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Article

The real-time application and effectiveness assessment of an intelligent physical fitness testing system in physical training

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Abstract: An intelligent physical fitness testing system leverages advanced technologies to monitor and evaluate individuals' fitness levels accurately. It integrates real-time data acquisition, and analysis, to support personalized physical training and health management. This study aims to evaluate the practical application and effectiveness of an intelligent system for real-time physical fitness testing in the context of physical training. Our suggested model employs portable sensing devices and we proposed a novel Northern Goshawk optimization-driven Gate Customized Long Short-Term Memory (NG-GC-LSTM) for enhancing accuracy in evaluating the individuals' physical fitness levels. Data acquisition involves gathering bio-sensing data from 25 individuals during diverse physical training activities. The Min-Max Scaling algorithm is utilized to pre-process the obtained sensor data. We employed a Short-Time Fourier Transform (STFT) for extracting crucial features from the processed data. In our proposed framework, the NG optimization algorithm iteratively fine-tunes the GC-LSTM architecture for the accurate evaluation of an established intelligent physical fitness testing system. The recommended model is executed in Python software. During the result analysis phase, we assess the efficacy of our model's performance across a variety of parameters. Additionally, we conduct comparative analyses with existing methodologies. The obtained outcomes demonstrate the efficacy and superiority of the suggested framework.

Keywords: intelligent physical fitness testing system; real-time application and effectiveness assessment; northern goshawk optimization-driven gate customized long short-term memory (NG-GC-LSTM)

1. Introduction

Physical exercise is critical for preserving and improving overall health, wellness, and efficiency [1]. It includes a range of exercises and activities aimed at increasing endurance, flexibility, power, and coordination. Physical fitness, as measured by morphological structure, psychological characteristics, physiological functions, physical fitness, and capacity to exercise, is a comprehensive and generally constant quality of the human body that is obtained from innate genetics and acquired during the developing procedure. It refers to the body's ability to function optimally at work and play, maintain good health, withstand hypokinetic disease, and respond to emergencies. Attaining and sustaining a high level of physical fitness needs frequent physical activity and a well-rounded workout routine [2].

Obesity is responsible for two-thirds of all fatal noncommunicable diseases worldwide [3]. Exercise on a regular basis can assist people lose weight and improve their overall well-being. School children are especially encouraged to seek exercise since it is an important objective for a life of wellness [4]. But physical education lessons in schools sometimes fall short of properly imparting required fitness information. An excellent fitness training program may expose students to fitness activities, while designing a tailored aerobics routine that includes variables such as Body Mass Index (BMI), Basal Metabolic Rate (BMR), welfare issues, fitness levels, health issues, and calorie burning is difficult [5].

The incorporation of advanced physical fitness testing technologies into physical education has transformed the measurement and assessment of fitness intensity. These sophisticated systems use cutting-edge technology, containing sensors, data analysis, and machine learning (ML) techniques, to provide accurate, real-time feedback on a variety of fitness indicators. Intelligent fitness monitoring systems may give individualized insights and recommendations by continually monitoring crucial cryptograms, immediate models, and performance data. This enhances the efficacy of training regimens.

The purpose of this study is to evaluate the practical use and efficacy of an intelligent physical fitness assessment system in real-time physical training settings. Previous research in the topic has shown substantial advances in monitoring and measuring physical fitness; yet, it also has certain limits. Numerous existing systems lack the incorporation of modern optimization algorithms, resulting in less accurate evaluations and longer response times [6]. Furthermore, these systems frequently do not give individualized training suggestions using real-time data, which limits their practical value in varied physical training contexts.

To overcome these constraints, the proposed study presents the Northern Goshawk optimization-driven Gate Customized Long Short-Term Memory (NG-GC-LSTM) model. This approach is intended to improve the accuracy and effectiveness of fitness evaluations by combining portable sensing devices for real-time data gathering with powerful machine learning algorithms for data analytics. The NG-GC-LSTM model uses the Northern Goshawk optimization technique to fine-tune the GC-LSTM architecture, assuring optimum efficiency in assessing physical fitness levels.

The NG-GC-LSTM model not only enhances the precision of fitness tests, but it also provides real-time suggestions and individualized training suggestions, creating it a valuable tool for a wide range of applications, containing professional sports, rehabilitation, and overall health monitoring. This research will describe the technique utilized to create and apply the model, provide the outcomes of its use, and analyse its possible influence on physical fitness monitoring and training programs.

The contributions of this paper are as follows:

- The introduction of the NG-GC-LSTM model, which uses the Northern Goshawk optimization method to improve the accuracy and effectiveness of physical fitness evaluations.
- Demonstration of the model's applicability utilizing real-time data acquired from portable sensing devices during different physical training sessions.
- Comparison of the NG-GC-LSTM model's effectiveness against previous models, emphasizing advances in accuracy, precision, and real-time feedback abilities.

The study is structured as follows: Section 2 examines similar works, focusing on existing approaches and their constraints. Section 3 describes the methodology employed in this study, including the design and execution of the NG-GC-LSTM model. Section 4 contains the model's application results and inferences, as well as a full discussion of their implications. Section 5 concludes the paper by summarizing major findings and making recommendations for further research. This organized approach guarantees a thorough knowledge of the NG-GC-LSTM model's abilities and its ability to transform physical fitness evaluation and training.

2. Related works

Qualitative analysis [7] and a combination of the novel were used to develop a new hypothetical construction for evaluating and considering physical education parameters. There were four main concepts identified as follows adding a new, quantifiable element, elucidating measurements of training effects, incorporating sport performance outcomes, and strengthening connections between contextual and individual elements. The recognition of everyday actions using accelerometers included in smartphones was investigated in [8]. Twenty-five volunteers who were engaged in five different daily activities provided accelerometer data to the researchers. They used pre-processing methods, trained nine machine learning (ML) models, and retrieved fifteen statistical characteristics. The AdaBoost classifier fared better than any other model.

A group of human Digital Twins (DTs) [9] recorded behaviour metrics related to an athlete's level of fitness for the study. When training, the DTs forecast performance and offer suggestions for changes when less-than-ideal outcomes arise. SmartFit is a software framework that helps coaches and trainers keep an eye on and manage athletes' fitness activities. The athlete's team was connected to it. SmartFit continually captured measurements through the use of Internet of Things (IoT) sensors in wearable and manual recording apps. It enabled dynamic data adaption and prediction. After analysis, the measurements were saved as historical data, which was then processed once again to provide accurate forecasts. The IoT [10] to develop an intelligent physical fitness monitoring system was used. It monitored the physical state of athletes using variables including body composition, quick leg raises, and vertical jump. Athletes are marked using radio frequency identification (RFID) technology, and an evaluation model was established using particle swarm optimization (PSO). A new technology and scientific tool to increase the effectiveness of physical training and make it more scientific is the use of simulations, which can forecast athletes' physical conditions with great accuracy. The method was made to satisfy the needs of athlete training monitoring and smartphone popularity.

College students' physical fitness exams, as part of the traditional teaching style, sometimes lack impartiality and scientific validity [11]. Data analysis and interview techniques were used to employ intelligent information technology (IT) to investigate and enhance the system. By emphasizing the value of health, the research attempts to offer a more appropriate approach for the physical exam of college students. The Intelligent Physical Education Tracking System (IPETS) utilizes information and communication technology (ICT) [12] to enhance athletic training techniques. It includes learning platforms, application programs, and performance monitoring. The system also assessed athletic knowledge through computer evaluation, promoting Artificial intelligence (AI)-powered instruction.

To improve college students' physical health and integrate sports, education, and medical care, a cloud-based platform for physical assessment and examination data analysis was developed [13]. It entailed building a cloud-based intelligent construction module for non-medical health intervention and scientific physical education curriculum, in addition to an intelligent early warning and screening module for physical fitness test levels and prevalence rates. A wearable, intelligent method [14] for evaluating physical fitness that uses smart wristbands to gather physiological data while exercising was suggested. After extracting important characteristics, the system was examined using back propagation neural networks (BPNN) and generalized regression neural networks (GRNN). Traditional fitness tests may be effectively supplemented or replaced with the neural network-based technique, which is more accurate than multiple linear regressions (MLR).

Big data analysis to develop an intelligent control mechanism for the training progress of athletes was used [15]. The model guarantees efficient operation and enhances the algorithm. The high accuracy and fluency of the model were confirmed by simulation trials. The model can accomplish intelligent operations, solve data volatility, and swiftly create training plans. The use of digital and intelligent image processing [16] in sports fitness was investigated using a treadmill as an example. It analyzed the motion model of the primary control motor, suggested an upper and lower computer control scheme, and created the calculation model for calorie intake and heart rate regulation. The outcomes demonstrated that the treadmill industrial control system can precisely acquire and convey data, get a high degree of accuracy in ultrasonic distance detection, and gather the human body's heart rate pulse through the use of digital technology.

Furthermore, Recent research has looked into numerous methods for improving physical fitness and evaluating training. Yuan et al. [17] created a motion sensor-based system with neural networks for basketball and fitness testing. Zhamardiy et al. [18] concentrated on fitness technologies for young students, whereas Kosholap et al. [19] emphasized neuropsychological aspects of fitness for future teachers. Chaabene et al. [6] evaluated home-based exercise programs for older persons, while Cocca et al. [20] investigated the effects of game-based physical education on children's fitness and mental health. Ramirez-Campillo et al. [21] explored plyometric jump training for basketball players, whereas Kljajević et al. [22] analyzed physical activity among university students. Simonsen et al. [23] connected high-intensity training to post-surgery recovery, whereas Neil-Sztramko et al. [24] examined school-based physical activity programs. Zhamardiy et al. [25] studied fitness technologies in teaching. Nuzzo [26] questioned the significance of flexibility in fitness, whereas Sánchez-Muñoz et al. [27] analyzed elite padel players' fitness profiles. Saunders et al. [28] reviewed fitness training for stroke patients. Each study provides unique insights on fitness measurement and training methods.

Research gap

These existing physical fitness assessment systems frequently suffer from multiple drawbacks, containing low accuracy, a lack of real-time feedback, and inadequate customization. These conventional approaches do not include complex optimization techniques, resulting in longer response times and less exact assessments. Furthermore, numerous existing systems do not give personalized training suggestions, which are critical for optimal fitness training. These constraints emphasize the necessity for more complex methods that can provide precise, real-time evaluations and individualized feedback. The presented NG-GC-LSTM model addresses these gaps by using the Northern Goshawk optimization algorithm to improve the precision and effectiveness of the Gate Customized Long Short-Term Memory (GC-LSTM) architecture. This connection enables for the continuous monitoring of numerous fitness indicators via portable sensing devices, resulting in rapid and personalized feedback that increases the overall efficacy of fitness training regimens.

3. Methodology

This research employs a comprehensive research design focused on the novel NG-GC-LSTM model, which integrates sophisticated sensing technology and advanced data processing techniques. Data collection included 50 individuals who wore bio-sensing devices to record physiological parameters in real time throughout physical training sessions. Preprocessing was performed on the obtained data using Min-Max scaling to standardize the sensor values and assure consistency. To extract key properties from time-series data, the Short-Time Fourier Transform (STFT) was used. The NG-GC-LSTM model then used these processed attributes to properly examine and assess the individuals' physical fitness levels. This methodological strategy, which combines cutting-edge technology and powerful machine learning techniques, seeks to improve the precision and efficacy of real-time fitness assessments.

3.1. Data set

The data includes biosensing data obtained from 50 people (25 males and 25 females) using smart bands throughout different physical training activities. Each participant is uniquely recognized by a participant ID, and their gender, age, and geographic area are recorded, as shown in **Table 1**. The participants range in age from teenagers to older adults, and they come from a variety of fitness backgrounds, comprising those who routinely participate in physical activities and those who don't. Geographic variety is also reflected, with individuals from urban, suburban, and rural settings. As shown in **Figure 1**, the data includes the sorts of activities (Running, Walking, Cycling, Jumping Jacks, Swimming, and Ascending) that each person participated in, as well as the duration in minutes. Additionally, the dataset records individuals' average heart rate (bpm) during activities, the number of steps taken, and the estimated calories burned during each movement. The goal of this dataset is to evaluate how successfully the NG-GC-LSTM model determines an individual's physical fitness level during in-person training sessions.

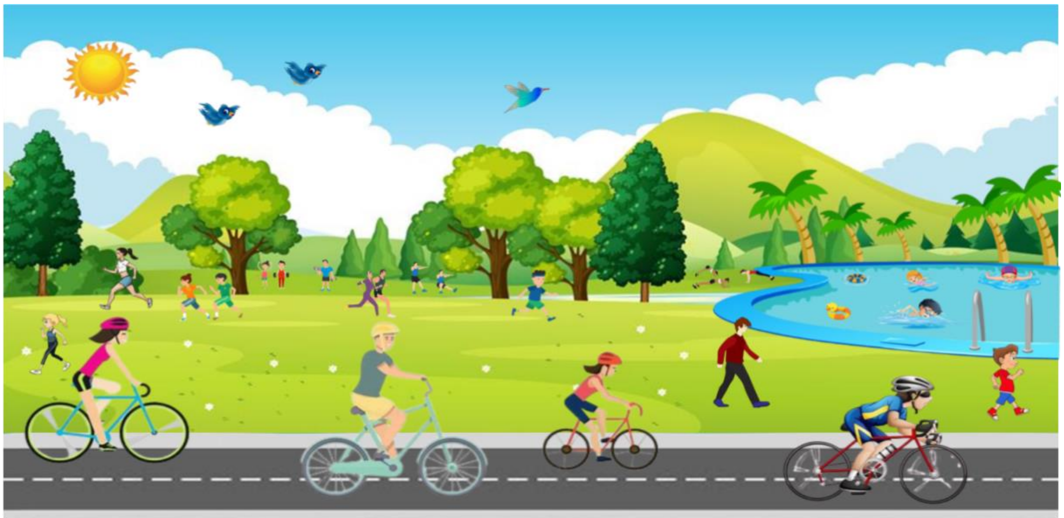

Figure 1. Physical training activities.

Table 1. Participant bio-sensing during physical activity.

Participant ID	Gender	Age	Location	Fitness Level	Activity Type	Duration	Heart Rate	Steps	Calories Burnt
1	Male	16	Urban	Regular	Running	40	160	5000	400
2	Female	21	Suburban	Occasional	Walking	30	120	3000	250
3	Male	26	Rural	Regular	Cycling	55	150	7000	500
4	Female	31	Urban	None	Jumping Jacks	20	170	2500	200
5	Male	37	Suburban	Regular	Swimming	40	140	3500	350
...	...	...	...	...	...	...	...	...	...
50	Female	55	Rural	Occasional	Ascending	30	144	3600	330

3.2. Min-max scaling algorithms for pre-processing

Min-max normalization is an extensively used method for normalizing information, mainly useful for transforming values within a specified range, usually [0–1]. This method preserves the relationships within the data, making it ideal for preparing bio-sensing data for analysis in physical fitness assessments. In this study min-max normalization is applied to the bio-sensing data collected from 25 individuals during various physical training activities. The transformation is performed in Equation (1).

$$u' = \frac{u - \mathrm{min}_B}{\mathrm{max}_B - \mathrm{min}_B}\left(\mathrm{new}_{\mathrm{max}_B} - \mathrm{new}_{\mathrm{min}_B}\right) + \mathrm{new\_min}_B \quad (1)$$

where $u'$the new normalized value, u is the original value for the given feature, max_B is the maximum value for the given feature B, min_B is the minimum value for the given feature B, while $\mathrm{new}_{\mathrm{max}_B}$ and $\mathrm{new}_{\mathrm{min}_B}$ represent the maximum and minimum values for the new considered range.

In this research, min-max normalization is used to guarantee that all bio-sensing data attributes are scaled proportionally, making it easier to compare and combine diverse features throughout the analysis. This approach aids in preserving the relative differences between the original results, which is critical for effectively measuring physical fitness. By normalizing attributes like heart rate, steps walked, and calories burnt, the NG-GC-LSTM model may learn more efficiently from the data, resulting in better model performance and more trustworthy fitness assessments.

Furthermore, min-max normalization accelerates the convergence of the optimization techniques utilized in the NG-GC-LSTM model. When features have comparable sizes, the model can better explore the solution space during training. This preprocessing phase lowers the likelihood of features with wider ranges dominating the learning procedure, guaranteeing a balanced contribution from all features. Overall, using min-max normalization in preprocessing improves the resilience and accuracy of the NG-GC-LSTM model's forecasts, allowing for a more accurate and personalized evaluation of physical fitness.

3.3. Short-time Fourier transform (STFT) for feature extraction

Bearing vibration signals are intricate and include a wealth of information. The vibration signals will alter concurrently with changes in the bearing condition. A well-crafted analytic system may clearly articulate the alterations, simplifying and enhancing the diagnostic process. A common time-frequency analysis technique that is often employed in the field of signal processing is STFT. This method multiplies time series using a window function, where the non-stationary signal is roughly regarded as locally stationary, and then converts them into a time-frequency domain. Using this technique, we may identify the spectral components in a spectrogram as discrimination. Equation (2) is a description of STFT.

$$T(s,e) = \int w(s+\tau)x(\tau)\exp(-2\ i\pi e\tau)\ c\tau, \tag{2}$$

where s is the time, e is the frequency, $x(t)$ is the sliding window function (also known as the Hanning window), and $w(s)$ is the signal to be taken into consideration. Due to the ease of handling the amplitude spectrum, the phase of $T(s,e)$, is typically disregarded. As a result, we solely evaluate the detected signals' amplitude spectrum. Even though wavelet transform is frequently utilized in the field of signal analysis, the wavelet basis function has a significant impact on the outcomes that follow. Vibration signals in an industrial setting are typically impacted by many components. Additionally, when the fault develops, other localized features, such as a single-sided impulse component and a double-sided impulse component, are present for varying fault severities. The signal in this case is too complex to be broken down by a very small wavelet, even when attempts are made to minimize the impact of artificial elements and combine all the previously discussed components. The STFT approach's simple premise and excellent capacity are the reasons it is selected as a suitable instrument.

STFT enables real-time assessment of vibration signals by giving a precise and thorough time-frequency representation. This allows the identification of transient events and localized variations in the signal, which is critical for early defect discovery in bearings. STFT aids in detecting the precise point at which a problem begins to occur and how its features vary over time by gathering both time and frequency data. This capacity is especially useful in predictive maintenance, where early intervention can avoid more serious damage and minimize downtime. The NG-GC-LSTM model uses the comprehensive attributes retrieved by STFT to improve the accuracy of its fitness level forecasts. By including time-frequency domain attributes, the model could better grasp and interpret complicated patterns in biosensing data, resulting in more accurate and personalized fitness assessments.

Furthermore, using a window function in STFT allows for the effective analysis of complicated and non-stationary data by isolating brief parts of the signal. This localized assessment is useful for differentiating between various types of errors and their severity levels. For instance, single-sided and double-sided impulse components could be detected and classified more precisely, resulting in improved diagnostic conclusions. STFT's flexibility and resilience make it an ideal choice for industrial applications where the operational setting might introduce noise and disturbances that hinder signal processing. The NG-GC-LSTM model's integration of the STFT for feature extraction and the GC-LSTM network for time series analytics enables thorough monitoring and forecasting of fitness levels, resulting in high-performance and dependable physical fitness evaluation in real-time.

These data preprocessing techniques used—Min-Max Scaling and STFT—were selected for their effectiveness in preparing and analyzing biosensing data for physical fitness evaluations.

3.4. Northern goshawk optimization-driven gate customized long short-term memory (NG-GC-LSTM)

Our proposed model combines the NGO algorithm with the GC-LSTM network. NGO simulates goshawk hunting to efficiently explore the solution space, enhancing global exploration and convergence. The GC-LSTM model with the modified forgets gate and cell input states, accurately processes continuous sensor data for fitness tracking. By integrating NGO for optimal parameters tuning and GC-LSTM for advanced time series analysis, the NG-GC-LSTM provides precise, real-time physical fitness evaluation, ensuring personalized and accurate fitness assessments.

3.4.1. NG optimization algorithm

The NGO algorithm's search mechanism is derived from its effective prey-hunting and catch process. Prey identification, prey capture, and population initialization make up the three steps of the method.

- Initialization: First, matrix X may be used to display the northern goshawk's initialization population, which is displayed in Equation (3).

$$W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_M \end{bmatrix} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,M} \\ w_{2,1} & w_{2,1} & \cdots & w_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ w_{M,1} & w_{M,2} & \cdots & w_{M,N} \end{bmatrix} \tag{3}$$

W_j, $1 \leq j \leq M$ indicates the j-th person in the populace as a whole. M and N indicate the population mass and the dimension of the objective function, respectively. The elements of W_j may be calculated for the optimization of a single objective setback with lower bound LB and upper bound UB by Equation (4).

$$w_{j,i} = \mathrm{LB} + \mathrm{rand.}(\mathrm{UB} - \mathrm{LB}), 1 \leq j \leq M; 1 \leq i \leq N \tag{4}$$

- Prey identification: In the early stages, the northern goshawk would select its victim and try to attack it. Considering that the prey is selected at random, this behavior might point to the algorithm's ability to explore the whole possible space globally. Equation (6) replicates the northern goshawk attacking its prey if the target selected by the individual $W_j$is the $prey_j$, as shown by Equation (5).

$$\mathrm{prey}_j = W_o, j = 1,2,\cdots,M; o = 1,2,\cdots,j-1,j+1,\cdots,M \tag{5}$$

$$\begin{cases} W_j^{\mathrm{new}} = W_j + q(\mathrm{prey}_j - JW_j), & \mathrm{Fit}(\mathrm{prey}_j) < \mathrm{Fit}(W_j), \\ W_j^{\mathrm{new}} = W_j + q(W_j - \mathrm{prey}_j), & \mathrm{Fit}(\mathrm{prey}_j) \geq \mathrm{Fit}(W_j), \end{cases} \tag{6}$$

where J is a vector made up of one or two values, and q is a random vector with numbers in the range [0, 1]. To increase the algorithm's unpredictability and conduct a more thorough search of the space, q and J are utilized. Equation (7) will then update each W_j.

$$\begin{cases} W_j = W_j^{\mathrm{new}}, \mathrm{Fit}(W_j^{\mathrm{new}}) < \mathrm{Fit}(W_j), \\ W_j = W_j, \mathrm{Fit}(W_j^{\mathrm{new}}) \geq \mathrm{Fit}(W_j), \end{cases} \tag{7}$$

- Capture of prey: When the northern goshawk pounces and starts fighting its victim, it will become agitated and start to run. This is the time for the northern goshawk to keep chasing its prey. The swiftness of the northern goshawk's pursuit allows it to track and eventually capture prey in almost any situation. Equation (8) may be used to replicate this stage when the chasing behavior is within a circle of radius r.

$$W_j^{\mathrm{new}} = W_j + Q(2q-1)W_j, \tag{8}$$

$Q = 0.02(1 - t/T)$. The current iteration was denoted by t, and T is the utmost number of iterations. After that, Equation (9) modifies each W_j individually. The original NGO algorithm's flow chart is shown in **Figure 2**.

$$\begin{cases} W_j = W_j^{\mathrm{new}}, \mathrm{Fit}(W_j^{\mathrm{new}}) < \mathrm{Fit}(W_j), \\ W_j = W_j, \mathrm{Fit}(W_j^{\mathrm{new}}) \geq \mathrm{Fit}(W_j). \end{cases} \tag{9}$$

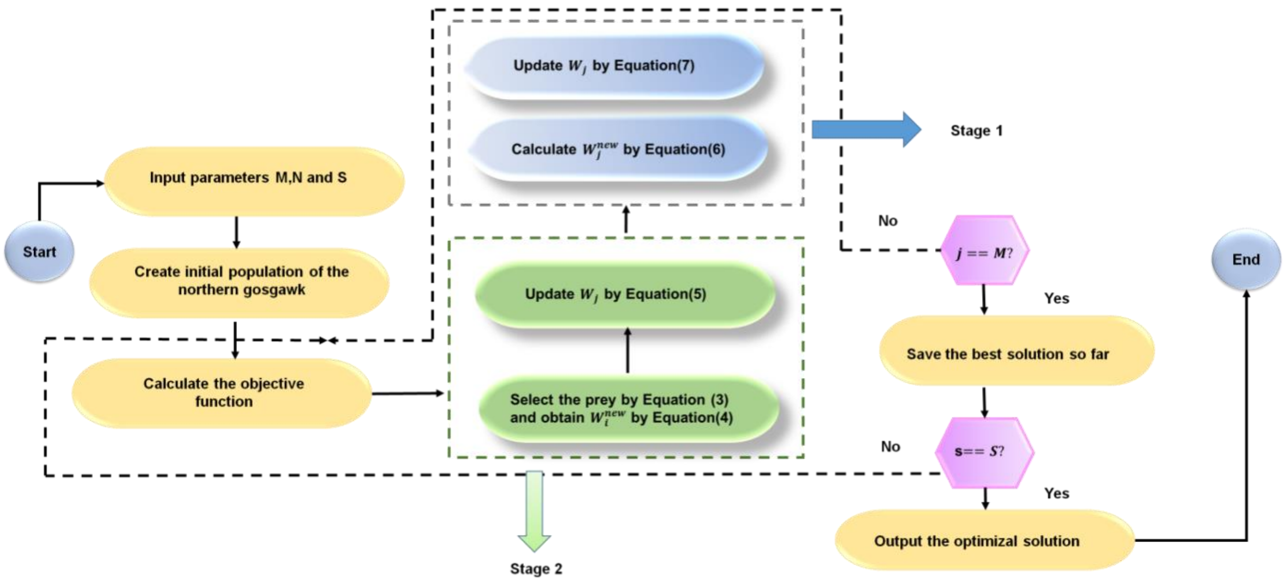

Figure 2. NG optimization algorithm flow chart.

3.4.2. Gate customized long short-term memory (GC-LSTM)

The LSTM network is a type of RNN designed to handle time series data by maintaining long-term-series data by maintaining long-term dependencies between subsequent time steps. This makes it particularly suitable for analyzing continuous sensor data in real-time physical fitness evaluation. In the context of our intelligent physical fitness testing system, the LSTM processes sensor data w collected at each time step s during physical training activities. The core idea is to create a constant error path, ensuring accurate tracking and prediction of an individual's fitness levels over time. The equations for the LSTM are expressed in Equations (10)–(15).

$$h_s = \text{tang}(X_{hw}w_s + X_{hg}g_{s-1} + a_h) \tag{10}$$

$$j_s = \sigma(X_{jw}w_s + X_{jg}g_{s-1} + a_j) \tag{11}$$

$$j_s = \sigma(X_{jw}w_s + X_{jg}g_{s-1} + a_j) \tag{12}$$

$$d_s = e_s \odot d_{s-1} + j_s \odot h_s \tag{13}$$

$$p_s = \sigma\left(X_{pw}x_s + X_{pg}g_{s-1} + a_p\right) \tag{14}$$

$$e_s = p_s \odot \text{tang}(d_s) \tag{15}$$

here, h stands for the input block. The input, forget, and output gates are denoted by the letters j, e, and p. The variables d, e, σ, and $\odot$ represent the memory cell values, block output, sigmoid function, and element-wise Hadamard product, respectively. The multiplicative forget gate was not a part of the original LSTM design. However, the ability to ignore previous inputs lets LSTM handle longer sequences without interfering with the error signal's back-propagation.

The unit known as the Gate Customized Long Short-Term Memory (GC-LSTM) represented in **Figure 3**, provides adjustments to the cell input state and the for-get gate, as seen in Equations (16) and (17). This improvement enables the computation to include the cell state from the preceding time step as well, enabling the determination of adding and forgetting information at the same time.

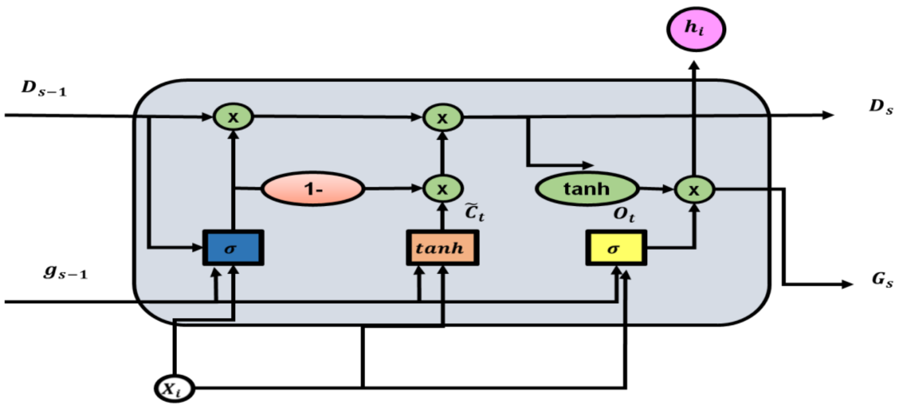

Figure 3. Improved diagram of the LSTM unit structure.

$$d_s = g_s D_{s-1}(1 - g_s)\widetilde{D}_s \tag{16}$$

$$e_s = \sigma(X_e \begin{bmatrix} D_{s-1} \\ e_{s-1} \\ w_s \end{bmatrix} + c_e \tag{17}$$

The GC-LSTM model enhances the conventional LSTM by modifying the cell input state and forgetting gate. This improvement allows concurrent assessment of information addition and forgetfulness, crucial for accurately evaluating physical fitness levels in real-time. The GC-LSTM process continues sensor data, enhancing the effectiveness of our intelligent physical fitness testing system.

The NG-GC-LSTM model improves physical fitness assessments by combining the NGO algorithm with the GC-LSTM network. The NGO method optimizes parameter tuning by using prey identification, capture, and pursuit phases, which are parameterized by a population matrix (*W*), lower (LB), and upper boundaries (UB), as well as random vectors (*q* and *J*). The GC-LSTM network, modified to omit particular gate and cell input states, evaluates continuous sensor data using equations that include input (*h*), forget (*j*), and output (*p*) gates, as well as cell memory (*d*) and output (*e*). These configurations were selected to raise the NGO's effective solution space exploration and GC-LSTM's expertise in processing time-series data, resulting in accurate, real-time physical fitness evaluations by collecting intricate bio-sensing data correlations.

During the optimization process, The NGO algorithm initially creates a population matrix to depict possible solutions. It then detects and chases prey by simulating the goshawk's hunting behavior utilizing random vectors, allowing it to examine the solution space more extensively. The method iteratively refines solutions by adjusting spots in response to fitness assessments. This strategy provides comprehensive parameter exploration and fine-tuning, which improves the model's capacity to converge on optimum solutions. These methods improve the NG-GC-LSTM model's performance by efficiently tweaking its parameters, resulting in more precise and trustworthy real-time physical fitness assessments.

4. Experimental result

4.1. System configuration

The NGLSTM system for physical fitness testing was implemented using Python 3.8. It utilized TensorFlow 2.4 for deep learning and required 16 GB of RAM for optimal performance. The system included customized gate functions tailored to enhance the prediction accuracy of fitness test outcomes.

4.2. Performance evaluation

In comparison to the conventional one-class support vector machine (OC-SVM) and deep neural network (DNN) [29] our study's precision, recall, and F-measure values provide insights into how effectively our proposed model detects different physical activities.

- Precision: The model accuracy is determined by how well its optimistic prediction matches reality. The excellent accuracy of the model indicates a low false positive rate.
- Recall: True positive rate also known as recall is a metric that measures how successfully the model can identify each relevant episode in the data set. High recall rates indicate that the model's false negative rate is low.
- *F*-Measure: It shows the Harmonic mean of recall and precision and it provides a particular measure that point's equilibrium between recall and precision, which is mainly supportive when one has to strike that balance. Each evaluation metric and its formulas are shown in **Table 2**.

Table 2. Metrics and their formulas.

Metrics	Formula
Precision	$\frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$
Recall	$\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$
F-Measure	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

Table 3 depicts the accuracy percentages of the proposed model in distinguishing diverse physical activities from biosensing data. Running and cycling achieved the highest precision at 99.7% and 99.6%, respectively, indicating excellent accuracy. Walking and ascending also showed strong accuracy at 95.2% and 95.4%. Jumping jacks and swimming had slightly lower accuracy of 94.9% and 94.5% respectively, but still demonstrated effective performance. These results highlight the model's robustness in accurately evaluating a range of physical activities, validating its effectiveness for real-time fitness monitoring. This is also graphically represented by **Figure 4**.

Table 3. Accuracy for various physical activities.

Physical activities	Accuracy (%)
Running	99.7
Walking	95.2
Cycling	99.6
Jumping jacks	94.9
Swimming	94.5
Ascending	95.4

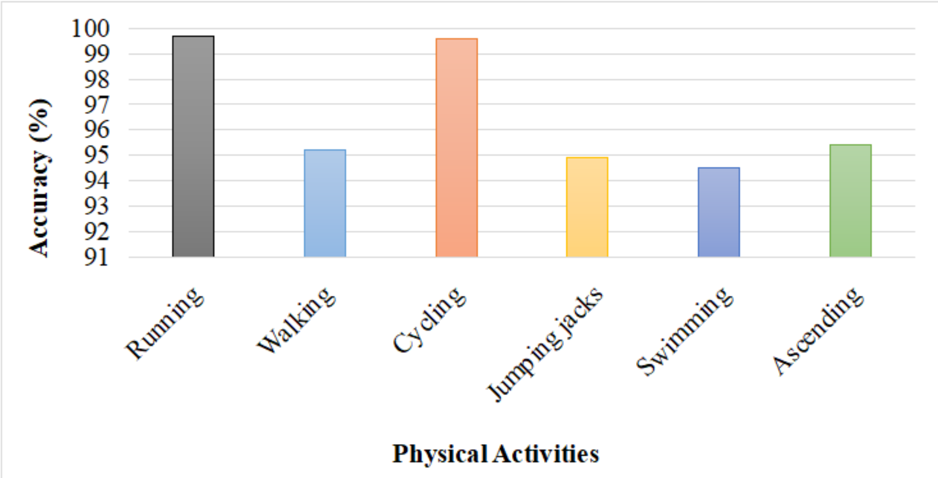

Figure 4. Accuracy for various physical activities.

Table 4 compares the precision percentages of three models OC-SVM, DNN, and NG-GC-LSTM model demonstrates superior precision in all activities: Running (99.7%), Cycling (99.6%), and Ascending (95.4%), outperforming both OC-SVM and DNN models. These outcomes are also graphically represented in **Figure 5** to indicate the superior performance of the proposed model.

Table 4. Precision of physical activity recognition across different model.

Precision (%)			
Physical activities	**OC-SVM**	**DNN**	**NG-GC-LSTM (Proposed)**
Running	90.4	99.3	99.7
Cycling	82.6	99.3	99.6
Ascending	82.4	93.5	95.4

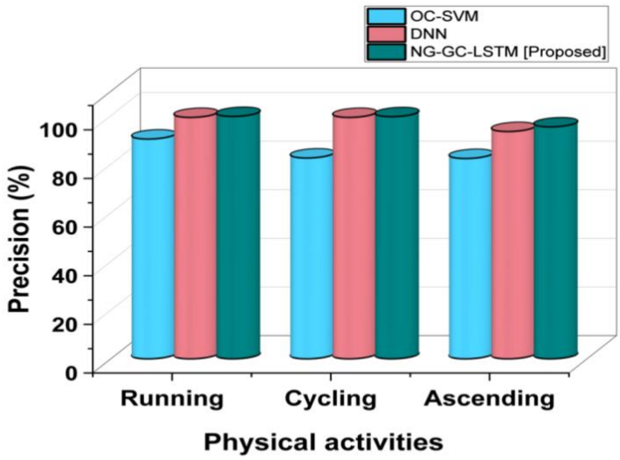

Figure 5. Comparison of precision.

The recall percentages for the DNN, OC-SVM, and our suggested NG-GC-LSTM models in recognizing activities are shown in **Table 5**. Recall rates are higher for our proposed. Running (98.9%), Cycling (98.8%), and Ascending (97.9%), indicating its exceptional ability to correctly identify positive instances of these activities compared to OC-SVM and DNN. The result is also represented graphically in **Figure 6** to visualize the superior performance of our suggested model.

Table 5. Recall of physical activity recognition across different model.

Recall (%)			
Physical activities	**OC-SVM**	**DNN**	**NG-GC-LSTM(Proposed)**
Running	88.2	98.3	98.9
Cycling	81.2	97.8	98.8
Ascending	78.8	96.3	97.9

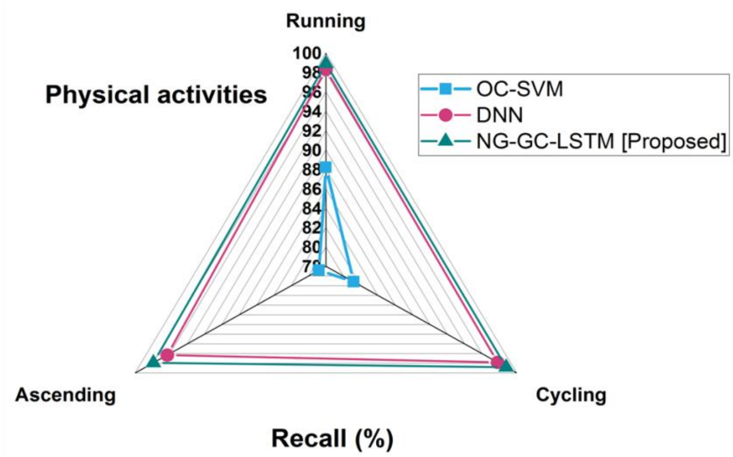

Figure 6. Comparison of recall.

Table 6 presents the *F*-measure percentages that maintain the balance between recall and precision, for the OC-SVM, DNN, and NG-GC-LSTM models. Our suggested method shows the highest F-measure scores: Running (99.2%), Cycling (98.9%), and Ascending (95.9%), underscoring it's on the whole better performance in recognizing physical fitness actions exactly and constantly. These are also represented graphically in **Figure 7** to offer a visual comparison of the performance of all the models.

Table 6. *F*-Measure of physical activity recognition across different model.

***F*-measure (%)**			
Physical activities	**OC-SVM**	**DNN**	**NG-GC-LSTM(Proposed)**
Running	91.2	98.8	99.2
Cycling	89.8	98.5	98.9
Ascending	80.5	94.9	95.9

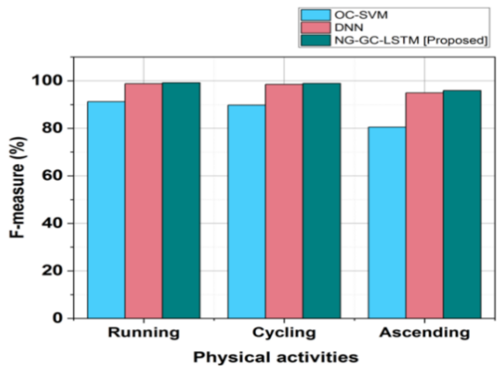

Figure 7. Comparison of *F*-measure.

The presented NG-GC-LSTM model surpasses previous models like OC-SVM and DNN because of its novel integration of NGO and GC-LSTM. This hybrid strategy uses the advantages of both strategies to improve accuracy, precision, recall, and F-measure scores in physical activity identification. The NGO method improves the model's capacity to effectively explore the solution space and improve parameters, resulting in faster convergence and global discovery. This leads to better feature selection and parameter tweaking, both of which are necessary for precise analysis of biosensing data.

GC-LSTM, on the other hand, is specially built to manage time-series data, like continuous sensor data collected during physical activities. By changing the cell input state and forgetting the gate, GC-LSTM may effectively capture temporal relationships and complicated patterns in data. This enables the model to retain long-term associations between subsequent time steps, which is required for accurate monitoring and forecasting of physical fitness levels. The model's capacity to incorporate the cell state from prior time steps guarantees that it can properly predict both short-term and long-term trends in the biosensing data.

The comparison findings in **Tables 3–6**, as well as **Figures 4–7**, clearly show that the NG-GC-LSTM model performs better. For example, running and cycling have considerably better accuracy rates (99.7% and 99.6%, respectively), indicating that the algorithm can accurately recognize these activities. The recall rates for running, cycling, and ascending are 98.9%, 98.8%, and 97.9%, respectively, demonstrating the model's remarkable capability to identify positive instances of these activities. The F-measure values support the model's balanced efficiency in terms of precision and recall, with the highest scores for ascending (95.9%), cycling (98.9%), and running (99.2%).

The NG-GC-LSTM model's high accuracy, precision, recall, and *F*-measure scores lead to considerable real-world applications and advantages. High accuracy guarantees that the model accurately recognizes different physical activities, thereby reducing errors. High precision shows that the model's forecasts are accurate and consistent, which reduces the possibility of false positives. High recall reflects the model's capacity to catch all important instances of physical activities, resulting in thorough monitoring. At last, a high *F*-measure, which considers both precision and recall, represents the model's overall performance.

In practical terms, these metrics indicate that the model may give dependable and precise feedback for fitness enthusiasts, athletes, and healthcare practitioners, hence improving individualized training programs and correctly tracking physical activity levels. This can result in improved fitness results, injury prevention, and optimal training routines, creating the NG-GC-LSTM model a useful tool in sports science, personal fitness, and healthcare.

The findings show that the NG-GC-LSTM model surpasses standard models such as OC-SVM and DNN in identifying diverse physical activities with higher accuracy, precision, recall, and *F*-measure scores. The model's remarkable efficiency, particularly in sports such as running and cycling, demonstrates its dependability and efficacy for real-time fitness tracking. The high accuracy rates for walking and rising indicate its durability in a variety of settings, whereas the somewhat lower but still great efficiency in jumping jacks and swimming demonstrates its adaptability. These results suggest that the NG-GC-LSTM model could be an effective tool for improving physical fitness evaluations and treatments, since it provides accurate and consistent activity detection that could enable tailored fitness programs and enhance overall health results.

Overall, the NG-GC-LSTM model outperforms other models due to its improved optimization and specific management of time-series data. The combination of NGO and GC-LSTM enables the model to attain more accuracy and resilience in physical activity identification, making it ideal for real-time fitness monitoring purposes. This mixture not only enhances overall detecting abilities, however, also provides stable and dependable performance over a wide range of physical activities.

4.3. User experience

The system communicates with end users via a user-friendly application that shows real-time data from portable sensing devices. These devices are intended for ease of use, with simple controls and comfortable wear to allow seamless incorporation into exercises. Participants expressed excellent satisfaction with the system's straightforward interface and the accuracy of the feedback supplied. The simplicity of monitoring physical activities and getting actionable data led to a favorable user experience, with participants applauding the system's capacity to successfully customize training suggestions.

5. Conclusion

This study shows that the NG-GC-LSTM model is effective for real-time physical fitness evaluation by utilizing modern bio-sensing technology and unique machine learning approaches. The suggested model attains high accuracy, precision, recall, and *F*-measure scores across a wide range of physical activities by combining portable sensing devices with advanced data processing. This improved performance when compared to existing techniques demonstrates the model's potential for improving physical fitness monitoring and individualized training. The results highlight the importance of intelligent fitness systems in offering personalized insights and real-time feedback, which contributes to better health results.

Future work may focus on expanding the dataset, incorporating additional features for analysis, and exploring development in diverse physical training environments to further validate the model's efficacy and generalizability. Because, this study may have biases due to the particular activities selected, like running, cycling, walking, and others, which may not reflect all possible physical activities. Furthermore, the wearable devices employed may have altered the outcomes, as various devices have variable degrees of accuracy and sensitivity. Future research should overcome these constraints by integrating a broader range of physical activities and use a variety of wearable devices to improve generalizability. Expanding the dataset to incorporate more diverse activities, as well as evaluating the model under various training situations, will aid in determining its resilience and application in real-world contexts.

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