Pattern recognition techniques for the identification of Activities of Daily Living using mobile device accelerometer

Ivan Miguel Pires Corresp., [1, 2, 3] , **Nuno M. Garcia** Corresp., [1] , **Nuno Pombo** [1] , **Francisco Flórez-Revuelta** [4] , **Susanna Spinsante** [5] , **Maria Canavarro Teixeira** [6, 7] , **Eftim Zdravevski** [8]

[1] Instituto de Telecomunicações, Universidade da Beira Interior, Covilhã, Portugal
[2] Altranportugal, Lisbon, Portugal
[3] ALLab - Assisted Living Computing and Telecommunication Laboratory, Computer Science Department, Universidade da Beira Interior, Covilhã, Portugal
[4] Department of Computer Technology, Universidad de Alicante, Alicante, Spain
[5] Università Politecnica delle Marche, Ancona, Italy
[6] UTC de Recursos Naturais e Desenvolvimento Sustentável, Instituto Politécnico de Castelo Branco, Castelo Branco, Portugal
[7] CERNAS - Research Centre for Natural Resources, Environment and Society, Instituto Politécnico de Castelo Branco, Castelo Branco, Portugal
[8] Faculty of Computer Science and Engineering, St. Cyril and Methodius University, Skopje, Macedonia

Corresponding Authors: Ivan Miguel Pires, Nuno M. Garcia
Email address: impires@it.ubi.pt, ngarcia@di.ubi.pt

This paper focuses on the recognition of Activities of Daily Living (ADL) applying pattern recognition techniques to the data acquired by the accelerometer available in the mobile devices. The recognition of ADL is composed by several stages, including data acquisition, data processing, and artificial intelligence methods. The artificial intelligence methods used are related to pattern recognition, and this study focuses on the use of Artificial Neural Networks (ANN). The data processing includes data cleaning, and the feature extraction techniques to define the inputs for the ANN. Due to the low processing power and memory of the mobile devices, they should be mainly used to acquire the data, applying an ANN previously trained for the identification of the ADL. The main purpose of this paper is to present a new method based on ANN for the identification of a defined set of ADL with a reliable accuracy. This paper also presents a comparison of different types of ANN in order to choose the type for the implementation of the final model. Results of this research probes that the best accuracies are achieved with Deep Neural Networks (DNN) with an accuracy higher than 80%. The results obtained are similar with other studies, but we compared tree types of ANN in order to discover the best method in order to obtain these results with less memory, verifying that, after the generation of the model, the DNN method, when compared with others, is also the fastest to obtain the results with better accuracy.

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27225v1 | CC BY 4.0 Open Access | rec: 19 Sep 2018, publ: 19 Sep 2018

Pattern recognition techniques for the identification of Activities of Daily Living using mobile device accelerometer

Ivan Miguel Pires[1,2,3], Nuno M. Garcia[1], Nuno Pombo[1] , Francisco Flórez-Revuelta[4], Susanna Spinsante[5], Maria Canavarro Teixeira[6,7] and Eftim Zdravevski[8]

[1] Instituto de Telecomunicações, Universidade da Beira Interior, Covilhã, Portugal
[2] Altranportugal, Lisbon, Portugal
[3] ALLab - Assisted Living Computing and Telecommunications Laboratory, Computer Science Department, Universidade da Beira Interior, Covilhã, Portugal
[4] Department of Computer Technology, Universidad de Alicante, Spain
[5] Department of Information Engineering, Marche Polytechnic University, Ancona, Italy
[6]UTC de Recursos Naturais e Desenvolvimento Sustentável, Polytechnique Institute of Castelo Branco, Castelo Branco, Portugal
[7] CERNAS - Research Centre for Natural Resources, Environment and Society, Polytechnique Institute of Castelo Branco, Castelo Branco, Portugal
[8]Faculty of Computer Science and Engineering, University Ss Cyril and Methodius, Skopje, Macedonia

Corresponding Author:
Ivan Miguel Pires
Computer Science Department,
Universidade da Beira Interior,
Rua Marquês d'Ávila e Bolama
6201-001 Covilhã, Portugal
Email address: impires@it.ubi.pt

ABSTRACT

This paper focuses on the recognition of Activities of Daily Living (ADL) applying pattern recognition techniques to the data acquired by the accelerometer available in the mobile devices. The recognition of ADL is composed by several stages, including data acquisition, data processing, and artificial intelligence methods. The artificial intelligence methods used are related to pattern recognition, and this study focuses on the use of Artificial Neural Networks (ANN). The data processing includes data cleaning, and the feature extraction techniques to define the inputs for the ANN. Due to the low processing power and memory of the mobile devices, they should be mainly

used to acquire the data, applying an ANN previously trained for the identification of the ADL. The main purpose of this paper is to present a new method based on ANN for the identification of a defined set of ADL with a reliable accuracy. This paper also presents a comparison of different types of ANN in order to choose the type for the implementation of the final model. Results of this research probes that the best accuracies are achieved with Deep Neural Networks (DNN) with an accuracy higher than 80%. The results obtained are similar with other studies, but we compared tree types of ANN in order to discover the best method in order to obtain these results with less memory, verifying that, after the generation of the model, the DNN method, when compared with others, is also the fastest to obtain the results with better accuracy.

INTRODUCTION

An accelerometer is a sensor commonly available in off-the-shelf mobile devices (Salazar, Lacerda et al. 2013) that measures the acceleration of the movement of the mobile device, allowing the creation of a method for the recognition of Activities of Daily Living (ADL) (Foti and Koketsu 2013). After the development of a method for the identification of ADL, it could be integrated in the creation of a personal digital life coach (Garcia 2016), important for the monitoring of elderly persons, and persons with some type of impairment, or for the training of the lifestyle.

The methods related to the recognition of the ADL with accelerometer may be used for the recognition of the daily activities with movement, including running, walking, walking on stairs, and standing. Following the previous research studies (Pires, Garcia et al. 2015, Pires, Garcia et al. 2016, Pires, Garcia et al. 2016), the recognition of the ADL is composed by several steps, such as data acquisition, data processing, composed of data cleaning, data imputation, and feature extraction, data fusion, and artificial intelligence methods for concrete identification of the ADL. However, this study only uses the accelerometer sensor, removing some steps of the proposed architecture. Based on the assumption that the sensor was always acquiring the data, the final steps used are the data acquisition, the data cleaning, and the application of the artificial intelligence methods.

During the last years, the recognition of ADL has been studied by several authors (Akhoundi and Valavi 2010, Banos, Damas et al. 2012, Dernbach, Das et al. 2012, Paul and George 2015, Hsu, Chen et al. 2016, Shen, Chen et al. 2016), where Artificial Neural Networks (ANN) are widely used (Wang 1993, Doya and Wang 2015). This paper proposes the creation of a method for the recognition of ADL using the accelerometer, comparing three types of ANN, such as Multilayer Perception (MLP) with Backpropagation, Feedforward Neural Network (FNN) with Backpropagation, and Deep Neural Network (DNN), in order to verify the method that achieves the best accuracy in the recognition of running, walking, going upstairs, going downstairs, and standing. The ADL were selected based on the literature review, where the different studies analysed and reported reliable results for these activities. The main contribution of this study is the comparison of three different architectures of ANN methods in order to achieve the best results in the recognition of the considered ADL. The datasets used are composed with the raw accelerometer data acquired by individuals aged between 16 and 60 years old and with distinct lifestyles, performing their activities with a mobile device in the front pocket of the pants for the acquisition of the different data from the sensors available. For the implementation of these types of ANN are used several datasets with different sets of features, identifying the best features to increase the accuracy of the recognition, and three Java libraries are used for the implementation of the different methods, such as Neuroph (Neuroph 2017), Encog (Research 2017), and DeepLearning4j (Chris Nicholson 2017), reporting the best average accuracy with DNN method.

The remaining sections of this paper are organized as follows: Section 2 presents a brief literature review related to the identification of ADL using accelerometer. Section 3 presents the methodology used for the creation of a solution for the recognition of the ADL using the accelerometer sensor. Section 4 presents the results obtained during the research presented. In section 5, the discussion and conclusions about the results are presented.

2. RELATED WORK

The identification of the Activities of Daily Living (ADL) (Foti and Koketsu 2013) may be performed with several classification methods using the data acquired from the accelerometer sensor available in the off-the-shelf mobile devices. To data, based on the studies available in the IEEE Xplore library, presented in the Table 1, which only uses the accelerometer data for the recognition of several ADL, there are verified that the different authors recognized between 1 and 7 ADL, where the most used methods with best accuracy are the different types of Artificial Neural Networks (ANN), including MLP and DNN methods, reporting reliable results with statistic features (*i.e.,* mean, standard deviation, maximum, minimum, median, and others).

With the studies presented in the Table 1, we can verify that the most recognized ADL are the walking, standing, going up stairs going down stairs, sitting, running and jogging, reporting an average of accuracies between 83.97% and 89.21% with the different methods used (see Table 2).

Regarding the ADL recognized in the analysed studies, the Table 3 shows the distribution of the different features used, verifying that the mean, minimum, maximum, standard deviation, correlation, median, FFT spectral energy, and variance are the most used features, with more relevance for mean and standard deviation.

The distribution of the classification methods used in the studies analyzed is presented in the Table 4, verifying that the methods that reports better accuracy than others are ANN methods, decision tree methods, KNN methods and their variants, and the Random Forest method, reporting and average accuracy between 90.39% and 92.84%.

In conclusion, the accuracies reported depends on the number of ADL recognized with the different methods used, as well as the particular dataset, where the best accuracies reported were achieved in studies that recognized few ADL. Therefore, our study is focused on the recognition of 5 ADL, including standing, walking, running, going up stairs and going down stairs, implementing different types of ANN, because these are ones of the most recognized ADL and methods that reported better accuracies in their recognition.

3. METHODS

Following the previous research studies analyzed in the section 2, and based on the proposed architecture of a framework for the recognition of ADL in (Pires, Garcia et al. 2015, Pires, Garcia et al. 2016, Pires, Garcia et al. 2016), the methods that should be defined for each module of the framework, are: data acquisition, data processing, data fusion, and artificial intelligence. The data processing methods proposed include the data cleaning, data imputation, and feature extraction methods. However, this study assumes that the data acquired from the accelerometer is always complete, therefore not considering the use of the data imputation methods in this study. Due to the fact that this study only uses the accelerometer available in off-the-shelf mobile devices, the data fusion methods are not necessary. As for data cleansing, because the mobile application was developed by us, it already collected properly aligned data which is already clean.

Firstly, the data acquisition method for the architecture implemented is presented in the section 3.1. Secondly, in the presentation of the data processing methods, in section 3.2, the solution is forked in data cleaning (section 3.2.1), and feature extraction methods (section 3.2.2). Finally, the implementation of artificial intelligence methods is detailed in the section 3.3.

3.1 Data Acquisition

The data acquisition process was performed with a mobile application developed for Android platform (Bojinov, Michalevsky et al. 2014, Katevas, Haddadi et al. 2016) with a BQ Aquaris device (Bq.com 2017), where the values of the accelerometer data are received every 10ms, but the frequency of the capture may varies based on the processing capabilities available at the moment. The mobile application acquires 5 seconds of accelerometer data every 5 minutes. The captures where performed with the mobile device in the front pocket of the user's pants. For the definition of the experiments, 25 individuals aged between 16 and 60 years old were selected. The individuals selected had distinct lifestyles, where 10 individuals are active and the remaining 15 individuals are mainly sedentary. During the data acquisition, the ADL captured were running, walking, going upstairs, going downstairs, and standing, because these ADL are included in the most recognized ADL with the best reported accuracies in the previous studies. The data acquired was saved in text files, and it has 2000 captures of 5 seconds for each ADL. The mobile application allows the user to select the ADL performed, for further processing. The data acquired is available in the ALLab MediaWiki (ALLab 2017).

3.2 Data Processing

After the data acquisition, the data processing is performed with data cleaning and feature extraction methods. The first stage of the data processing is data cleaning, where the data is filtered, removing the noise. The filter used in the mobile application for the data acquired from accelerometer is the low-pass filter, because this method allows the cleaning of the data, and, based on the literature, it reports better results than other methods (Graizer 2012). After the application of the low-pass filter, the noise will be removed, allowing the correct extraction of the features. Based on the related work presented in the section 2, a set of features was extracted from the filtered data with lightweight methods, where the considered features are the 5 greatest distances between the maximum peaks, the Mean, Standard Deviation, Variance of the maximum peaks and Median of the maximum peaks, and the Standard Deviation, Mean, Maximum, Minimum, Variance and Median of the raw signal.

3.3 Artificial Intelligence

After the extraction of the features, five datasets of features have been created with 2000 records for each ADL, these are:

- **Dataset 1:** Composed by the 5 greatest distances between the maximum peaks, the mean, standard deviation, variance and median of the maximum peaks, and the standard deviation, mean, maximum, minimum, variance and median of the raw signal;
- **Dataset 2:** Composed by the mean, standard deviation, variance and median of the maximum peaks, and the standard deviation, mean, maximum, minimum, variance and median of the raw signal;
- **Dataset 3:** Composed by the standard deviation, mean, maximum, minimum, variance and median of the raw signal;
- **Dataset 4:** Composed by the standard deviation, mean, variance and median of the raw signal;
- **Dataset 5:** Composed by the standard deviation and mean of the raw signal.

The goal of creating these 5 different datasets is to identify the best features for the recognition of ADL, which achieves better results than others, because in the literature different sets of features have been used.

Following the previous studies presented in the section 2 and shown in Table 3, the method selected for the implementation of the framework for the recognition of ADL, based on the accelerometer of the mobile device are the different types of ANN, because the ANN and DNN methods reports highest accuracies than the other analyzed studies.

After the creation of the datasets, three types of ANN were applied for the verification of the best type of ANN for the recognition of ADL, these are:

- MLP method with Backpropagation, applied with Neuroph framework (Neuroph 2017);
- FNN method with Backpropagation, applied with Encog framework (Research 2017);
- DNN method, applied with DeepLearning4j framework (Chris Nicholson 2017).

There are different configurations of the neural networks implemented that are presented in the Table 5, and the Sigmoid as activation function and backpropagation parameters are implemented in all neural networks.

The MLP with Backpropagation was applied to each dataset in two variants, these are the application with dataset without normalization, and the application with the dataset with the application of a MIN/MAX normalizer (Jain, Nandakumar et al. 2005).

The FNN with Backpropagation was applied to each dataset in two variants, these are the application in a dataset without normalization, and the application in a the dataset with the application of a MIN/MAX normalizer (Jain, Nandakumar et al. 2005).

The DNN was applied to each dataset in two variants, these are the application in a dataset with the L_2 regularization (Ng 2004), and the application in a dataset with the L_2 regularization and normalized with mean and standard deviation (Ng 2004, Brocca, Melone et al. 2010).

For the application of these neural networks, three maximum numbers (*i.e.,* 10^6, $2x10^6$, and $4x10^6$) of training iterations have been defined for the identification of the correct number of iterations for the training stage of the neural network.

Finally, the best ANN method should be implemented in the framework for the recognition of ADL using the mobile devices' accelerometer.

4. RESULTS

The three types of neural networks, proposed in the previous section, were implemented with the three different frameworks and a training dataset with a total of 10000 records. After the creation of the neural network with Neuroph framework as MLP with Backpropagation, the neural network was tested, and the results obtained are presented in the figure 1. In general, the results obtained with the trained neural networks with 10^6, $2x10^6$, and $4x10^6$ iterations, and different sets of features have very low accuracy (between 20% and 40%) with data without normalization, presented in figure 1-a, and very low accuracy (between 20% and 30%) with normalized data, presented in figure 1-b.

After the test of the MLP with Backpropagation, the FNN with Backpropagation was created with Encog framework, obtaining the results presented in the figure 2. In general, the results obtained with the trained neural networks with 10^6, $2x10^6$, and $4x10^6$ iterations, and different sets of features have very low accuracy (between 20% and 40%) with data without normalization, presented in figure 2-a, where, as exceptions, the neural networks trained with the dataset 3 with $2x10^6$ iterations obtains an accuracy around 50%, and with the dataset 5 with $4x10^6$ iterations obtains an accuracy around 75%. On the other hand, when the data is normalized, the results presented in figure 2-b, shows that the reduction of the number of the features in the datasets increases the accuracy of the neural network.

After the verification that results obtained with MLP with Backpropagation, and FNN are not satisfactory, the DNN method was implemented with DeepLearning4j framework, obtaining the results presented in the Figure 3. In general, the results obtained with the trained neural networks with 10^6, $2x10^6$, and $4x10^6$ iterations, and the different sets of features have an accuracy higher than 70%, but, with data without normalization (Figure 3-a), the results obtained with the datasets 1 and 2 are above the expectations with an accuracy lower than 40%, and, with the normalized data (figure 3-b), the results obtained are higher with dataset 1, decreasing with the reduction of the number of features in the dataset.

The maximum accuracies obtained with the MLP with Backpropagation, FNN with Backpropagation, and DNN methods are shown in the Table 6, concluding that the results obtained by MLP with Backpropagation and FNN with Backpropagation are not satisfactory, obtaining best accuracies with the DNN method.

In conclusion, the type of neural networks that should be used in the framework for the identification of ADL is the DNN method with all features extracted from the accelerometer data (dataset 1), normalizing the data with mean and standard deviation method and applying the L_2 regularization method, because, based on the tests performed with the acquired data, the results obtained are constantly higher than the reported other methods, showing the results with *precision* value of 86.21%, a *recall* value of 85.89% and a *F1 score* value of 86.05%.

5. DISCUSSION

The comparison between MLP with Backpropagation, applied with Neuroph framework (Neuroph 2017), FNN with Backpropagation, applied with Encog framework (Research 2017), and DNN method, applied with DeepLearning4j framework (Chris Nicholson 2017), reports that the use of DNN method increases the accuracy of the recognition of the ADL. The datasets used in the neural networks were composed by 10000 records, *i.e.*, 2000 records for each ADL. The best results are obtained with DNN method with L_2 regularization and normalized data.

The low accuracies verified with MLP with Backpropagation, and FNN with Backpropagation are related to the fact of the neural networks created are overfitting, and the possible solutions are the acquisition of more data, the stopping of the training when the network error increases for several iterations, the application of dropout regularization, the application of L_2 regularization, the application of the batch normalization, or the reduction of the number of features in the neural network.

The number of the maximum iterations may influence the training of the neural network, and, in some cases, it also increases the accuracy of the neural network, but the influence if the number of iterations are not substantial.

Although the accuracy obtained in this study with DNN method is lower than the accuracy reported in (Zhang, Wu et al. 2015), this is probably due to the fact that the number of ADL recognized, the number of records for each ADL, and the features extracted are different in our study. We expect that in similar conditions of (Zhang, Wu et al. 2015) we obtain the same or better results. Nevertheless, this will be impossible to test as authors in (Zhang, Wu et al. 2015) did not make their data publicly available.

6. CONCLUSIONS

This paper presents a method for the identification of several ADL, including running, walking, going upstairs, going downstairs, and standing, comparing the results obtained with different types of neural networks. The development of the method presented in this paper was based in (Pires, Garcia et al. 2015, Pires, Garcia et al. 2016, Pires, Garcia et al. 2016), including only the data acquisition, data processing with data cleaning and feature extraction, and artificial intelligence methods, requiring low processing for the correct implementation in the mobile devices.

In conclusion, the method implemented in the framework for the recognition of the ADL using only the accelerometer sensor available in off-the-shelf mobile devices should be based in DNN method, applied with DeepLearning4j framework (Chris Nicholson 2017), because it achieves an accuracy above 80% with a neural network trained with all features proposed in this study, these are the 5 greatest distances between the maximum peaks, the mean, standard deviation, variance and median of the maximum peaks, the standard deviation, mean, maximum value, minimum value, variance and median of the raw signal. This research proves the reliability of the use of ANN for the identification of the ADL using the accelerometer.

ACKNOWLEDGEMENTS

This work was supported by FCT project **UID/EEA/50008/2013** (*Este trabalho foi suportado pelo projecto FCT UID/EEA/50008/2013*).

The authors would also like to acknowledge the contribution of the COST Action IC1303 – AAPELE – Architectures, Algorithms and Protocols for Enhanced Living Environments.

REFERENCES

Aguiar, B., J. Silva, T. Rocha, S. Carneiro and I. Sousa (2014). "Monitoring Physical Activity and Energy Expenditure with Smartphones." 2014 Ieee-Embs International Conference on Biomedical and Health Informatics (Bhi): 664-667.

Akhoundi, M. A. A. and E. Valavi (2010). "Multi-Sensor Fuzzy Data Fusion Using Sensors with Different Characteristics." arXiv preprint arXiv:1010.6096.

ALLab. (2017). "August 2017- Multi-sensor data fusion in mobile devices for the identification of activities of daily living - ALLab Signals." Retrieved September 2nd, 2017, from https://allab.di.ubi.pt/mediawiki/index.php/August_2017-_Multi-sensor_data_fusion_in_mobile_devices_for_the_identification_of_activities_of_daily_living.

Anjum, A. and M. U. Ilyas (2013). "Activity Recognition Using Smartphone Sensors." 2013 Ieee Consumer Communications and Networking Conference (Ccnc): 914-919.

Bai, L., C. Efstratiou and C. S. Ang (2016). "weSport: Utilising Wrist-Band Sensing to Detect Player Activities in Basketball Games." 2016 Ieee International Conference on Pervasive Computing and Communication Workshops (Percom Workshops): 1-6.

Bajpai, A., V. Jilla, V. N. Tiwari, S. M. Venkatesan and R. Narayanan (2015). "Quantifiable fitness tracking using wearable devices." Conf Proc IEEE Eng Med Biol Soc **2015**: 1633-1637.

Banos, O., M. Damas, H. Pomares and I. Rojas (2012). "On the use of sensor fusion to reduce the impact of rotational and additive noise in human activity recognition." Sensors (Basel) **12**(6): 8039-8054.

Bayat, A., M. Pomplun and D. A. Tran (2014). "A Study on Human Activity Recognition Using Accelerometer Data from Smartphones." 9th International Conference on Future Networks and Communications (Fnc'14) / the 11th International Conference on Mobile Systems and Pervasive Computing (Mobispc'14) / Affiliated Workshops **34**: 450-457.

Bojinov, H., Y. Michalevsky, G. Nakibly and D. Boneh (2014). "Mobile device identification via sensor fingerprinting." arXiv preprint arXiv:1408.1416.

Bq.com. (2017). "Smartphones BQ Aquaris | BQ Portugal." Retrieved 2 Sep. 2017, from https://www.bq.com/pt/smartphones.

Brocca, L., F. Melone, T. Moramarco, W. Wagner, V. Naeimi, Z. Bartalis and S. Hasenauer (2010). "Improving runoff prediction through the assimilation of the ASCAT soil moisture product." Hydrology and Earth System Sciences **14**(10): 1881-1893.

Bujari, A., B. Licar and C. E. Palazzi (2012). "Movement Pattern Recognition through Smartphone's Accelerometer." 2012 Ieee Consumer Communications and Networking Conference (Ccnc): 502-506.

Cardoso, N., J. Madureira and N. Pereira (2016). "Smartphone-based Transport Mode Detection for Elderly Care." 2016 Ieee 18th International Conference on E-Health Networking, Applications and Services (Healthcom): 261-266.

Chris Nicholson, A. (2017). "Deeplearning4j: Open-source, Distributed Deep Learning for the JVM." Retrieved 2 Sep. 2017, from https://deeplearning4j.org/.

Dangu Elu Beily, M., M. D. Badjowawo, D. O. Bekak and S. Dana (2016). A sensor based on recognition activities using smartphone. 2016 International Seminar on Intelligent Technology and Its Applications (ISITIA), Lombok, Indonesia, IEEE.

Dernbach, S., B. Das, N. C. Krishnan, B. L. Thomas and D. J. Cook (2012). Simple and Complex Activity Recognition through Smart Phones. 2012 8th International Conference on Intelligent Environments (IE), Guanajuato, Mexico, IEEE.

Doya, K. and D. Wang (2015). "Exciting Time for Neural Networks." Neural Networks **61**: xv-xvi.

Duarte, F., A. Lourenco and A. Abrantes (2013). Activity classification using a smartphone. e-Health Networking, Applications & Services (Healthcom), 2013 IEEE 15th International Conference on, Lisbon, Portugal, IEEE.

Fahim, M., S. Lee and Y. Yoon (2014). "SUPAR: Smartphone as a ubiquitous physical activity recognizer for u-healthcare services." Conf Proc IEEE Eng Med Biol Soc **2014**: 3666-3669.

Fan, L., Z. M. Wang and H. Wang (2013). "Human activity recognition model based on Decision tree." 2013 International Conference on Advanced Cloud and Big Data (Cbd): 64-68.

Foti, D. and J. S. Koketsu (2013). "Activities of daily living." Pedretti's Occupational Therapy: Practical Skills for Physical Dysfunction **7**: 157-232.

Garcia, N. M. (2016). A Roadmap to the Design of a Personal Digital Life Coach. ICT Innovations 2015, Springer.

Graizer, V. (2012). Effect of low-pass filtering and re-sampling on spectral and peak ground acceleration in strong-motion records. Proc. 15th World Conference of Earthquake Engineering, Lisbon, Portugal.

Guo, H., L. Chen, G. Chen and M. Lv (2015). An Interpretable Orientation and Placement Invariant Approach for Smartphone Based Activity Recognition. Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom), 2015 IEEE 12th Intl Conf on, Beijing, China, IEEE.

Hsu, Y.-W., K.-H. Chen, J.-J. Yang and F.-S. Jaw (2016). Smartphone-based fall detection algorithm using feature extraction. 2016 9th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Datong, China, IEEE.

Jain, A., K. Nandakumar and A. Ross (2005). "Score normalization in multimodal biometric systems." Pattern Recognition **38**(12): 2270-2285.

Katevas, K., H. Haddadi and L. Tokarchuk (2016). Sensingkit: Evaluating the sensor power consumption in ios devices. Intelligent Environments (IE), 2016 12th International Conference on, IEEE.

Khalifa, S., M. Hassan and A. Seneviratne (2014). Feature selection for floor-changing activity recognition in multi-floor pedestrian navigation. Mobile Computing and Ubiquitous Networking (ICMU), 2014 Seventh International Conference on, Singapore, Singapore, IEEE.

Kim, Y. J., B. N. Kang and D. Kim (2015). "Hidden Markov Model Ensemble for Activity Recognition using Tri-axis Accelerometer." 2015 Ieee International Conference on Systems, Man, and Cybernetics (Smc 2015): Big Data Analytics for Human-Centric Systems: 3036-3041.

Kumar, A. and S. Gupta (2015). "Human Activity Recognition through Smartphone's Tri-Axial Accelerometer using Time Domain Wave Analysis and Machine Learning." International Journal of Computer Applications **127**(18): 22-26.

Kwapisz, J. R., G. M. Weiss and S. A. Moore (2011). "Activity recognition using cell phone accelerometers." ACM SIGKDD Explorations Newsletter **12**(2): 74.

Kwon, Y., K. Kang and C. Bae (2015). "Analysis and Evaluation of Smartphone-based Human Activity Recognition Using a Neural Network Approach." 2015 International Joint Conference on Neural Networks (Ijcnn): 1-5.

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27225v1 | CC BY 4.0 Open Access | rec: 19 Sep 2018, publ: 19 Sep 2018

Lau, S. L. (2013). Comparison of orientation-independent-based-independent-based movement recognition system using classification algorithms. Wireless Technology and Applications (ISWTA), 2013 IEEE Symposium on, Kuching, Malaysia, IEEE.

Lau, S. L. and K. David (2010). Movement recognition using the accelerometer in smartphones. Future Network and Mobile Summit, 2010, IEEE.

Lau, S. L., I. Konig, K. David, B. Parandian, C. Carius-Dussel and M. Schultz (2010). Supporting patient monitoring using activity recognition with a smartphone. Wireless Communication Systems (ISWCS), 2010 7th International Symposium on, York, UK, IEEE.

Ling, Y. and H. Wang (2015). "Unsupervised Human Activity Segmentation Applying Smartphone Sensor for Healthcare." 1730-1734.

Liu, Y. Y., F. Zhao, W. H. Shao and H. Y. Luo (2016). "An Hidden Markov Model based Complex Walking Pattern Recognition Algorithm." Proceedings of 2016 Fourth International Conference on Ubiquitous Positioning, Indoor Navigation and Location Based Services (Ieee Upinlbs 2016): 223-229.

Mitchell, E., D. Monaghan and N. E. O'Connor (2013). "Classification of sporting activities using smartphone accelerometers." Sensors (Basel) **13**(4): 5317-5337.

Neuroph. (2017). "Java Neural Network Framework Neuroph." Retrieved 2 Sep. 2017, from http://neuroph.sourceforge.net/.

Ng, A. Y. (2004). Feature selection, L 1 vs. L 2 regularization, and rotational invariance. Proceedings of the twenty-first international conference on Machine learning, ACM.

Nguyen, P., T. Akiyama, H. Ohashi, G. Nakahara, K. Yamasaki and S. Hikaru (2015). "User-friendly Activity Recognition Using SVM Classifier and Informative Features." 2015 International Conference on Indoor Positioning and Indoor Navigation (Ipin): 1-8.

Oshin, T. O. and S. Poslad (2013). "ERSP: An Energy-efficient Real-time Smartphone Pedometer." 2013 Ieee International Conference on Systems, Man, and Cybernetics (Smc 2013): 2067-2072.

Paul, P. and T. George (2015). "An Effective Approach for Human Activity Recognition on Smartphone." 2015 Ieee International Conference on Engineering and Technology (Icetech): 45-47.

Pires, I., N. Garcia, N. Pombo and F. Flórez-Revuelta (2016). "From Data Acquisition to Data Fusion: A Comprehensive Review and a Roadmap for the Identification of Activities of Daily Living Using Mobile Devices." Sensors **16**(2): 184.

Pires, I. M., N. M. Garcia and F. Flórez-Revuelta (2015). Multi-sensor data fusion techniques for the identification of activities of daily living using mobile devices. Proceedings of the ECMLPKDD 2015 Doctoral Consortium, European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases, Porto, Portugal.

Pires, I. M., N. M. Garcia, N. Pombo and F. Flórez-Revuelta (2016). Identification of Activities of Daily Living Using Sensors Available in off-the-shelf Mobile Devices: Research and

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27225v1 | CC BY 4.0 Open Access | rec: 19 Sep 2018, publ: 19 Sep 2018

Hypothesis. Ambient Intelligence-Software and Applications–7th International Symposium on Ambient Intelligence (ISAmI 2016), Springer, Cham.

Piyare, R. and S. R. Lee (2014). "Mobile Sensing Platform for Personal Health Management." 18th Ieee International Symposium on Consumer Electronics (Isce 2014): 1-2.

Research, H. (2017). "Encog Machine Learning Framework." Retrieved 2 Sep. 2017, from http://www.heatonresearch.com/encog/.

Salazar, L. H. A., T. Lacerda, J. V. Nunes and C. Gresse von Wangenheim (2013). "A Systematic Literature Review on Usability Heuristics for Mobile Phones." International Journal of Mobile Human Computer Interaction **5**(2): 50-61.

Sen, S., K. K. Rachuri, A. Mukherji and A. Misra (2016). Did you take a break today? Detecting playing foosball using your smartwatch. 2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), Sydney, NSW, Australia, IEEE.

Shen, C., Y. F. Chen and G. S. Yang (2016). On Motion-Sensor Behavior Analysis for Human-Activity Recognition via Smartphones. 2016 Ieee International Conference on Identity, Security and Behavior Analysis (Isba), Sendai, Japan, IEEE.

Torres-Huitzil, C. and M. Nuno-Maganda (2015). "Robust smartphone-based human activity recognition using a tri-axial accelerometer." 2015 Ieee 6th Latin American Symposium on Circuits & Systems (Lascas): 1-4.

Vavoulas, G., C. Chatzaki, T. Malliotakis, M. Pediaditis and M. Tsiknakis (2016). "The MobiAct Dataset: Recognition of Activities of Daily Living using Smartphones." Proceedings of the International Conference on Information and Communication Technologies for Ageing Well and E-Health (Ict4awe): 143-151.

Wang, C., Y. Xu, J. Zhang and W. Yu (2016). SW-HMM: A Method for Evaluating Confidence of Smartphone-Based Activity Recognition. Trustcom/BigDataSE/ISPA, 2016 IEEE, Tianjin, China, IEEE.

Wang, C. and W. Zhang (2015). "Activity Recognition Based on Smartphone and Dual-tree Complex Wavelet Transform." 2015 8th International Symposium on Computational Intelligence and Design (Iscid), Vol 2: 267-270.

Wang, D. (1993). "Pattern recognition: neural networks in perspective." IEEE Expert **8**(4): 52-60.

Wannenburg, J. and R. Malekian (2016). "Physical Activity Recognition From Smartphone Accelerometer Data for User Context Awareness Sensing." IEEE Transactions on Systems, Man, and Cybernetics: Systems: 1-8.

Weiss, G. M., J. W. Lockhart, T. T. Pulickal, P. T. McHugh, I. H. Ronan and J. L. Timko (2016). "Actitracker: A Smartphone-based Activity Recognition System for Improving Health and Well-Being." Proceedings of 3rd Ieee/Acm International Conference on Data Science and Advanced Analytics, (Dsaa 2016): 682-688.

Zainudin, M. N. S., M. N. Sulaiman, N. Mustapha and T. Perumal (2015). "Activity Recognition based on Accelerometer Sensor using Combinational Classifiers." 2015 Ieee Conference on Open Systems (Icos): 68-73.
Zdravevski, E., P. Lameski, V. Trajkovik, A. Kulakov, I. Chorbev, R. Goleva, N. Pombo and N. Garcia (2017). "Improving Activity Recognition Accuracy in Ambient-Assisted Living Systems by Automated Feature Engineering." IEEE Access **5**: 5262-5280.
Zhang, L., X. Wu and D. Luo (2015). Real-Time Activity Recognition on Smartphones Using Deep Neural Networks. Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom), 2015 IEEE 12th Intl Conf on, Beijing, China, IEEE.
Zhao, K. L., J. Z. Du, C. Q. Li, C. L. Zhang, H. Liu and C. Xu (2013). "Healthy: A Diary System Based on Activity Recognition Using Smartphone." 2013 Ieee 10th International Conference on Mobile Ad-Hoc and Sensor Systems (Mass 2013): 290-294.

Table 1(on next page)

Summary of the studies available in the IEEE Xplore library

Summary of the studies available in the IEEE Xplore library

1
2 **Table 1.** Summary of the studies available in the IEEE Xplore library

Study:	**# of ADL:**	**ADL recognized:**	**Methods:**	**Features:**	**Accuracy:**
Aguiar, B., *et al.* (Aguiar, Silva et al. 2014)	5	running; walking; standing; sitting; laying	decision tree	Mean; Median; Maximum; Minimum; Root Mean Square (RMS); standard deviation; interquartile range; energy; entropy; skewness; kurtosis	99.5% (decision tree)
Anjum, A., *et al.* (Anjum and Ilyas 2013)	7	walking; running; going up stairs; going down stairs; driving; cycling; standing	Naïve Bayes; C4.5 Decision Tree; K-Nearest Neighbor (KNN); Support Vector Machine (SVM)	Mean; standard deviation; cross-axis signals correlation; Fast Fourier Transform (FFT) spectral energy; frequency domain entropy; log of FFT	84.7% (Naïve Bayes); 95.2% (C4.5 Decision Tree); 88.7% (KNN); 73.8% (SVM)
Bai, L., *et al.* (Bai, Efstratiou et al. 2016)	1	shooting	Combination of Random Forest, SVM and KNN methods	Mean; standard deviation; median; maximum; minimum; zero crossing rate; number of peaks; correlation; FFT coefficients	94.31%
Bajpai, A., *et al.* (Bajpai, Jilla et al. 2015)	6	standing; walking; cycling; jogging; running; driving	MLP	Mean; Maximum; Minimum; difference between maximum and minimum; standard deviation; RMS; correlation between axis; kurtosis; skewness; ratio and difference of the maximum and minimum values in the FFT; median and number of peaks and troughs; average distance between two consecutive peaks and between two consecutive troughs; ratio of the average values of peaks and troughs	97.58% (MLP)
Bayat, A., *et al.* (Bayat, Pomplun et al. 2014)	5	running; walking; aerobic dancing; going up stairs; going down stairs	MLP; SVM; Random Forest; Logistic Model Trees (LMT);	mean along z-axis; maximum, minimum, standard deviation and RMS from the magnitude of the acceleration; average of peak frequency (APF),	89.48% (MLP); 72.27% (SVM); 85.15% (Random Forest); 85.04% (LMT); 85.05% (Simple Logistic);

Study:	**# of ADL:**	**ADL recognized:**	**Methods:**	**Features:**	**Accuracy:**
			Simple Logistic; Logit Boost	standard deviation, RMS, maximum and minimum along x-axis and z-axis; correlation between z-axis and y-axis	82.24% (Logit Boost)
Bujari, A., *et al.* (Bujari, Licar et al. 2012)	1	walking	MLP	Mean; standard deviation	98% (MLP)
Cardoso, N., *et al.* (Cardoso, Madureira et al. 2016)	6	walking; standing; travel by car; travel by bus; travel by train; travel by metro	J48 decision tree; SMO; Naïve Bayes	Mean; Median; Maximum; Minimum; RMS; standard deviation; interquartile range; minimum average; maximum average; maximum peak height; average peak height; entropy; FFT spectral energy; Skewness; kurtosis	95.6% (J48 decision tree); 92.4% (SMO); 61.9% (Naïve Bayes)
Dangu Elu Beily, M., *et al.* (Dangu Elu Beily, Badjowawo et al. 2016)	1	playing tennis	Naïve Bayes; MLP; J48 decision tree; SVM	Mean; Variance; correlation	98.12% (Naïve Bayes); 99.61% (MLP); 99.91% (J48 decision tree); 100% (SVM)
Duarte, F., *et al.* (Duarte, Lourenco et al. 2013)	4	walking; cycling; running; standing	Naïve Bayes; KNN; Decision Tree; SVM	Mean; standard deviation; correlation; power spectral density	98% (Naïve Bayes); 83% (KNN); 95% (Decision Tree); 96% (SVM)
Fahim, M., *et al.* (Fahim, Lee et al. 2014)	4	walking; running; cycling; hopping	SVM	RMS; Variance; Correlation; energy	97.69% (SVM)
Fan, L., *et al.* (Fan, Wang et al. 2013)	5	standing; walking; running; going up stairs; going down stairs	decision tree	Mean; Median; Variance; standard deviation; maximum; minimum; range; RMS; FFT coefficients; FFT spectral energy	88.32% (decision tree)
Guo, H., *et al.* (Guo, Chen et al. 2015)	5	running; walking; sitting; going up stairs; going down stairs	SVM	Mean; Variance; standard deviation; median; maximum; minimum; RMS; zero crossing rate; skewness; kurtosis; spectral entropy	80% (SVM)
Khalifa, S., *et*	3	going up stairs;	Decision	mean, standard deviation,	80.59% (decision

Study:	**# of ADL:**	**ADL recognized:**	**Methods:**	**Features:**	**Accuracy:**
al. (Khalifa, Hassan et al. 2014)		going up on an escalator; walking on a ramp	tables; J48 Decision tree; Naïve Bayes; KNN; MLP	skewness, kurtosis, average absolute deviation, and pairwise correlation of the tree axis of accelerometer; mean of the resultant acceleration	tables); 82.97% (J48 Decision tree); 87.49% (Naïve Bayes); 89.20% (KNN); 87.86% (MLP)
Kim, Y.J., *et al.* (Kim, Kang et al. 2015)	6	walking; going up stairs; going down stairs; sitting; standing; laying	Hidden Markov Model Ensemble (HMME)	Mean; standard deviation	83.55% (HMME)
Kumar, A., *et al.* (Kumar and Gupta 2015)	4	sitting; standing; walking; running	Combination of SVM, J48 decision tree and Random Forest methods	average of peak values; average of peak rising time; average of peak fall time; average time per sample; average time between peaks	98.8283%
Kwapisz, J.R., *et al.* (Kwapisz, Weiss et al. 2011)	6	walking; jogging; going up stairs; going down stairs; sitting; standing	J48 decision tree; logistic regression; MLP; Straw Man	Mean; standard deviation; average absolute difference; average resultant acceleration; time between peaks; binned distribution	85.1% (J48 decision tree); 78.1% (logistic regression); 91.7% (MLP); 37.2% (Straw Man)
Kwon, Y., *et al.* (Kwon, Kang et al. 2015)	4	walking; running; standing; sitting	MLP	Mean; Maximum; Minimum; Median; standard deviation	99% (MLP)
Lau, S.L. (Lau 2013)	5	walking; sitting; standing; going up stairs; going down stairs	KNN; decision tree; rule-based learner (JRip); MLP	Mean; standard deviation; variance	92.44% (KNN); 90.77% (decision tree); 90.4% (JRip); 92.91% (MLP)
Lau, S.L., *et al.* (Lau, Konig et al. 2010)	5	walking; sitting; standing; going up stairs; going down stairs	decision tree; KNN; SMO	Mean; standard deviation; variance; FFT energy; FFT information entropy	91.37% (decision tree); 94.29% (KNN); 84.42% (SMO)
Lau, S.L., *et al.* (Lau and David 2010)	5	walking; standing; sitting; going up stairs; going down stairs	decision tree; Bayesian Network; Naïve Bayes; KNN; rule-based learner (JRip)	mean, standard deviation and correlation of the raw data; energy of FFT; mean and standard deviation of the FFT components in the frequency domain	95.62% (Bayesian Network); 97.81% (Naïve Bayes); 99.27% (KNN); 93.53% (JRip)

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27225v1 | CC BY 4.0 Open Access | rec: 19 Sep 2018, publ: 19 Sep 2018

Study:	# of ADL:	ADL recognized:	Methods:	Features:	Accuracy:
Ling, Y., *et al.* (Ling and Wang 2015)	4	walking; running; sitting; standing	decision tree	Mean; Variance; bin distribution in time and frequency domain; FFT spectral energy; correlation of the magnitude	98.69% (decision tree)
Liu, Y.Y., *et al.* (Liu, Zhao et al. 2016)	3	walking; going up stairs; going down stairs	Combination of Hidden Markov Model (HMM), decision tree and Random Forest methods	Mean; Variance; standard deviation; median; minimum; maximum; range; Interquartile range; Kurtosis; Skewness; spectrum peak position	93.8%
Mitchell, E., *et al.* (Mitchell, Monaghan et al. 2013)	6	walking; jogging; going up stairs; going down stairs; sitting; standing	Naïve Bayes; MLP	energy and variances of the coefficients of discrete wavelet transform (DWT)	79.9% (Naïve Bayes); 82.3% (MLP)
Nguyen, P., *et al.* (Nguyen, Akiyama et al. 2015)	5	running; standing; walking; going up stairs; going down stairs	SVM	Mean; Minimum; Maximum; standard deviation; energy; mean absolute deviation; binned distribution; percentiles	94.3% (SVM)
Oshin, T.O., *et al.* (Oshin and Poslad 2013)	3	walking; jogging; marching	Combination of J48 decision tree, decision table and Naïve Bayes	number of peaks; number of troughs; difference between the maximum peak and the minimum trough; sum of all peaks and troughs	93.4%
Paul, P., *et al.* (Paul and George 2015)	4	walking; running; standing; sitting	Clustered KNN	Mean; Minimum; Maximum; standard deviation	92% (Clustered KNN)
Piyare, R., *et al.* (Piyare and Lee 2014)	7	walking; jogging; going up stairs; going down stairs; sitting; standing; laying down	Bayesian Network; MLP; Naïve Bayes; C4.5 decision tree; Random Tree; Radial Basis; Function Network; Sequential Minimal	Mean; standard deviation; mean absolute deviation; time between peaks	77.81% (Bayesian Network); 94.44% (MLP); 58.06% (Naïve Bayes); 95.40% (C4.5 decision tree); 94.67% (Random Tree); 73.03% (Radial Basis Function Network); 90.27%

Study:	# of ADL:	ADL recognized:	Methods:	Features:	Accuracy:
			Optimization (SMO); Logistic Regression		(SMO); 92.71% (Logistic Regression)
Sen, S., *et al.* (Sen, Rachuri et al. 2016)	1	playing fosball	MLP	Mean; Variance; Covariance; Energy; entropy	95% (MLP)
Torres-Huitzil, C., *et al.* (Torres-Huitzil and Nuno-Maganda 2015)	5	standing; walking; going up stairs; going down stairs; running	MLP	Mean; standard deviation; percentiles	92% (MLP)
Vavoulas, G., *et al.* (Vavoulas, Chatzaki et al. 2016)	7	standing; walking; jogging; jumping; going up stairs; going down stairs; sitting	J48 decision tree; Logistic regression; MLP	Mean, Median, standard deviation, skewness, kurtosis, minimum, maximum and slope for each axis and for the absolute value	85.1% (J48 decision tree); 78.1% (Logistic regression); 91.7% (MLP)
Wang, C., *et al.* (Wang, Xu et al. 2016)	5	walking; standing; running; going up stairs; going down stairs	Sliding-Window-based Hidden Markov Model (SW-HMM)	Mean; Variance; quartiles	80% (SW-HMM)
Wang, C., *et al.* (Wang and Zhang 2015)	6	standing; sitting; going up stairs; going down stairs; walking; jogging	J48 decision tree; Random Forest; Instance-based learning (IBk); rule based (J-Rip)	Dual-tree complex wavelet transform (DT-CWT) statistical information and orientation	76% (Random Forest); 73.8% (IBk); 67.4% (J48 decision tree); 67.4% (J-Rip)
Wannenburg, J., *et al.* (Wannenburg and Malekian 2016)	5	sitting; standing; laying; walking; jogging	SVM; MLP; Naïve Bayes; KNN; Decision tree; kStart	Mean; Maximum; Minimum; Median; standard deviation; Signal Magnitude Area (SMA); mean deviation; Principal Component Analysis (PCA); Interquartile range; Skewness; kurtosis	94.32% (SVM); 98.74% (MLP); 91.1% (Naïve Bayes); 99% (KNN); 98.8% (Decision tree); 99.01% (kStart)
Weiss, G.M., *et al.* (Weiss, Lockhart et al. 2016)	7	walking; jogging; going up stairs; going down stairs; standing;	Random Forest	mean and standard deviation for each axis; bin distribution; heuristic measure of wave periodicity	90% (Random Forest)

Study:	# of ADL:	ADL recognized:	Methods:	Features:	Accuracy:
		sitting; lying down			
Zainudin, M.N.S., *et al.* (Zainudin, Sulaiman et al. 2015)	6	going down stairs; jogging; sitting; standing; going up stairs; walking	J48 decision tree; MLP; Likelihood Ratio (LR)	Minimum; Maximum; Mean; standard deviation; zero crossing rate for each axis; correlation between axis	92.4% (J48 decision tree); 91.7% (MLP); 84.3% (LR)
Zdravevski, E., et al. (Zdravevski, Lameski et al. 2017)	6	walking, standing, sitting, walking up-stairs, walking down-stairs, lying	SVM; Random Forest (RF); Extremely Randomized Trees (ERT), Naïve Bayes (NB), KNN, Logistic regression (LR)	Automated feature selection from a variety of time and frequency domain features	From 83% to 99% (pocket with SVM), depending on used dataset and smartphone position.
Zhang, L., *et al.* (Zhang, Wu et al. 2015)	7	walking; running; standing; sitting; lying; going up stairs; going down stairs	DNN	Mean; Minimum; Maximum; standard deviation	77% (DNN)
Zhao, K.L., *et al.* (Zhao, Du et al. 2013)	5	walking; jogging; cycling; going up stairs; going down stairs	Combination of decision tree and probabilistic neural network (PNN) methods	mean of the acceleration; standard deviation, binned distribution and average energy for each axis	97.1%

Table 2 (on next page)

Distribution of the ADL extracted in the studies analyzed.

Distribution of the ADL extracted in the studies analyzed.

Table 2. Distribution of the ADL extracted in the studies analyzed.

ADL:	Number of studies:	Average of accuracy:
Walking	36	87.29%
Standing	29	87.07%
Going up stairs	22	84.41%
Going down stairs	21	84.30%
Sitting	17	86.37%
Running	16	89.21%
Jogging	11	83.97%
Laying down	7	89.30%
Cycling	5	91.52%
Driving	2	97.58%
Playing tennis	1	99.41%
Hopping	1	97.69%
Playing fosball	1	95.00%
Shooting	1	94.31%
Marching	1	93.40%
Going up on an escalator	1	85.62%
Walking on a ramp	1	85.62%
Jumping	1	84.97%
Travel by car	1	83.30%
Travel by bus	1	83.30%
Travel by train	1	83.30%
Travel by metro	1	83.30%
Aerobic dancing	1	83.21%

Table 3(on next page)

Distribution of the features extracted in the studies analyzed.

Distribution of the features extracted in the studies analyzed.

Table 3. Distribution of the features extracted in the studies analyzed.

Features:	Number of Studies:	Average of accuracy:
Mean (Z axis, X axis, Y axis, Acceleration, Velocity, Gravity, Peaks, Toughs)	32	89.05%
Standard Deviation (Acceleration, X axis, Y axis, Z axis, Gravity)	28	88.38%
Minimum (Acceleration, X axis, Y axis, Z axis)	15	89.33%
Maximum (Acceleration, X axis, Y axis, Z axis)	15	89.33%
FFT spectral energy (Acceleration)	11	91.41%
Variance (Acceleration, X axis, Y axis, Z axis)	10	92.65%
Correlation (X axis, Y axis, Z axis)	10	91.52%
Median (Acceleration, Peaks, Toughs)	7	89.98%
Skewness (Acceleration, X axis, Y axis, Z axis)	7	89.36%
Kurtosis (Acceleration, X axis, Y axis, Z axis)	7	89.36%
Root Mean Square (Acceleration, X axis, Y axis, Z axis)	7	86.59%
Entropy (Acceleration)	5	88.28%
Interquartile-Range (Acceleration)	3	96.78%
Number of peaks (Acceleration)	3	95.10%
zero crossing rate (Acceleration)	3	88.54%
Mean Absolute Deviation (X axis, Y axis, Z axis)	3	85.63%
time between peaks (Acceleration)	3	82.10%
Number of troughs (Acceleration)	2	95.49%
Percentiles (10, 25, 75, and 90) (Acceleration)	2	93.15%
FFT coefficients (Acceleration)	2	91.32%
Range (Acceleration, X axis, Y axis, Z axis)	2	91.06%
Average Peak rising time (Acceleration)	1	98.83%
Average Peak fall time (Acceleration)	1	98.83%
Average Time per sample (Acceleration)	1	98.83%
Average Time between peaks (Acceleration)	1	98.83%
Difference between the maximum peak and minimum trough (Acceleration)	1	97.58%
Signal Magnitude Area (SMA) (Acceleration)	1	96.83%
Principal Component Analysis (PCA) (Acceleration)	1	96.83%
Covariance (Acceleration, X axis, Y axis, Z axis)	1	95.00%
Spectrum peak position (Acceleration)	1	93.80%
Sum (Acceleration, Peaks, Troughs)	1	93.40%
Log of FFT (Acceleration)	1	85.60%
Slope (Acceleration)	1	84.97%
Quartiles (Acceleration)	1	80.00%

Table 4(on next page)

Distribution of the classification methods used in the studies analyzed.

Distribution of the classification methods used in the studies analyzed.

Table 4. Distribution of the classification methods used in the studies analyzed.

Method:	**Number of Studies:**	**Average of accuracy:**
ANN (MLP, PNN, DNN)	18	92.84%
Decision Tree (C4.5, J48)	20	92.23%
KNN/IBk/kStart	10	92.20%
Random Forest	7	90.39%
SVM/SMO	13	89.89%
Decision tables	2	87.00%
Bayesian Network	2	86.72%
Hidden Markov Model (HMME, HMM, SW-HMM)	3	85.78%
Naïve Bayes	10	85.05%
Simple Logistic	1	85.05%
LMT	1	85.04%
LR	1	84.30%
Rule-based learner (JRip)	3	83.78%
Logistic Regression	3	82.97%
Logit Boost	1	82.24%
Radial Basis Function Network	1	73.03%
Straw Man	1	37.20%

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27225v1 | CC BY 4.0 Open Access | rec: 19 Sep 2018, publ: 19 Sep 2018

Table 5 (on next page)

Configurations of the neural networks implemented.

Configurations of the neural networks implemented.

Table 5. Configurations of the neural networks implemented.

Parameters	**MLP**	**FNN**	**DNN**
Activation function	Sigmoid	Sigmoid	Sigmoid
Learning rate	0.6	0.6	0.1
Momentum	0.4	0.4	N/A
Maximum number of training iterations	$4x10^6$	$4x10^6$	$4x10^6$
Number of hidden layers	0	0	3
Weight function	N/A	N/A	Xavier
Seed value	N/A	N/A	6
Backpropagation	Yes	Yes	Yes
Regularization	N/A	N/A	L_2

Table 6 (on next page)

Best accuracies obtained with the different frameworks, datasets and number of iterations.

Best accuracies obtained with the different frameworks, datasets and number of iterations.

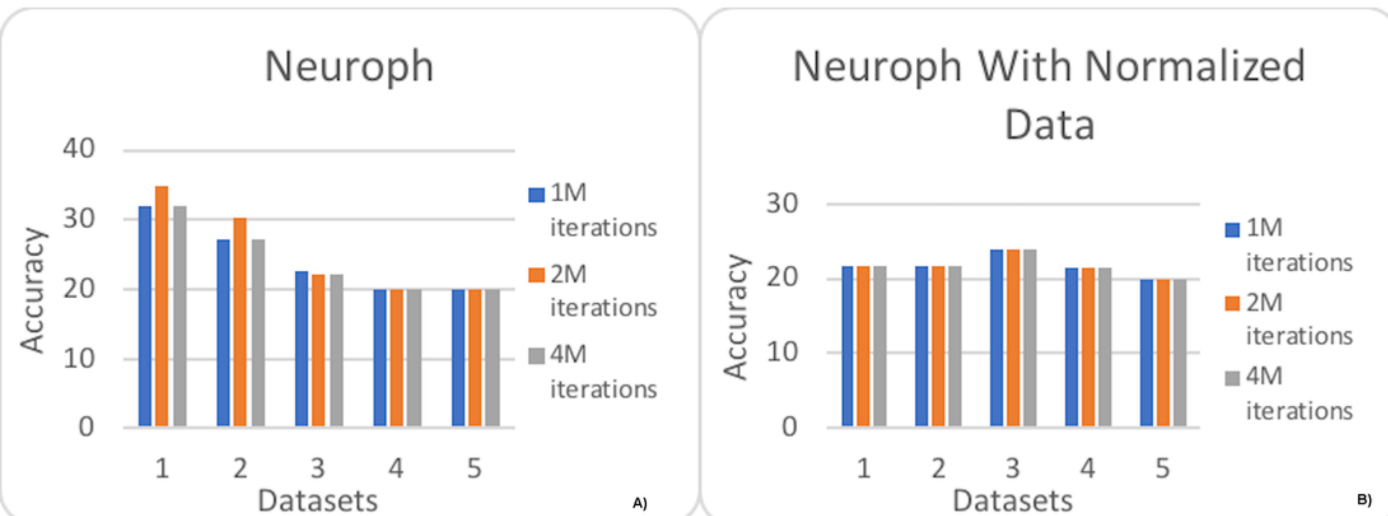
Table 6. Best accuracies obtained with the different frameworks, datasets and number of iterations.

	FRAMEWORK	DATASET	ITERATIONS NEEDED FOR TRAINING	BEST ACCURACY ACHIEVED (%)
NOT NORMALIZED DATA	NEUROPH	1	$2x10^6$	34.76
	ENCOG	5	$4x10^6$	74.45
	DEEPLEARNING4J	3	$4x10^6$	80.35
NORMALIZED DATA	NEUROPH	3	10^6	24.03
	ENCOG	4	10^6	37.07
	DEEPLEARNING4J	1	$4x10^6$	85.89

Figure 1

Results obtained with Neuroph framework for the different datasets (horizontal axis) and different maximum number of iterations (series), obtaining the accuracy in percentage (vertical axis). The figure a) shows the results with data without normalization

Results obtained with Neuroph framework for the different datasets (horizontal axis) and different maximum number of iterations (series), obtaining the accuracy in percentage (vertical axis). The figure a) shows the results with data without normalization. The figure b) shows the results with normalized data.



PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27225v1 | CC BY 4.0 Open Access | rec: 19 Sep 2018, publ: 19 Sep 2018

Figure 2

Results obtained with Encog framework for the different datasets (horizontal axis) and different maximum number of iterations (series), obtaining the accuracy in percentage (vertical axis). The figure a) shows the results with data without normalization.

Results obtained with Encog framework for the different datasets (horizontal axis) and different maximum number of iterations (series), obtaining the accuracy in percentage (vertical axis). The figure a) shows the results with data without normalization. The figure b) shows the results with normalized data.

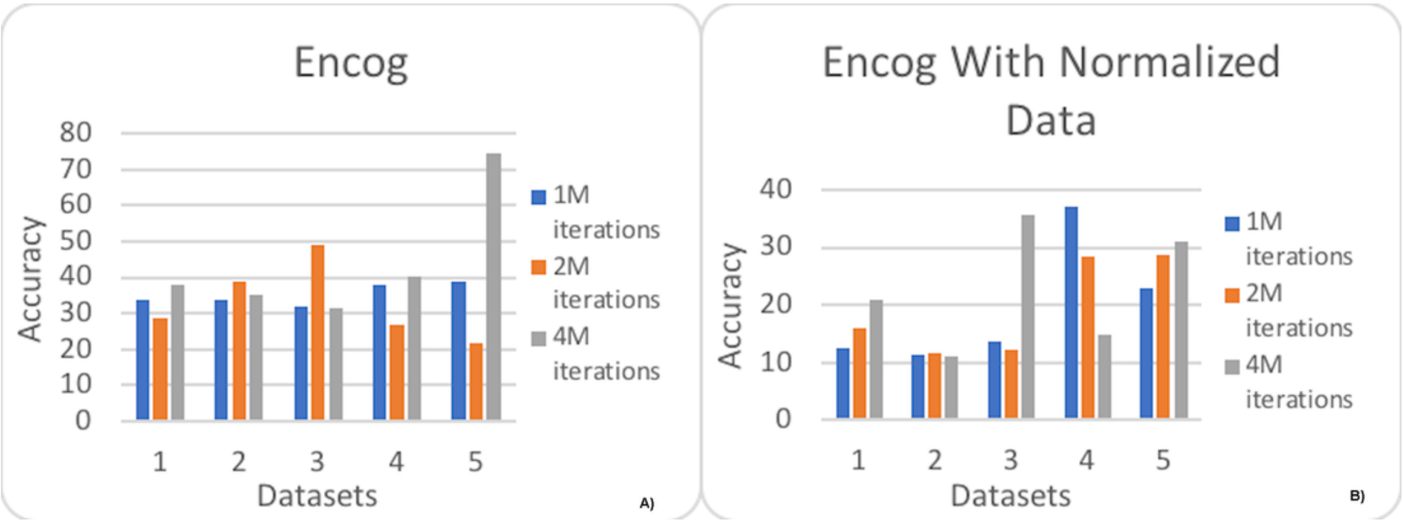


Figure 3

Results obtained with DeepLearning4j framework for the different datasets (horizontal axis) and different maximum number of iterations (series), obtaining the accuracy in percentage (vertical axis). The figure a) shows the results with data without normal

Results obtained with DeepLearning4j framework for the different datasets (horizontal axis) and different maximum number of iterations (series), obtaining the accuracy in percentage (vertical axis). The figure a) shows the results with data without normalization. The figure b) shows the results with normalized data.