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Identification of Activities of Daily Living through Artificial Intelligence: an accelerometry-based approach

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Abstract

The accelerometer is available on most of these mobile devices. It allows the acquisition and calculation of different physical parameters. Due to the use of pattern recognition, it also enables the identification of several Activities of Daily Living (ADL), such as walking, running, going downstairs, going upstairs, and standing. The feature extraction step performs the extraction of the five most significant distances between peaks, the average, standard deviation, variance and median of extracted peaks and raw data, and the maximum and minimum of raw data. The focus of this paper is the implementation of multiple artificial intelligence methods for the recognition of ADL, including Logistic Regression, Combined nomenclature rule inducer, Neural Network, Naive Bayes, Support Vector Machine, Decision Tree, Stochastic Gradient Descent, and k-Nearest Neighbor. The Decision tree reported the average accuracy of 85.22% between classes. This method also presents an F1-score value of 85,13% and a precision value of 85,08%. Nevertheless, the study has limitations associated with the use of mobile devices. The position and location of the device in the data collection phase need further investigation, and the system architecture demands higher energy consumption.

Keywords: Activities of Daily Living (ADL); Mobile devices; Accelerometer; Pattern recognition; Artificial intelligence.

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1. Introduction

Nowadays, people are using mobile devices in the different Activities of Daily Living (ADL) that allow the acquisition of various physical and physiological data with the sensors embedded in them. The processing of data acquired from the accelerometer data with different artificial intelligence techniques allows the recognition of different activities.

Mobile devices include relevant processing properties and include accelerometry units [1,2]. Furthermore, these devices also include multiple communication technologies such as General Packet Radio Service (GPRS), 3G, High-Speed Downlink Packet Access (HSDPA), 4G, and 5G for long-range communication and Bluetooth, Near-field communication (NFC) and Wi-Fi for short-range communication [3–5]. Therefore, these devices are a fundamental element used for personalized healthcare and are carried by most people every day [6–8].

Moreover, standard mobile devices incorporate accelerometry units, which can support the data collection of physical parameters, using this data for multiple activities in the healthcare domain [9–11]. Currently, different medical assessment procedures use accelerometry-based systems [12,13]. Support decision making on several diseases related to people's mobility conditions also uses this type of sensors [14–17]. The connection between the computer science domain and the medical field promote the design and development of reliable systems supported by artificial intelligence methods for multiple objectives such as the classification of ADLs [18–21]. The activity recognition accuracy can be improved by personalized models while also aiding in determining of emerging medical conditions [34].

The literature shows different researchers who study automatic ADL identification using accelerometer data. This study performs the recognition of five ADL, including walking, running, standing, going upstairs, and going downstairs, with different artificial intelligence methods. These ADLs have been selected, taking into account the literature review conducted by the authors. The use of data acquired from the accelerometer sensor fused with the data retrieved from the magnetometer and gyroscope sensors is available in the literature [22]. Other approaches in the literature rely on environmental sensors that are less obtrusive but also less accurate [33]. Mobile devices are also proved to be successful in detecting the environment with acoustic sensors, which can complement activity recognition with a wider context [35].

The main contribution of this study is to continue the research related to the recognition of ADL, implemented the Logistic Regression, Combined nomenclature (CN2) rule inducer, Neural Network, Naive Bayes, Support Vector Machine (SVM), Decision Tree, Stochastic Gradient Descent (SGD), and k-Nearest Neighbor (kNN) methods with different parameters. The best results will be the basis of the implementation of a framework for the recognition of ADL. Therefore, the primary motivation of this study is to recommend the best method for ADL classification using accelerometer data. Also, the authors aim to verify the F1 score, precision, and recall score of the different implementations. The results presented, the worst average accuracy between all the studied activities was reported by the kNN method (65.55%), and the best performance was presented by the Decision Tree method (85.22%).

This article continues with Section 2 that presents the methodology of the framework for the recognition of ADL. The results of the classification methods implemented are presented and discussed in Section 3. Finally, Section 4 presents the main conclusions of this study.

2. Methods

The recognition of ADL may be possible with the sensors available in the off-the-shelf mobile devices. This study presents a methodology with three steps (see Fig. 1), including data acquisition (Section 2.1), data processing (Section 2.2), and artificial intelligence methods (Section 2.3). Initially, we start with the description of the environment for the data acquisition, and the different constraints. Data processing methods include the data cleaning and the extraction of the various features from the accelerometer signal. The core of the work presented in this paper consists in the implementation of different artificial intelligence methods, including Logistic Regression, CN2 rule inducer, Neural Network, Naive Bayes, SVM, Decision Tree, SGD, and kNN. These methods have been applied using open-source python software on a MacBookPro 15", 6-Core Intel Core i7 with 2.6 GHz processing power, and 16 GB MB. The machine learning methods have been applied and the confusion matrix extracted. Moreover, the accuracy, F1 score, precision and recall performance metrics have been computed.

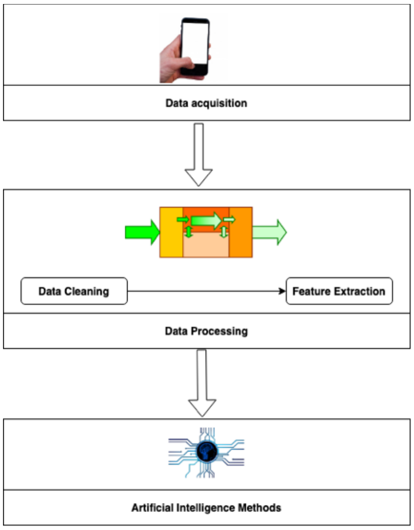

Fig. 1. Architecture of the proposed method for the identification of Activities of Daily Living (ADL)

2.1. Data acquisition

This study is based on the accelerometer data acquired by a BQ Aquaris 5.7 smartphone used during the walking, going upstairs and downstairs, running, and standing activities (see Fig. 2). The data acquisition was performed with the mobile device in a pocket of the user's trousers with a collection of 5 seconds of data every 5 minutes during the whole day. The different experiments related to the various activities were performed between 1st June 2017 and 31st December 2017, where it consists of 36 hours for each ADL.

The accelerometer data was acquired by 25 subjects aged between 16 and 60 years old with different lifestyles, including sportspeople, sedentary people, and others. In detail, ten individuals regularly practice physical exercise, but the remaining 15 have a sedentary lifestyle. For each stream of data acquisition, the user should define the ADL performed.

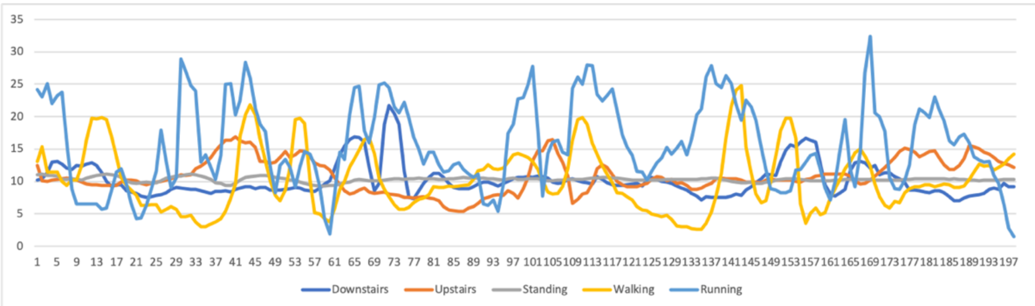

Fig. 2. Acceleration (m/s^2) for each Activity of Daily Living (ADL)

2.2. Data Processing

After the data acquisition, the text files are processed for the extraction of the different features to apply artificial intelligence methods for the automatic recognition of ADL based on the accelerometer data. Initially, the data cleaning was performed with the implementation and execution of a low-pass filter [23] to reduce the noise of the accelerometer data to minimize the effects of the different constraints.

The final step of data processing consists of the extraction of different features [24]. As presented in Table 1, the extracted features are provided by various sources. After the data acquisition, the average, standard deviation, variance, median, maximum, and minimum of the raw data were extracted. Besides, the peaks available in the raw data were obtained. And, it is calculated the average, standard deviation, variance, and median of them. Finally, the timestamp of each peak was considered, and the five most enormous distances between peaks were calculated.

Table 1. Features extracted from the accelerometer data

Source	Feature
Peaks	Five most enormous distances between peaks Average Standard deviation Variance Median
Raw signal	Average Standard deviation Variance Median Maximum Minimum

2.3. Identification of Activities of Daily Living

This paper extends the research on the recognition of simple ADL with other methods, implementing Logistic Regression, CN2 rule inducer, Neural Network, Naive Bayes, SVM, Decision Tree, SGD, and kNN. Logistic regression is similar to linear regression with binomial response variable [25]. CN2 rule inducer combined the Michalski's Automation Quotient, and Quinlan's ID3 algorithms [26]. Neural Network methods consist of a group of neurons based on a computational model for information change, which it is adapted with the information provided [27]. Naive Bayes algorithm implements the Bayes theorem with strong independence assumptions between the different features [28]. SVM performs the map of inputs into high-dimensional feature spaces with a non-linear classification [29]. Decision Tree uses a branching method for the illustration of every outcome of a decision [30]. SGD uses an iterative method for optimizing an objective function with suitable smoothness properties [31]. The kNN is a non-parametric method used for classification and regression [32]. Table 2 summarizes the configurations of each artificial intelligence method implemented.

Table 2. Configurations of the different methods

Method	Configurations
Logistic Regression	**Regularization:** Ridge (L2), C=1
CN2 (Combined nomenclature) rule inducer	**Rule ordering:** ordered; **Covering algorithm:** exclusive; **Gamma:** 0.7; **Evaluation measure:** entropy; **Beamwidth:** 5; **Minimum rule coverage:** 1; **Maximum rule length:** 5; **Default alpha:** 1.0; **Parent alpha:** 1.0
Neural Network	**Hidden layers:** 100; **Activation:** Logistic; **Solver:** SGD; **Alpha:** 0.0001; **Maximum iterations:** 200; **Replicable training:** True
Naive Bayes	Standard parameters
SVM (Support Vector Machine)	**Kernel:** Radial Basis Function (RBF), $\exp(-\text{auto}\lvert x-y\rvert^2)$; **Numerical tolerance:** 0.001; **Iteration limit:** 100
Decision Tree	**Pruning:** at least two instances in leaves, at least five instances in internal nodes, maximum depth 100; **Splitting:** Stop splitting when the majority reaches 95% (classification only); **Binary trees:** Yes
SGD (Stochastic gradient descent)	**Classification loss function:** Hinge; **Regression loss function:** Squared Loss; **Regularization:** Ridge (L2); **Regularization strength (α):** 1e-05; **Learning rate:** Constant; **Initial learning rate ($\eta 0$):** 0.01; **Shuffle data after each iteration:** Yes
kNN (k-Nearest Neighbor)	**Number of neighbors:** 5; **Metric:** Euclidean; **Weight:** Uniform

3. Results and Discussion

As previously presented, it is possible to recognize the ADL with artificial intelligence methods based on the already used dataset. We implemented different methods, such as the Logistic Regression, the CN2 rule inducer, the Neural Network, the Naive Bayes, the SVM, the Decision Tree, the SGD, and the kNN. Table 3 presents the average results of different metrics, including accuracy, F1 score, precision, and recall.

Following the results presented, the worst accuracy was reported by the kNN method (65.55%), and the best accuracy was reported by the Decision Tree method (85.22%). The F1 score measures the test accuracy. Thus, the best test accuracy was achieved by the Decision Tree method (85.13%), but the worst test accuracy was reported by the kNN method (65.69%). The best precision was reported by the Decision Tree method (85.08%), and the worst precision was reported by the kNN method (65.98%). Finally, the best recall value was reported by the Decision Tree method (85.22%), and the worst recall value was reported by the kNN method (65.55%).

Table 3. Results obtained with different features and methods for all Activities of Daily Living (ADL).

Model	Accuracy	F1 Score	Precision	Recall
Logistic Regression	0.8184	0.8158	0.8174	0.8184
CN2 rule inducer	0.8088	0.8099	0.8115	0.8088
Neural Network	0.8037	0.8007	0.8002	0.8037
Naive Bayes	0.7833	0.7718	0.7857	0.7833
SVM	0.6917	0.6836	0.6845	0.6917
Decision Tree	**0.8522**	**0.8513**	**0.8508**	**0.8522**
SGD	0.8139	0.8103	0.8135	0.8139
kNN	0.6555	0.6569	0.6598	0.6555

Table 4 presents the recognition accuracy by each ADL, verifying that running activity reported the best accuracy with Logistic Regression (98.71%), Neural Networks (98.68%), Naïve Bayes (98.19%), SVM (99.06%), SGD (98.3%), and kNN (96.52%), and standing activity reported the best accuracy with CN2 rule inducer (98.92%), and Decision Tree (99.01%). Thus, the method that reported the best accuracy in recognition of one ADL is the SVM.

Table 4. Accuracies obtained for each Activity of Daily Living and each model.

	Going Downstairs	Going Upstairs	Running	Standing	Walking
Logistic Regression	0.8819	0.8833	0.9871	0.9805	0.9040
CN2 rule inducer	0.8612	0.8616	0.9847	0.9892	0.9209
Neural Network	0.8694	0.8772	0.9868	0.9813	0.9017
Naive Bayes	0.8607	0.8681	0.9819	0.9655	0.8904
SVM	0.7799	0.8093	**0.9906**	0.9873	0.8163
Decision Tree	**0.8893**	**0.8944**	0.9834	**0.9901**	**0.9472**
SGD	0.8791	0.8802	0.983	0.9792	0.9063
kNN	0.7963	0.7809	0.9652	0.8640	0.9046

As this framework should be adapted to a mobile device that has low resources, a smaller number of implemented methods is better. Thus, the implementation of ensemble learning methods is not the best option to use. The framework for the recognition of ADL with an accelerometer should implement the Decision Tree method because it has the best performance and results in most of the ADL. Still, as an exception, the recognition of running activity is better with the SVM method.

4. Conclusions

This paper presents the implementation of multiple machine learning methods, such as Logistic Regression, CN2 rule inducer, Neural Network, Naive Bayes, SVM, Decision Tree, SGD, and kNN for the identification of ADL. The five ADLs recognized are walking, running, standing, going upstairs, and going downstairs. The dataset used includes fifteen features. The main contribution of this study is to present a comparative analysis to recommend the most accurate method for ADLs recognition. Therefore, the use of the Decision Tree method provides 85.22 % of accuracy. Moreover, this method presents an F1-score value of 85.13%, a precision value of 85.08%, and a recall value of 85.22%. Furthermore, the authors also find some limitations closely associated with the use of mobile devices. On the one hand, the most accurate position and location of the device in the data collection phase need further investigation. On the other hand, the data collection and processing using mobile devices require high processing activities, which are related to higher energy consumption.

Future research aims to investigate and explore the study of feature selection to increase the accuracy of the proposed methods for further development of an optimized version of a personal digital life coach. Sometimes there are some problems with the data acquisition, and it is crucial the research of data imputation methods for the recognition of complex activities in different environments.

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References

[1] Luxton DD, McCann RA, Bush NE, Mishkind MC, Reger GM. mHealth for mental health: Integrating smartphone technology in behavioral healthcare. Professional Psychology: Research and Practice 2011;42:505–12. https://doi.org/10.1037/a0024485.

[2] Charani E, Castro-Sánchez E, Moore LS, Holmes A. Do smartphone applications in healthcare require a governance and legal framework? It depends on the application! BMC Medicine 2014;12. https://doi.org/10.1186/1741-7015-12-29.

[3] Bisio I, Lavagetto F, Marchese M, Sciarrone A. Smartphone-centric ambient assisted living platform for patients suffering from co-morbidities monitoring. Communications Magazine, IEEE 2015;53:34–41. https://doi.org/10.1109/MCOM.2015.7010513.

[4] Iglesias R, Parra J, Cruces C, de Segura NG. Experiencing NFC-based touch for home healthcare, ACM Press; 2009, p. 1–4. https://doi.org/10.1145/1579114.1579141.

[5] Kakria P, Tripathi NK, Kitipawang P. A Real-Time Health Monitoring System for Remote Cardiac Patients Using Smartphone and Wearable Sensors. International Journal of Telemedicine and Applications 2015;2015:1–11. https://doi.org/10.1155/2015/373474.

[6] Majumder S, Deen MJ. Smartphone Sensors for Health Monitoring and Diagnosis. Sensors 2019;19:2164. https://doi.org/10.3390/s19092164.

[7] Haghi M, Thurow K, Stoll R. Wearable Devices in Medical Internet of Things: Scientific Research and Commercially Available Devices. Healthc Inform Res 2017;23:4. https://doi.org/10.4258/hir.2017.23.1.4.

[8] Guo J, Zhou X, Sun Y, Ping G, Zhao G, Li Z. Smartphone-Based Patients' Activity Recognition by Using a Self-Learning Scheme for Medical Monitoring. J Med Syst 2016;40:140. https://doi.org/10.1007/s10916-016-0497-2.

[9] Chung P-C, Hsu Y-L, Wang C-Y, Lin C-W, Wang J-S, Pai M-C. Gait analysis for patients with Alzheimer'S disease using a triaxial accelerometer. 2012 IEEE International Symposium on Circuits and Systems (ISCAS), 2012, p. 1323–6. https://doi.org/10.1109/ISCAS.2012.6271484.

[10] Ibrahim A, Eltawil A, Na Y, El-Tawil S. Accuracy Limits of Embedded Smart Device Accelerometer Sensors. IEEE Transactions on Instrumentation and Measurement 2020:1–1. https://doi.org/10.1109/TIM.2020.2964912.

[11] Trisno R, Nair P, Martin D, Baghini MS, Chung H, Pendharkar G, et al. Using accelerometer as a diagnostic tool to detect drug-induced parkinsonism (DIP) secondary to first-generation anti-psychotic medications. Australas Psychiatry 2020:1039856220901467. https://doi.org/10.1177/1039856220901467.

[12] Biagetti G, Crippa P, Falaschetti L, Orcioni S, Turchetti C. Human activity monitoring system based on wearable sEMG and accelerometer wireless sensor nodes. BioMed Eng OnLine 2018;17:132. https://doi.org/10.1186/s12938-018-0567-4.

[13] Miao F, He Y, Liu J, Li Y, Ayoola I. Identifying typical physical activity on smartphone with varying positions and

orientations. Biomedical Engineering Online 2015;14:32.
[14] Weiss A, Sharifi S, Plotnik M, van Vugt JPP, Giladi N, Hausdorff JM. Toward Automated, At-Home Assessment of Mobility Among Patients With Parkinson Disease, Using a Body-Worn Accelerometer. Neurorehabil Neural Repair 2011;25:810–8. https://doi.org/10.1177/1545968311424869.
[15] Poewe W, Seppi K, Tanner CM, Halliday GM, Brundin P, Volkmann J, et al. Parkinson disease. Nature Reviews Disease Primers 2017;3:1–21. https://doi.org/10.1038/nrdp.2017.13.
[16] Deng H, Wang P, Jankovic J. The genetics of Parkinson disease. Ageing Research Reviews 2018;42:72–85. https://doi.org/10.1016/j.arr.2017.12.007.
[17] Learmonth YC, Ensari I, Motl RW. Cognitive Motor Interference in Multiple Sclerosis: Insights From a Systematic Quantitative Review. Archives of Physical Medicine and Rehabilitation 2017;98:1229–40. https://doi.org/10.1016/j.apmr.2016.07.018.
[18] Kunkle S, Christie G, Yach D, El-Sayed AM. The Importance of Computer Science for Public Health Training: An Opportunity and Call to Action. JMIR Public Health and Surveillance 2016;2:e10. https://doi.org/10.2196/publichealth.5018.
[19] Molina Recio G, García-Hernández L, Molina Luque R, Salas-Morera L. The role of interdisciplinary research team in the impact of health apps in health and computer science publications: a systematic review. BioMed Eng OnLine 2016;15:77. https://doi.org/10.1186/s12938-016-0185-y.
[20] Free C, Phillips G, Galli L, Watson L, Felix L, Edwards P, et al. The Effectiveness of Mobile-Health Technology-Based Health Behaviour Change or Disease Management Interventions for Health Care Consumers: A Systematic Review. PLOS Medicine 2013;10:e1001362. https://doi.org/10.1371/journal.pmed.1001362.
[21] Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthc J 2019;6:94–8. https://doi.org/10.7861/futurehosp.6-2-94.
[22] Pires IM, Marques G, Garcia NM, Flórez-Revuelta F, Canavarro Teixeira M, Zdravevski E, et al. Pattern Recognition Techniques for the Identification of Activities of Daily Living Using a Mobile Device Accelerometer. Electronics 2020;9:509. https://doi.org/10.3390/electronics9030509.
[23] Zdravevski E, Risteska Stojkoska B, Standl M, Schulz H. Automatic machine-learning based identification of jogging periods from accelerometer measurements of adolescents under field conditions. PLoS One. 2017;12(9):e0184216. Published 2017 Sep 7. doi:10.1371/journal.pone.0184216
[24] Ignatov A. Real-time human activity recognition from accelerometer data using Convolutional Neural Networks. Applied Soft Computing 2018;62:915–22. https://doi.org/10.1016/j.asoc.2017.09.027.
[25] Sperandei S. Understanding logistic regression analysis. Biochem Med 2014:12–8. https://doi.org/10.11613/BM.2014.003.
[26] Clark P, Niblett T. The CN2 induction algorithm. Mach Learn 1989;3:261–83. https://doi.org/10.1007/BF00116835.
[27] Hopfield JJ. Neural networks and physical systems with emergent collective computational abilities. Proceedings of the National Academy of Sciences 1982;79:2554–8. https://doi.org/10.1073/pnas.79.8.2554.
[28] Webb GI, Boughton JR, Wang Z. Not So Naive Bayes: Aggregating One-Dependence Estimators. Mach Learn 2005;58:5–24. https://doi.org/10.1007/s10994-005-4258-6.
[29] Cortes C, Vapnik V. Support-vector networks. Mach Learn 1995;20:273–97. https://doi.org/10.1007/BF00994018.
[30] Kamiński B, Jakubczyk M, Szufel P. A framework for sensitivity analysis of decision trees. Cent Eur J Oper Res 2018;26:135–59. https://doi.org/10.1007/s10100-017-0479-6.
[31] Taddy M. Business data science: combining machine learning and economics to optimize, automate, and accelerate business decisions. 1 Edition. New York: McGraw-Hill Education; 2019.
[32] Altman NS. An Introduction to Kernel and Nearest-Neighbor Nonparametric Regression. The American Statistician 1992;46:175–85. https://doi.org/10.1080/00031305.1992.10475879.
[33] A. Dimitrievski, E. Zdravevski, P. Lameski and V. Trajkovik, "Towards application of non-invasive environmental sensors for risks and activity detection," 2016 IEEE 12th International Conference on Intelligent Computer Communication and Processing (ICCP), Cluj-Napoca, 2016, pp. 27-33, doi: 10.1109/ICCP.2016.7737117.
[34] Zdravevski E, Lameski P, Trajkovik V, Pombo N, Garcia N. Importance of Personalized Health-Care Models: A Case Study in Activity Recognition. Studies in Health Technology and Informatics. 2018 ;249:185-188.
[35] Pires, I.M.; Marques, G.; Garcia, N.M.; Pombo, N.; Flórez-Revuelta, F.; Spinsante, S.; Teixeira, M.C.; Zdravevski, E. Recognition of Activities of Daily Living and Environments Using Acoustic Sensors Embedded on Mobile Devices. Electronics 2019, 8, 1499.