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Article

Development of personalized physical education teaching plan: Research on evaluating students' physical fitness and sports adaptability using biosensors

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Abstract: Physical education plays an essential role in the growth of students' overall health, fitness, and well-being. Wearable biosensors revolutionize physical performance monitoring by providing real-time data on physiological parameters, providing valuable insights into students' fitness and flexibility during physical activities. The research aims to develop an approach for assessing students' athletic adaptation and physical fitness using biosensors. Traditional monitoring systems have complexity in managing the huge volumes of data collected from several sensors because of noise and ambiguity. These research difficulties are addressed with the help of a deep learning (DL) based assessment model, which monitors students' fitness using biosensor data. This research proposed a novel dynamic Bumblebee mating refined deep neural networks (DBBM-RDNN) to forecast student physical fitness and sports adaptability levels using biosensors. The biosensor dataset provides different data types that capture various aspects of physical activity and fitness. The data was preprocessed using low-pass filters to remove noise from the achieved data. Principal Component Analysis (PCA) is developed to extract the features from preprocessed data. DBBM is utilized to optimize the features in sensor data and RDNN to classify or predict fitness and adaptability levels in students based on data from sensors in real time. In a comparative analysis, the research assessed various performance metrics, such as accuracy (98.05%), precision (90.9%), recall (90.1%), F1-score (88.55%), MAE (1.915) and RMSE (2.505). Experimental results indicate the proposed model achieved superior performance in predicting student physical fitness compared to other conventional algorithms. The research highlights the integration of biosensor technology with DL, which provides an accurate and dependable system for tracking students' physical performance.

Keywords: physical education; physical fitness; sports adaptability; teaching plans; biosensors; dynamic bumble bee mating refined deep neural networks (DBBM-RDNN)

1. Introduction

Sports activities have a greater impact on individuals' quality of life, although it might be difficult to determine the causes of injuries. Real-time information on players' blood pressure, running distance, electrocardiogram (ECG), and lactic acid buildup levels can be obtained through live broadcasts, enabling more equitable sanctions. The biosensors, which are tiny, thin, and wirelessly transmit data, can be placed like tattoos and band-aids and perform a wider range of precise tasks. The possibilities of these biosensors in martial arts sports systems as they can offer more precise and accurate data [1]. Teenagers' physical fitness is receiving more and more attention, from a life cycle perspective, adolescence is a critical time for physical and health development. The physical health of teenagers does not the future of the country and the contentment of their families. Teenagers' physical fitness should be a major focus for researchers in the fields of education, psychology, and healthcare to provide them with a healthier and more promising future [2]. Smart sensors are becoming more common in daily life, especially in sports. These gadgets offer mobile, ubiquitous, and remote health monitoring services. They can be multifunctional devices or specialized medical equipment, such as pulse oximeters for stress levels or smart watches for heart rate monitoring [3]. Sports performance, early illness detection, individualized medical care, and health monitoring have been transformed by wearable biosensors. They are perfect for athletes, providing continuous, real-time tracking procedures. However, extensive analyses cannot be performed with existing wearable devices; they can only measure one biomarker at a time. A thorough knowledge of human health requires wearable sensors that continually measure a variety of chemical states [4]. It is preferred in contemporary professional sports for athletes' levels of physical effort to be regularly measured. Athletes' physical fitness increases and their ability to perform well in sports activities is aided by the efficient allocation of physical effort during various training phases. A thorough assessment of an athlete's fitness level is essential for effectively communicating diagnoses both before and during exercise [5]. With the quick advancement of wearable technology, biosensors, and Internet of Things (IoT) technologies, mobile health monitoring has advanced significantly, making wearable technology can be used to check health. A wide range of smart wearable devices, including smart accessories, smart eyewear, and smart wristbands, have gained popularity in recent years [6]. **Figure 1** represents the students' physical fitness and sports adaptability using biosensors.

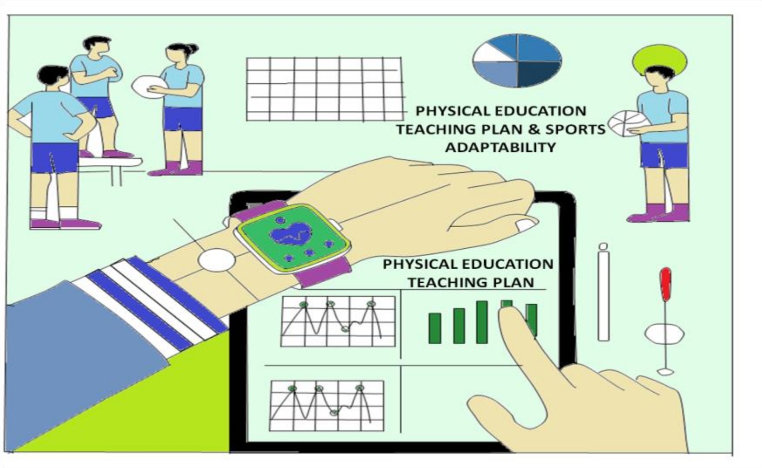

Figure 1. Students' physical fitness and sports adaptability using biosensors.

Accelerometers are frequently employed in public health assessments of physical activity because they offer accurate data on energy expenditure and duration of various exercise situations. Activity detection using certain algorithms makes it possible to evaluate the risk of overweight and sedentary lifestyles in both youngsters and the elderly [7]. Each sensor's data collection could possess distinct properties when tracking a target utilizing measurement data from several sensors. These consist of each sensor's data collecting moment, place, data expression form, frequency, and degree of confidence, as well as each sensor's position in the data fusion process [8]. Regular exercise enhances students' physical and mental well-being and maximizes their academic output. Due to their lack of enthusiasm, hectic schedules, and ignorance of particular exercises, the majority of students struggle to manage their normal exercise routines. Wearable sensor technology is created to provide unique chances to enhance their physical activity [9]. The sensitive components' composition and design determine the biosensors' capacity for selective recognition. The following essential elements are crucial for the body's selective recognition of particular substances: interaction between antigen and antibody: Antibodies are often employed as sensitive components in immuno sensors because of their ability to selectively identify and fix to antigens. Biosensors can identify certain infections or biomarkers due to the specificity of this interaction [10]. Flexible wearables, which can be defined by their capacity to analyze data in real-time, their advanced architecture, flexibility, mobility, and remote functionality, have garnered increasing attention, particularly in the sports domain. Originally developed for medical health monitoring, their use has spread to the world of sports, which are essential in helping athletes monitor their fatigue and enabling customized training modifications [11]. The use of biomedical and healthcare personal devices for sports has advanced quickly in recent years. Examples comprise optical sensors for blood pressure, heart rate, stress level, and oximetry, as well as mobile sensors for electroencephalogram (EEG)/ECG investigation. Such personal gadgets are designed to provide a persistent (real-time), mobile, ubiquitous, and distant health monitoring service [12].

1.1. Objective of the research

The goal of this research is to present an approach that evaluates the athletic adaptation and physical fitness of students with wearable biosensors. DL techniques can be employed to overcome difficulties faced while handling massive sensor data. It aims at accurate estimation of fitness levels in real-time by optimizing the DBBM-RDNN biosensor data.

1.2. Contribution of the research

1) Using real-time biosensor data, the research suggests a unique DBBM-RDNN model for forecasting students' physical health and sports adaptation.
2) This research introduces a sophisticated preprocessing pipeline using low-pass filters and PCA to eliminate noise and extract pertinent characteristics from the highly informative biosensor data.
3) The proposed method ensures accurate fitness predictions because it outperformed conventional algorithms in significant parameters, including F1-score, recall, accuracy, precision, MAE, and RMSE.
4) Using the integration of biosensor technology and DL, this research offers a reliable method for continuous, monitoring pupils' flexibility and physical performance in real time while they participate in sports.

This research is organized as follows: Comparable studies are examined in Section 2, with an emphasis on current methods and their limitations. The technique used in this research, including the creation and implementation of the DBBM-RDNN model, is explained in Section 3. The model's application findings with a thorough explanation of their results, are presented in Section 4. The work is concluded in Section 5 with a summary of the main conclusions and suggestions for more research.

2. Related works

Monitoring oxygen saturation in the blood of female athletes following a test of maximal activity was closely linked to determining the second ventilatory threshold, commonly referred to as the anaerobic threshold. The ventilatory threshold appearance, desaturation time, total test time, and maximal oxygen uptake were all shown to be significantly correlated. It challenges stereotypes about women's participation in sports by demonstrating that pulse oximetry is an easy, precise, and non-invasive technique for evaluating athletes' physical conditions while they are exercising [13]. They developed a Förster Resonance Energy Transfer (FRET) biosensor, using intrinsically disordered protein regions (IDRs), of expressing disordered protein 1 (SED1), that could monitor intracellular changes due to osmotic stress. AtLEA4-5 was employed in the biosensor and showed remarkable sensitivity to macromolecular crowding and produced major FRET differences among the forms of life, thus providing the potential for IDR as an environmentally responsive molecular instrument [14]. To monitor intracellular changes induced by osmotic stress, a FRET biosensor, SED1, is based on intrinsic IDRs. The biosensor used the AtLEA4-5 protein, which possesses extraordinary sensitivity to macromolecular crowding and profound differences in FRET in various life forms, illustrating the potential of IDR as environmentally responsive molecule instruments [15].Through the help of biomarkers, wearable technology allowed for monitoring rapid physiological changes in an environmentally friendly manner in athletes. It is hard to appreciate the inside physiology of an athlete. They investigated how to increase undergraduates' physical fitness through the use of intelligent technology in physical education (PE). Using a senseless exercise behaviors monitoring (EBM) technology on an intelligent PE platform, an adjustable fitness enhancement model (AFEM) was developed [16]. The model suggests that in an EBM environment, high-frequency aerobic exercise more strongly enhanced endurance qualities whereas low-frequency anaerobic activity more substantially boosted strength characteristics. The AFEM model further explored the possibilities of intelligent technology in individualized physical education by optimizing the impact of exercise and modifying control factors to suit users' demands. Nano-conjugated materials can monitor the sport's status, enhance the equipment's quality and increase the training's impact. The findings show that accurate data is crucial for athlete performance and safety [17]. The sports scientists used point-of-care testing (POCT) devices as analytical instruments to analyze rapidly at the site. It can be possible to follow health, performance, recovery, and doping control among athletes. Using these systems, trainers were able to track nutrition, prevent injuries, enhance training, and impose doping control rules. The research gave an integrative perspective on designing POCT platforms for various applications [18]. A developed glassy carbon electrode hybrid concentrated graphene oxide-metal organic framework electrochemical biosensor rGO-MOFs/GCE for the recognition of synthetic testosterone (TST) in athletes was recently reported. The sensor was a potential tool in TST detection; its linear range and detection limit were comparable to that of other electrochemical sensors. Interferents in food samples and physiologic fluids did not affect the selectivity of the sensor, and hence, was consistent. The synergetic characteristics of rGO and MOF enhanced its performance, which therefore justified its utilization for purposes in biological standards[19]. These sensors were vital for long-term medical treatment and sports health, as well as for monitoring physiological signals and supplying energy for biosensor equipment [20]. Emerging research areas that allow for sensitive, non-invasive detection of a variety of analyses include wearable biosensors. Real-time physiological signal, biochemical, and personal parameter monitoring was possible with these devices. They were employed in biomedical societies and research disciplines to evaluate accurate medical diagnoses. Students' physical fitness was examined with the use of sophisticated technologies. A developed using a smart PE platform and senseless technology [21]. High-frequency aerobic exercise more strongly increased endurance traits in an EBM environment, while low-frequency anaerobic activity more substantially developed strength attributes. By optimizing the impact of exercise and tailoring control variables to users' requirements, the AFEM model expanded on the possibilities of intelligent technology in individualized physical education. By utilizing optical topological sensor technology and sophisticated mobile network protocol, the system enhances data transmission speed, accuracy, and latency. The testing findings demonstrate the quickly evolving IoT and its dependability in real-world applications [22]. Disease identification, tracking, and bodily reaction monitoring were made possible by biosensors, which are transforming research and healthcare. They provided affordable, effective medical equipment that makes prompt intervention and care possible. With an emphasis on cardiovascular disorders, it examines the developments in biosensor technology and their possible uses in healthcare, emphasizing the possibility of novel treatments and individualized approaches [23]. They introduced a quaternion algorithm-based motion attitude identification system for physical education. Chips and electronic modules are used in the system to increase the precision of azimuth data gathering. Data fusion is achieved by combining gyroscope and accelerometer data with Kalman filtering. The quaternion used to calculate joint angles is continuously updated by the system [24]. The model's accuracy within error was confirmed by experiments with various loads. Instructors can utilize the terminal system to precisely gauge students' movements, guaranteeing successful instruction at colleges and institutions.

3. Methodology

Using biosensor data, the suggested technique incorporates a DBBM-RDNN model to evaluate and maximize students' physical fitness and adaptability. Based on biosensor inputs, including movement and heart rate, it predicts fitness levels using an RDNN. By choosing the fit students for additional development and maximizing fitness measurements through data processing, the DBBM algorithm dynamically modifies training schedules. This method makes it possible to create individualized, flexible physical education programs based on each student's development. **Figure 2** demonstrates the suggested technique flow below.

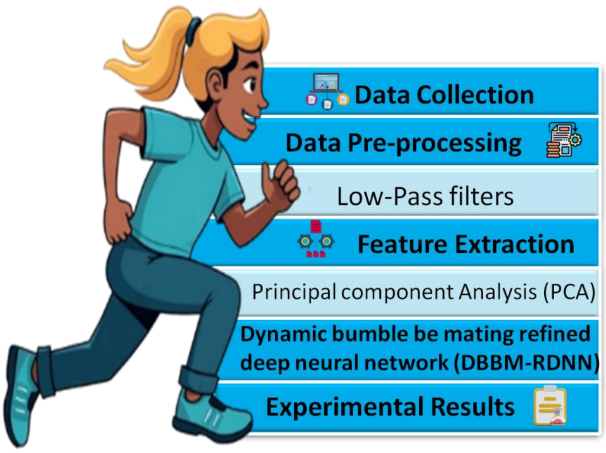

Figure 2. Proposed methodology flow.

3.1. Data collection

The information obtained from the open-source Kaggle website:https://www.kaggle.com/datasets/diegosilvadefrana/fisical-activity-dataset**.** There is a rising need to comprehend user behaviors and the connections between activities as wearable technology, including smartwatches, cellphones, wristbands, and more widely used. It used the PAMAP2 physical activity monitoring dataset to address this, which initially included data from 18 distinct physical activities (e.g., walking, cycling, soccer, etc.), carried out by 9 people wearing a heart rate monitor and three inertial measurement units. The included information from biosensors, such as blood oxygen saturation and heart rate, to improve comprehension of patterns of physical activity and users' physiological reactions. An examination of user behavior and activity performance would be more thorough as a result.

3.2. Using low-pass filters in adapted physical education plans to improve biosensor accuracy in assessing sports adaptability and physical fitness

By executing a weighted average across an area of the same size as the filter, a low-pass filter efficiently eliminates high-frequency information while keeping low-frequency information networks' self-attention mechanism calculates weighted sums of input characteristics, where the weights (also known as attention score) represent the relative importance of various features according to their temporal or geographical context. For instance, in Equation (1), the filter kernel $I(y)$ computes the output of a filter $e(w)$ as a weighted sum of pixels W_{xy}, where $x\, and\, y$ stand for pixel coordinates, and the filter weights fulfill $W_{xy} = 1\, and\, W_{xy} \geq 0$:

$$e(w) = \mathcal{F}\big(I(y)\big) = \sum_y W_{xy} I(y)(1) \tag{1}$$

The attention weights are calculated using query $R(F)$, key $L(F)$, and value $U(F)$ matrices in the case of the self-attention mechanism, as illustrated in Equation (2). The attention scores are normalized using a softmax function:

$$Y = S \times V = soft\max \frac{R(F)\mathcal{K}(F)^S}{\sqrt{c_k}} \tag{2}$$

In this case, matrices generated from the input data F which in this research corresponds to the biosensor data obtained from students during physical activity are represented by $R(F), L(F) and\ U(F)$. To ensure that the weighted values (or features) are spread evenly among the various input data points, the rows in the attention score matrix S are normalized to add up to 1, function. It tracks the modification of biosensor data with the assistance of a self-attention-based model according to the performance of a student in a set of physical exercises. It decreases the noise content while keeping high features of attention to consider when formative adaptation and fitness in physical activity. The adaptive low-pass filter can assist in monitoring students' physical activity, adaptive low-pass filtering, improve the handling of unpredictable data coming from numerous biosensors, and also make certain exact assessments of the performances.

3.3. Principal component analysis (PCA)for feature extraction

When investigating the effect of data analysis on the evaluation of students' physical fitness, PCA is a helpful technique for lowering dimensionality. PCA reduces a high-dimensional dataset of students' fitness to a set of variables that symbolize the most important differences in the data are linearly uncorrelated. Assuming that each feature has a variance of one and a mean of zero, the first step is to stabilize the data matrix Y. This step is essential to make characteristics similar it standardizes the scales of the qualities in Equation (3):

$$Y_{stand} = \frac{Y - mean\ (Y)}{std\ (Y)} \tag{3}$$

Determine the standardized data's covariance matrix or A. The pairwise covariance of characteristics is captured by the covariance matrix, which also offers information on the correlations and fluctuations between them, shown in Equation (4):

$$W = \frac{1}{o - 1} Z_{stand}^{A} Y_{stand} \tag{4}$$

The variable o denotes the dataset's total number of observations. It is necessary to determine the eigenvalues and eigenvectors W of the covariance matrix to examine the impact of data analysis in finding important determinants of students' physical fitness across different groups. As illustrated by Equation (5), the eigenvalues display the amount of variance along these dimensions, whereas the primary components, or eigenvectors, depict the directions of greater variation. The findings of this research highlight significant elements that can significantly improve learning outcomes for various student demographics.

$$Wb = \lambda b \tag{5}$$

The eigenvalues represented by λ in this case correspond to the eigenvector b. Based on the eigenvalues, determine the S main components most effectively represent the variance in the data. According to the Kaiser Index, components with eigenvalues larger than one are frequently kept in Equation (6):

$$Top\ S\ components\ b_1, b_2, \dots, b_S \tag{6}$$

The original data (Y) should be shown over the updated coordinate system created by the chosen main elements. At this stage, the data's most important features are retained while its dimensionality is decreased, as seen in Equation (7):

$$Y_{PCA} = Y_{stand}V_S \tag{7}$$

The matrix corresponding to the initial S eigenvectors is called U_T. The basic components can be used to rebuild the data so that it resembles the original dataset. This facilitates the comprehension of the modified data and the execution of the analysis in Equations (8) and (9):

$$E = V_S^A \tag{8}$$

$$U = mean\,(Y) + V_S e \tag{9}$$

The data might be utilized to identify significant factors influencing student performance and improve outcomes for various groups, the research employs the dimensionality reduction technique. It reduces the impacts on students' physical fitness by increasing the accuracy and efficiency of the DL algorithms applied in predictive maintenance systems. With PCA, important features are highlighted, resulting in more specific interventions to help a variety of student populations.

3.4. Dynamic bumble bee mating refined deep neural networks (DBBM-RDNN) for forecasting physical activity and fitness

The DBBM-RDNN method is applied to predict physical activity and fitness. To improve the prediction accuracy, the DBBM-RDNN model dynamically tunes its parameters based on biosensor data. The model improves the fitness assessment by adaptive learning through the dynamic optimization powers of the DBBM algorithm along with the efficiency of RDNNs. This approach is a better tool for individualized physical education planning and the enhancement of general fitness training results. It gives an exact prediction of students' physical performance and adaptation. DBBM-RDNN is far superior compared to conventional techniques due to its ability to catch minute details in fitness performance.

3.4.1. Refined deep neural networks (RDNN)

With a specific focus on multi-layer Perceptrons (MLP) with ReLU activations, provide an RDNN architecture-based approach for assessing students' physical fitness and sports adaptation using biosensor data. The objective is to estimate an unknown function $e^*(w)$that quantifies the correlation between biosensor measurements $W \in \mathbb{R}^c$ and the result Z, which is the student's degree of physical fitness and adaptability. An RDNN-based model is used for needs to minimize the predicted per-observation loss function, which is how the estimate is accomplished. The biosensor supplies data inputs (such as mobility, heart rate, and acceleration sensors) as covariates W, and the output Z represents adaptation measures like endurance, flexibility, and coordination or physical fitness scores. The issue might be stated as follows in Equation (10):

$$e^* = arg\underset{e}{min}\,\mathbb{E}[k(e,Y)] \tag{10}$$

where $k(e, Y)$the per-observation loss is function and $Y = (Z, W)$ is the combined vector of observed fitness and biosensor data. Finding the function $e^*(w)$ that minimizes the expectation of the loss function $k(e, Y)$, which quantifies the difference between expected and actual fitness values is the aim. To ensure that the RDNN model converges increasingly, assume that the loss function $k(e, Y)$ is continuous in e and fulfills a curvature condition around the optimum function f^*. In particular, subject $k(e, Y)$ to the following constraints in Equation (11):

$$|k(e, y) - k(h, y)| \leq D_k |e(w) - h(w)| \tag{11}$$

And for the performance of generalization in Equation (12):

$$d_1 \mathbb{E}[(e - e^*)^2] \leq \mathbb{E}[k(e, Y) - k(e^*, Y)] \leq d_2 \mathbb{E}[(e - e^*)^2] \tag{12}$$

where the limited constants $D_k, d_1, and\ d_2$ that bounded away from zero and solved with acceptable computing bounds. It is common practice to estimate physical fitness using the least squares loss function, where the goal function $e^*(w)$indicates the predicted fitness level given sensor data w. This is equivalent to the goal function and loss listed below in Equation (13):

$$e^*(w) \coloneqq \mathbb{E}[Z|W = w], \;\; k(e, y) = \frac{1}{2}(z - e(w))^2 \tag{13}$$

where W is the sensor data and Z is the degree of physical fitness. A logistic regression model can be utilized in more intricate applications, including forecasting students' athletic adaptability when the result Z is binary in Equation (14):

$$e^*(w) \coloneqq log\left(\frac{\mathbb{E}[Z|W = w]}{1 - \mathbb{E}[Z|W = w]}\right), \qquad k(e, y) = -ze(w) + \log\left(1 + f^{e(w)}\right) \tag{14}$$

where $e^*(w)$ is the log odds of the chance that a student is highly athletically adaptive, and $k(e, y)$ is the log-likelihood loss. This is a feed-forward neural network using several layers with ReLU activation to model the relationship of sensor inputs with fitness outcomes, and it uses gradient-based optimization techniques for the minimization of loss functions for efficient convergence. The depth and complexity of networks affect the convergence of the model; it also facilitates fast and accurate prediction forecasts for tailored exercise planning.

3.4.2. Dynamic bumble bee mating (DBBM)

Combinational neighborhood topology bumble bee mating optimization is based on the core of DBBM. Students' athletic flexibility and fitness are improved via biosensor data usage that manages and monitors performance metrics in physical action. The computer selects by randomness a colony of bumble bees and then uses the fitness profile of the bees to determine biosensor data. Bumble bees are generated in three different varieties: workers, drones, and queens. New queens signify significant gains in fitness, drones demand attention, and workers indicate intermediate advancement. This individualized training improves fitness levels. The following Equations (15) and (16) are part of the selection criteria:

$$K1 = (vbound - kbound) \times \left(x1 - \frac{x1}{itermax} \times s\right) + kbound \tag{15}$$

$$K1 = (vbound - kbound) \times \left(x2 - \frac{x2}{itermax} \times s \right) + kbound \tag{16}$$

where t is the current iteration (showing how physical training is progressing), $Itermax$ is the maximum number of iterations or training sessions, and the upper and lower boundaries of the fitness parameters (such as heart rate and strength levels) are denoted by $v\ bound$ and $k\ bound$, To guarantee that $x2 > x1$, $x1\ and\ x2$ regulate the range of values for the fitness criteria. This research refines students' fitness levels through breeding and mutation using a variable neighborhood search algorithm in response to real-time biosensor data. To ensure student fitness, only the fit students make it through, and their biosensor data is used to optimize plans. Based on real-time data from biosensors, the DBBM algorithm improves fitness characteristics such as physical endurance, joint mobility, and heart rate. Training sessions, iterations, the number of students, and fitness metrics like $vbound$, and $kbound$ are among the variables it modifies. These variables change in real-time as students' fitness levels increase. The algorithm ensures the fitness profile parameters match changing student demands by updating parameters like $x1$ and $x2$ when no progress is seen over successive rounds. To promote variety, the algorithm also modifies the student body, adding new ones. The following are the Equations (17)–(21) for parameter updates:

$$x1 = x1opt + \frac{x1 - x1opt}{x1opt} \tag{17}$$

$$x2 = x2opt + \frac{x2 - x2opt}{x2opt} \tag{18}$$

$$vbound = VB + \frac{vbound - VB}{VB} \tag{19}$$

$$kbound = KB + \frac{kbound - KB}{KB} \tag{20}$$

$$LocalSearchIter = LS + \frac{LocalSearchIter - LS}{LS} \tag{21}$$

where, $x1opt$, $x2opt$, VB, KB, and LS represent the ideal values for the fitness parameters and local search iterations, respectively. The algorithm's progress is used to dynamically modify the number of students (bumble bees) in Equation (22):

$$Bees = MB + \frac{Bees - MB}{MB} \tag{22}$$

where MB stands for the current student population's best fitness value. Using biosensors, the DBBM algorithm optimizes students' athletic adaptability and fitness to provide a customized physical education program. Each student's physical education program is customized to their current level of fitness due to the dynamic modification of training regimens based on real-time biosensor data, which encourages continual progress without the need for manual intervention. The algorithm's primary innovation is its capacity to maximize fitness metrics throughout workouts, providing a highly customized flexible method of physical education. Algorithm 1 depicts the hybrid DBBM-RDNN algorithm below.

Algorithm 1 DBBM-RDNN

$Initialize\ RDNN\ Model\ for\ Fitness\ Prediction$
$initialize\_RDNN()$
$Train\ RDNN\ with\ biosensor\ data$
$for\ each\ student\ in\ biosensor\_data$:
$W\ =\ student.biosensor\_data$
$Z\_true\ =\ student.fitness\_level$
$Predict\ fitness\ using\ RDNN$
$Z\_pred\ =\ predict\_fitness(W)$
$Calculate\ the\ loss\ between\ predicted\ and\ actual\ fitness$
1: $loss\ =\ calculate\_loss(Z\_pred, Z\_true)$
$Update\ RDNN\ model$
$update\_RDNN\_weights(loss)$
$Initialize\ DBBM\ for\ Fitness\ Optimization$
2: $initialize\_DBBM\_population()$
$Start\ DBBM\ optimization$
$for\ iteration\ in\ range(100)$:
$for\ the\ bee\ in\ population$:
3: $W\ =\ bee.biosensor\_data$
4: $Z\_pred\ =\ predict\_fitness(W)$
$Evaluate\ the\ fitness\ of\ the\ student\ based\ on\ RDNN\ prediction$
$fitness\ =\ evaluate\_fitness(Z\_pred, bee)$
$Fitness\ Evaluation\ \&\ Update$
$If\ fitness\ >\ threshold$:
$select\_as\_queen(bee)$
$else$: $If\ a\ bee\ is\ unfit$
$mutate\_bee(bee)$
$Update\ Fitness\ Boundaries$
$update\_fitness\_boundaries()$
$Stop\ if\ all\ bees\ have\ optimal\ fitness$
5: $if\ all\_bees\_optimal()$:
$Break$
$Return\ Optimized\ Fitness\ for\ All\ Students$
$return\ optimized\_fitness$

To estimate student fitness using biosensor data, the combined DBBM-RDNN strategy begins with training an RDNN model. DBBM optimization then selects the fittest as "queen", improves the unfit through mutations, and evaluates students (bees) to fine-tune fitness levels. The method is repeated once every student reaches optimal fitness, returning to the ideal fitness levels after dynamically updating the fitness bounds.

4. Experimental results

4.1. System configuration

Python 3.8 was used in the implementation of the NGLSTM system for physical fitness assessment. For best results, it needed 16 GB of RAM and used TensorFlow 2.4 for DL. The system included specially created gate functions to increase the prediction accuracy of fitness test results.

4.2. Performance evaluation

The accuracy, precision, recall, F1-score, MAE, and RMSE values of this research's comparison to the traditional ResNetCNN-BILSTM (Residual Network Convolutional Neural Network with Bidirectional Long Short-Term Memory) [25] and RP + CNN (Recurrence Plot + convolutional neural network) [26] shed light on how well the suggested model DBBM-RDNN recognizes various physical activities.

4.3. Accuracy and loss

The term accuracy and loss describes the decline in forecast accuracy brought on by elements such as model limits, data noise, or inaccurate sensors. It affects the validity of fitness tests based on biosensors in individualized physical education. By using biosensors, the research to assess students' athletic adaptation and physical fitness. To evaluate performance and guarantee the correctness of biosensor data, it integrates measures for accuracy and loss. By incorporating this data into a lesson plan, the research seeks to improve comprehension of students' physical capabilities. They increase students' flexibility in physical education exercises and improve teaching methods. **Figure 3** depicts the accuracy and loss below.

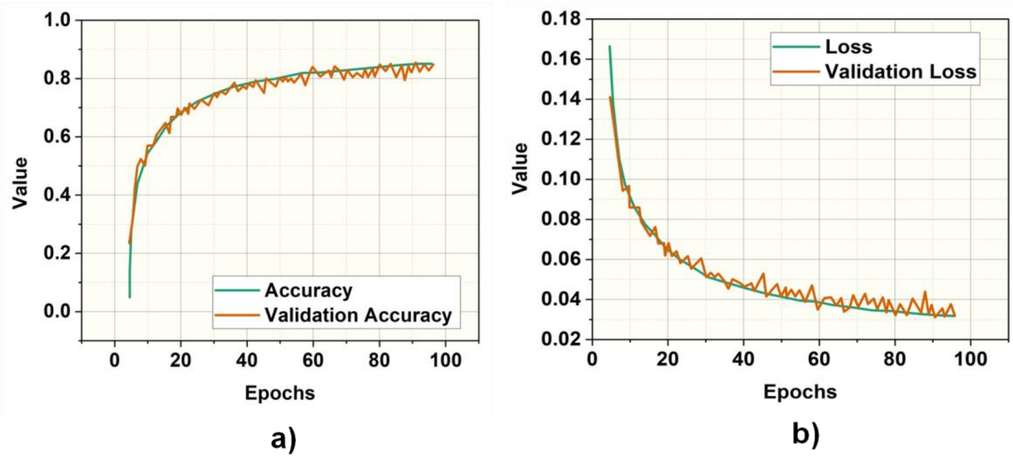

Figure 3. Outcome of:**(a)** Accuracy;**(b)** Loss.

4.4. Accuracy

The capacity to regulate a movement's direction or intensity is known as physical fitness accuracy. The capacity of a model or algorithm to correctly forecast outcomes or results is known as prediction accuracy. It is commonly used to evaluate the ability of suggested methods and is generally regarded as the main advantage of using a hybrid design. The use of biosensors to gather data in real-time during physical education exercises, to assess students' athletic adaptability and physical fitness. Creating a lesson plan that incorporates biosensor technology to evaluate and enhance student performance is the goal. Through data analysis, teachers can customize physical education programs to meet the requirements of each student, improving fitness results overall. The investigates the relationship between fitness, technology, and individualized instruction in physical education. **Table 1** and **Figure 4** illustrate the accuracy comparing findings.

Table 1. Comparison outcomes of accuracy.

Methods	Accuracy (%)
ResNetCNN-BILSTM [25]	91.5
RP+CNN [26]	96.89
DBBM-RDNN [Proposed]	98.05

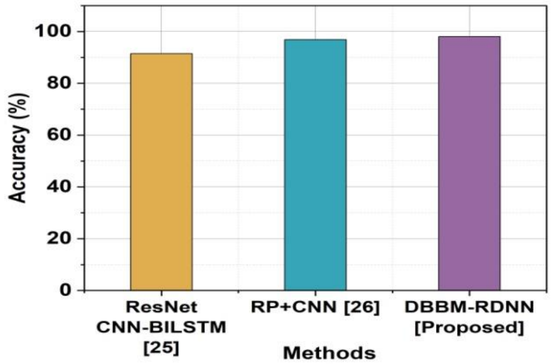

Figure 4. Comparison result of accuracy.

The accuracy of the RP+CNN approach was greater at 96.89% than that of the ResNetCNN-BILSTM technique, which was 91.5%. The suggested DBBM-RDNN approach performed better than both, with the greatest accuracy of 98.05%.

4.5. Precision

A fitness and medical strategy known as precision, exercise tailors workout plans to each person's unique traits and reactions. It's predicated on the notion that biological variables and genetic alterations cause individuals to react to exercise in various ways. To improve physical education teaching methods, the research investigates the use of biosensors to assess students' athletic adaptability and physical fitness. It attempts to create customized exercise regimens for improved student results by using precision health data. That employ real-time biosensor feedback to enhance sports performance and flexibility.

4.6. Recall

One technique for evaluating physical activity is physical activity recall, which involves asking participants to recollect their physical activity over a predetermined amount of time. The percentage of pertinent items that were recovered out of those that should have been retrieved is known as recall. The percentage of real positive cases that are detected out of all genuine positives constitutes a recall. Recall would assess how well the biosensor system identifies students with high levels of physical fitness or sports adaptation for this research, reducing false negatives and missed detections of fit or adaptable students.

4.7. F1-Score

The F1 score is calculated using the physical activity accuracy and recall harmonic means. Consequently, it symmetrically provides recall and accuracy in a single measure. One of accuracy or recall is valued higher than the other in the general score, which adds extra weight. The F1-score offers a fair assessment of model performance as it is the harmonic mean of accuracy and recall. Because it combines the sensitivity to detect all pertinent cases with the capacity to accurately evaluate students' health and adaptability, it is especially helpful in situations when there is an unequal distribution of classes. **Table 2** and **Figure 5** depict the comparison outcomes of the recall, precision, and F1-score.

Table 2. Comparison outcomes of recall, precision & F1-score.

Methods	Recall (%)	Precision (%)	F1-Score (%)
ResNetCNN-BILSTM [25]	89.5	89.7	-
RP+CNN [26]	-	-	86.76
DBBM-RDNN [Proposed]	90.1	90.9	88.55

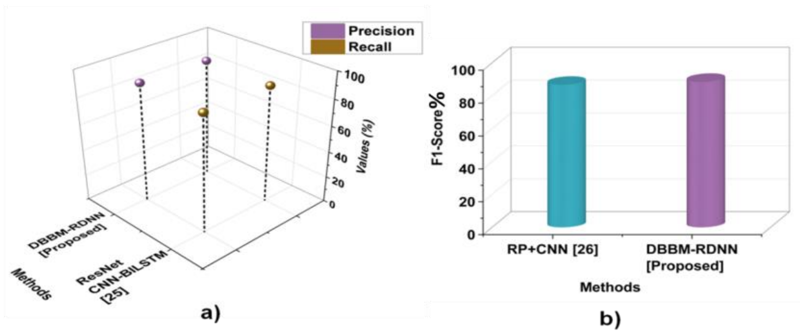

Figure 5. Comparison result of:**(a)** recall, precision; **(b)** F1-score.

The ResNetCNN-BILSTM model obtains a precision of 89.7% and a recall of 89.5%. The RP+CNN model reports an F1-score of 86.76%, however, the DBBM-RDNN The algorithm's F1-score of 88.55% indicates improved performance, recall of 90.1%, and precision of 90.0%.

4.8. MAE

The mean absolute error (MAE) is the average absolute difference between the sports adaptation or physical fitness assessments that biosensors provide and the actual results. Prediction accuracy is measured; a lower MAE denotes more accurate assessments of students' performance. MAE calculates the average magnitude of errors between anticipated and observed values to assess students' athletic adaptation and physical fitness. With a lower MAE signifying superior performance in fitness evaluations, it offers insight into the overall accuracy of the biosensor-based system and aids in evaluating the dependability of predictions in physical assessments.

4.9. RMSE

The Root mean square error (RMSE) statistic is commonly used to evaluate the difference between predicted and actual values in data-driven models. RMSE can be used to evaluate how well biosensor-based forecasts of students' athletic ability and physical fitness work out. The difference between expected and observed values is quantified by RMSE, which assigns greater weight to higher mistakes. Lower RMSE values indicate a better degree of precision and accuracy in evaluating students' sports adaptation and fitness levels, which is helpful in physical fitness evaluations as it helps determine the extent of inaccuracy in biosensor data predictions. The findings from the comparison of the MAE and RMSE are shown in **Table 3** and **Figure 6**.

Table 3. Comparison outcomes of MAE & RMSE.

Methods	MAE	RMSE
ResNetCNN-BILSTM [25]	2.012	3.019
DBBM-RDNN [Proposed]	1.915	2.505

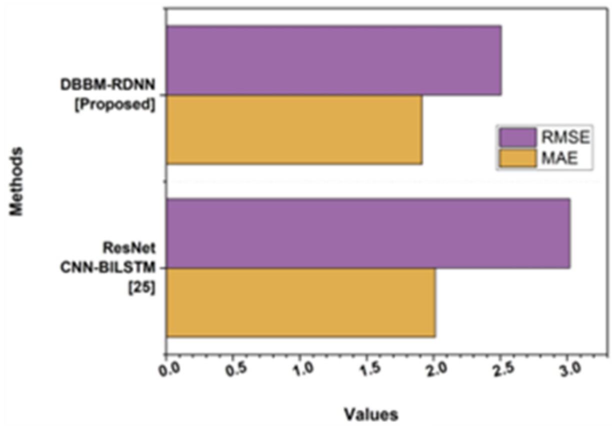

Figure 6. Comparison results of MAE & RMSE.

The ResNetCNN-BILSTM model obtained an RMSE of 3.019 and an MAE of 2.012. Comparatively, the suggested DBBM-RDNN model performed better, with an RMSE of 2.505 and MAE of 1.915.

4.10. Discussion

The ResNetCNN-BILSTM [25] model might have difficulties in managing a wide variety of biosensor data that could decrease its accuracy of prediction and individual fitness levels, and thus hinder real-time applications in customized physical education programs with big datasets. The main disadvantage of the ResNetCNN-BILSTM model in physical education is that it is computationally complex, thus limiting real-time application in large classrooms. Furthermore, biosensors can be an issue because their calibration or placement can be incorrect, causing accuracy problems. Because RP+CNN [26] relies on high-quality sensor data, is prone to possible noise or errors, and cannot generalize to different groups of students with different fitness levels and sports adaptation, the model has limitations in specific procedures in physical education. Potential shortcomings in the RP+CNN model adopted by this research include its sensitivity to quality sensor data, which not always be available in realistic environments. Furthermore, due to the complexity of this model, it can fail to scale up and generalize with very diversified student populations. The model DBBM-RDNN bypasses all these constraints because it uses an advanced optimization procedure that reduces the effects of noisy or inaccurate biosensor data.

It is more reliable for individualized physical education programs due to its dynamic adaptability, which improves the accuracy of forecasts. These challenges in the proposed DBBM-RDNN model can be overcome by employing model pruning and parameter reduction to optimize computational efficiency for real-time applicability in large classrooms. Other techniques include adaptive calibration to biosensors that minimize errors within data collection. Finally, techniques such as transfer learning and domain adaptation improve the scalability of the model and generalizability across diverse student populations. The suggested DBBM-RDNN model performs better than the ResNetCNN-BILSTM and RP+CNN models because of its improved capacity to collect temporal and spatial information using a more effective DL architecture. This enables a deeper integration of dynamic and static data representations, which improves performance in complicated operations.

5. Conclusion

Through the use of physical education, the research seeks to enhance students' well-being, fitness, and health. Wearable biosensors' real-time physiological parameter data was used to track physical performance and provide insight into fitness and flexibility during exercise. The research issues related to noise and ambiguity of conventional monitoring methods are addressed through an assessment approach based on DL that tracks students' fitness using biosensor data. This research proposed using biosensors to predict unique DBBM-RDNN for the levels of the student's physical fitness as well as sports adaptation. The data formats included many facets of fitness and different physical activity in the biosensor dataset. Low-pass filters were applied in preprocessing to remove noise from the acquired data. The properties of the preprocessed data were extracted using PCA. Based on real-time sensor data, DBBM was used to optimize the features in sensor data, and RDNN was used to categorize or forecast students' levels of fitness and adaptability. The comparative analysis is used to assess several performance indicators, including F1 score (88.55%), recall (90.1%), accuracy (98.05%), precision (90.9%), RMSE (2.505), and MAE (1.915). The suggested approach outperformed other traditional algorithms in predicting students' physical fitness, according to experimental data. This research emphasized how DL combined with biosensor technology offers a reliable and accurate to monitor students' physical performance.

Limitation and future scope

The quality and precision of the biosensor data are limitations because measurement mistakes and sensor noise might compromise prediction accuracy. Furthermore, it could be difficult for the model to generalize to different student groups with different physical circumstances. To improve prediction accuracy, future studies might investigate the combination of multi-modal data fusion and more sophisticated sensor technologies. The customized exercise regimens might be enhanced by adding real-time adaptive learning algorithms and broadening the dataset to encompass a greater range of physical activities.

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