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ORIGINAL ARTICLE

Enhanced Prediction of Swimmer Fitness Using Modified Resilient PSO Algorithm

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Abstract
Sports develop both physical and mental growth of an individual. In order to enhance the physical and mental health effectively and effortlessly, swimming is considered to be one of the healthier activities, in developing the metabolism via flexibility, weight loss, reducing asthma and enhancing the fitness levels of the body. In most of the cases, existing studies provide the current status of the swimmer by delivering details like time taken by the swimmers to finish the lap or location of the swimmer, however they lack in identifying the calorie level reduction of the swimmer during the swimming, as, the detection of calories burnt by the swimmer helps in overcoming issues like loss of weight and other health risk rates. Therefore, proposed study intensifies in achieving the prediction of the fitness of a swimmer as the primitive activity in view of reducing the calories by using PSO algorithm using resilient based techniques for enhanced exploration ability and using modified resilient PSO in order to tune the hyper parameter of the random forest for better optimization outcome. Modified resilient PSO helps in preventing the over-fitting of the model and delivering enhanced global solutions. Besides, hyper parameter are tuned in the Random Forest (RF), Decision Tree (DT), AdaBoost and Support Vector Machine (SVM) regression model for an error free outcome and with satisfactory performance analytical values. Finally, the performance of the proposed model is assessed using performance metrics such as R-square, RMSE, MSE and MAE, unveiling the effectiveness of the projected approach MPSO-XG-Boost. The projected model has achieved effectual outcomes encompassing less error rate based outcomes in ranges of 0.037, 0.191, 0.059, 0.9. Further, the proposed is compared with the existing models in order to determine the efficiency of the proposed framework.

Keywords Particle Swarm Optimisation · Hyperparameter tuning · Global maxima values · Exploration ability

Introduction

With a notable development of medicine and other vital disciplines, increased requirements and expectations for the daily healthcare and disease diagnosis were initiated. At present, the detection and evaluation of daily activities under various physiological indicators such as the glucose, O_2 and CO_2 levels reflects the human health are still under a crucial examination (Song et al. 2021). In recent decades, many research works were inducted in combining the human body with carious sensor parts for capturing the data under the conditions of body movements and for the evaluation of the physiological indices (Kim et al. 2019), which are used in the detection of temperature, heart rate and the breathing conditions, used in providing a convenience and a proper health care monitoring and for a proper medical diagnosis (Chung 2019).

Some of the commercial sensors are manufactured and are used in case of sport monitoring applications and technologies, especially in monitoring the sport person ability and in making the effective schedule of scientific training plans (Zhai et al. 2020). Metabolic and the other associated health profile monitoring are some of the key approaches in establishing a precise healthcare and metabolic activated used in enhancing the working mechanism if the individuals (Wilson and Forse 2023).

Also, with a development in the modern internet and in health assessment model based technologies in computer

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domains have now become a research hotspot resulting in crucial development of health analysis and examination in aim of providing the suitable health management assessments (Deng and Shaoyi 2020). In view of this, the physical activity and the training programmes are being an integral part of the obesity management and in maintaining a healthier lifestyle approaches (Stine, et al. 2023). Aerobic and non-aerobic exercise approaches have been carried out on case of the health management techniques, which are some of the integral part in reducing and in maintaining the calorie levels (Oppert et al. 2023). But high levels of calorie are burnt only in continuous cases of physical endeavours and workouts. In view of these, swimming are one of the most physical activity in physical health and stability maintenance, especially maintaining the levels of the white adipose tissue levels and in the reduction of adipocyte tissue sizes (Santos Cardoso, et al. 2023).

The occurrence and possibility of the ischemic heart disease are one of the leading causes of death and the morbidity levels in the world. The secondary prevention levels, are essential in enhancing the patient's prognosis and quality of life (Romano et al. 2023). The continuous physical exercises, has a possibility in reducing the adversity of potential risk factors, such as the lipoprotein levels, and dilated blood concentration maintenance levels (Pedamallu et al. 2023).

The developing technology associated with the fitness in aspects of skeleto-muscular strength, and a positive attribute in keeping the body in healthier and in improving the tasks of individual, will be an adherence to a healthier lifestyle and an innovation in bringing a complete decorum of the fitness in each of the individual. In view of this, some of the existing algorithms and approaches were used in the analysis of the exercise style of the individual, such as the repetition counting (Ferreira et al. 2021), fitness testing of the students physical performance during the time of competition (Kuo et al. 2021), but these model are less limited to the other applicable applications due to their low memory and taking more of time in proceeding the computational time, the prosed study aims in monitoring the calorie levels of the individual by the seeming as a primitive fitness activity.

These are calculated using the Fitbit dataset collected by using the Redmi Fuel Track watch, by the swimmers. These data are collected in aim of evaluating the calorie level burnt by the simmers during the swimming. These are done by the PSO algorithm which are one of the metaheuristic algorithm considering only few of the parameters for tuning the data (Zhuo et al. 2023). Whereas the other tuning algorithms are more complex and are also time consuming in tuning the parameters for bringing optimised results. As the position of each of the particle updates in each of the iteration levels, in accordance with the particle own group of attaining the best values. Therefore, unlike other conventional and evolutionary algorithms, PSO algorithm do not implement any of the policy for being the survival of fittest (Fofanah et al. 2023).

The hyper parameters of the PSO algorithm are tuned in order to reduce the complexity of the network, in the dimensionality in the optimisation issues, as there are more of local optima values. When the hyper parameter is tuned, the optimisation will converge towards the optimum, and the global optimum is slim and are easily achieved (Vigneshwaran et al. 2022).

The modified PSO algorithm are compared with the other four metaheuristic algorithms, such as XG-Boost algorithms, AdaBoost algorithm, SVM and the DT algorithm. These are used in analysing the best metaheuristic algorithm in achieving the global maxima values taking less number of iteration, with less convergence rate. These are analysed using the performance metrics comprising Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) and R-Square. These are analysed for the best algorithm finding the global maxima values with less convergence rates.

Aim and Objectives

The aim of the proposed study is to make the fitness evaluation based on the swimming as a primitive fitness activity and to analyse whether swimmers loose calories via swimming. These are achieved by the objectives framed as,

- To tune the PSO's hyper parameters for better optimization results.
- To compare the Modified PSO algorithm with different metaheuristic algorithms for detecting the best optimal values.
- To perform the evaluation using performance metrics, comprising R-square, RMSE, MSE, and MAE for analysing the performance of the proposed model for evaluating the prediction data.

Paper Organisation

The remaining section of the paper is categorised into "Review on Existing Works" section used in deliberating some of the existing approaches carried put in fitness evaluation using different algorithms, "Proposed Methodology" section explaining the complete proposed methodology. Followed by "Results and Discussions" section deliberating the results obtained after implementation and finally the "Conclusion" section finalising the study with the appropriate conclusion.

Review on Existing Works

The suggested study for the prediction of health of football players, using wearable technology and RNN methods for the extraction of the deep features. But these methods required high range of computational cost which are continuous in making the monitoring, as these methods are non-intrusive and patient-friendly methods (Alghamdi 2023).

Some of the wearable sensors are used in monitoring the risk assessment and optimising them during the industrial sports activities, which are related to the biomechanical applications, using bio-wearable sensors, such as force sensors, Inertial Measurement Units (IMU) and others. But these sensors are more cost prohibitive and are little critical in making health and safety decision making mechanisms (McDevitt et al. 2022). Fall detection in case of ergonomics are done in case of analysing the human movement, by wearing a stretch sensor, used also in case of monitoring the movements. This suggested study also uses the Soft Robotic Stretch for the process. But these sensors even detect the normal movements of ankle resulting in high false detection rates (Chander et al. 2020).

The levels of O_2 consumption during the lifting activity are recognised using the wearable sensors, in passive assisted industrial exoskeleton, during the lifting tasks, along with the evaluation of muscle activity levels, but the models lagged among the complex designing and the easy to approach methods (Qu et al. 2021). People involving in continuous motions in wrist and in forearm suffer from lateral epicondylitis, leading to high treatment costs. These are monitored using the wearable sensors especially in the textile logistics, for validating the effectiveness of the movement correction. They are also recommended for workplace exercises and the training sessions which are recorded (Michaud et al. 2023).

As a part of health evaluation, the analysis and the evaluation of the gait based hemiplegic disorders by a quantitative analysis were done based on the IMU, by wearing these wearable sensors on the wrist and in lower limbs, for recording the data. These are used in measuring the walking ability of the patients and in evaluating the rehabilitation of the patients. Moreover, the designing and the implementation of the wireless sensor systems in the athletes for evaluating the heart rate and the agility level index are framed based on the zero-crossing algorithms, which are made of rubber and spun lace fabrics for a comfortable feel during the training phase. These methods are more of complex when designed in use of healthcare and more of human energy expenditure are needed (Xu 2022). Monitoring the nutrition data of the sport residents using genetic algorithm were carried out in the suggested study, for the evaluation of eating cycle and in the evaluating the physical health, done by appropriate feature selection methods for effective case of feature recognition (Zhou 2022).

Followed by the monitoring of physical health of the college students in their behavior during a physical exercise done using the association rule data mining process. But the suggested study lagged in bringing the appropriate association degree among various body measurement and indices, using the Apriori algorithm (Pan 2021). The evaluation using flexible strain sensors for the analysis of volleyball training patterns. These are based on the estimation of human posture technique, with the leg and hand movement calculations. The RFID with the LANDMARC algorithm are used which comprises the Wireless sensor form of networks, but lagged in the number of monitoring channels, and the synchronised monitoring and in the comparative among other algorithms (Yin et al. 2022). Wearable Gait sensors are used in the evaluation of the kinematics of lower limbs, during the Time-Up and Go (TUG) test which is known as TU, and the analysis of Locomotive Syndrome were carried out in the suggested study, consisting 140 participants, dividing them into two different groups, they were noted for the hip flexibility and movement during walking phase, were H-Gait system is difficult for test and for the evaluation (Kataoka et al. 2023).

In vivo form of electrochemical biosensors are used in dissecting the chemical releases from the Central Nervous System, but are more complex in designing involving increased manufacturing cost and periodical maintenance systems (Wang et al. 2023). The sprint techniques of athletes were improved by continuous training methods and plans of the sprinters, by a basic training and improvement in the coordinate strength and the core strength, using the motion sensing technology providing the further efficient tools and practices for the analysis during sports training. Further improvement can be made in case of analyzing the characteristics of the athletes and conduct both the scientific and systematic analysis for enhancing the athlete speed quality and performance (Huang and Xu 2021).

Wearable biochemical sensors are used in the monitoring of the metabolites and the levels of nutrients, which are non-invasive and are wearable in nature are used in the continuous monitoring of the metabolites and the sweat levels in higher concentrations, during vigorous exercise phase in view of generating sufficient quantity of the bio fluid levels (Wang et al. 2022). During the steady state of sports training, the maximal levels of lactate levels are monitored using the self-powered biosensors, especially during the exercise phase, in view of developing the intelligent assisting training systems. By the active piezoelectric signals, and the coupling effect, and the motion monitoring application, used in the assistance of training systems, which had opened up ways for human motion monitoring but laid back in formulating the scientific and the effective exercise prescription for some special groups (Mao et al. 2020).

Healthcare monitoring have been developed with the enhancement of sensing and the enabling opportunities, used in many applications such as body fluid monitoring, gas, COVID-19, cancer cell detection, for mega-data analysis and in prediction. But these sensor detection methods lagged in terms of data security and can also be further improved in case of using block chain and other conventional protocols, for wearable data networks (An et al. 2023).

As a further part of improvement, Surface enhanced Raman Spectroscopic methods are used in case of cancer detection using the label-free sensing materials. But these spectroscopic analysis procures more of cost and requires complex computation model for the evaluation (Constantinou et al. 2022). Though more of research works were conducted on the basis of health care monitoring and evaluation in various aspects some of the studies laid back in considering the vital attributes and aspects contributing for the physical wellbeing and development, where, our proposed study uses a portable and a wearable biosensor in the calorie level burn monitoring especially during swimming by swimmers as a vital part of their physical activity.

Problem Identification

- Though the suggested approach intended in performing the human movement monitoring, in future the study can be made to study and examine the fall detection also using the close the wearable gap (Chander et al. 2020).
- Due to the limitations of the EMG channels, the O_2 range of consumption in things and in the abdominal are not completed in the same time. Thus, in future, the 8-channeled device can be used in completing the tests. Future work can also encompass the design improvements in IPAE on resolving these issues (Qu et al. 2021).

Proposed Methodology

The proposed methodology uses the fitbit dataset in predicting, whether the swimmer losses or burns the calorie levels during swimming. These data are collected from redmi-fuel the band recorder. The proposed study vitally intensifies the fitness of the swimmer by the primary activity of swimming in view of reducing or maintain the optimal levels of calories. In order to resolve some of the factors such as inaccurate measuring, high rates of loss the proposed study exhibits a framework which is depicted in Fig. 1. Initially, the data from the dataset are loaded and are taken for the pre-processing method which is used in removing the unwanted noises and other attributes, to make the data more precise and easy for further processing. The pre-processing of the raw data also aids in enhancing the reliability and the accuracy rates making it more reliable. These data are then split into train and test data, in ratios of 80:20, respectively. These are then taken for the regression model,

In the proposed study, PSO algorithm is used, in view of hyper-parameter tuning, especially in the regression model. The rate of convergence of the velocity will be zero and will remain the same, until the complete iteration is completed and will not be able to recognise the global optimal values, by remaining idle in the local optima. This results in the lower performance and complexity in the complete model. To overcome these circumstances, the modifications are made in the PSO algorithm by updating the weight. This hyper-parameter is tuned in view of making the complete model to be in a controlled behaviour, and in producing more optimal form of results. The main aim in tuning the parameters is to prevent the model from over-fitting situations.

The projected framework makes use of resilient-based techniques to enhance the performance of the Particle

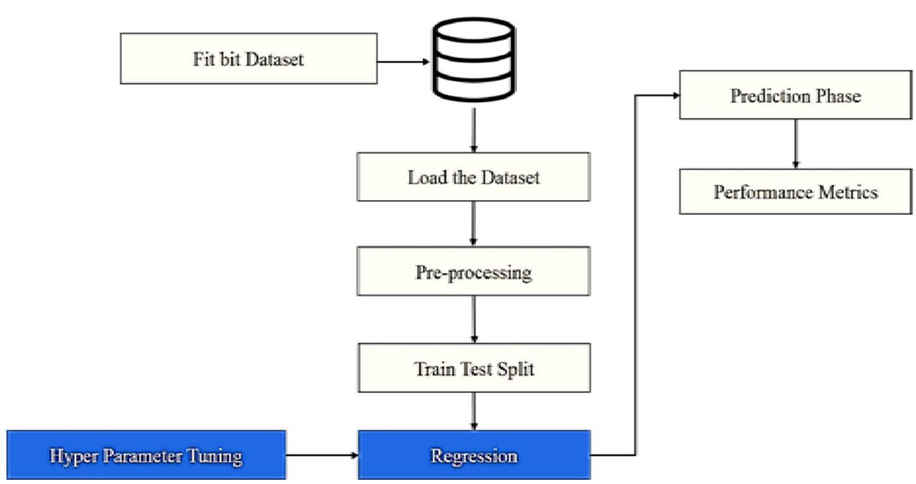

Fig. 1 Overall flow of the projected study

Swarm Optimization (PSO) algorithm. Moreover, the Resilient-based techniques are one of the optimization algorithms which makes use of adaptive learning rates to improve the convergence speed and stability of the optimization process.

In this proposed method, the Modified PSO (MPSO) algorithm is used with resilient-based techniques to tune hyper parameters in the Random Forest (RF), Decision Tree (DT), Ada Boost, and Support Vector Regression (SVR) models. The MPSO algorithm incorporates changes in the inertial weight values and learning factors to achieve better global and local search capabilities.

The proposed methodology initiates by loading the Fit bit dataset, which are retrieved from the Redmi-Fuel band recorder. The data are effectually pre-processed by removing the noise and other unwanted attributes, to ensure data precision and reliability. The pre-processed data is then split into train and test data in 80:20 ratio. These sets are then used for regression modelling.

The MPSO algorithm used in the proposed approach with resilient-based techniques are used in tuning the hyper parameters present in the RF, DT, Ada Boost, and SVR models to prevent over fitting and in delivering an enhanced global solutions. The overall performance of the model are evaluated using metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-Squared values.

The proposed methodology aims in the prediction of swimmer, losing or burning the calorie levels by swimming, and focusing on improving the swimmer's fitness by effectual management of calorie levels. The use of resilient-based techniques in the MPSO algorithm enhances the exploration ability, resulting in better optimization outcomes.

This in turn enhances the way of searching and in finding the global best optima values using less number of iterations. These tuned parameters are used in different regression models such as XG Boost, AdaBoost, DT and in SVR models, and are compared to bring satisfactory results and better outcomes. The complete evaluation of the model is done using the performance metrics which comprises MSE, RMSE, MAE and R-SQUARE values.

Modified PSO- Modified Particle Swarm Algorithm

PSO algorithm is one of the stochastic algorithm, which are based on the movement and the intelligence of the swarm. These are optimised and are used in many optimisation tasks, as they use only few important parameters to tune resulting in obtaining the best solutions, from the interaction of particles. They use number of particles that constitutes a swarm which moves around the search space for finding the best solution. Each of the particle in the swarm, looks for a positional coordinate in the search space, which are closely associated with the best solution, and had been achieved by the particle, known as Personal Best (P_{best}). The Global best (G_{best}) is the other best value tracked by the PSO, which had been obtained by the neighbourhood particle. But, as a contra, the PSO uses high dimensional solution space. PSO being a heuristic model, it cannot find the exact global and the local optimal values, but reaches close to it. To overcome these situations, in the PSO the hyper parameters (inertia Weight values) are tuned in view of obtaining the optimal results by tweaking the model performance. As PSO are strongly affected by the inertial weight values, which fixes the ability in finding the G_{best} values and local search. This is resolved by introducing huge number of inertial weight strategies, where initially the weight are decreased linearly using

$$\omega 0(t) = \frac{t_{max} - 1}{t_{max}}\left(\omega_{max} - \omega_{\min}\right) + \omega_{min}. \tag{1}$$

For each value of t from 1 to t_{max} plug into the equation and calculate $\omega 0(t)$.

If the value of t is given as 1, then $\omega 0(t) = \frac{tmax-1}{tmax}(\omega max - \omega \min) + \omega min.$

Then, $\omega 0(t)$ is calculated $for\, t = 2, 3, \dots t_{\max}$.

Followed by this it is found that the small number of large inertial weight can enhance the global search, whereas a small value can increase the ability of G_{best}. To overcome these issues, using.

$$\omega 1(t) = \begin{cases} 1 * \frac{1}{t_{max}} + 0.4, (0 \leq \frac{t}{t_{max}} \leq 0.5) \\ -1 * \frac{1}{t_{max}} + 1.4, (0.5 \leq \frac{t}{t_{max}} \leq 1) \end{cases}, \text{which is used in updating the inertial weight} \tag{2}$$

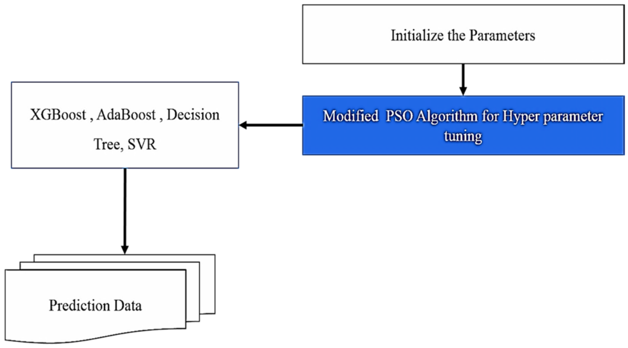

Fig. 2 Modified PSO

If, the time varies from $0 \le \frac{t}{t\_max} \le 0.5$ then the weight is calculated as, A set of functions$\omega_1(t) = 1 \times \frac{1}{t_{max}} + 0.4$ and can be written as,

$$\omega_1(t) = \frac{1}{t_{max}} + 0.4$$

Similarly, for $0.5 \le \frac{t}{t\_max} \le 1$, then the weight is calculated as,$\omega_1(t) = -1 \times \frac{1}{t_{max}} + 1.4$ and it can be simplified as,

$$\omega_1(t) = -\frac{1}{t_{max}} + 1.4$$

Hence, the $\omega_1(t)$ can be calculated for $t = 1, 2, 3, \ldots, t_{\max}$.
By calculating $\omega_0(t)$ and $\omega_1(t)$ for each value of t, then the vector representation can be obtained by the inertia weight evolution over time according to Eqs. (1) and (2). This inertial weights are given to subsequent process (Fig. 2).

Where there is a decrease in the performance of the concave function, based on the decreasing inertial weights which are better than the continuous optimisation problems. The widely used activation function is the Sigmoid,

$$Y = \left(\frac{1}{(1 + \exp(-X))} \right) \tag{3}$$

which is used in achieving the trade-off among linear and the non-linear behaviour. Here, the inertial weights and the learning factors are kept constant, where the model is prone to pre-mature convergence falling into the local optima. The inertial weight (ω) and the individual learning factor C1 decrease the concave learning function, and the C2 increases using the concave function, which is described using

$$\omega = \omega max - (\omega max - \omega \min) * \frac{4}{\pi} \arctan \frac{t}{tmax} \tag{4}$$

This in a later stage of algorithm for a better local search are done slower to find the Gbest values using PSO. The Pseudocode of the complete MPSO is presented in Pseudocode 1.

PSEUDOCODE I- MODIFIED PSO ALGORITHM

inertia weight → wgt
individual particle learning factor → LF_1
population learning factor → LF_2
Current iteration → iter
Maximum number of iterations → $iter_{max}$
v → velocity
P → position

$$w = wgt_{max} - (wgt_{max} - wgt_{min}) \times \frac{4}{\pi} \arctan \frac{iter}{iter_{max}}$$

$$LF_1 = LF_{1max} - (LF_{1max} - LF_{1min}) \times \frac{4}{\pi} \arctan \frac{iter}{iter_{max}}$$

$$LF_2 = LF_{2min} - (LF_{2max} - LF_{2min}) \times \frac{4}{\pi} \arctan \frac{iter}{iter_{max}}$$

$$wgt_o(iter) = \frac{iter_{max} - iter}{iter_{max}} (wgt_{max} - wgt_{min}) + wgt_{min}$$

$$wgt_1(iter) = \begin{cases} 1 \times \frac{iter}{iter_{max}} + 0.4, \left(0 \le \frac{iter}{iter_{max}} \le 0.5\right) \\ -1 \times \frac{iter}{iter_{max}} + 1.4, \left(0.5 \le \frac{iter}{iter_{max}} \le 1\right) \end{cases}$$

$$wgt_2(iter) = -(wgt_{start} - wgt_{end}) \left(\frac{iter}{iter_{max}}\right)^2 + wgt_{start}$$

$$wgt_3(iter) = \begin{cases} 0.9, (iter \le alpiter_{max}, alp = 0.2) \\ \frac{1}{1+e^{10iter-2iter_{max}/iter_{max}}} + 0.4, (otherwise) \end{cases}$$

while termination condition = false **do**
for a = 1 to number of particles do
for b = 1 to number of dim do
Evaluate fitness = f (x);
end
end
Update Per_{best} and G_{best};
for a = 1 to number of particles **do**
for b = 1 to number of dim **do**

$$vel_{ab}^{iter+1} = wgt_n v_{ab}^{iter} + LF_1 r_1 (Per_{best,ab} - Per_{ab}^{iter}) + LF_2 r_2 (G_{best,b} - Per_{ab}^{iter})k;$$

$$Per_{ab}^{iter+1} = Per_{ab}^{iter} + vel_{ab}^{iter+1}$$

If vel_{ab}^{iter+1} exceeds the upper limit
Set vel_{ab}^{iter+1} to the upper limit
end
if Per_{ab}^{iter+1}exceeds the upper limit
Set vel_{ab}^{iter+1} to the upper limit;
end
end
end
// hybridization mechanism
For a=1 to the number of particles do
If random number< $hybridation_{probability}$ then
Apply local search operator to the particle's position
Evaluate fitness after local search
If $new_{fitness} < old_{fitness}$ then
Accept the new position
else
Reject the new position
end if
end if
end
end
Output: G_{best}

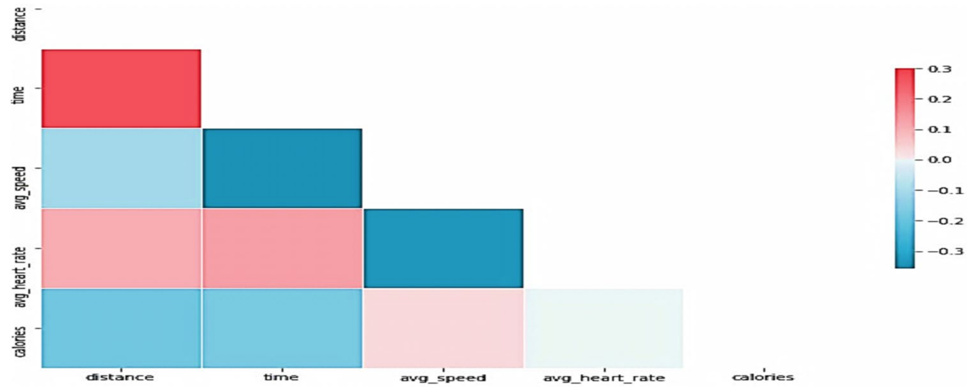

Fig. 3 Correlation matrix of the proposed dataset

XG-Boost- Extreme Gradient Boost

This XG-Boost algorithm are associated with much of advantage such as the enhanced accuracy rated and the high values of prediction accuracy. XG-Boost algorithm contains many DT's, which are typically used in the classification and in regression. The XG-Boost adds a second order Taylor expansion to the loss function using

$$J(f1) = \sum_{i=1}^{n}[L(yi, Yit - 1) + gifi(xi) + \frac{1}{2}hifi2(xi)] + \Omega(ft). \tag{5}$$

Followed by this the normalisation, is used in the objective function in view of preventing the over-fitting and in reducing the complexity of the model. XG-Boost being a flexible and an effective model with high accuracy rates and speed of convergence, the optimal values are gained using

$$\omega j *= -\frac{\sum^{i} \in Ijgi}{\sum^{i} \in Ijhi + \gamma}. \tag{6}$$

The complete pseudocode of the XG-Boost algorithm is presented in Pseudocode 2.

PSEUDOCODE III XG-BOOST ALGORITHM

m_i, n_i
$= G_{best}$ //hyperparameter values
$D = \{(m_i, n_i)\}(i = 1,2, \ldots, N)$

$$\hat{p}_i = \phi(m_i) = \sum_{k=1}^{k} f_k(m_i), f_k \in F$$

$$F = \{f(m) = \omega_{q(m)}\}$$

$$\hat{n}_i^t = \hat{n}_i^{t-1} + f_t(m_i)$$

$$J(f_t) = \sum_{i=1}^{n} L(n_i, \hat{n}_i^{t-1} + f_t(m_i) + \Omega(f_t)$$

$$\Omega(f_t) = \Upsilon.T_t + \lambda\frac{1}{2}\sum_{j=1}^{t}\omega_j^2$$

$$J(f_t) = \sum_{i=1}^{n}[L(n_i, \hat{n}_i^{t-1}) + g_i f_t(m) + \frac{1}{2}h_i f_t^2(r_i)] + \Omega(f_t)$$

$$g_i = \frac{\partial L((n_i, \hat{n}_i^{t-1})}{\partial \hat{n}_i^{t=1}}$$

$$h_i = \frac{\partial^2 L((n_i, \hat{n}_i^{t-1})}{\partial \hat{n}_i^{t=1}}$$

$$J(f_t) = \sum_{i=1}^{n}[g_1\ \omega_{q(r_i)} + \frac{1}{2}\ h_i\omega_{q(r_i)}^2] + \gamma T + \lambda\frac{1}{2}\sum_{j=1}^{t}\omega_j^2$$

$$\omega_j^* = -\frac{\sum_{i\epsilon I_j} g_i}{\sum_{i\epsilon I_j} h_i + \lambda}$$

$$J(f_t) = -\frac{1}{2}\sum_{j=1}^{T}\frac{\left(\sum_{i\epsilon I_j} g_i\right)^2}{\sum_{i\epsilon I_j} h_i + \lambda} + \Upsilon T$$

AdaBoost Algorithm

These are one of the ensemble learning algorithm, which are combined in view to solve the particular computational intelligence issues. These are used in enhancing the performance of the model characteristics, leaving multiple learners in resolving the respective problem. The AdaBoost uses a solid theoretical foundation which offers accurate prediction and are with great simplicity. This algorithm uses the updated weight distribution and also the training set in order to generate the updated weight distribution and the training set in the generation, using the other weaker learner. This is repeated for T times, where the majority of voting of the T weak learners and the weights of these models are determined at the training phase. By here the final model is obtained. The complete set of pseudocode is presented in Pseudocode 3.

PSEUDOCODE IV- ADABOOST ALGORITHM

$m_i, n_i = G_{best}$ //hyperparameter values
Dataset D $= \{(m_i, n_i)(i = 1,2, \ldots., N)\}$;
Base learning algorithm L;
Number of learning rounds T.
Process:
$D_1(i) = \frac{1}{M}$ % Initialize the weight distribution
for in = 1,.,T:
$h^1 = L(D, D^1)$; % Train a weak learner
h_i from D using distribution D_i
$\in_t = P\, r_{in \sim D_{in}} [h_{in}(m_{in} \neq n_{in})]$; % Measure the error of h_{in}
$\propto_t = \frac{1}{2} \ln\left(\frac{1-\in_t}{\in_t}\right)$; % Determine the weight of h_t
$D_{t+1}(in) = \frac{D_t(in)}{Z_t} \begin{cases} \exp(-\propto_t) \text{if } h_t(m_{in}) = n_{in} \\ \exp(-\propto_t) \text{ if } h_t(m_{in}) \neq n_{in} \end{cases}$

$D_{t+1}(in) = \frac{D_t(in)\exp(-\propto_t y_{in} h_t(m_{in}))}{Z_t}$ % Update the distribution,
where Z_t, is % a normalization factor which enables
$D_t + 1$ be a distribution end.
Output: $H(m) = \text{sign}\left(\sum_{t=1}^{T} \propto_t h_t(m)\right)$

Decision Tree Algorithm

These DT algorithm are easier for the implementation process, easier in working with the interpretation of results, as they do not require any normalisation process. These DT do not require much of scaling and pre-processing techniques. Also, these algorithm are able to handle the missing values where the time required for training the data are comparatively lower than the other algorithms, and are also easier for the process of implementations. But there are much of parameters that affects the results of DT, giving more of control over the results, with efficacy and performance. They denote X instance space, using $Y = \{-1, +1\}$ which will consider a weak learning algorithm, and the training set as,

$$D = (9x1, y1), (x2, Y2), \ldots (xm, ym)\{xi\epsilon X, yi\epsilon Y, i = 1, 2, \ldots, m\}. \tag{7}$$

The complete pseudocode of DT is provided in Pseudocode 4.

PSEUDOCODE V DECISION TREE ALGORITHM

Attr = G_{best} // hyperparameter values
Tree − Learning (Tr, Target, Attr)
Tr: instances of training
Target: attribute of target
Attr: set of descriptive attributes
{
Create the approriate node for
the respective tree.
If training has the identical value of t_i,
Thenreturn back the
single node of the respective = t_i
If Attr = empty
Then Return the single − node tree
Otherwise
{
select the respective attribute
A that is best in classifying the
tree completly based on the value of entropy
which is measure based values
set the value of attribute A for
the respective node root
For individual legal value for the Attribute (A), Vi, do
additionally add one more root to
the respective A = Vi
if Tr_{vi} be theA = v_i for the subset
If Tr_{vi} is empty, then additionally add
one more leaf node which is below the branch
which has a target value of = most common value of
Target is represented as Tr
Else teh subtree of the branch is leraned using
Tree − used in Learning(Tr_{vi}, Target, Attr − {A})
}
}
Return (root)
}

SVM- Support Vector Machine Algorithm

The SVM algorithm are the set of supervised learning methods, which are used in the process of classification, regression and also in the outlier detection. These are more effective in high dimensional space regions. These model are robust to the outliers and can also be easily updated. This SVM has high generalisation capability with high accuracy in predictions with easier implementation process. The main aim of the SVM lies in separating the datasets, into separate classes for finding the Maximum Marginal Hyper Plane, known as MMH. This algorithm needs less computational power. The SVM is ideally used in finding the best boundary that is used in finding the best boundary which maximises the margin which is the distance among the boundary and the closer data points from each of the classes. These SVM can also be used for regression tasks, by allowing some of the data to lie within the margin than lying in the boundary. This flexible boundaries can aid in making better and flexible predictions. These SVM are advantageous in handling the high-dimensional data and are able to perform better in case of small datasets too. The complete pseudocode of SVM is presented in Pseudocode 5.

PSEUDOCODE VI SUPPORT VECTOR MACHINE
Inputs: load the training and test data.
Outputs: calculate error_rate.
Set G_{best} hyperparameter as a parameter for the SVR
while (stopping condition of the parameter is not met) do
Implement SVR train step for each data point.
Implement SVR for testing data points.
end while
Return error_rate

According to the projected study, the MPSO is used in aspects of making a viable optimisation over the DL approaches used in the proposed study. Moreover, several applications such as the optimisation of swimming performance, optimisation of the training time, improvement in the analysis of stroke occurrence, expenditure optimisation over swimming and other several applications such as the heart rate optimisation, performance prediction, and injury prevention can also be analysed. Furthermore, the MPSO algorithm to this dataset, specific swimming-related goals or optimization objectives should be defined and are adapted the PSO algorithm to work with the data, and create a feedback loop in aspects of adjust recommendations based on an individual's progress and feedback. This in the future applications, can be used as a valuable tool for swim coaches, athletes, and fitness enthusiasts looking to improve their swimming performance and overall health. Thus, the application of MPSO are used for the optimisation and have produced liable outcomes having less error rates, being applicable for vast real-time applications.

Results and Discussions

The complete results obtained after the modification in PSO in obtaining the global optimal values and are compared with the other heuristic algorithm are presented in the respective section.

Dataset Description

The data used in the respective study are obtained using the Redmi Fuel Band Record Tracker Which is used in watching the fitness levels and maintaining them. The study uses swimming as a primitive activity as a goal in maintain the fitness levels by burning mark able levels of calories. This band constitutes various attributes such as distance, time, level of calorie burnt, maximum and minimum heart rate and others.

The provided link provides a clear overview upon the dataset considered in the projected study.

Dataset: https://www.kaggle.com/datasets/tanisha1416/my-redmi-fuel-band-record-tracker-fitbit-dataset.

The **provided dataset** is a record of daily physical activity generated using the Redmi GPS Watch (Model: REDMIWT02). The watch makes use various sensors to collect the data, such as an accelerometer to track steps and distance, whereas, a heart rate monitor is used in estimating the measure of heart rate, and GPS to track outdoor activities.

The Column Description is provided with respect to the dataset considered.

Activity Day: Date of activity performed

Workout Type: This can range from Outdoor Running, Treadmill, Outdoor Cycling, Indoor Cycling, Freestyle,

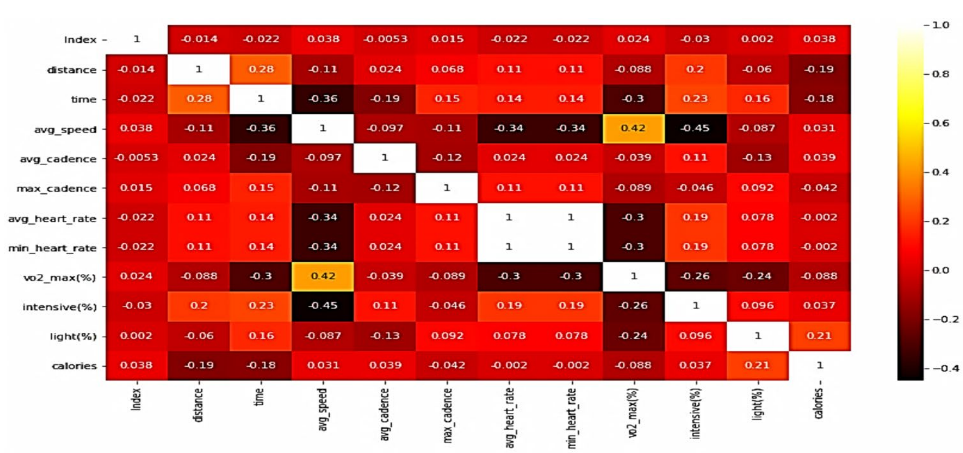

Fig. 4 Heat map of proposed dataset

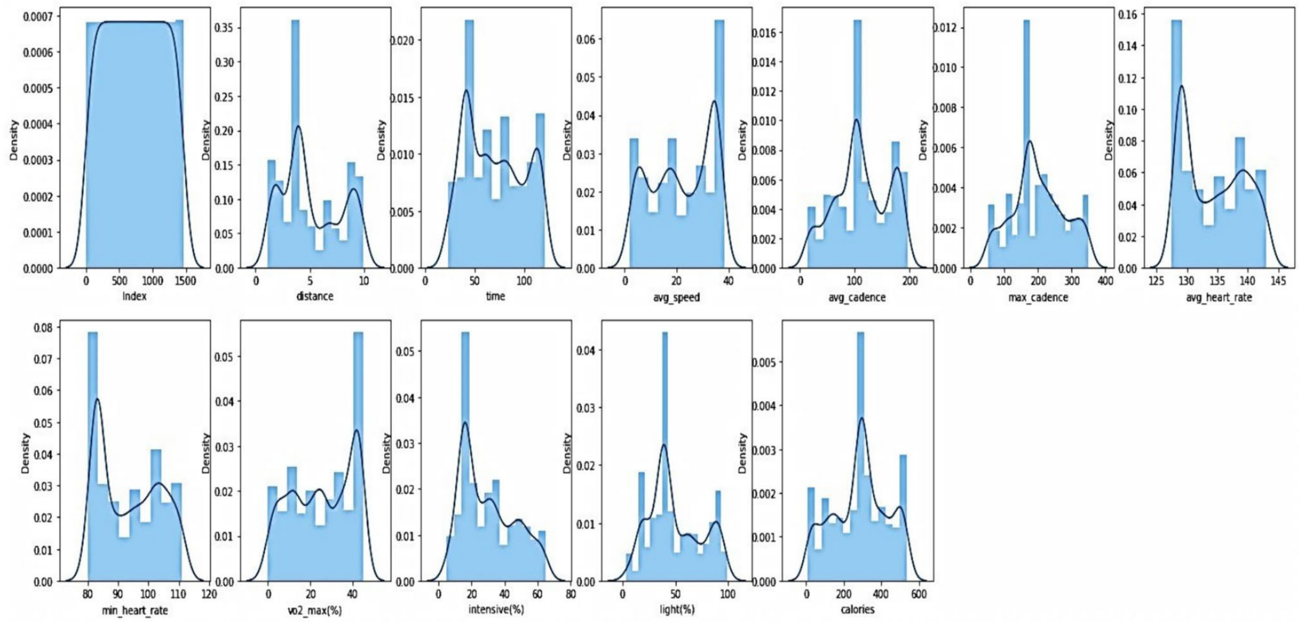

Fig. 5 Histogram of proposed dataset

Table 1 Performance analysis of the proposed model

Model	MSE	RMSE	MAE	R-square
MPSO-SVR	2.054	2.137	1.988	2.25
MPSO-DT	1.258	1.546	0.985	1.5
MPSO-AdaBoost	0.952	1.25	0.912	1
MPSO-XG Boost	0.037	0.191	0.059	0.9

Walking, Trekking, Trail Run, Pool Swimming, Open Water, and Cricket
Distance: Distance Covered (in km)
Time: Duration of the workout (in minutes)
Calories: Total number of active calories burned (kcal)
Total Steps: Steps count per day
Avg Speed: Average speed (km/h)

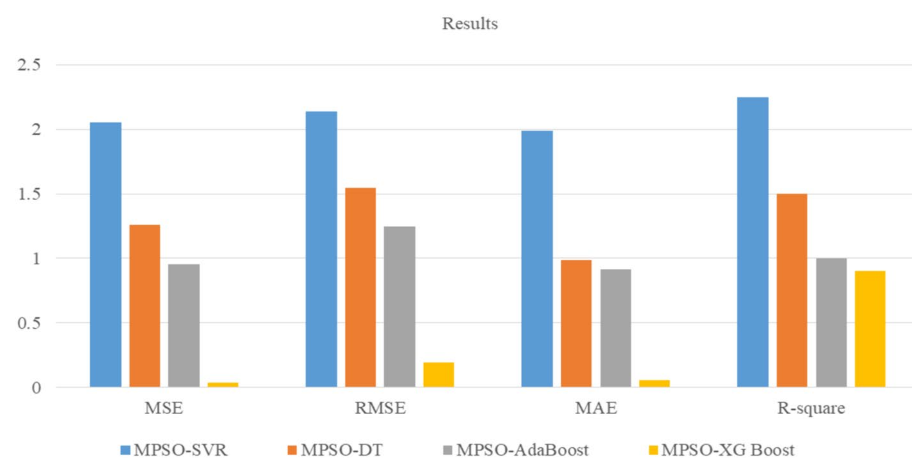

Fig. 6 Performance analysis of proposed model

Table 2 Symbol and definition for projected model

Symbol	Definition
m_i, n_i	Hyper parameter values
G_{best}	Best set of hyper parameter values
$\widehat{p}_i$	Estimated parameter $\widehat{p}_i$ based on $\phi(mi)$
F	A set of functions f k (m) where f (k) belongs to F
n_i-	The predicted value for n i at time t
Σ	Summation symbol
∂	Partial derivative symbol
λ	Regularization parameter
ϒ	A variable representing time or an iteration
T	A variable representing time or an iteration
I_j	set of indices of jth subset

Avg Cadence: Average Stride Rate, number of steps a runner takes per minute (SPM)
Max Cadence: Maximum number of steps taken per minute in the entire workout
Avg Pace: Average time taken to cover a kilometre
Max Pace: Maximum time taken to cover a kilometre
Min Pace: Minimum time taken to cover a kilometre
Avg Heart Rate: Average BPM (beats per minute) whilst the workout
Max Heart Rate: Maximum BPM (beats per minute) during the workout
Min Heart Rate: Minimum BPM (beats per minute) during the workout
VO_2 max: Maximum volume of oxygen used by the body while exercising
Anaerobic: Includes explosive exercises like sprinting which involve quick bursts of energy and are performed at a maximum for a short amount of time
Aerobic: These include cycling or brisk walking and are a type of cardiovascular conditioning
Intensive: High intense workouts like swimming, sprinting
Light: Low intense workouts like freestyle/walking
PS: This dataset comprises of both real time as well as synthetically generated data

Following sensors may be needed to collect the data:

Accelerometer: To track steps and distance
Heart rate monitor: To measure heart rate
GPS: To track outdoor activities and calculate distance
Gyroscope: To measure orientation and rotation
Barometer: To measure altitude and air pressure
Ambient light sensor: To measure light levels
Temperature sensor: To measure ambient temperature

Table 3 Symbol and definition for modified PSO

Symbol	Definition
wgt_max	Maximum weight
wgt_min	Minimum weight
iter	Current iteration
wgt_1	it is based on the iter and iter_max
$wgt\_2(iter)$:	Represents a weight at a specific iteration
Particlevelocities	$(vel_a b(iter + 1)$, particle positions—$(Per_a b(iter + 1))$

From these attributes, the work type of swimming using SMOTE technique have been used in aspects of increasing the size of the dataset.

Exploratory Data analysis (EDA)

EDA is used to validating the data via various visualization methodologies. For instance, EDA is utilized in determining the patterns or to legalise the assumptions by implementing a graphical representations and statistical summaries. Moreover, EDA offers data which helps in understanding the dataset.

Figures 3, 4 and 5 in the respective section explains the correlation map which is used in correlating the values of the data. This is also used in showing the possible pairs of the values which can be created from the table. This is one of a powerful tool in recognising and in envisaging the patterns in the given data. Followed by this, the Fig. 4 represents the heat map of the dataset used, which is used in explaining the complex data by different colour representations. Finally, the histogram of the used data comprising various attributes such as volumes of O_2, calorie levels, light rate, time, speed, average maximum and minimum cadence are represented.

Performance Analysis

The fitness maintenance using the swimming activity recorded from the fitbit data, are analysed for their performance using various performance metrics such as MSE, RMSE, MAE and the R-square values.

The Table 1 and Fig. 6 represents the overall analysis of the performance of the proposed model under the

Table 4 Symbol and Definition for AdaBoost

Symbol	Definition
T	Number of learning rounds or iterations
$Dt(i)$	Weight distribution at round t
$Y(in)$	True label of the i-th data point (1 or −1)

comparison of MPSO with different metaheuristic algorithms such as DT, SVM, AdaBoost and the XG-Boost algorithms. On comparing all of the performance metrics attributes were achieved at the higher rates at MSE, RMSE, MAE and the R-square values using MPSO-XG-Boost than the other models.

Conclusion

The fitbit data used in finding the calorie burnt levels via swimming as a primitive fitness module, were collected from the Redmi Fuel tracker, which were then taken for the hyper parameter tuning process using the metaheuristic algorithm PSO, which had the advantageous features of using few parameters to tune. The inertial weight values were tuned for further optimisation in aim of finding the Gbest and Pbest values without convergence in shorter period of time. These are compared with the other metaheuristic models such as SVM, DT, AdaBoost and the XG-Boost algorithms, in finding the best optimal values with less iteration, time and less in convergence rates. The better results were determined using the performance metrics such as MSE which are achieved at the rates of 2.054 when MPSO is compared with SVR, 1.258 when MPSO is with DT, 0.952 when MPSO is with AdaBoost and 0.037 when MPSO is with XG-Boost. Followed by the RMSE values obtained at the range of 2.137, 1.546, 1.25 and 0.191 when MPSO are compared with the SVR, DT, AdaBoost and the XG-Boost algorithm. Next, the MAE values which are obtained in the range of 1.98, 0.985, 0.912 and 0.59 when the proposed MPSO are compared with the SVR, DT, AdaBoost and the XG-Boost algorithm. Finally, the R-square values when proposed MPSO are compared with the SVR, DT, AdaBoost and the XG-Boost algorithm are at the ranges of 2.25, 1.5, 1 and 0.9 respectively. The overall analysis showed that the MPSO-XG boost algorithm obtained better results than the other meta-heuristic algorithms (Tables 2, 3, 4).

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Data Availability Data sharing not applicable to this article as no datasets were generated.

Declarations

Conflict of Interest The author reports that there is no conflict of interest.

Ethical Statement None.

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