PSO trained Artificial Neural Networks Methods for Estimating Human Energy Expenditure

MSc Research Project
Data Analytics

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PSO trained Artificial Neural Networks Methods for Estimating Human Energy Expenditure

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MSc Research Project in Data Analytics

17th September 2018

Abstract

Technology is shaping the world around us and there is a continuous debate on the impacts of technology on human health. New-age Machines have reduced human labor and adversely affected our health but the advancement in the medical science and integration of high grade sensor and wearable devices have revolutionized the knowledge about the health issues. Obesity is growing at a staggering pace and much worse are its effects in terms of diabetes, hypertension and cardiovascular disorders. The control and cure for obesity primarily lies in losing calories through various exercises. The precise measurement of the energy expenditure from the human body is therefore of critical importance in curing obesity and thereby many other implied disorders. Despite of several attempts, accurate measurement of the energy estimation is still an unsolved puzzle. Most researchers have uses different machine learning algorithms to predict the energy expenditure. The ANN combined with PSO worked well on concepts of structural engineering, efficient energy usage which instilled an idea of using this to solve the EE riddle. In this research, we utilized the public repository data of activities and ran state of the art techniques along with proposed PSO-ANN model. The results obtained were compared and discussed with evaluation metrics like RMSE and MAE.

Abbreviations

MET – Metabolic Equivalent of a Task

EE – Energy Expenditure

ANN – Artificial Neural Networks

PSO - Particle Swarm Optimization

SVR – Support Vector Regression

RF – Random Forest

MLP – Multi Layer Perceptron

LightGBM – Light Gradient Boost Method

RMSE – Root Mean Square Error

MAE – Mean Absolute Error

SVM – Support Vector Machine

PCA – Principal Component Analysis

BDTR – Boosted Regression Tree

1 Introduction

Health is gaining the attention in this new-age technology era as so many health parameters are present and available for monitoring diagnosis that it has now added new dimensions to maintaining body fitness. Obesity is one of the topmost disorders in the US and also in rest of the world. The solution to obesity lies in burning of the body fats through energy consuming exercises like running, sports, gym etc. The critical factor for reducing obesity and thereby avoiding the disorders that come along with it, is to monitor the energy expenditure data of the body on a day to day basis. Many mobile phone applications have been launched to track the food intake and also measuring or estimating the energy expenditure but the critical factor is their accuracy. Lack of accuracy can lead to major complications in the data analysis and can change the predictions by several thousand calories, thus, making the whole exercise fruitless.

Previous studies for estimating EE have used calorimetry and indirect calorimetry methods, but these methods are not practical to use whereas the sensors such as heart rate sensing devices cannot produce output in energy expenditure terms, hence, mathematical models using machine language are needed to analyze the data collected through sensors and predict Energy Expenditure as accurately as ideally possible.

Internet of Things (IoT) devices can be worn and a complete spreadsheet of data for the pulse rate, activity, hourly tracking, sports or breathing can be collected for analysis through the developed mathematical model. The Artificial Neural Networks (ANN) along with PSO have been used successfully for estimation of the energy consumption of the physical structures like commercial buildings etc. but this research explores its suitability to evaluate the Energy Expenditure of the human body.

The research comprises two main sections- one is the literature review which examines the various scholarly works on the given subject and investigates them with an intent to find gaps and then justify the usefulness of this research in context of the identified gaps in the previous literature. The second section is the Methodology part. This section elaborates the theme and protocols for the research work including the selection of the data collection method, data filtration, Analysis, outcomes in terms of the EE prediction etc.

1.1 Research Problem

The main research aim is to formulate a method that is more accurate than the existing techniques in the estimation of EE using PSO trained Artificial Neural Networks.

1.2 Research Question

How efficient is PSO trained ANN technique in estimating the human Energy Expenditure when compared to the several existing methods?

2 Related Work

This literature review section is meant for exploring the different scholarly research papers from the reputed journals and international conferences related to the topic in discussion. Critical analysis of the various research papers is conducted in the sections below with an intent to identify the gaps in the researches and establish the fact that this research is justified and adds value to the existing pool of literature that exists on the topic and how the answer to the research question is of critical importance.

2.1 EE estimation using Body Sensor data

Catal and Akbulut (2018)highlight the importance of prediction of the Energy Expenditure for maintaining a healthy lifestyle. The research uses cloud based data collected using heart and breathe rate sensors. The model employs BDTR in combination with Aggregation of the median method and the results are proved to be much more accurate than five other regression model results illustrated and compared in the research paper. The conclusion of the research advocates for the use of cloud computing as a platform for complex evaluations and stresses on the use of the suggested regression method for enhancement in the EE data predictions.

Kim et al. (2016) presented an "Excess post-exercise oxygen consumption (EPOC)" based EE estimation algorithm. The data was collected using heart rate senor and the EE was evaluated using machine learning. The results were highly stable with 88% correlation and RMSE of around 0.23 which still is a significant amount of error. But the major limitation of the experiment was the selection of data recorded in a controlled experiment environment instead of a real-time physical one

2.2 EE calculation using Accelerometer data

Zhu et al. (2015) mentions that tracking of the ambulatory activities is indeed a challenging task and proposed a Convolution Neural Network (CNN) based research method for accurately predicting the Energy Expenditure. The method used the data collected through various heart rate sensors and triaxial accelerometer. The CNN technique is used for automatic detection of the important data elements from the collected sensors output data. The comparison of the results with the other state-of-the-art methods like the ANN or Activity-specific Linear Regression techniques shows that the accuracy of the obtained results was much higher. The Root Mean Square Error recorded in the results was noted to be 1.12 which is approx. 30 percent lesser than the other existing models.

Alvarez et al. (2017)presented a paper on classification of the activities especially in terms of ascending descending stairs. The paper aims to identify the signal from the body using various sensors and filters them for extracting the useful features like the signal from the gyroscope or from the accelerometer. The data is then processed through

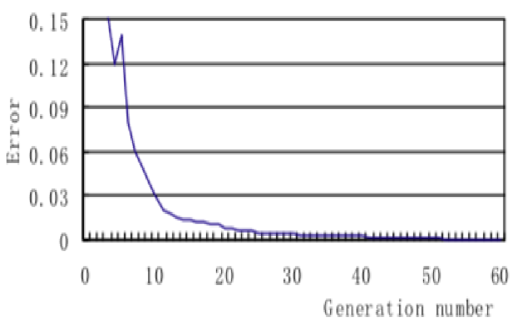
PCA and SVM which are applied to identify and categorize the motion. The method is a quite robust one and has a high accuracy percentage of 98.76 percent.

2.3 EE estimation using Smartphone Apps

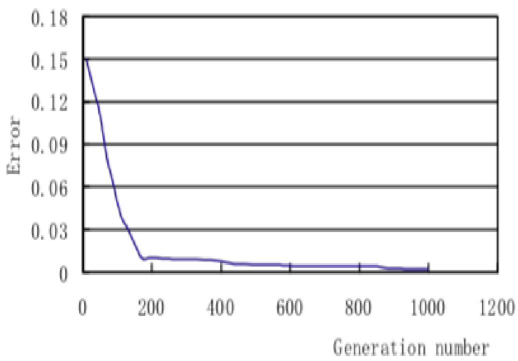
Andrés et al. (2016)used DAPHNE cloud platform to use a mobile application named HealthTracker to sense the various physical activities using simple devices such as accelerometer Gyroscope. The data was used to be stored on the cloud using ICT application had the flexibility to transport for real-time EE estimation or examination by a physician. The research was concluded a landmark for bridging the guidance time distance between the doctor and the patient. The research had a major drawback as the error was ignorable during less or no physical activities but rose to whopping 30% while being highly active such as during sports or gym. Thus, the error was unchecked.

2.4 EE estimation using ANN

Chang and Xu (2008) in the research paper mention the limitations of the neural network method as it often encounters challenges when it is trained with back-propagation (BP). The research bases its methodology on the PSO trained Artificial Neural Networks (ANN). The model has been successfully depicted for estimation of the energy requirements of the Chinese city Xi'an. The conclusion is based on the comparison of the results obtained through BP-based ANN approach and the PSO trained ANN technique, the results evidently settle the odds in the favor of PSO trained ANN method case. The research establishes the higher precision of PSO trained ANN method compared to other regression algorithms.



(a) **Error convergence in PSO-based**



(b) **Error convergence in BP based**

Figure 1: Error convergence rate in PSO and BP based ANN

The error convergence comparison for the two methods in the research is shown in the Figure 1. The methodology however limits the use of PSO based ANN technique to the energy estimation of the buildings and other physical structures.

Montoye et al. (2017) compare the linear and non-linear methods used for the prediction of the energy estimation. The research develops four different types of EE prediction methods Linear, Linear mixed and two ANN based. The results of the outputs through the four methods were compared using regression analysis and RMSE. RMSE for ANN methods (1.26-1.32) was less compared to linear (1.55-1.61) methods. The research scope is limited to ANN alone and does not combine it with any other method and as seen the error is still quite high and therefore it cannot be considered as the most accurate method for the estimation of EE.

Pande et al. (2013) made a similar attempt to measure EE with the help of smartphone sensors. The research used ANN technique and got around 89% of correlation with actual EE readings. But as understandable, the major shortcoming was the low accuracy of the method especially during the heavy physical activity.

2.5 EE estimation using different sensors data

Gjoreski et al. (2015) stresses on the importance of the measurement of EE and shows the impracticality of using direct methods of sensing like calorimetry. The research applies complex machine models on the data collected through various sensors and proposes Multiple Contexts Ensemble (MCE) technique which effectively extracts useful data from the sensors. The features of the data samples are processed through different regression models. The outcomes of the models prove the higher relatability of the data obtained through the suggested technique with respect to basic regression models, BodyMedia, Bagging Random Subspace etc. The method described in the research still leaves a significant error percentage which may not be desirable for high accuracy requirements.

Cvetković et al. (2016) presented their research on EE estimation using multiple models for the data collected through wearable sensors. The proposed model of regression was 10.2 percent more accurate than the average of all other regression models. This research also had the drawback of low accuracies during heavy exercise.

2.6 Literature Review Summary

As a summary, it can be understood that the past researchers have explored the topic in detail and mostly with the intent of attaining higher accuracy for the EE estimations. The various researches were based on the different types sensing methods and the methodology of processing the collected data. The main sensing methods were identified as the body sensors, Smartphones, Accelerometer data, Gyroscope etc. and the most of the methods applied involved regression analysis. As identified from the critical review most of the methods had a high error percentage denoted as RMSE. This explains the need for a much better technique to have its full effect in the health sector enhancement.

This research proposes PSO trained ANN method which no research has used for EE estimations for the human beings. It is although a proven method for EE estimations of the physical structures. Therefore, the research covers the gaps in the literature and adds a unique proposition to the literature.

3 Methodology

In this chapter we trained Artificial Neural Networks with Particle swarm Optimization for estimating Energy Expenditure and Other regression techniques like Support Vector Regression and Deep Neural Networks were performed for EE Estimation. First section of the chapter explains Data Collection and Data Pre-processing, then Architecture of the proposed Machine Learning Models are explained in second section and later part cover implementation of the methods.

3.1 Data Collection and Description

The research makes use of the scholarly works of Gjoreski et al. (2015). The datasets from research journal Kaluža et al. (2012) have been selected for formulating the research models for this report. We transformed the data sets as shown in Figure 2 The attributes selected include "Breath Rate, Heart Rate, Arm Skin Temperature, Galvanic Skin Response, Chest Skin Temperature, NearBody Ambient Temperature, Activity and Acceleration peak counts " Kaluža et al. (2012). The above independent variables are calibrated with the help of different sensors namely shimmer sensor platform, BodyMedia sensor and Zephyr sensor worn on the body. With the aid of the Cosmed K4b2 portable portable indirect calorimeter, the independent variable is measured. This is done by calculating oxygen intake in the process of various of various activities performed and in final, all the inputs are averaged for 10 seconds. The activities include various level of physical stress like walk, bend, sit, cycle, run, kneel, lie down, all four, stand, and stand-leaning. Zephyr sensor wearable on the chest is used to record Breath rate, Heart rate and variable for chest skin temperature. "Bodymedia" sensor is worn on the upper end of the left arm and is employed to measure Arm Skin Temperature, Ambient temperature near the body and Galvanic skin response. Shimmer sensors were connected at two different locations- "chest" and "thigh" to recording the activities and measuring acceleration peak counts. The sensor measurements are directly used for all other variables other than activity and measurement of the acceleration peak count. The meaning of acceleration peak count is to denote the number of times an increase or reduction in the length of the acceleration vector is recorded in 10 secs.

ID No.	Dataset Description	No. of Rows
1	First person dataset	650
2	Second person dataset	530
3	Third person dataset	684
4	Fourth person dataset	425
5	Fifth Person dataset	683
6	Sixth person dataset	685
7	Seventh Person dataset	677
8	Eighth Person Dataset	437
9	Ninth Person Dataset	677
10	Tenth Person Dataset	524
11	Datasets other than first person	5322
12	Datasets other than second person	5442
13	Datasets other than third person	5288
14	Datasets other than fourth person	5547
15	Datasets other than fifth person	5289
16	Datasets other than sixth person	5287
17	Datasets other than seventh person	5295
18	Datasets other than eighth person	5535
19	Datasets other than Ninth person	5295
20	Datasets other than tenth person	5448
	Total	59720

Figure 2: **Data Description**

3.2 Evaluation Techniques and Metrics

The evaluation method employs a technique to exclude one person at a time and validate the results using cross-verification Venables and Ripley (2002). The model training was done on the sample of nine persons and the testing was done the remaining one person. The process was performed ten time, keeping one different person out every time. The activity recognition classifier process was also carried out using the same procedure and its outcome was used as an attribute for the EE consumption estimation. The explained technique is commonly employed for ML community while using the model for the users other than the ones inducted for training, that is the event case in the estimation of EE Staudenmayer et al. (2009). The method also provides a prediction on its applicability on the users for which it was not trained. To evaluate the accuracy, RMSE and MAE have been used for the fact that these count for some of the commonly employed metric for the EE estimation criteria. The two elements RMSE and MAE are defined as below.

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(EE_{estimated} - EE_{true})^2}$$

$$MAE = \frac{1}{n}\sum_{1}^{n}|EE_{estimated} - EE_{true}|$$

Here, n is the no. of samples, EE estimated is the figure estimated for EE while EE true is stands for ground-truth EE measurement using Cosmed device.

3.3 Optimizing Artificial Neural Networks using PSO

PSO(Particle swarm optimization) is an optimization technique based on randomness inspired by flocking of birds or fish schooling Banda and Folly (2015). It is better than existing genetic algorithms in the aspect of considering minimum parameters adjustment thereby ease in implementation. In PSO, each particle are assigned "fitness" values with the help of functions aimed at optimizing the solution. For every iteration, each particle is identified with two best possible values Geethanjali et al. (2008) . PSO uses swarm intelligence Banda and Folly (2015), the learning from evolution between particles to identify the function's global minima or maxima Banda and Folly (2015). The particle with best fitness value helps in training for other particles and mutually enhance the performance of the optimizer. It is applied to ANN techniques to improve the accuracy of the outcomes.

ANN, developed by inspiration of how neurons in human body work aims at solving complex data problems like classification, regression, pattern recognition etc. The different topologies used in ANN are feed-forward (which is shown in figure), back propagation, recurrent networks etc. It works in a way of continuous learning. Each neuron learns from other neuron by understanding the output of previous neurons in a feed-forward process. For every neuron, input data is assigned weights and with the help of a transfer function, it solves problems of non-linearity. In this type of fee-forward method, the neurons transfer the input via a hidden layer, which transforms it into understandable format for output layer with help of activation functions. But these training and algorithm's back propagation for understanding the variance between input and output, makes the whole process tedious and long. Even the values may suffer with convergence issues. These are solved by training the ANN with PSO for flexible convergence, efficient capability to search and improve performance Geethanjali et al. (2008).

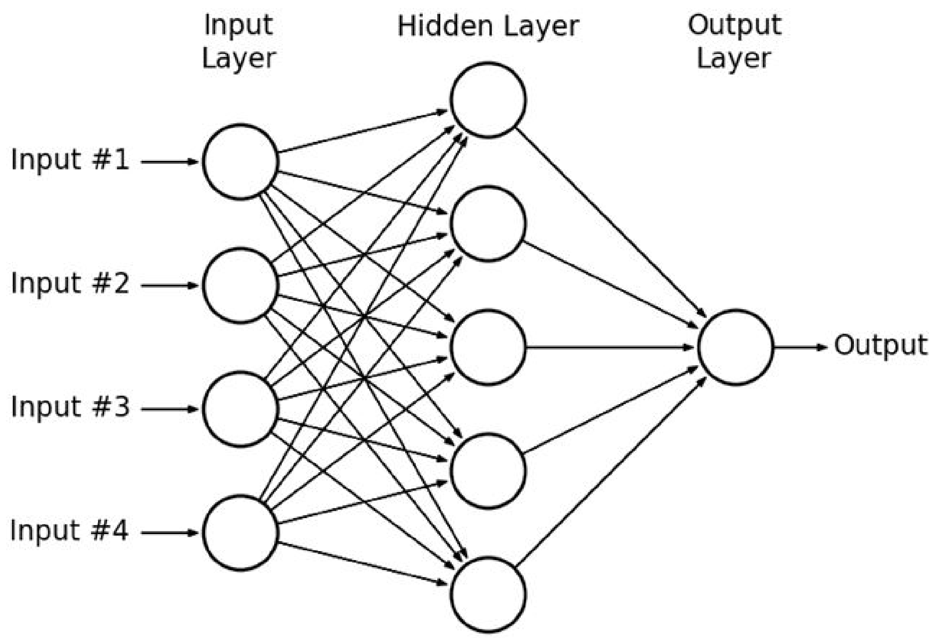


Figure 3: **Artificial neural network architecture**

3.4 Support Vector Machines

Support Vector Machines (SVM) are actively "learning" algorithms which work on the principle of structural risk minimization(SRM) in order to achieve maximum performance by minimizing the general error(s) and minimum learning patterns. Here we focus on two important functions of SVM - support vector classification (SVC) and support vector regression (SVR). SVM regression model had been put forth in Basak et al. (2007) naming it as support vector regression (SVR). SVR - a methodology for "regression" functions which can be performed on arbitrary data type(s) from training data, which allows dimensionality reduction, avoiding the problem of over-fitting thereby increasing the algorithms efficiency. The main ideology behind SVR is utilising linear regression models for solving non-linear high dimensional inputs. The SVR approach had been used in applications involving interpolation, Communications, prediction of disaster location, non-linearity problems, identification, data analysis Scholkopf et al. (1997).

3.5 Random forest Regression

RF is similar to bagging technique but with an additional "randomness" layer which helps in flexible split of nodes with variable dependency at those nodes randomly. RF are efficient and robust in handling noise. Random forests can be effectively used for both prediction and classification. Rf is good at handling overfit. Using multiple independent predictors with the understanding of their correlations provides deeper insights of RF abilities in prediction Breiman (2001) Liaw et al. (2002).

3.6 LightGBM

LightGBM is preferred when handling large data sets with high dimensionalities. While dealing with these kind of data, scalability and efficiency are unreliable. This is in accordance of required to read and analyse the information it requires large processing time. For solving these issues, two new techniques - Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) combinedly called LightGBM Ke et al. (2017) . GOSS - for estimating information with a small subset of data to understand data knowledge and EFB is primarily for reducing the attributes by bundling out mutually exclusive features Ke et al. (2017). It is used for multiple functionalities like regression, optimization, classification, complex evaluation metrics, data validation etc.Ke et al. (2017). LightGBM helps in improving training speed when compared to existing regular techniques but achieves similar accuracies.

3.7 MLP(Multi-layer perceptron)

MLP is a type of ANN which works on feed forward method. It is a combination of at least 3 layer nodes. The hidden and output layers contain non-linear activation function as opposed to general case. The main difference of MLP is it can be used for either regression or classification based on type of activation function whereas basic perceptron can only do binary classification. MLP – Regression process consists training for each iteration to avoid overfitting and also modelling parameters. MLP is equipped with back propagation while training the data. It supports both multiple and logistic regression .

4 Implementation

Technologies Used for Implementation
Python
Tableau
Microsoft Excel
Spyder IDE – for Implementing python code

Table 1: Technologies Used for Implementation

4.1 Data Preparation

Data collected for 10 persons was divided into 10 sets with data for 1 person being the test set and data for the other 9 persons being the training set. Categorical column 'Activities' was one Hot Encoded into 10 columns (representing 10 possible categories) and column 'Subjects' was removed from the dataset. The label column for dataset i.e. 'cosmedk2' column was removed from the training test set and was stored in y_train y_test variable respectively. For each run RMSE MAE was stored in a list and mean/ median values were calculated.

4.2 ANN-PSO

Training ANN using PSO is a relatively new technique which uses PSO for getting optimum values for weights and bias parameters instead of traditionally used back propagation. In the current implementation, we have a regression problem so for forward pass we have defined 1 hidden layer with 20 neurons and used standard equations to calculate output for the network. Activation used for the hidden layer output is 'ReLu'. Mean squared loss is used as the loss function for optimizing the weights and bias values. Function f is the optimization function which will be optimized via PSO. f calculates the loss values for all the particles using the forward pass function ('forward_prop'). Function predict makes use of optimized weights and bias values to predict the output for the test set. For optimization via PSO Parameters used by optimizer are – c1 = 0.5, c2 = 0.3, w = 0.9. Value of Dimensions variable for the PSO optimizer is the same as total number of parameters in the Neural network (i.e. weights bias values) Panigrahi et al. (2010) and total number of particles used for this exercise is 50. Number of iterations used for PSO were 500. During each iteration, the loss/ cost is calculated for the particles and is then used to optimize the values for the particles.

4.3 Alternate Algorithms

We performed alternate algorithms along with ANN PSO and compared the results.

4.3.1 Multilayer Perceptron

We implemented MLP Perception using MLPRegressor - from Scikit-learn library. Defined 2 hidden layers – (32,16), Used Relu activation Function, Defined random state as 15.

4.3.2 RandomForestRegressor

Scikit-learn's RandomForestRegressor implementation was used. 250 estimators, 0.4 as max_features used for creating these trees and minimum samples_leaf value as 1 to ensure diverse trees and hence more enhanced performance/ accuracy from RandomForestRegressor was achieved.

4.3.3 Support Vector Machine (SVM) – Regression

Scikit-learn's SVR implemented with penalty parameter "C=100" for regularization with default settings.

4.3.4 LightGBM

Microsoft's LightGBM was used as it is one of the fastest and most robust implementation of the gradient boosting framework (GBM). It uses tree-based learning algorithms. While training the models num_leaves, colsample_bytree & subsample were reduced slightly and n_estimators were increased as compared to the standard values to reduce overfitting and ensure a more generalized behavior from the models created during the 10 iterations.

5 Evaluation

In this section we are evaluating the results of different models by their ability to predict energy expenditure, Visualizations are provided for each model which shows Estimated MET values Vs True MET values.

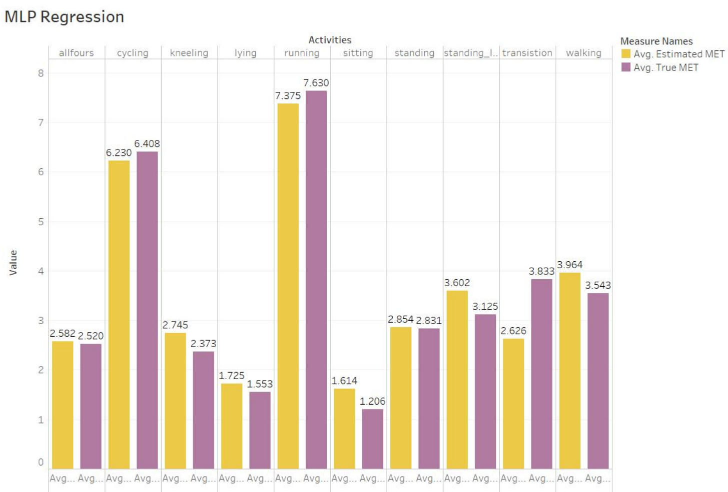


Figure 4: **MLP Outputs - True MET V/s Estimated MET**

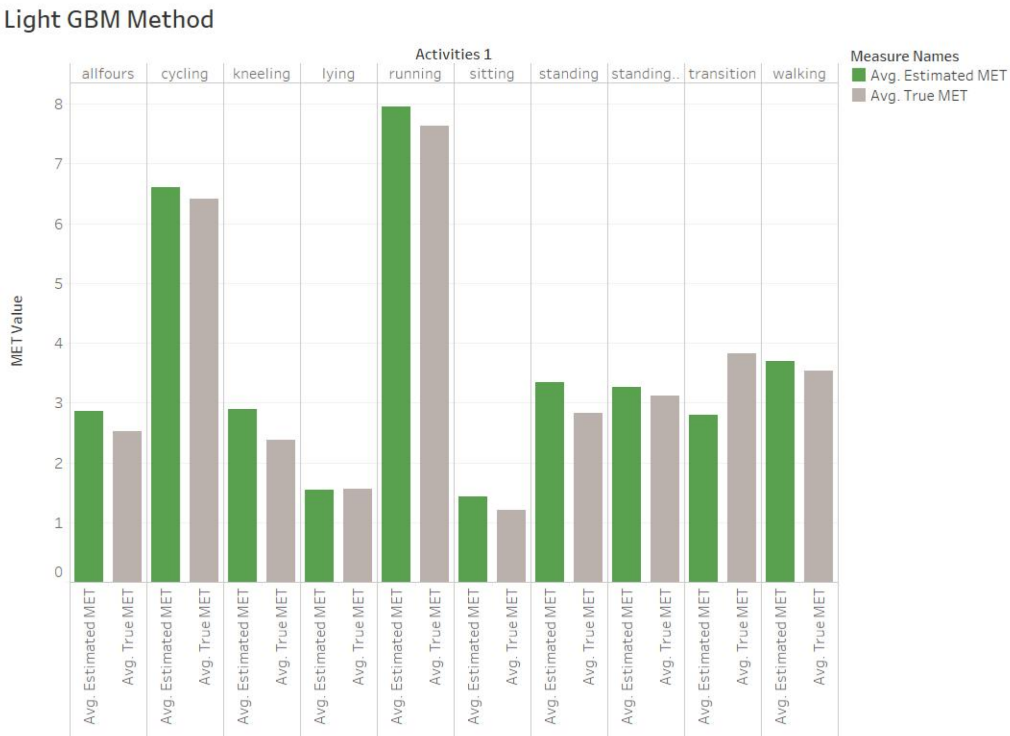


Figure 5: **LightGBM Outputs - True MET V/s Estimated MET**

Figure 6: **ANN-PSO Outputs - True MET V/s Estimated MET**

Figure 7: **Random Forest Outputs - True MET V/s Estimated MET**

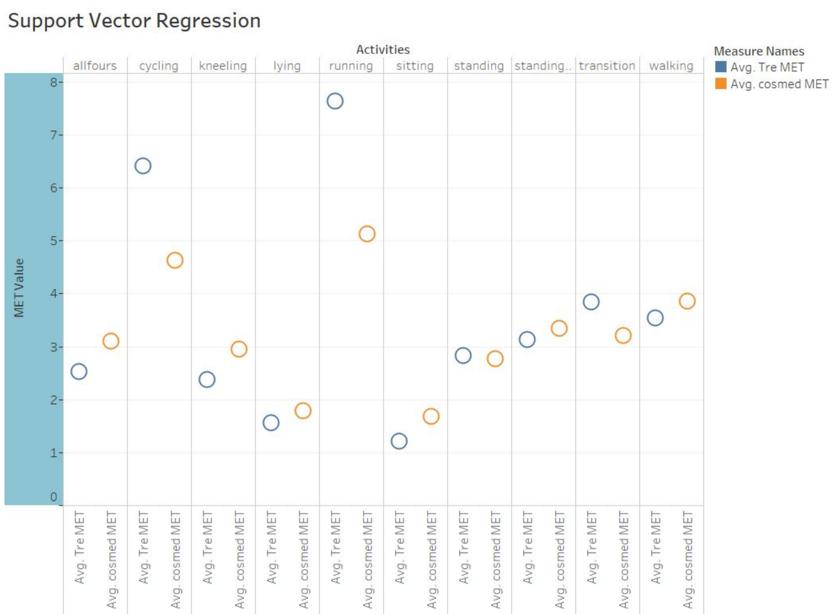


Figure 8: **SVR Output - True MET V/s Estimated MET**

		RMSE		MAE	
	Base learner	Average	Median	Average	Median
Gjoreski H. et al	SVR	0.851	0.825	0.613	0.601
	ANN	0.850	0.840	0.613	0.594
	MLR	0.854	0.830	0.622	0.610
	GPR	0.883	0.872	0.645	0.637
	M5P	0.887	0.893	0.637	0.633

(Support Vector Regression Artificial Neural Network (ANN), Multiple Lin- ear Regression (MLR), Gaussian Processes for Regression (GPR), and Model Tree (M5P).)

		RMSE		MAE	
	Base learner	Average	Median	Average	Median
Proposed Method	ANN PSO	1.125	0.861	0.855	0.632
	MLP	0.909	0.779	0.675	0.582
	Random Forest	0.920	0.755	0.693	0.565
	SVR	1.411	1.356	1.047	0.963
	Light GBM	0.984	0.791	0.723	0.594

(Particle Swarm Optimization (PSO), multi-layer perceptron (MLP))

Figure 9: **Results Table showing RMSE and MAE values**

5.1 Discussion

The paper tends to find as to which method is efficient enough in prediction of the energy expenditure. PSO trained ANN model was preferred as a base learner. The PSO algorithm optimizes continuous nonlinear functions which is motivated by perceptions of social and aggregate conduct on the motion of bird flocks looking for nourishment or survival. It is propelled on the motion of the best individual from a group and in the meantime additionally individual experience. Along with ANN PSO, 4 other state-of-art techniques such as Random Forest Regressor, ANN, SVR and LightGBM have been used to understand the difference in the performance of these methods by comparing each other in the process of obtaining robust evaluation model. The experiment or the framework was developed in python using sci-kit learn package which is a machine learning package. The experimental results of the algorithms are shown in the table and performance of ANN and ANN PSO has been marked in red along with RF which is the better technique.

The experimental results shown in Figure 9 stipulate that using Random forest gives lesser error rate compared to other learner(s) i.e. 0.565. MLP also give better performance based on the result obtained as the RMSE and MAE error is less i.e. 0.582. ANN with particle swarm optimization increases the error rate compared to using only ANN alone. The ANN PSO gives 0.632 median MAE. On comparison with Gjoreski et al. (2015), which uses only ANN on the same dataset, this proposed model of using ANN with PSO decreases the performance. Hence ANN provides relatively better performance. The Figure 10 shows the calculation of mean and median for the proposed method. As per the result, Random forest regressor has less RMSE and MAE median value(s) i.e., the prediction rate is much more accurate than other learners, thereby providing better performance. The ANN PSO error rate can still be reduced by fine tuning the dataset. The ANN PSO can be improved by introducing one or more than one layer and increasing the number of neurons. Further, the system should be trained for a longer time, in order to give accurate prediction for energy expenditure. Figure 11 gives an insight of the performance of the proposed methods.

```
ANN PSO Results:
Mean score:  1.1250271884023464
Median score:  0.8610620523982941
Mean MAE score:  0.8559577537802268
Median MAE score:  0.6320369412669726
MLP Regressor Results:
Mean score:  0.9098628244635141
Median score:  0.7791935625241155
Mean MAE score:  0.6758383807012833
Median MAE score:  0.5822710015209809
Random Forest Regressor Results:
Mean score:  0.9200830314576178
Median score:  0.7556969469044114
Mean MAE score:  0.6931188187475199
Median MAE score:  0.5658028513882541
SVR Results:
Mean score:  1.4112037962769515
Median score:  1.35643336218204
Mean MAE score:  1.0478628430514922
Median MAE score:  0.9636795515902226
[LightGBM] [Warning] Unknown parameter categorical_column=
Lightgbm Results:
Mean RMSE score:  0.9409610629306465
Median RMSE score:  0.7681862119838769
Mean MAE score:  0.6885898305341565
Median MAE score:  0.5812850796620406
                   algos  RMSE_mean  RMSE_median  MAE_mean  MAE_median
0                ANN_PSO   1.125027     0.861062  0.855958    0.632037
1                    MLP   0.909863     0.779194  0.675838    0.582271
2  RandomForestRegressor   0.920083     0.755697  0.693119    0.565803
3                    SVR   1.411204     1.356433  1.047863    0.963680
4               LightGBM   0.940961     0.768186  0.688590    0.581285
```

Figure 10: **Results**

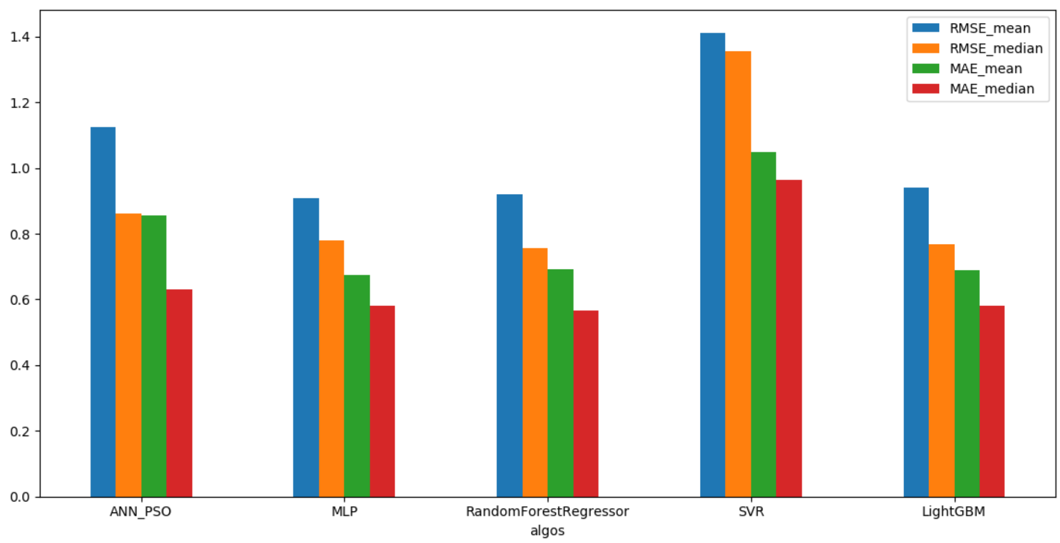


Figure 11: **RMSE and MAE values comparisons of all models**

6 Conclusion and Future Work

In this paper different learners have been used for predicting the human energy consumption. This paper opted for PSO trained ANN for prediction of the Energy Expenditure (EE). The previous researches were more focused on deep learning techniques without any optimizations. So, this research aimed at performance enhancement using swarm intelligence from PSO technique. To better the performance of existing EE models, ANN PSO method was considered. But the results proved to be not so fruitful. The neural network efficiency is better with a large dataset. As per our dataset, the input nodes are fixed to 17. Since this is considerably a small dataset, the model efficiency cannot be fixated. Cao et al. (2016) suggests, as the input nodes are increased, irrespective of the data size the performance of the model increase as ANN is constant learning algorithm. As PSO is for optimal solution with best fit, we could not replicate the success we had with unseeded dataset result. Based on the proposed methods it is found that Random forest regressor has lesser error value compared to the other implemented methods. It can be argued of using these complex methods in EE predictions but once we obtain a feasible model solution, it becomes easier to train and learn simultaneously, there by increasing the efficiency of the models.

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