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

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***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.**

***Index Terms*— Activities of Daily Living (ADL); sensors; mobile devices; data fusion; feature extraction; pattern recognition.**

I. Introduction

An accelerometer is a sensor commonly available in off-the-shelf mobile devices [1] that measures the acceleration of the movement of the mobile device, allowing the creation of a method for the recognition of ADL [2]. After the development of a method for the identification of ADL, it could be, for example, integrated in the creation of a personal digital life coach [3], 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 several motion activities, including running, walking, walking on stairs, and standing. Following the previous research studies [4-6], 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 method.

During the last years, the recognition of ADL has been studied by several authors [7-12], where ANN were widely used [13, 14]. This paper proposes the creation of a method for the recognition of ADL using the accelerometer, comparing three implementations of ANN, such as the Multilayer Perception (MLP) with Backpropagation, the Feedforward Neural Network (FNN) with Backpropagation, and the DNN. The ultima goal is to find the model that 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.

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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.

II. Related Work

The identification of the Activities of Daily Living (ADL) [2] 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 ANN, including MLP and DNN methods, using statistic features.

TABLE I
Summary of the studies available in the IEEE Xplore library

Study	# of ADL	ADL recognized	Methods	Features	Accuracy
Aguiar, B., *et al.* [15]	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.* [16]	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.* [17]	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.* [18]	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.* [19]	5	running; walking; aerobic dancing; going up stairs; going down stairs	MLP; SVM; Random Forest; Logistic Model Trees (LMT); Simple Logistic; Logit Boost	mean along z-axis; maximum, minimum, standard deviation and RMS from the magnitude of the acceleration; average of peak frequency (APF), standard deviation, RMS, maximum and minimum along x-axis, y-axis and z-axis; correlation between z-axis and y-axis	89.48% (MLP); 72.27% (SVM); 85.15% (Random Forest); 85.04% (LMT); 85.05% (Simple Logistic); 82.24% (Logit Boost)
Bujari, A., *et al.* [20]	1	walking	MLP	Mean; standard deviation	98% (MLP)
Cardoso, N., *et al.* [21]	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.* [22]	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.* [23]	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.* [24]	4	walking; running; cycling; hopping	SVM	RMS; Variance; Correlation; energy	97.69% (SVM)
Fan, L., *et al.* [25]	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)

Study	# of ADL	ADL recognized	Methods	Features	Accuracy
Guo, H., *et al.* [26]	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 al.* [27]	3	going up stairs; going up on an escalator; walking on a ramp	Decision tables; J48 Decision tree; Naïve Bayes; KNN; MLP	mean, standard deviation, skewness, kurtosis, average absolute deviation, and pairwise correlation of the tree axis of accelerometer; mean of the resultant acceleration	80.59% (decision tables); 82.97% (J48 Decision tree); 87.49% (Naïve Bayes); 89.20% (KNN); 87.86% (MLP)
Kim, Y.J., *et al.* [28]	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.* [29]	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.* [30]	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.* [31]	4	walking; running; standing; sitting	MLP	Mean; Maximum; Minimum; Median; standard deviation	99% (MLP)
Lau, S.L. [32]	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.* [33]	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.* [34]	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)
Ling, Y., *et al.* [35]	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.* [36]	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.* [37]	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.* [38]	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.* [39]	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.* [9]	4	walking; running; standing; sitting	Clustered KNN	Mean; Minimum; Maximum; standard deviation	92% (Clustered KNN)
Piyare, R., *et al.* [40]	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 Optimization (SMO); Logistic Regression	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% (SMO); 92.71% (Logistic Regression)
Sen, S., *et al.* [41]	1	playing fosball	MLP	Mean; Variance; Covariance; Energy; entropy	95% (MLP)

Study	# of ADL	ADL recognized	Methods	Features	Accuracy
Torres-Huitzil, C., *et al.* [42]	5	standing; walking; going up stairs; going down stairs; running	MLP	Mean; standard deviation; percentiles	92% (MLP)
Vavoulas, G., *et al.* [43]	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.* [44]	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.* [45]	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.* [46]	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.* [47]	7	walking; jogging; going up stairs; going down stairs; standing; sitting; lying down	Random Forest	mean and standard deviation for each axis; bin distribution; heuristic measure of wave periodicity	90% (Random Forest)
Zainudin, M.N.S., *et al.* [48]	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. [49]	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.* [50]	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.* [51]	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%

With the studies presented in the Table I, 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 II).

TABLE II
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%

Regarding the ADL recognized in the analysed studies, the Table III 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.

TABLE III
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%

The distribution of the classification methods used in the studies analyzed is presented in the Table IV, 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%.

TABLE IV
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%

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.

III. METHODS

Based on the literature combined with the proposed architecture of a framework for the recognition of ADL in [4-6], the methods that should be defined for each module of the framework, are as follows: data acquisition, data processing, data fusion, and artificial intelligence. The data processing methods proposed include the data cleaning, data imputation, and feature extraction methods. In addition, due to the fact that the proposed method uses a single sensor, *i.e.,* the accelerometer, the data fusion methods are not necessary. Finally, the data cleaning methods is also unnecessary in this context, because the data is already cleaned into the mobile application in which are collected.

A. *Data Acquisition*

This study was based in the data previously acquired for the study [52], which consists on the acquisition of data related to five ADL, such as running, walking, going upstairs, going downstairs, and standing. The data used for this study is publicly available in the ALLab MediaWiki [53].

B. *Data Processing*

This study comprehends the use of the accelerometer data with the application of the low-pass filter to clean the data [54]. It consists in the first step of the data processing, and this module is finalized with the extraction of the different features, which are the same as extracted in [52], but only provided by the accelerometer data.

C. *Artificial Intelligence*

Using the same frameworks and configurations [52],this study aims to recognize the five proposed ADL using only the accelerometer sensors, based on the datasets presented in the Figure 1. The granularity of the features included varies between the datasets 1 and 5, *e.g.,* the dataset 5 includes all features of datasets 1 to 5.

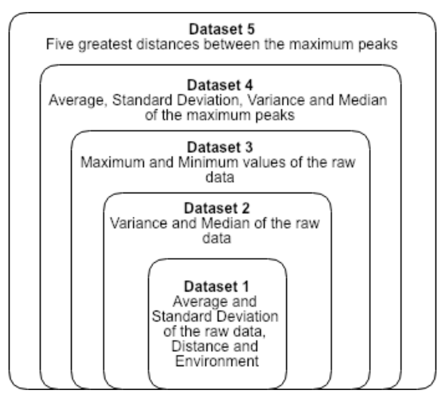

Fig. 1. Datasets created for the analysis and recognition of the different ADL

IV. RESULTS

Taking in account the implementation of the different frameworks and implementations, *i.e.,* Neuroph framework as MLP with Backpropagation, Encog framework as FNN with Backpropagation and DeepLearning4j as DNN method, with a maximum number of training iterations equals to $4x10^6$ iterations, the results reported are presented in Figure 2.

Firstly, after the implementation of MLP method with Backpropagation, the results obtained have very low accuracy (between 20% and 40%) with data without normalization, and very low accuracy (between 20% and 30%) with normalized data.

Secondly, after the implementation of FNN method with Backpropagation, the results obtained have very low accuracy (between 20% and 40%) with data without normalization, where, as exceptions, the neural networks trained with the dataset 5 reports an accuracy around 75%. On the other hand, when the data is normalized, the results shown that the reduction of the number of the features in the datasets increases the accuracy of the ANN

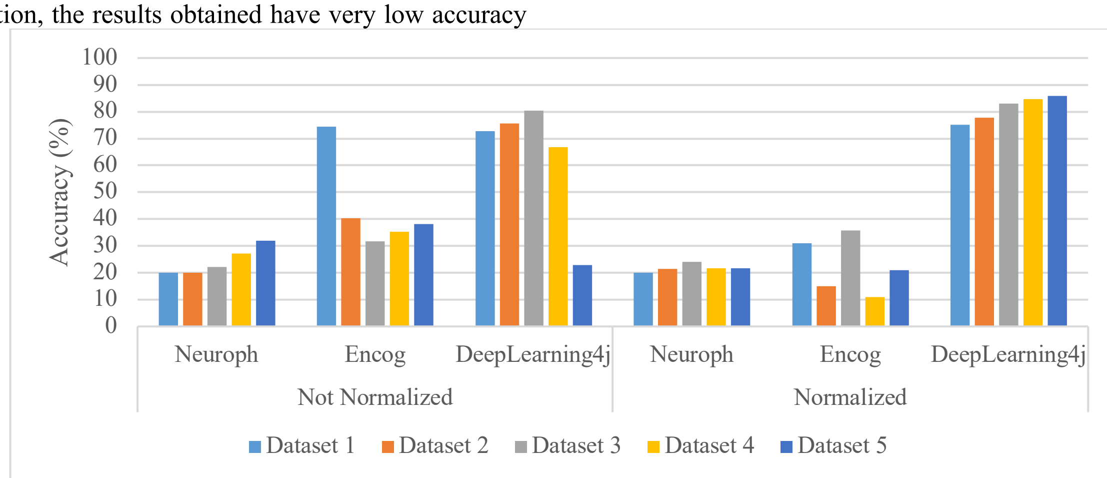

Fig. 2. Results obtained with Neuroph, Encog and DeepLearning4j frameworks (horizontal axis) for the different datasets (series), obtaining the accuracy in percentage (vertical axis).

Thirdly, after the implementation of DNN method, the results obtained are higher than 70%, but, with data without normalization, the results obtained with the datasets 1 and 2 are above the expectations with an accuracy lower than 40%, and, with the normalized data, the results obtained are higher with dataset 1, decreasing with the reduction of the number of features in the dataset.

There are two types of normalization implemented with the accelerometer data, these are normalization with MIN/MAX, and normalization with mean and standard deviation. The accuracy reported with data without normalization is better than the accuracy reported with data normalized with MIN/MAX. However, the application of L_2 regularization and normalization with mean and standard deviation increases the accuracy with all defined datasets.

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

TABLE VI
BEST ACCURACY OBTAINED WITH THE DIFFERENT FRAMEWORKS AND DATASETS.

	Framework	Dataset	Best accuracy achieved (%)
Not normalized data	**Neuroph**	5	32.02
	Encog	1	74.45
	DeepLearning4j	3	80.35
Normalized data	**Neuroph**	3	24.03
	Encog	2	37.07
	DeepLearning4j	5	85.89

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 5), 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%.

V. Discussion And 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 [4-6], 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.

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 ANN. The best results are obtained with DNN method with L_2 regularization and normalized data.

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 is not substantial.

Although the accuracy obtained in this study with DNN method is lower than the accuracy reported in [50], 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 [50] we obtain the same or better results. Nevertheless, this will be impossible to test as authors in [50] did not make their data publicly available.

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 [55], because it achieves an accuracy above 80% with a neural network trained with all features proposed in this study, these are the five 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.

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