Automatic energy expenditure measurement for health science

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Abstract #

Background and Objective It is crucial to predict the human energy expenditure in any sports activity and health science application accurately to investigate the impact of the activity. However, measurement of the real energy expenditure is not a trivial task and involves complex steps. The objective of this work is to improve the performance of existing estimation models of energy expenditure by using machine learning algorithms and several data from different sensors and provide this estimation service in a cloud-based platform.

Methods In this study, we used input data such as breathe rate, and hearth rate from three sensors. Inputs are received from a web form and sent to the web service which applies a regression model on Azure cloud platform. During the experiments, we assessed several machine learning models based on regression methods.

Results Our experimental results showed that our novel model which applies Boosted Decision Tree Regression in conjunction with the median aggregation technique provides the best result among other five regression algorithms.

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Conclusion This cloud-based energy expenditure system which uses a web service showed that cloud computing technology is a great opportunity to develop estimation systems and the new model which applies Boosted Decision Tree Regression with the median aggregation provides remarkable results.

Keywords Human energy expenditure · machine learning · energy prediction

1 Introduction

Obesity, which is a common disorder and health threat all around the world, increases the risk of several diseases such as diabetes and heart attacks. In the United States, it was reported that two-thirds of adults are overweight [22]. Several mobile applications and projects are being developed to track the food intake of people. The artifacts of these projects such as devices and mobile applications can help people to measure energy expenditure accurately and people might modify their personal habits so that they can improve their personal health [25].

The measurement of energy expenditure (EE) accurately has many advantages for several application areas such as weight control, and sports training [8, 19, 5]. However, it's not an easy task to estimate the exact calorie consumption. Due to the simple modeling approaches applied in the exercise equipments, display which shows the calorie consumption cannot provide accurate data [13]. Several techniques, which are listed as follows, have been developed for the reliable estimation of EE [8]:

- Direct calorimetry: This approach measures the heat output of the person accurately. However, it can only be used in laboratory condition.
- Indirect calorimetry: This approach is less precise and checks the respiratory gases. For example, pulmonary gas exchange is used in COSMED K4b2 calorimeter to measure the expenditure [26]. However, it is not practical because a breathing mask must be worn during the measurement.
- Doubly labeled water: Although it is accurate, it measures the long term EE. Therefore, it is not appropriate for short term usage.
- Sensor-based: Several sensors might be used to measure the metabolic activity indirectly such as temperature and heart rate. However, the estimation of EE based on these sensor outputs is challenging.

The main motivation of this study is to improve the performance of existing estimation models of energy expenditure by combining acceleration data with the other measurements such as heart rate, skin temperature, near-body ambient temperature and galvanic skin response which are automatically obtained from wearable sensor devices.

While there are several consumer-based activity monitors such as heart rate monitors relying on only one chest-mounted sensor and wrist-worn activity monitors, it was recently shown that devices which combine multiple sensors such as thermometer, accelerometer, and heat-flux sensor significantly improve the performance of EE models [35]. Also, the consumer device called

BodyMedia which has multiple sensors was recently shown the most accurate EE estimation device in a recent review paper [16]. Therefore, the benefit of using all of the measurements and devices over the commonly used consumer devices is the high performance of the EE models. Since all of these devices are wearable ones, they will not cause any difficulty for the end users.

Even a small performance increase in the models might significantly improve the weight control, sports training, and metabolic disorder management. Therefore, we decided to implement software systems which will enable us to apply the state-of-the-art machine learning techniques in conjunction with cloud computing technologies.

In this study, we modeled our experiments using Azure Machine Learning Studio platform and applied several regression methods to estimate the energy expenditure accurately. The best model was transformed into a web service and deployed to Azure cloud platform. The reasoning behind building a cloud-based system over local on-device calculations is that the system will provide some monthly reports to the users regarding their exercises and energy expenditures. Depending on the expectations of the possible user groups, different experts will be integrated into this system to inform the users about their future daily activities. In addition, a further analysis on the whole recorded data will be performed to improve the performance of the current EE estimation system. The data on a local system is hard to reach from anywhere. For this reason, we intend to have high accessibility of the system data by storing it on the cloud. The last but not the least reason for building a cloud-based system is the obvious computational requirements of the chosen machine learning methods.

We also implemented a web-based client application using Asp.NET technology and connected it to the web service deployed on Azure cloud computing platform. This client application is used to receive the appropriate data from the end users.

The main contributions of this paper are shown as follows:

- We developed a cloud-based energy expenditure system and implemented a web service which estimates the energy expenditure.
- We applied a new set of popular machine learning algorithms to a public dataset.
- We demonstrated that our model based on Boosted Decision Tree Regression algorithm and the median aggregation technique provides the best performance in terms of RMSE and MAE parameters.
- We conducted our trials on 10 individuals' data as performed by Gjoreski et al. [8] and showed that our model is superior.

The rest of this article is organized as follows: Section 2 provides an overview of related work. Section 3 explains the methodology used during the experiments. Section 4 shows the experimental results. Section 5 provides discussion and Section 6 explains the threats to the validity. Section 7 shows the conclusions.

2 Related Work

Sensor-based estimation techniques have been applied by researchers. Nowadays, the use of accelerometers are very popular for consumer electronics devices. Devices such as Apple Watch, Microsoft Band, Nike+ Fuelband, Jawbone Up, Fitbit apply machine learning algorithms and utilize from the accelerometer sensors. However, a recent study showed that methods which use accelerometer values in conjunction with heart rates cannot be used for children with disabilities [23]. Therefore, models which work for normal adults might not provide good performance for some cases.

Different sensors such as barometer were used in these studies [34, 1, 36, 33]. Voleno et al. [34] developed an EE system based on barometric pressure sensor and triaxial accelerometer. They investigated the effect of adding barometric sensors into the EE estimation models and worked with 13 healthy volunteers. They showed that barometric pressure sensor helps to improve the performance. Anastasopoulou et al. [1] presented a method to recognize the physical activity and predict the EE based on barometry and accelerometry. Not only the recognition step, but also the EE estimation step achieved high performance. They reported that the other populations such as children and elderly people must be investigated to optimize the model parameters in EE estimation. Yamazaki et al. [36] proposed a new algorithm by using accelerometer and barometer data. They concluded that the estimation of the new algorithm is more precise compared to the model using accelerometry alone.

However, they did not take into account the effect of several characteristics such as height, weight, body mass index, age, and excess post-exercise oxygen consumption (EPOC) for the estimation of EE [13]. Researchers successfully used machine learning techniques for this purpose and achieved high performance [8, 24, 32, 17, 35, 7]. Also, EPOC effect has been considered by a few researchers recently [28, 13].

Pande et al. [24] applied smartphone sensors such as barometer and accelerometer sensor to estimate the EE accurately. They reported that fusing the barometer data and accelerometer data provides significant benefits.

So far, there have been many studies related to the physical activity and EE prediction. According to these studies, it was observed that the analysis of the physical activity directly affects the EE estimation. Montoye et al. [20] worked with forty-four healthy adults who attended to a 90-minute simulated free-living activity experiment. During this experiment, all the participants were asked to perform 14 different sedentary, lifestyle, ambulatory, and exercise activities within three to 10 minutes intervals. Four accelerometers positioned on the right hip, right thigh, and right wrist and left wrist were used to predict EE with Artificial Neural Networks (ANNs). As a result of this research, a single accelerometer placed on the thigh provided the best prediction result compared to using four accelerometers simultaneously.

Van Hees et al. [11] compared the EE in 35 pregnant and 73 non-pregnant Swedish women with accelerometers banded to their hips or waists. Experimental results showed that there was no remarkable connection between body mass and EE. In another research, ActiDote [10] system which utilizes multimodal fusion and machine learning was developed to analyze the activities and energy consumption of the wheelchair users. Five wheelchair-based activities were classified with the F1-score 0.97%. Beltrame et al. [2] aimed to forecast the oxygen uptake dynamics during the walking exercises based on the heart rate and treadmill ergometer devices. Ten healthy young attendees performed walking exercises and their collected data was used to train the ANN. Results show that the predicted oxygen uptake was extremely correlated with the measured data.

Nathan et al.[21] developed a video game based application employing predictive algorithmic models to approximate the subsequent metabolic energy. In their experiments, 19 college students' movements were captured by two Kinect cameras. The EE estimate was not only performed by the perception of the movements, but also by the help of Cortex Metamax 3B automated gas analysis system used by the participants. The data collected from both channels were compiled with various machine learning approaches such as k-Nearest Neighbour, Gaussian process and linear regression.

A recent review article published by Plasqui [27] summarizes technological advancements about the accurate assessment of EE and the physical activity.

3 Methodology

In this study, six regression techniques have been investigated in detail, namely Bayesian Linear Regression [3], Boosted Decision Tree Regression [4], Decision Forest Regression [31], Linear Regression [29], Neural Network Regression [30], and Poisson Regression [15]. Bayesian Linear Regression applies Bayesian statistics to create the regression model. Boosted Decision Tree Regression algorithm uses boosting ensemble approach to build an ensemble of regression trees. In Azure Machine Learning Studio, MART gradient boosting algorithm is used for the implementation of boosted decision trees. Decision Forest Regression creates a regression model based on ensemble of decision trees. Linear Regression technique uses the online gradient descent method or the ordinary least squares method. Neural Network Regression algorithm applies Artificial Neural Networks algorithm to create the regression model. Poisson Regression assumes that the dependent variable has a Poisson distribution and creates a regression model to predict the counts.

In Figure 1, model creation based on Boosted Decision Tree Regression algorithm in Azure ML Studio is depicted. In this figure, Train Model component is used to identify the parameter values of the regression algorithm, Score Model component generates predictions based on the trained regression model, and Evaluate component measures the accuracy of the regression model. Later two components, namely Web Service Input and Web Service Output are connected to this experiment to transform this model into a web service.

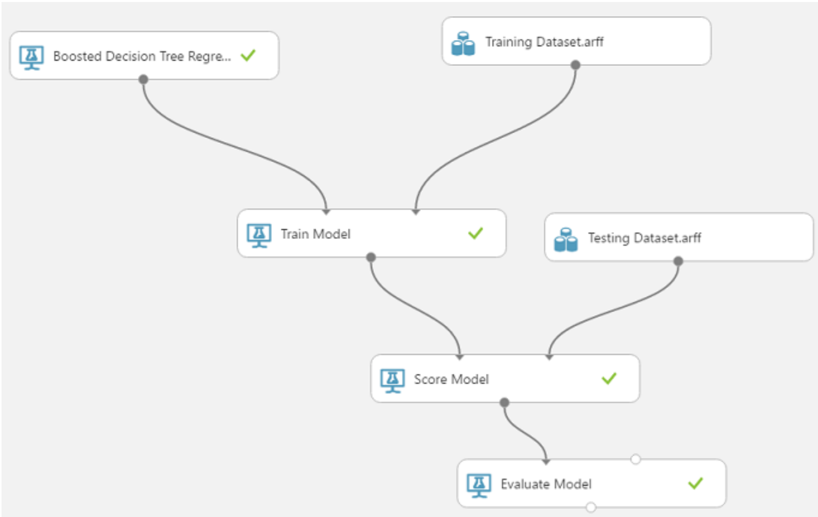

Fig. 1 Model Creation in Azure Machine Learning Studio

To build the models and benchmark with previous studies in the literature, we used the datasets published by Gjoreski et al. (2015) [8]. Datasets are available in their Ambient Intelligence (AmI) repository [12] (http://dis.ijs.si/ami-repository/index.php?d=16). The following eight features have been used during the design of models: Activity, Acceleration Peak Counts, Breath Rate (BR), Heart Rate (HR), Arm Skin Temperature, Galvanic Skin Response (GSR), Near-Body Ambient Temperature, and Chest Skin Temperature. These independent variables are measured using the following three wearable sensors: Zephyr sensor, BodyMedia sensor, and Shimmer sensor platform. The dependent variable, which is used as the ground truth, is measured using Cosmed K4b2 portable indirect calorimeter. This device measures oxygen uptake during different activities and it is averaged every 10 seconds [8]. In Figure 2, these sensors are shown. From left to the right, Zephyr sensor, BodyMedia sensor, and Shimmer sensor are depicted.

Fig. 2 Sensor Equipments to Measure Features

Zephyr, which is worn on the chest, measures Heart Rate, Breath Rate, and Chest Skin Temperature features. BodyMedia, which is worn on the left upper arm, measures Galvanic Skin Response, Near-Body Ambient Temperature, and Arm Skin Temperature. Two Shimmer sensors are attached to chest and thigh of the participants to measure Activity and Acceleration Peak Counts. Six features, except Activity and Acceleration Peak Counts, are directly measured from these sensors, but these two features are first filtered using band-pass filter [18]. Acceleration Peak Counts feature indicates how many times the acceleration vector's length stops increasing or decreasing in the 10 seconds. Activity feature is determined using a Random Forest classification model [9, 14] which uses 128 features obtained from two accelerometers. The possible categories for this feature are cycling, running, kneeling, bending, allfours, lying, standing, transition, standing-leaning, walking, and sitting. To make our EE model accessible by end users, a web-based client application was developed using Asp.NET technology. This client application shown in Figure 3 was used to get data from the user, send to the web service, and return the prediction results to the user.

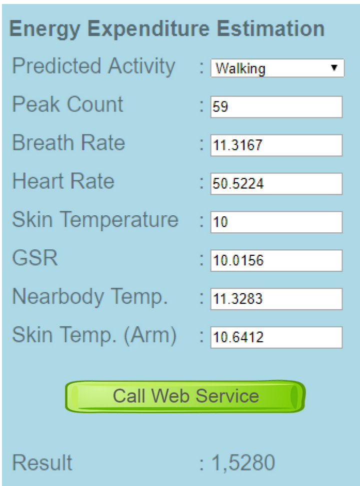

Fig. 3 User Interface of Client Application

In Figure 4, a state diagram which explains how the client application communicates with the web service is depicted. In this figure, it is seen that after the input validation is performed, the inputs are sent to the web service. Then, web service predicts the result, and the result is sent back to the web application.

Datasets retrieved from Aml repository [12] included data regarding to the ten participants. We transformed these datasets into twenty datasets as shown in Table 1 since leave-one-person-out cross-validation approach was required as performed in Gjoreski et al.'s study [8].

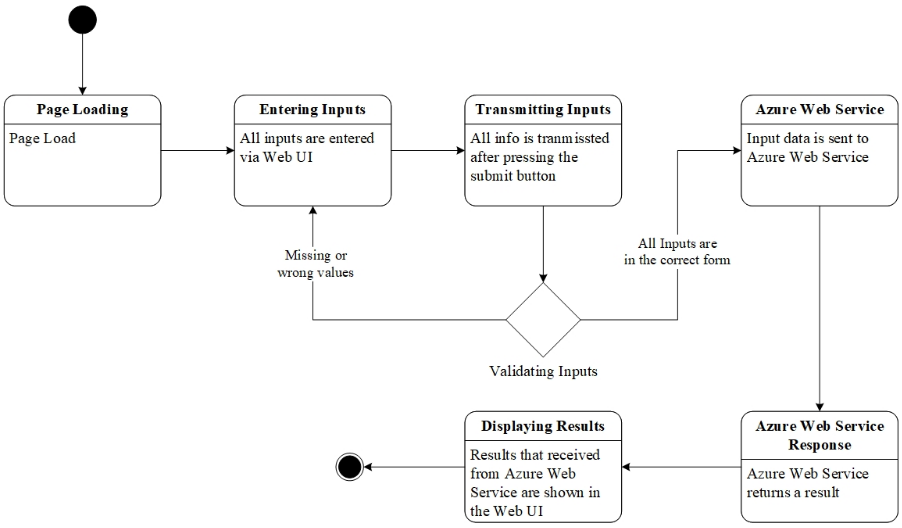

Fig. 4 State Diagram for the Web Application

Data from 10 individuals was used to build and evaluate our models. 20 datasets were created by using data of these 10 people as shown in Table 1. For example, dataset of the first person was represented as the first dataset and we created the dataset 11 which consists of the data rather than the first person. Similarly, dataset of the second person was represented as the second dataset and we created the dataset 12 which consists of the data rather than the second person. Therefore, we had 20 datasets based on 10 individuals and we performed 10 experiments based on these 20 datasets. For instance, the dataset 11 was used as the training dataset to build the model and the dataset called 1 was used as the test set to evaluate the performance of the model. This is the most common approach in EE estimation studies because the model will be used on a different user rather than the community used in the training step. Performance results of each regression method on these 10 test datasets were noted and the median result were selected for the comparison of the algorithms.

4 Experimental Results

Experimental results were compared in terms of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) evaluation parameters because they are the most common parameters for EE studies. RMSE and MAE equations are defined in Equation 1 and Equation 2, respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(EE_{est} - EE_{real})^2} \tag{1}$$

Table 1 Datasets After the Transformation

ID	Dataset Info	Number of Rows
1	Dataset of the first person	650
2	Dataset of the second person	530
3	Dataset of the third person	684
4	Dataset of the fourth person	425
5	Dataset of the fifth person	683
6	Dataset of the sixth person	685
7	Dataset of the seventh person	677
8	Dataset of the eighth person	437
9	Dataset of the ninth person	677
10	Dataset of tenth person	524
11	Datasets except the first person	5322
12	Datasets except the second person	5442
13	Datasets except the third person	5288
14	Datasets except the fourth person	5547
15	Datasets except the fifth person	5289
16	Datasets except the sixth person	5287
17	Datasets except the seventh person	5295
18	Datasets except the eighth person	5535
19	Datasets except the ninth person	5295
20	Datasets except the second person	5448

$$MAE = \frac{1}{n}\sum_{1}^{n} |EE_{est} - EE_{real}| \tag{2}$$

where n represents the number of data points, EE_{est} shows the estimated EE and EE_{real} is the real EE which is measured by the indirect calorimeter.

In Table 2, the results of Gjoreski et al. [8] and our study are shown in two different sections. In the first section, Gjoreski et al. [8] provide the experimental results of their approach called Multiple Contexts Ensemble (MCE) when the average and the median aggregation techniques were applied in conjunction with the several base learners. They reported that the best model was achieved when MCE was used with Support Vector Regression (SVR) base learner and median aggregation technique. The other base learners they applied are Artificial Neural Network (ANN), Multiple Linear Regression (MLR), Gaussian Processes for Regression (GPR), and Model Tree (M5P). In the second section of the Table 2, we show our experimental results of the regression algorithms in Azure ML Studio when we applied the average and the median aggregation techniques which were applied with 10 test results obtained from 10 test datasets. The results demonstrated that the BDTR with median aggregation method has a superior performance than the best model reported in Gjoreski et al.'s [8] study.

For each row in Table 2, the best performance is marked with bold. This bold results indicate that median approach should be preferred instead of average aggregation technique since median always provides better performance. The overall best performance for each evaluation metric is marked with a gray background and these gray cells in our study indicate that the best regres-

Table 2 Experimental results in terms of RMSE and MAE

	Base learner	RMSE		MAE	
		Average	Median	Average	Median
Gjoreski 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**
Our Study	**NNR**	0.974	**0.820**	0.779	**0.645**
	BLR	0.961	**0.854**	0.737	**0.673**
	BDTR	0.970	**0.757**	0.709	**0.526**
	LR	0.970	**0.883**	0.740	**0.666**
	PR	0.996	**0.844**	0.730	**0.650**
	DFR	0.964	**0.786**	0.712	**0.595**

sion algorithm is BDTR. Since our aim is to minimize the error parameters such as RMSE and MAE, we selected the algorithms which provide minimum RMSE and MAE values. According to the Table 2, the best algorithm was SVR in Gjoreski et al.'s [8] study because that algorithm provided the minimum RMSE. In this study, we achieved less RMSE value (0.757) and less MAE value (0.526) when we applied Boosted Decision Tree Regression algorithm for the same set of datasets.

Not only in Gjoreski et al.'s [8] study, but also in our study, it was observed that median aggregation technique is superior than the average technique. According to the Table 2, the highest performance among all 11 base learner is boosted decision tree regression with 0.526 MAE value.

5 Discussion

As the experimental results indicate, the results of our model which uses Boosted Decision Tree Regression algorithm in conjunction with the median aggregation technique are remarkable. Since we implemented the best model as a web service in Azure cloud platform, we can get benefit from several cloud characteristics such as elasticity, scalability, platform independency, and high computation capacity. Compared to the work of [8] which was performed on the same data, our proposed model provides relatively better performance and the median aggregation method is more appropriate compared to the average aggregation method.

6 Threats to Validity

Experimental studies consider different types of threats such as external, internal, conclusion, and construct validity. Since there is a conflict between these threats, increasing one type might decrease the other one. Therefore, prioritization of the validity types can be evaluated as an optimization problem [6]. In this section, we discuss these possible threats to the validity of the experiments. First, our experiments have been performed based on the data retrieved from a limited number of people since obtaining multi-sensor measurements during daily activities is a difficult task. Therefore, these models might be investigated again in a larger population and it is an open question whether the proposed model will provide the best performance or not. Since we used leave-one-out cross-validation technique due to the small size of our dataset, we believe that the results can be generalized outside of this population. Second, one might ask whether it is worth to apply a complex machine learning algorithm (an ensemble of decision trees) to increase the performance slightly or not. However, in this study, a small decrease in the error parameters reflects the change of hundreds of calories per day. This accurate estimation is especially critical for some groups of people such as people with diabetes and professional sportives who restrict calorie intake. Threats to the conclusion validity were reduced by using reliable measurements obtained from three sensor devices attached to different locations on the body and by applying non-biased evaluation parameters to evaluate machine learning models. Since the experimental environment was similar to the real one, threats to the external validity were reduced. Standard design methodology was applied for machine learning algorithms to reduce the design threats in construct validity.

7 Conclusions

In this study, a cloud-based human energy expenditure system was implemented and six regression techniques were investigated to build a high performance EE model. This EE prediction model was deployed as a web service in Azure cloud platform and a web-based client application was developed to access this web service.

We showed that the model using Boosted Decision Tree Regression and median aggregation technique is the best model in terms of RMSE, and MAE parameters. This model's performance is superior than the best model reported in Gjoreski et al.'s study [8]. Their best model achieved 0.825 RMSE and 0.601 MAE values when their approach called Multiple Contexts Ensemble (MSE) is used in conjunction with Support Vector Regression (SVR) base learner and the median aggregation technique. Also, it was demonstrated that results are always better when the median aggregation technique is applied instead of average aggregation technique. This observation is consistent with the results reported in Gjoreski et al.'s study [8]. In their study, they explained the rationale and stated that models which do not perform well for some specific cases are not taken into account when the median aggregation is used. Average aggregation evaluates all the models equally and therefore, the performance gets worse. Our novel EE model based on Boosted Decision Tree Regression achieved 0.757 RMSE and 0.526 MAE values when the median aggregation technique is used. In addition to the performance parameter, our model is not as complex as MCE approach suggested in the previous study. Even a small difference in the errors has a big impact on the calories calculated because some people try to match the caloric intake and output carefully [8]. This is the first study which uses cloud computing technologies for the energy expenditure prediction.

In the future, a different set of features is planned to be applied in conjunction with our model and a better performance might be achieved. Also, an integration with the popular iWatch device is considered to be established so that the user can easily see the results from the watch. In the current implementation, we do not use personal information such as age, weight, and length of leg, and we consider each participant equally. However, a customized model might provide a better performance. If different public datasets are obtained later, they will be tested with the proposed model.

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References

1. Anastasopoulou, P., Tansella, M., Stumpp, J., Shammas, L., Hey, S.: Classification of human physical activity and energy expenditure estimation by accelerometry and barometry. In: Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE, pp. 6451–6454. IEEE (2012)
2. Beltrame, T., Amelard, R., Villar, R., Shafiee, M.J., Wong, A., Hughson, R.L.: Estimating oxygen uptake and energy expenditure during treadmill walking by neural network analysis of easy-to-obtain inputs. Journal of Applied Physiology **121**(5), 1226–1233 (2016)
3. Bishop, C.M., Tipping, M.E.: Bayesian regression and classification. Nato Science Series sub Series III Computer And Systems Sciences **190**, 267–288 (2003)
4. Burges, C.J.: From ranknet to lambdarank to lambdamart: An overview. Learning **11**(23-581), 81 (2010)
5. Chen, K.Y., Sun, M.: Improving energy expenditure estimation by using a triaxial accelerometer. Journal of applied Physiology **83**(6), 2112–2122 (1997)
6. Claes, W., Per, R., Martin, H., Magnus, C., Björn, R., Wesslén, A.: Experimentation in software engineering: an introduction. Online Available: http://books. google. com/books (2000)
7. Ellis, K., Kerr, J., Godbole, S., Lanckriet, G., Wing, D., Marshall, S.: A random forest classifier for the prediction of energy expenditure and type of physical activity from wrist and hip accelerometers. Physiological measurement **35**(11), 2191 (2014)
8. Gjoreski, H., Kaluža, B., Gams, M., Milić, R., Luštrek, M.: Context-based ensemble method for human energy expenditure estimation. Applied Soft Computing **37**, 960–970 (2015)
9. Gjoreski, H., Lustrek, M., Gams, M.: Accelerometer placement for posture recognition and fall detection. In: Intelligent environments (IE), 2011 7th international conference on, pp. 47–54. IEEE (2011)
10. Grillon, A., Perez-Uribe, A., Satizabal, H., Gantel, L., Andrade, D.D.S., Upegui, A., Degache, F.: A wireless sensor-based system for self-tracking activity levels among manual wheelchair users. In: eHealth 360, pp. 229–240. Springer (2017)
11. van Hees, V.T., Renström, F., Wright, A., Gradmark, A., Catt, M., Chen, K.Y., Löf, M., Bluck, L., Pomeroy, J., Wareham, N.J., et al.: Estimation of daily energy expenditure in pregnant and non-pregnant women using a wrist-worn tri-axial accelerometer. PloS one **6**(7), e22,922 (2011)

12. Kaluža, B., Kozina, S., Luštrek, M.: The activity recognition repository: towards competitive benchmarking in ambient intelligence. In: Proc. Activity Context Representation Workshop, AAAI (2012)
13. Kim, S., Lee, K., Lee, J., Jeon, J.Y.: Epoc aware energy expenditure estimation with machine learning. In: Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on, pp. 001,585–001,590. IEEE (2016)
14. Kozina, S., Gjoreski, H., Gams, M., Luštrek, M.: Three-layer activity recognition combining domain knowledge and meta-classification. Journal of Medical and Biological Engineering **33**(4), 406–414 (2013)
15. Lambert, D.: Zero-inflated poisson regression, with an application to defects in manufacturing. Technometrics **34**(1), 1–14 (1992)
16. Lee, J.M., Kim, Y., Welk, G.J.: Validity of consumer-based physical activity monitors. Medicine & Science in Sports & Exercise **46**(9), 1840–1848 (2014)
17. Luštrek, M., Cvetković, B., Kozina, S.: Energy expenditure estimation with wearable accelerometers. In: Circuits and Systems (ISCAS), 2012 IEEE International Symposium on, pp. 5–8. IEEE (2012)
18. Mannini, A., Sabatini, A.M.: Machine learning methods for classifying human physical activity from on-body accelerometers. Sensors **10**(2), 1154–1175 (2010)
19. Marino, S., De Gaetano, A., Giancaterini, A., Giordano, D., Manco, M., Greco, A., Mingrone, G.: Computing dit from energy expenditure measures in a respiratory chamber: a direct modeling method. Computers in biology and medicine **32**(4), 297–309 (2002)
20. Montoye, A., Mudd, L.M., Biswas, S., Pfeiffer, K.A.: Energy expenditure prediction using raw accelerometer data in simulated free living. Med Sci Sports Exerc **47**(8), 1735–46 (2015)
21. Nathan, D., Huynh, D.Q., Rubenson, J., Rosenberg, M.: Estimating physical activity energy expenditure with the kinect sensor in an exergaming environment. PloS one **10**(5), e0127,113 (2015)
22. Ogden, C.L., Carroll, M.D., Kit, B.K., Flegal, K.M.: Prevalence of childhood and adult obesity in the united states, 2011-2012. Jama **311**(8), 806–814 (2014)
23. Pande, A., Mohapatra, P., Nicorici, A., Han, J.J.: Machine learning to improve energy expenditure estimation in children with disabilities: A pilot study in duchenne muscular dystrophy. JMIR Rehabilitation and Assistive Technologies **3**(2), e7 (2016)
24. Pande, A., Zeng, Y., Das, A.K., Mohapatra, P., Miyamoto, S., Seto, E., Henricson, E.K., Han, J.J.: Energy expenditure estimation with smartphone body sensors. In: Proceedings of the 8th International Conference on Body Area Networks, pp. 8–14. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering) (2013)
25. Pande, A., Zhu, J., Das, A.K., Zeng, Y., Mohapatra, P., Han, J.J.: Using smartphone sensors for improving energy expenditure estimation. IEEE journal of translational engineering in health and medicine **3**, 1–12 (2015)
26. Pinnington, H.C., Wong, P., Tay, J., Green, D., Dawson, B.: The level of accuracy and agreement in measures of feo2, feco2 and ve between the cosmed k4b2 portable, respiratory gas analysis system and a metabolic cart. Journal of Science and Medicine in Sport **4**(3), 324–335 (2001)
27. Plasqui, G.: Smart approaches for assessing free-living energy expenditure following identification of types of physical activity. Obesity Reviews **18**(S1), 50–55 (2017)
28. Rusko, H., Pulkkinen, A., Saalasti, S., Hynynen, E., Kettunen, J.: Pre-prediction of epoc: a tool for monitoring fatigue accumulation during exercise. Med Sci Sports Exerc **35**(5 Suppl 1), S183 (2003)
29. Seber, G.A., Lee, A.J.: Linear regression analysis, vol. 936. John Wiley & Sons (2012)
30. Specht, D.F.: A general regression neural network. IEEE transactions on neural networks **2**(6), 568–576 (1991)
31. Tong, W., Hong, H., Fang, H., Xie, Q., Perkins, R.: Decision forest: combining the predictions of multiple independent decision tree models. Journal of Chemical Information and Computer Sciences **43**(2), 525–531 (2003)
32. Trost, S.G., Wong, W.K., Pfeiffer, K.A., Zheng, Y.: Artificial neural networks to predict activity type and energy expenditure in youth. Medicine and science in sports and exercise **44**(9), 1801 (2012)

33. Trost, S.G., Zheng, Y., Wong, W.K.: Machine learning for activity recognition: hip versus wrist data. Physiological measurement **35**(11), 2183 (2014)
34. Voleno, M., Redmond, S.J., Cerutti, S., Lovell, N.H.: Energy expenditure estimation using triaxial accelerometry and barometric pressure measurement. In: Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE, pp. 5185–5188. IEEE (2010)
35. Vyas, N., Farringdon, J., Andre, D., Stivoric, J.I.: Machine learning and sensor fusion for estimating continuous energy expenditure. AI Magazine **33**(2), 55 (2012)
36. Yamazaki, T., Gen-No, H., Kamijo, Y.i., Okazaki, K., Masuki, S., Nose, H.: A new device to estimate vo2 during incline walking by accelerometry and barometry. Medicine and science in sports and exercise **41**(12), 2213–2219 (2009)