neural networks: Promote real-time physiological feedback and adaptive training in remote physical education. Molecular & Cellular Biomechanics, 21(3), pp.547-547.
14. Geng, Y., 2024. Comparative Study on Physical Education Learning Quality of Junior High School Students based on Biosensor Network. Natural and Engineering Sciences, 9(2), pp.125-144.
15. Zhang, Y., 2023. Track and field training state analysis based on acceleration sensor and deep learning. Evolutionary Intelligence, 16(5), pp.1627-1636.
16. Urukalo, D., Nates, F.M. and Blazevic, P., 2024. Sensor placement determination for a wearable device in dual-arm manipulation tasks. Engineering Applications of Artificial Intelligence, 137, p.109217.
17. Guo, J., Wan, B., Zheng, S., Song, A. and Huang, W., 2022. A Teenager Physical Fitness Evaluation Model Based on 1D-CNN with LSTM and Wearable Running PPG Recordings. Biosensors, 12(4), p.202.
18. Li, K., 2024. Using biosensors and machine learning algorithms to analyze the influencing factors of study tours on students' mental health. Molecular & Cellular Biomechanics, 21(1), pp.328-328.
19. Yang, L., Amin, O. and Shihada, B., 2024. Intelligent wearable systems: Opportunities and challenges in health and sports. ACM Computing Surveys, 56(7), pp.1-42.
20. Gerdin, G., Smith, W., Philpot, R., Schenker, K., Moen, K.M., Linnér, S., Westlie, K. and Larsson, L., 2021. Social justice pedagogies in health and physical education. Routledge.
21. Yu, S. and Peng, X., 2024. Wearable Sensor-Based Exercise Monitoring System for Higher Education Students Using a Multi-Attribute Fuzzy Evaluation Model. IEEE Access.
22. Liu, P., Song, Y., Yang, X., Li, D. and Khosravi, M., 2024. Medical intelligence using PPG signals and hybrid learning at the edge to detect fatigue in physical activities. Scientific Reports, 14(1), p.16149.
23. Asghar, A.B., Majeed, M., Taseer, A., Khan, M.B., Naveed, K., Jaffery, M.H. and Ejsmont, K., 2023. Comparative Performance Analysis of Machine Learning Algorithms for Arm and Shoulder Exercises using Wrist-worn Band. IEEE Access.
24. Dhanke, J.A., Maurya, R.K., Navaneethan, S., Mavaluru, D., Nuhmani, S., Mishra, N. and Venugopal, E., 2022. Recurrent neural model to analyze the effect of physical training and treatment of sports injuries. Computational Intelligence and Neuroscience, 2022(1), p.1359714.
25. Sun, X., Wang, Y. and Khan, J., 2023. Hybrid LSTM and GAN model for action recognition and prediction of lawn tennis sport activities. Soft Computing, 27(23), pp.18093-18112.