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Enhanced Aquatic Athlete Fitness Assessment with a Resilient PSO-XGBoost Technique

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Abstract: Being active is a key ingredient for a healthier lifestyle. When a body is kept active, the entire system uses more energy, and when are burned more than consumed to maintain a healthier state of being. Moreover, burning appropriate calorie levels lowers the risk of cardio diseases and lowers the stress and feeling of anxiety. Swimming is one of the primary sports activities that engages all muscle groups, and the cardio system offers virus health benefits and fitness. Unlike sports, swimming can work on every muscle, as sprint kicking streamlines position activities, which elevates the heart rate and higher calories burned. Wearable sensors such as smartwatches and calorie trackers are used in measuring these calorie ranges, which are burnt by swimming. Predicting the fitness of a swimmer as the primitive activity in reducing the calories by using a hyperparameter tuning approach for enhanced exploration ability using grid search and random search strategies and PSO to optimize the outcomes. Besides, hyperparameters are tuned in the Random Forest (RF), Decision Tree (DT), AdaBoost, and XG-boost 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. Further, the proposed model is compared with the existing models to determine the efficiency of the proposed framework.

Keywords: *PSO, Grid Search, Random Search, Regression, Hyper-parameter tuning*

I. Introduction

Sports psychology is a specialized field that focuses on the psychological factors influencing an individual's well-being and personal growth in sports [1]. This involvement can also aid in maintaining mental stress and enhance a healthier lifestyle [2]. Physical training and activities are integral to comprehensive obesity management approaches [3]. In order to have a keen watch on these healthcare approaches, wearable sensors such as bio-sensors have been a primitive approach among all age ranges of people, used in a patient, disease diagnosis, and fitness management [4]. Bio-sensors have higher potential rates, easy to use, and are ascendable procedures of medical devices [5]. Whereas physical inactivity, being a major concern in association with high-calorie level diet intake, increases the rate of risk factors for several chronic diseases such as obesity, Hypertension, and Diabetes. These can be overcome by a short duration nature of Higher Intensity Intervals of training known as HIIT, which has shown similar results in metabolic improvements and increased rate of electron-couple transport systems [6]. This can result in enhanced efficacy of glycolic enzymes and elevate the fatty-acid metabolism ranges [7]. In addition to these advantages, swimming performance as a primitive fitness approach enhances the structural and biochemical changes of the adipocyte locations and enhances the body-well composition rates[8]. In reference to these advantages, several state-of-art approaches have been carried out to prioritize the efficacy of swimming as a primitive fitness maintenance approach. This existing study has aimed to explore the effect of swimming training on increasing the muscle quality of the Chinese perch and their characteristics with the metabolic rates. This study used four different groups for a rate of 56-day experimental period. The results have shown that swimming has increased the rates of resilience, gumminess, chewiness, and hardness of the muscle fibers. Also, with increased rates of flow velocity, the mRNA of the protein regulatory molecules is also highly upregulated. The metabolomics showed significant intensity rates in the KEGG functional mechanism and increased carbohydrate metabolism rates [9].

Similarly, this approach has made an investigation of outdoor swimming behavior a diagnostic report in health maintenance ranges. This approach used five clusters of people categories who were separated based on mental health, neuro and cardiological diseases, and several other primitive health factors. This study used 722 outdoor swimmers, where 68.9% were women. This study on a complete investigation showed that swimming positively impacted all sorts of health factors and several reduction rates on several heath-affecting factors. However, these approaches laid back in prioritizing using bio-sensors in measuring the calorie rate measurements, inaccurate rates

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of prediction, and higher computational complexity rates, and endeavored to procure over-fitting results [10]. Thus, to overcome these laybacks and with consideration to referral with these beneficial scales of swimming as a primitive health approach to outdoor exercise to several health beneficiary concerns, the proposed study has aimed to maintain the calorie ranges of an individual by swimming as a primary fitness activity. The calorie levels that are burnt by the swimmer are calculated using smart-wearable gadgets (bio-sensors). The values are optimized using various approaches such as grid search, random search, and resilient PSO approaches. These are compared with other models such as XG-boost, AdaBoost, DT, and the RF models. The prediction data by the proposed model is evaluated using the probabilistic performance metrics constituting MSE, RMSE, MASE, and R2 values.

The main contributions of the paper are,

- To develop a hyper-parameter tuning approach of regression by grid search, random search, and using Resilient PSO approaches for obtaining better-optimized outcomes.
- To evaluate the model outcome by comparing the algorithm with various ML algorithms such as DT, RF, XG-boost, and AdaBoost models in detecting the best optimal values.
- To analyze the model's overall performance using appropriate metrics such as MSE, RMSE, MAE, and R-square in assessing the model for predicting the data.

1.1 Paper organization

The paper is organized in the following aspects. Initially, various approaches for fitness evaluation, either by prediction or classification by various fitness approaches, are explored in Section II. Following this, the methodology used in the proposed model is explained in Section III. The dataset used in the proposed system, insights, and experimental results are deliberated in Section IV. The conclusion and future work of the proposed model is determined in Section V.

II. Literature review

The review of existing methods based on fitness evaluation by various physical activities is discussed in this section. Further, the limitations obtained by evaluating such conventional studies are also conferred in this section.

This existing approach [11] used tennis as a primary sports activity to decrease the effects of dementia. Being one of an aerobic dominant sport, driven but phospagen, and are separated by longer rest periods. This sport enhances both the physical and cognitive decline and dementia. The results have shown that table tennis interventions have been a powerful strategy in preventing cognitive decline and in the rates of dementia in the elderly.

This suggested tactic [12] used the same table tennis as a primary approach to enhancing motor skills and exercise functions in children with ADHD. Several clinical tests, such as Gross Motor Development–2 and Wisconsin Card Sorting analysis, have been conducted before the intervention. After the interventions, children with ADHD practicing tennis regularly procured higher locomotive skills, word coordination, and object-controlling skills. A continuous 12-week tennis course has clinical relevance in enhancing the brain capabilities of children with ADHD.

This suggested study [13] considered comfort requirements during the exercise phase as elevated heat is produced due to metabolism. Temperature considerations are taken as a primitive approach to making a comfortable environment for making a war sensation and to be devoid of neutral temperatures. The results from tests indicated that temperatures at ranges of 22-24 °C and 24-26°C with air movement are needed.

Endurance-trained runners are taken as a sample in these suggested approaches [14] in identifying the Lactate Threshold (LT), with their minimal and maximal state, which are described with MLSS prediction results. This study aimed at reducing the aerobic-conditioned individuals to a well-established lactate-related threshold. However, minimal lactate levels proved to be the best single-case predictors of MLSS.

The diabetes management approach in this suggested study [15] uses the Nano-technology-based approach. This study used biosensors to monitor human biological interventions and monitoring for effective diagnosis and disease management. Glucose sensors based on bio-fluids are used in diagnosing diabetic levels and monitoring the diabetic levels.

Similarly, this suggested approach [16] used an improved sailfish optimization algorithm known to be with DL approaches (ISFO-DL) model to detect and classify Parkinson's disease. This is used in evaluating the survival rate of PD persons. This is initially done by retrieving the optimal features with maximum classification accuracy rates. Additionally, RSO with Bi-GRU is used in classifying the PD. A benchmark dataset is used in the analysis.

This considerable approach used athletes as a primary sports activity in maintaining the calorie levels and their advantages to a sporting individual by vitally considering sports nutrition. This study concentrated on providing micromacronutrients, proper calorie consumption, and supplements to the players. This is done to maintain the process developments of general health [17].

Concurrently, this suggestive approach [18] has aimed at estimating the chronic Daily intake (CDI) in predicting the attributes of predicting cancer as a lifetime threat. This is detected using the Hazard Index (HI) from direct exposure to chloroform, oral ingestion, and many other dermal contacts. These are conducted among 238 non-competitive attendees using Monte-Carlo simulations.

Similarly, this suggestive approach [19] has aimed to evaluate the age-related disease of Alzheimer's Disease (AD). This is done by estimating the nutrition levels and the antioxidant effects provided by Swimming along with the consumption of Royal Jelly (RJ). This is done using the hippocampus tissues of 20 rats having AD. These are divided into 4 groups, including the control group having continuous Swimming Training (ST). The groups were split into ST, RJ, and ST+RJ. The evaluation period has been set to 8 weeks. The results indicated that the groups of RJ+ST have resulted in higher anti-oxidant response with $P \leq 0.05$.

Correspondingly, the suggestive approach has resulted in analyzing the combined effects of swimming (S_HIIE) and the benefits of Intermittent Fasting (IF) in Wistar rats [20]. To study these combined effects, the study has implicated 74 male Wistar rates, 60 days old, and separated into 4 different groups. The results have shown that the rat groups with IF and the S_HIEE have resulted in higher body composition, weight, and feeding behavior. Moreover, the modifications of WAT metabolism are achieved by the browning process.

2.1 Problem identification

The major issues found from the analysis of existing studies are,

- Using these tests, full control over the body functioning is not examined as the dose and medication time for each child with ADHD varies [12].
- Continuous glucose monitoring requires invasive procedures with more appeal and promising factors [15].
- Large-scale studies are less possible using these methods in determining human thermal preferences in real-world settings [13].

III. Proposed methodology

Maintaining the fitness levels and their cyclic progression is a must in preserving the health status each of individual. More calorie levels are burnt on complete physical workouts and outdoor physical activity. Several cases of existing approaches have explored various physical fitness activities suitable for burning calorie rates, duration levels of workouts, and their benefits. However, these approaches lagged in evidencing the rates of calories burnt by the individual using these workouts. Thus, to overcome these laybacks, the proposed study has made a primitive approach to evaluating the levels of calories burnt by an individual via swimming as a primitive fitness workout or exercise. This is carried out initially by obtaining the data from the Redmi-fuel band recorder. This study has also aimed to preserve the lower calorie levels of an individual in retaining a healthier lifestyle. Aspects of resolving several laybacks, such as inaccurate measurements of calories, less-suitable fitness workouts, and non-optimal ranges of outcomes from existing approaches, are resolved by the proposed study by exhibiting a structured framework, as in Figure 1. Initially, the dataset is loaded, which is obtained from the Redmi-fuel-track. These data are pre-processed, which is a needed procedure to remove the outliners and other non-essential noises from the provided data. This enhances the model's accuracy and reliability, aiming to produce optimal outcomes. These data are split into train and test data in ratios of 80:20, respectively. The training data is used to train the model, and test data is used to validate the model performance.

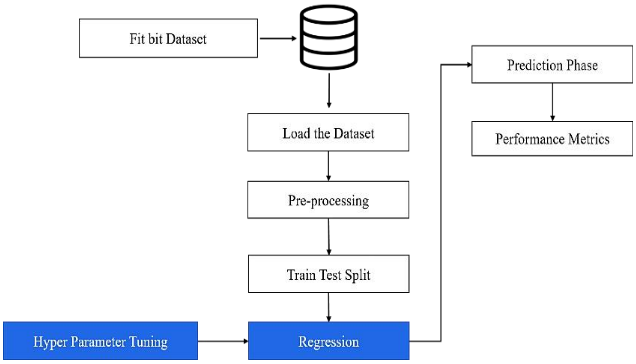

Fig 1 Overall Flow of the proposed approach

The test data are taken for the regression process, done by the PSO algorithm in aspects of hyperparameter tuning in the regression model. This is done by setting the hyperparameters of the PSO, such as population size iterations. Also, the initial position of the particles from the dataset is selected. Thus, the optimal solution can be detected quickly in the search space. The inertial weight (ω) used in determining both the global and the local search is crucial for the particles in determining the optimal solution. The inertial weight strategy is initially increased and then decreased. Substantially, the non-linear decreasing strategy is also used in updating the inertial weight. These are taken for the process of predicting the data. The model's overall performance in enhancing the search levels and bringing optimized outcomes is evaluated using the liable performance metrics.

Further, the parameters are initialized using three approaches, typically used in finding the optimal search solution as outcomes. These are done using Grid search, Random Search, and PSO algorithm. These are done in various approaches constituting the XG-Boost, AdaBoost, Decision tree (DT), and suing the Random Forest (RF) models. This is represented in Figure 2.

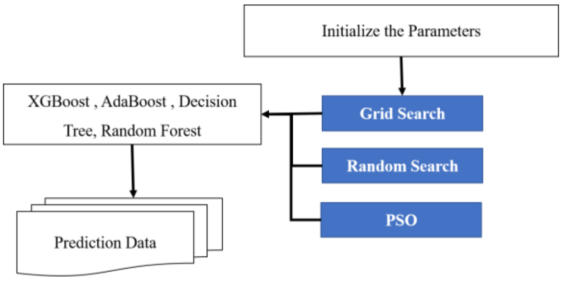

Fig 2 Novelty of the proposed system

3.1 Grid search

This approach is carried out by scanning the entire data in configuring the optimal range of parameters in a given model. Depending on the type of model being utilized, certain parameters are selected more precisely using this search approach. Grid search is used in finding the optimal hyperparameters of a model, which results in accurate model prediction. This approach makes use of various combinations which has specified hyperparameters and their attributes, which are used in calculating the performance for each of the combination. This aims to select the best value for the hyperparameters. The complete work is explained via algorithm I.

Algorithm I- Grid Search
Algorithm : Grid search
Input: $p-$ values: $\{a_i\}_{i=1}^{n_a}$, $k-$ values: $\{b_i\}_{i=1}^{n_b}$, n − epochs
for cross − validation
Output: correct rates a^* and b^*
Begin
for $j \leftarrow 1$ to n do
Split the training data randomly into training and val
for $j \leftarrow 1$ to n_b do
for $s \leftarrow 1$ to n_a do
Perform Md − FKNN
reg model with b(j)and a(s)and save the RMSEend
end
end
end
for $j \leftarrow 1$ to n_b do
for $s \leftarrow 1$ to n_a do
Average the RMSE over n − runs
end
end
Estimate the minimum RMSE average
and corresponding , a^* and b^* values
return a^* and b^*
ML algorithm(hyperparameter[a, b])

3.2 Random Search

The main objective of utilizing this search mechanism is to minimize the sum of all the individual objectives to minimize subtracting the sum of all the objectives to get maximized. In this approach, the random combinations of the hyperparameters of combinations are used in training the model. The best random hyperparameter is used in training the model. This is used in specifying the number of parameter values for testing the model. This approach tends to control the number of attempted combinations of hyperparameters. Unlike the grid search method, where every case of possible combination is attempted, random search allows only the specified number of models to be trained. The computational resources and iterations can be optimized as per the training epochs. The complete approach is explained via the algorithm in Algorithm II.

Algorithm II- Random Search
Input: N u m iterations, Problem Size, Search Space
Output: Best
Best + − − 0;
foreach iteri E N u m lterations do
candidatei + −
− RandomSolution(Probl emSize, SearchSpace) ;
if Cost (candidatei) < Cost (Best) then
Best + − − candidatei;
end
end
return Best

3.3 PSO- Particle Swarm Optimization

PSO handles the global search of the problem space to detect various solutions of different qualities. PSO algorithm is considered one of the most powerful and effective meta-heuristic optimization algorithms. PSO algorithm has been inspired by the behavior of a swarm. It is a meta-heuristic algorithm since it makes very few or even no assumptions regarding the problem begin optimized and can examine huge spaces of the candidate solutions. Similarly, these PSO algorithms possess several advantages, including rapid convergence, a very efficient global search algorithm, and the capability to solve various issues related to optimization. The overall algorithm is mentioned in Algorithm III.

Algorithm III- Particle Swarm Optimization

$\mathrm{iter}_{\max} \leftarrow$ Max number of iterations

$\mathrm{n}_{\mathrm{size}} \leftarrow$ Swarm size

for $\mathrm{i} = (1 \text{ to } \mathrm{n}_{\mathrm{size}})$ **do**

$\mathrm{P_i} \rightarrow$ initialize the position of the ith particle

$\mathrm{Loc}^{\mathrm{i}}_{\mathrm{best}} = \mathrm{P_i}$ ▷ local best of the ith particle

if $\mathrm{f}(\mathrm{Loc}^{\mathrm{i}}_{\mathrm{best}}) > \mathrm{f}(\mathrm{Glo}_{\mathrm{best}})$ **then**

$\mathrm{Glo}_{\mathrm{best}} = \mathrm{Loc}^{\mathrm{i}}_{\mathrm{best}}$

$\mathrm{vel_i} \leftarrow$ initialize the velocity of the ith particle

while $(\mathrm{t} < \mathrm{iter}_{\max})$ **do**

$\mathrm{t} = \mathrm{t} + 1$

for $\mathrm{i} = (1 \text{ to } \mathrm{n}_{\mathrm{size}})$ **do**

$\mathrm{vel_i} \leftarrow$ Update the velocity

$\mathrm{P}_{\mathrm{i(t)}} = \mathrm{P}_{\mathrm{i(t-1)}} + \mathrm{vel_i}$ //Update the position of the ith particle

if $\mathrm{f(P)} > \mathrm{f}(\mathrm{Loc}^{\mathrm{i}}_{\mathrm{best}})$ **then**

$\mathrm{Loc}^{\mathrm{i}}_{\mathrm{best}} = \mathrm{P_i}$

if $\mathrm{f}(\mathrm{Loc}^{\mathrm{i}}_{\mathrm{best}}) > \mathrm{f}(\mathrm{Glo}_{\mathrm{best}})$ **then**

$\mathrm{Glo}_{\mathrm{best}} = \mathrm{Loc}^{\mathrm{i}}_{\mathrm{best}}$

Output: $\mathrm{G}_{\mathrm{best}}$

ML algorithm(hyperparameter[$\mathrm{G}_{\mathrm{best}}$])

These are compared with each model constituting the XG-boost, RF, DT, and AdaBoost models. These are depicted in order with their appropriate algorithms.

3.4 XG-Boost

This approach uses a gradient-boosting framework. In this model, the parameters adjust themselves in an iterative form, which can be used in better learning with a fixed set of parameters for the entire XG-boost model. The result attained by the execution of the respective mechanism is presented in this section. Furthermore, the dataset description with the sample data, EDA, performance metrics, experimental results, and comparative analysis with existing techniques are presented. This is one of the scalable boosting algorithms used for their enhanced efficiency and higher rates of viable prediction accuracy. They contain many DTs, which are stereotypically adapted in cases of classification and reversion. Concurrently, normalization is also followed in the model in aspects of Objective Function (OF) to thwart the over-fitting possibilities and in plummeting the intricacy of the model. The model learns using the dataset, which is given by equation (1),

$$D = \{(x_i, y_i)\}(i = 1,2, \dots, n). \quad (1)$$

K number of trees are used in making the model learn, this is provided by Equation (2),

$$y_{i=\emptyset\,(x_i)=\sum_{K=1}^{K} f_k(x_i), f_k \in F} \quad (2)$$

Finally, if the OF is optimized, the optimal solution is obtained using equation (3)

$$\omega_j^* = -\frac{\sum i\in I_j g_i}{\sum i\in I_j h_i + \lambda} \quad (3)$$

The complete set of algorithm is provided in algorithm IV.

Algorithm IV- XG-Boost

$D = \{(a_i, b_i)\}(i = 1,2, \dots, N)$

$\widehat{p_i} = \phi(a_i) = \sum_{\mathrm{k=1}}^{\mathrm{k}} \mathrm{f_k}(\mathrm{a_i}), \mathrm{f_k} \in \mathrm{F}$

$\mathrm{F} = \{\mathrm{f}(a) = \omega_{\mathrm{q}(a)}\}$

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

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

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

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

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

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

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

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

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

3.5 AdaBoost

This approach is a simple and solid theoretical foundation that offers an accurate range of predictions. The X is the instance space, by$Y = \{-1, +1\}$. For all the training values, each is assigned with equal weights. This algorithm uses an updated weight distribution and training set to generate another weak learner. This is repeated as T-times. By weighing the majority voting of each of the weak learners, the final model is obtained. This is provided in Algorithm V.

Algorithm V- AdaBoost

$p_i, q_i = G_{best}$ //hyperparameter values

Dataset $Dt = \{(p_i, q_i)(i = 1,2, \ldots, N)\}$;

learning algorithm (base) $\rightarrow$ L;

Number of epochs for learning $\rightarrow$ R.

carried by:

$Dt_1(i) = \frac{1}{M}$ % Initialize the distribution of weight

for in $= 1, ., R$:

$w^1 = L(Dt, Dt^1)$; % Train a weak learner w_i from Dt usi

$\epsilon_t = P\, r_{in\sim Dt_{in}}[w_{in}(p_{in} \neq q_{in})]$; % Measure the error of w_{in}

$\propto_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$; % Determine the weight of w_t

$$Dt_{t+1}(in) = \frac{Dt_t(in)}{Z_t} \begin{cases} \exp(-\propto_t) \text{if } w_t(p_{in}) = q_{in} \\ \exp(-\propto_t) \text{ if } w_t(p_{in}) \neq q_{in} \end{cases}$$

$D_{t+1}(in) = \frac{Dt_t(in)\exp(-\propto_t y_{in} w_t(p_{in}))}{Z_t}$ % Update the distrib

where Z_t, is % a normalization factor which enables + 1 be a distribution end.

Output: $H(m) = \text{sign}\left(\sum_{t=1}^{R} \propto_t h_t(p)\right)$

3.6 Decision Tree

This approach picks up one quality at a time from the other available forms of attributes. An inheritor is created for each of the permissible values of this characteristic. The DT splits led to more nodes, consequently leading to a greater tendency of over-fitting. Conversely, the under-sampling method randomly detects the mainstream class until it matches the number of samples and the size of the minority class. These are evenly distributed. This is presented in Algorithm VI.

Algorithm VI- Decision Tree

DTree − L (Tr, T, At)

Tr: training examples

T: target attribute

At: set of exemplanary values

{

a node is created for each of the tree

If Tr have the similar target attribute value t_i,

Then getback the single − node tree = t_i

If At = empty

Then getback the single − node tree

Otherwise

{

Select value E from At that best

classify Tr based on an entropy − based measure

Set A attribute for each of the root

For legal value for each E, Vi, do

Add a branch below root, corresponding to E = Vi

Let Tr_{vi} is named to be the subset of Tr that have E = V_i

If Tr_{vi} is empty,

Then a leaf node is added beneath the

branch with target value = most common value of

Tr

Else lower part of the branch,

the subtree is learned using

Tree − Learning(Tr_{vi}, T, At − {E})

}

}

Return (root)

}

3.7 Random Forest

RF is an ensemble classification model used in constructing a number of decision tees, and compares all of the results from sub-decision trees in generating the final classification output. These operate in the bagging method. These make a selection of random features when generating the nodes of the sub-decision trees. In this case, the bagging filter is used in building the class of ensemble classifiers. This builds a DT on each bootstrap sample and generates the final output as the majority of votes of built section tree classification results. This is presented as an algorithm in Algorithm VII.

Algorithm VII- Random Forest

To generate e classifiers:

for a = 1 to c do

Randomly sample the training data D with replaceme

Create a root node, N, containing D

BuildTree(N) – Call

end for loop

Build Tree(N):

if N contains only one class then

return

else

distributively select x% of the

possible splitting features in

N Select the feature F with the highest information ga

split on Create f child nodes of N, N., N,, where F has

for a = 1 to f do

Set the contents of N to D,, where D is all instances in

F_i

Call BuildTree(N)

end for

end if

4. Results and discussions

The overall results are obtained after the implication of various search strategies of optimal values (global optimal values) and are compared with the other metaheuristic algorithms that are deliberated in this respective section.

4.1 Dataset Description

The dataset used in the projected approach is obtained using the Redmi Fuel Band Record Tracker. This is used in inspecting the fitness levels and maintaining them by any fitness activity. However, this respective study makes use of swimming as a primitive fitness activity as an approach to maintaining fitness levels by burning liable levels of calories. This band constitutes various attributes such as distance covered, time duration, ranges of calories burnt, maximum and minimum heart rate, and other health-defining attributes.

4.2 Exploratory Data analysis (EDA)

EDA is adapted in aspects of validating the data using various visualization methodologies. For this case, EDA is applied in defining the patterns or legalizing the assumptions. These are done using either a graphical representation or statistical summaries. Furthermore, EDA compromises the data which is used in understanding the entire dataset.

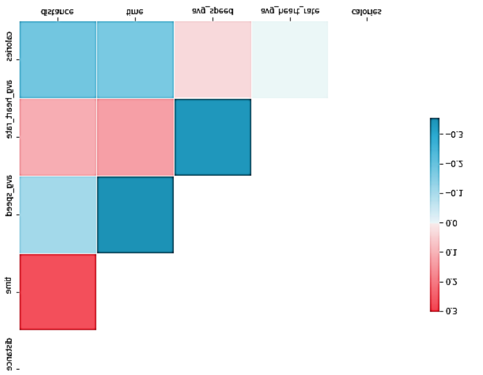

Fig 3 CM of Proposed model

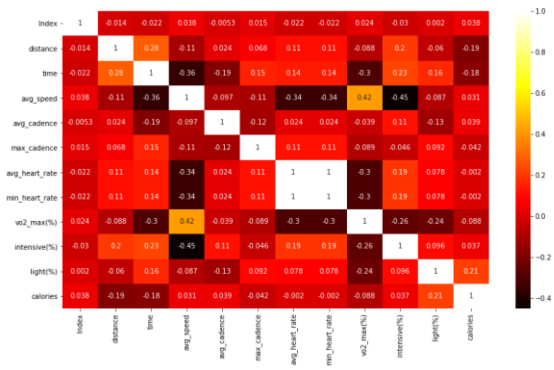

Fig 4 Heat map of propose model

4.3 Performance Metrics

The performance of the proposed model is validated using the probabilistic performance metrics comprising the MSE, RMSE, R2, and MAE rates.

4.3.1 Root Mean Square Error

This is one of the parameters used to evaluate the prediction quality made by the respective model. It represents the quantity of deviation from the actual measured true values, including the Euclidean distance. This is represented using the equation (4)

$$RMSE = \sqrt{\sum_{i=1}^{N}(Predicted - Actual)\Big/_2} \quad (4)$$

4.3.2 Mean Square Error

Mean squared error estimates the mean error value of the average square of the difference between actual and expected values. The formula respective to MSE is presented in equation 5.

$$MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(X(m,n) - Y(m,n))^2 \quad (5)$$

4.3.3 R-square value

This parameter explains how much variation in the dependent variable is explained by the independent variable. This is provided using equation (6)

$$\mathrm{R}^2 = 1 - \frac{\mathrm{RSS}}{\mathrm{TSS}} \quad (6)$$

4.3.4 Mean Absolute Error

This is the difference among the magnitude of individual measurements and the true values of the complete quantity. This is provided by equation (7)

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \quad (7)$$

4.3.5 Confusion Matrix

The correlation matrix demonstrates the co-related co-efficient values for various variables in the dataset. This represents all the possible pairs among the values in the data table.

4.4 Performance analysis

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

Table 1 Performance analysis of the proposed system

Model	MSE	RMSE	MAE	R-square
Grid-SVR	4.354	4.437	4.288	4.55
Random-SVR	2.954	2.635	2.788	3.155
PSO-SVR	2.254	2.637	2.388	2.53
Grid-DT	2.278	2.146	1.895	2.3
Random-DT	1.858	1.946	1.485	2.35
PSO-DT	1.458	1.846	1.185	1.65
Grid-AdaBoost	1.852	2.55	2.312	2.1
Random-AdaBoost	1.452	1.75	1.412	2.02
PSO-AdaBoost	1.152	1.47	0.992	1.23
Grid-XG Boost	0.931	0.781	0.989	1.8
Random-XG Boost	0.337	0.591	0.69	1.3
PSO-XG Boost	**0.057**	**0.291**	**0.19**	**1.1**

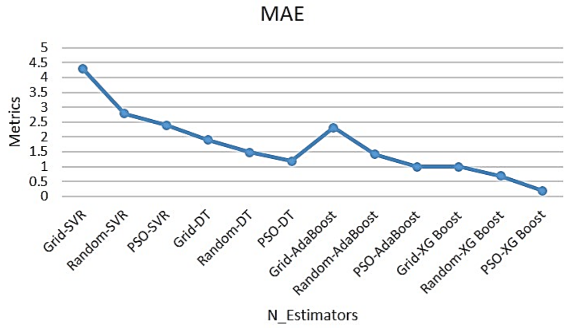

Fig 5 MAE of Proposed Model

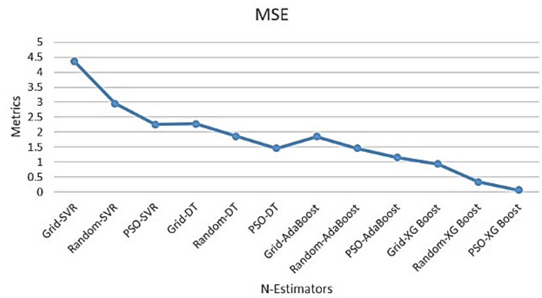

Fig 6 MSE of Proposed Model

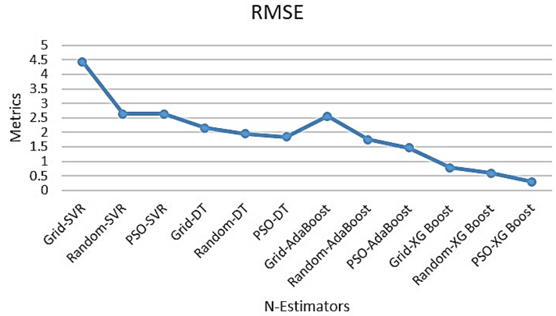

Fig 7 RMSE of Proposed Model

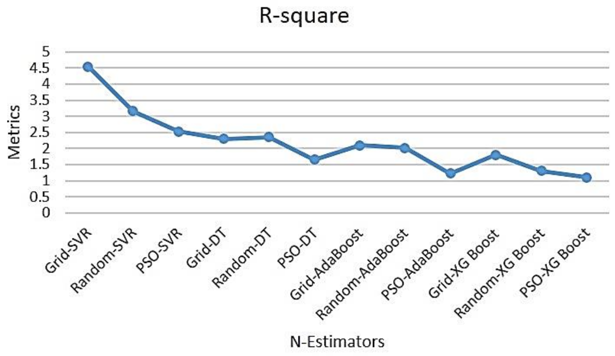

Fig 8 R-squared values of Proposed Model

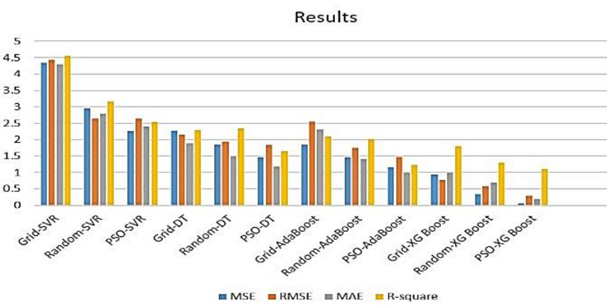

Fig 9 Overall comparison of proposed with other algorithms under the aspects of performance metrics

Table 1 and Figure 9 depict the overall analysis of the performance of the proposed model under the comparison of the proposed model with different metaheuristic algorithms such as DT, SVR, AdaBoost, and the XG-Boost algorithms. On comparing the performance metrics attributes, the proposed model achieved lesser metrics rates on MSE, RMSE, MAE, and the R-square values using MPSO-XG-boost than the other models, showing the efficacy of the proposed model.

V. Conclusion

The Fitbit data was used in finding the burnt levels of calories by swimming as a primary fitness activity module. The data was collected from the Redmi Fuel tracker, which was then taken for the process of hyperparameter tuning using various approaches such as grid search, random search, and resilient PSO, where all of these approaches have advantageous features that make use of only a few parameters to tune. The inertial weight values were tuned for further approaches of optimization, which aim to find the Gbest and Pbest values without any chances of convergence within a shorter duration of time. These are compared with the other metaheuristic models, such as RF, DT, AdaBoost, and the XG-Boost algorithms, in finding the best optimal values with less iteration, time, and less in convergence rates. The results proved that the proposed model had outperformed the existing algorithms, obtaining the optimal output rates for the PSO-XG-boost algorithm. This model attained the MSE in rates of 0.057, RMSE in rates of 0.291, followed by MAE in ranges of 0.19, and finally, the R-squared in ranges of 1.1. These values are comparatively lower than the other models, such as DT, RF, and AdaBoost. This showed the efficacy of the model's performance. As a part of future enhancement, the proposed model can be adapted to many other hyper-parameter tuning methods and approaches, which can be used for vast domains in optimal value recognition.

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