UNIVERSITÀ POLITECNICA DELLE MARCHE
Repository ISTITUZIONALE

Identification of activities of daily living through data fusion on motion and magnetic sensors embedded on mobile devices

This is the peer reviewd version of the followng article:

*Original*
Identification of activities of daily living through data fusion on motion and magnetic sensors embedded on mobile devices / Pires, Ivan Miguel; Garcia, Nuno M.; Pombo, Nuno; Flórez-Revuelta, Francisco; Spinsante, Susanna; Teixeira, Maria Canavarro. - In: PERVASIVE AND MOBILE COMPUTING. - ISSN 1574-1192. - ELETTRONICO. - 47:(2018), pp. 78-93. [10.1016/j.pmcj.2018.05.005]

*Availability:*
This version is available at: 11566/258875 since: 2022-06-08T18:16:06Z

*Publisher:*

*Published*
DOI:10.1016/j.pmcj.2018.05.005

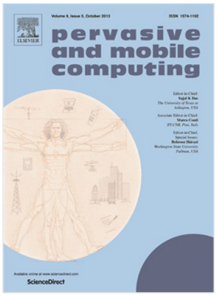
*Terms of use:*

The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. The use of copyrighted works requires the consent of the rights' holder (author or publisher). Works made available under a Creative Commons license or a Publisher's custom-made license can be used according to the terms and conditions contained therein. See editor's website for further information and terms and conditions.
This item was downloaded from IRIS Università Politecnica delle Marche (https://iris.univpm.it). When citing, please refer to the published version.

(Article begins on next page)

12 October 2024

# Accepted Manuscript




Identification of activities of daily living through data fusion on motion and magnetic sensors embedded on mobile devices

Ivan Miguel Pires, Nuno M. Garcia, Nuno Pombo, Francisco Flórez-Revuelta, Susanna Spinsante, Maria Canavarro Teixeira

PII: S1574-1192(18)30046-4
DOI: https://doi.org/10.1016/j.pmcj.2018.05.005
Reference: PMCJ 936

To appear in: *Pervasive and Mobile Computing*

Received date : 23 January 2018
Revised date : 6 May 2018
Accepted date : 18 May 2018

Please cite this article as: I.M. Pires, N.M. Garcia, N. Pombo, F. Flórez-Revuelta, S. Spinsante, M.C. Teixeira, Identification of activities of daily living through data fusion on motion and magnetic sensors embedded on mobile devices, *Pervasive and Mobile Computing* (2018), https://doi.org/10.1016/j.pmcj.2018.05.005

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

ACCEPTED MANUSCRIPT

# Identification of Activities of Daily Living through Data Fusion on Motion and Magnetic Sensors embedded on Mobile Devices

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

[1]Instituto de Telecomunicações, Covilhã, Portugal
[2]Altranportugal, Lisbon, Portugal
[3]ALLab - Assisted Living Computing and Telecommunications Laboratory, Computer Science Department, Universidade da Beira Interior, Covilhã, Portugal
[4]Universidade Lusófona de Humanidades e Tecnologias, Lisbon, Portugal
[5]Department of Computer Technology, Universidad de Alicante, Spain
[6]Università Politecnica delle Marche, Ancona, Italy
[7]UTC de Recursos Naturais e Desenvolvimento Sustentável, Polytechnique Institute of Castelo Branco, Castelo Branco, Portugal
[8]CERNAS - Research Centre for Natural Resources, Environment and Society, Polytechnique Institute of Castelo Branco, Castelo Branco, Portugal

impires@it.ubi.pt, ngarcia@di.ubi.pt, ngpombo@di.ubi.pt, francisco.florez@ua.es, s.spinsante@univpm.it, ccanavarro@ipcb.pt

**Abstract**

Several types of sensors have been available in off-the-shelf mobile devices, including motion, magnetic, vision, acoustic, and location sensors. This paper focuses on the fusion of the data acquired from motion and magnetic sensors, *i.e.,* accelerometer, gyroscope and magnetometer sensors, for the recognition of Activities of Daily Living (ADL). Based on pattern recognition techniques, the system developed in this study includes data acquisition, data processing, data fusion, and classification methods like Artificial Neural Networks (ANN). Multiple settings of the ANN were implemented and evaluated in which the best accuracy obtained, with Deep Neural Networks (DNN), was 89.51%. This novel approach applies $L_2$ regularization and normalization techniques on the sensors' data proved it suitability and reliability for the ADL recognition.

**Keywords:** Mobile devices sensors; sensor data fusion; artificial neural networks; identification of activities of daily living.

## 1. Introduction

Off-the-shelf mobile devices have several sensors available, which are capable for the acquisition of several physical and physiological parameters [1], including the accelerometer, magnetometer, and

ACCEPTED MANUSCRIPT

gyroscope sensors, allowing the recognition of Activities of Daily Living (ADL) [2]. The correct identification of ADL is one of the stages for the development of a personal digital life coach [3], which can be used in several areas, including sports and geriatrics, among others.

For the use of several sensors in the development of a method for the recognition of ADL, data fusion techniques should be used before the application of the classification methods. This paper focuses on the use of motion and magnetic sensors available on mobile devices, where the most commonly available are the accelerometer, the magnetometer, and the gyroscope, proposing the recognition of ADL with movement, including running, walking, walking on stairs, and standing. The architecture for the method for the recognition of ADL was proposed in [4-6], which is composed by data acquisition, data processing, data fusion, and classification methods. Taking in account that the data acquired from the sensors is fulfilled, the data processing methods are forked in two types of methods, namely data cleaning, and features extraction methods. After the feature extraction, the data will be fused and the classification methods will be applied.

Following the use of the data fusion techniques with the accelerometer, the gyroscope and the magnetometer sensors, this study proposes a creation of a new method that combine multiple sensors suitable for the off-the-shelf mobile devices such as smartphones.

Recently, several studies have been done regarding the recognition of ADL using several sensors [7-12]. Artificial Neural Networks (ANN) are widely used, proving their reliability for the automatic learning and recognition of several patterns of sensors' data [13, 14]. Due to the limitation of number of sensors available in the off-the-shelf mobile devices, and based on the previous study [15] that uses only the accelerometer sensor, this study proposes the creation of two different methods for the recognition of ADL using different number of sensors in order to adapt the method according to the number of sensors available. Firstly, it proposes the fusion of the data acquired from the accelerometer, and the magnetometer sensors. Secondly, it proposes the fusion of the data acquired from the accelerometer, gyroscope, and magnetometer sensors. The ADL proposed for recognition are running, walking, going upstairs, going downstairs, and standing, consisting this research on the analysis of the performance of three implementations of ANN, namely, Multilayer Perception (MLP) with Backpropagation, Feedforward Neural Network (FNN) with Backpropagation, and Deep Neural Networks (DNN). A dataset used for this research is composed by the sensors' data acquired in several experiments with users aged

ACCEPTED MANUSCRIPT

between 16 and 60 years old, having distinct lifestyles, and a mobile device in the front pocket of their trousers, performing the proposed ADL. This research was conducted with the use of three Java libraries, Neuroph [16], Encog [17], and DeepLearning4j [18], and different datasets of features, in order to identify the best dataset of features and implementation of ANN for the recognition of ADL, verifying that the best accuracy for the recognition of ADL with the two different methods proposed was achieved with Deep Learning methods.

This paragraph concludes the section 1, and this paper is organized as follows: Section 2 summarizes the literature review for the use of data fusion techniques with accelerometer, gyroscope, and magnetometer sensors; Section 3 presents the methods used on each stage of the architecture proposed. The results obtained are presented in the Section 4, presenting the discussion about these results in the Section 5. The conclusions of this study are presented in the Section 6.

## 2. Related Work

Data fusion techniques may be used with the data acquired from motion and magnetic sensors available in the off-the-shelf mobile devices, *i.e.,* accelerometer, gyroscope, and magnetometer, in order to improve the reliability of the methods for the recognition of Activities of Daily Living (ADL) [2].

Following the main focus of this paper, the accelerometer, the gyroscope, and the magnetometer are used by the authors of [19] with the Random Forest classifier for the recognition of standing, going downstairs, going upstairs, sitting, walking, and running activities. Based on a myriad of features such as the variance, the mean, the frequency of the point with maximum amplitude, the energy of the extremum value, the value of the point with maximum amplitude, the mean and the period of the extremum value, the sum of the difference between extremum values, the maximum, the minimum and the mean value around the midpoint, reporting an average accuracy of 99.7%.

In addition, Shoaib *et al.* [20] presented a method that also uses the Global Positionning System (GPS) receiver, implementing ANN, *i.e.,* Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), Naïve Bayes, Logistic regression, decision tree, K-Nearest Neighbor (KNN), and rule based classifiers. The features extracted included the mean and the standard deviation of the raw signal from the accelerometer, gyroscope, and magnetometer, and the distance from the GPS data, in order to

ACCEPTED MANUSCRIPT

recognize running, walking, standing, sitting, going downstairs, and going upstairs with a reported accuracy between 69% to 99%.

For the recognition of going upstairs and downstairs, standing, walking on an escalator and taking an elevator, the authors of [21] extracted several features from the accelerometer, magnetometer and gyroscope sensors, including mean, median, variance, standard deviation, 75$^{th}$ percentile, inter-quartile range, average absolute difference, binned distribution, energy, Signal Magnitude Area (SMA), Zero-Crossing Rate, Number of Peaks, Absolute Value of short-time Fourier Transform, Power of short-time Fourier Transform and Power Spectral Centroid. They used these features with a decision tree method, reporting an accuracy between 80% to 90% [21].

The majority of the studies in the literature only fuses the accelerometer and gyroscope data. For example the authors of [22] do not present the features extracted, but they implemented the Random Forests (RF) variable importance in order to help in the selection of the best features for the recognition of walking, going upstairs and downstairs, sitting, standing and laying activities. After the feature extraction, the implementation of the Two-stage continuous Hidden Markov Model (HMM) reported an accuracy of 91.76%. The Hidden Markov Model (HMM) was also implemented in [23], which also implemented the decision tree and Random Forest methods, with accelerometer and gyroscope data for the recognition of going downstairs and upstairs, and walking. The features included: variance, mean, standard deviation, maximum, minimum, median, interquartile range, skewness, kurtosis, and spectrum peak position of the accelerometer and gyroscope data, reporting an accuracy of 93.8%.

In [24], the authors recognized walking, standing, running, laying activities, going downstairs and upstairs, and with accelerometer and gyroscope data, extracting the mean, the energy, the standard deviation, the correlation, and the entropy of the sensors' data. Several models were implemented such as the J48 decision tree, the logistic regression, the MLP, and the SVM reporting an accuracy between 89.3% and 100%.

The authors of [25] implemented the Signal Magnitude Vector (SMV) algorithm with a Threshold based algorithm for feature extraction in order to recognize some ADL, such as walking, standing, sitting, and running with a reported accuracy around 90%.

According to [26], the Gaussian mixture model (GMM) and the time series shapelets, applied to the accelerometer and gyroscope data, allow the recognition of sitting, standing, walking, and running

ACCEPTED MANUSCRIPT

activities with mean and standard deviation as features, reporting an accuracy of 88.64%. The authors of [27] also used the mean and standard deviation as features for the application of KNN and SVM methods, in order to recognize walking, resting, running, going downstairs, and going upstairs with a reported accuracy higher than 90%.

The standard deviation, maximum, minimum, correlation coefficients, interquartile range, mean, Dynamic time warping distance (DTW), Fast Fourier Transform (FFT) coefficients, and wavelet energy were extracted as features from accelerometer and gyroscope sensors. In order to recognize walking, jumping, running, going downstairs and upstairs several methods were implemented, such as SVM, KNN, MLP, and Random Forest, reporting an accuracy between 84.97% and 90.65% [12]. The authors of [28] extracted the same features for the recognition of walking, going upstairs and downstairs, jumping, and jogging activities, The KNN, the Random Forests and the SVM methods were implemented, reporting an accuracy of 95%.

The authors of [29] extracted the variance, mean, minimum and maximum along the Y axis of the accelerometer, and the variance and mean along the X axis of the gyroscope, and implemented the SVM method for the recognition of running, walking, going downstairs and upstairs, standing, cycling and sitting, which reports an accuracy of 96%.

In [30], the authors extracted the skewness, mean, minimum, maximum, standard deviation, kurtosis, median, and interquartile range from the accelerometer and gyroscope data, implementing the MLP, the SVM, the Least Squares Method (LSM), and the Naïve Bayes classifiers for the recognition of falling activities with a reported accuracy of 87.5%.

The SVM, Random Forest, J48 decision tree, Naïve Bayes, MLP, Rpart, JRip, Bagging, and KNN were implemented in [31] for the recognition of going downstairs and upstairs, lying, standing, and walking with the mean and standard deviation along the X, Y and Z axis of the accelerometer and the gyroscope signal as features, reporting an accuracy higher than 90%.

The Root Mean Square (RMS), minimum, maximum, and zero crossing rate for X, Y, and Z axis were extracted from the accelerometer and gyroscope data, and the ANOVA method was applied for the correct recognition of sitting, resting, turning, and walking with a maximum reported accuracy of 100% [32].

ACCEPTED MANUSCRIPT

The driving, walking, running, cycling, resting, and jogging were recognized by ANN with mean, minimum, maximum, standard deviation, difference between maximum and minimum, Parseval's Energy either in the frequency range 0 - 2.5 Hz, or in the frequencies greater than 2.5 Hz. In addition, RMS, kurtosis, correlation between axis, ratio of the maximum and minimum values in the FFT, skewness, difference between the maximum and minimum values in the FFT, median of troughs, median of peaks, number of troughs, number of peaks, average distance between two consecutive troughs, average distance between two consecutive peaks, indices of the 8 highest peaks after the application of the FFT, and ratio of the average values of peaks were also considered. The observed accuracy varies between 57.53% to 97.58% [33].

The Threshold Based Algorithm (TBA) was applied to the values of the acceleration, and the difference between adjacent elements of the heading, extracted from the accelerometer and gyroscope sensors, in order to recognize going downstairs and upstairs, running, walking, and jumping with a reported accuracy of 83% [34].

The median absolute deviation, minimum, maximum, absolute mean, interquartile range, Signal Magnitude Range, skewness, and kurtosis were extracted from accelerometer and gyroscope signal for the application of KNN, SVM, Sparse Representation Classifier, and Kernel-Extreme Learning Machine, in order to recognize standing, running, going upstairs, walking, and going downstairs, reporting an average accuracy of 94.5% [35].

The jogging and walking activities are recognized with mean, variance, minimum, and maximum of the X, Y and Z axis of the accelerometer and gyroscope sensors as features applied to the SVM method, reporting an accuracy of 95.5% [36].

The authors of [37] implemented sparse approximation, KNN, SVM, Spearman correlation, Fuzzy c-means, MLP, and linear regression classifiers for the recognition of running, cycling, sitting, walking, and standing, using the standard deviation, mean, median, power ratio of the frequency bands, peak acceleration, and energy extracted from the accelerometer and gyroscope signal, reporting an accuracy of 98%.

In [38], the implementation of SVM and Random Forest methods was used for the recognition of standing, sitting, laying, walking, going downstairs and upstairs, with the extraction of the angle, the

ACCEPTED MANUSCRIPT

minimum, the maximum, and the mean values of the accelerometer and gyroscope signal, reporting an accuracy around 100%.

The authors of [39] used the accelerometer and gyroscope sensors for the recognition of the movements related to up and down buses, implementing the C4.5 decision tree, Naïve Bayes, KNN, logistic regression, SVM, and MLP with mean, standard deviation, energy, correlation between axis, and magnitude of FFT components as features, reporting an accuracy of 95.3%.

The accelerometer, gyroscope, barometer, and GPS were used for the recognition of standing, sitting, washing dishes, going downstairs and upstairs, walking, running, and cycling with standard deviation, mean, interquartile range, mean squared, altitude difference in meters, and speed as features applied to the SVM method, whose the authors reported an accuracy around 90% [40].

For the recognition of walking, lying, running, cycling, jogging, washing dishes, vacuum cleaning, playing piano, playing cello, playing tennis, brushing teeth, wiping cupboard, driving, taking an elevator, doing laundry, working on a computer, eating, reading a book, going downstairs, going upstairs, and folding laundry, the authors of [41] used the features extracted from the accelerometer, the gyroscope, and the camera, including the variance and mean for each axis, the movement intensity, the energy, the energy consumption, and the periodicity, applying them to the HMM, the SVM, the Naïve Bayes methods, and obtaining a reported accuracy of 81.5%.

The J48 decision tree, IBk, MLP, and Logistic regression methods were implemented with the median, the mean, the standard deviation, the kurtosis, the skewness, the maximum, the minimum, the slope, difference between maximum and minimum, the spectral centroid, the entropy of the energy in 10 equal sized blocks, the short time energy, the spectral roll off, the zero crossing rate, the spectral flux, and the spectral centroid for each axis and the absolute value of the accelerometer, gyroscope, and orientation sensors [42], in order to recognize walking, standing, jogging, going downstairs, going upstairs, jumping, and sitting activities, reporting an accuracy of 94%.

According to the analysis previously presented, Table 1 shows the ADL recognized, in more than one study, with the use of the accelerometer, gyroscope and/or magnetometer sensors, verifying that the walking, standing/resting, going downstairs and upstairs, running, and sitting are the most recognized ADL. The lines in Table 1 are sorted in decreasing manner regarding the number of studies found for each activity highlighting the activities reported in at least 10 papers.

ACCEPTED MANUSCRIPT

*Table 1 - Distribution of the ADL extracted in the studies analyzed.*

| ADL: | Number of Studies: |
|---|---|
| Walking | 21 |
| Going downstairs | 17 |
| Going upstairs | 17 |
| Standing/resting | 16 |
| Running | 13 |
| Sitting | 11 |
| Laying | 5 |
| Jogging | 5 |
| Cycling | 5 |
| Jumping | 4 |
| Taking an elevator | 2 |
| Driving | 2 |
| Washing dishes | 2 |

Based on the literature review, the features used for the recognition of the ADL, in more than 1 studies, are presented in Table 2, showing that the mean, standard deviation, maximum, minimum, energy, inter-quartile range, correlation coefficients, median, and variance are the most used features, with more relevance for mean, standard deviation, maximum, and minimum. The Table 2 is sorted in decreasing order of the number of studies that reportedly used a specific feature highlighting that ones used in 6 or more papers.

*Table 2 - Distribution of the features extracted in the studies analyzed.*

| Features: | Number of Studies: |
|---|---|
| Mean | 20 |
| Standard deviation | 15 |
| Maximum | 12 |
| Minimum | 12 |
| Energy | 10 |
| Inter-quartile range | 7 |
| Variance | 6 |
| Median | 6 |
| Correlation coefficients | 6 |
| Skewness | 5 |
| Kurtosis | 5 |
| Zero-Crossing Rate | 3 |
| Power Spectral Centroid | 3 |
| Frequency Domain Entropy | 3 |
| period of the extremum value | 2 |
| Mean of absolute values | 2 |
| Signal Magnitude Area (SMA) | 2 |
| Dynamic time warping distance (DTW) | 2 |
| Fast Fourier Transform (FFT) coefficients | 2 |
| Root Mean Square (RMS) | 2 |
| Difference between maximum and minimum | 2 |

ACCEPTED MANUSCRIPT

Finally, the methods implemented in the literature that report the achieved accuracy, are presented in Table 3, concluding that the methods with an accuracy higher than 90% are MLP, logistic regression, random forest and decision tree methods, verifying that the method that reports the best average accuracy in the recognition of ADL is the MLP, with an average accuracy equal to 93.86%.

*Table 3 - Distribution of the classification methods used in the studies analyzed.*

| Methods: | Number of Studies: | Average of Reported Accuracy: |
|---|---|---|
| Artificial Neural Networks (ANN) / Multi-Layer Perceptron (MLP) | 9 | 93.86% |
| Logistic regression | 4 | 92.18% |
| Random Forest | 6 | 90% |
| Decision trees (J48, C4.5) | 3 | 90.89% |
| ANOVA | 1 | 88% |
| Support Vector Machine (SVM) | 15 | 88.1% |
| K-Nearest Neighbor (KNN) | 8 | 85.67% |
| Hidden Markov Model (HMM) | 3 | 84.22% |
| Threshold Based Algorithm (TBA) | 1 | 83% |
| Naïve Bayes | 6 | 82.86% |
| Least Squares Method (LSM) | 1 | 80% |
| Rule-based classifiers (J-Rip, Rpart) | 3 | 76.35% |
| IBk | 1 | 76.28% |

As the ANN are the methods that report the best accuracies in the literature for the recognition of ADL, this paper focuses on the research on what implementation of ANN reports the best results in the recognition of a set of 5 ADL (*i.e.,* walking, going downstairs, going upstairs, standing and running) with a dataset previously acquired. Moreover, the comparison of our results with the results available in the literature is not possible, because the authors didn't make their datasets publicly available and the efficiency of the methods depends on the number of ADL each tries to recognize. The following sections of this paper focus on the comparison between three implementations of ANN, such as the MLP method with backpropagation, the FNN method with backpropagation and the DNN method. Their implementation parameters will be presented in the next section.

## 3. Methods

Based on the related work presented in the previous section and the proposed architecture of a framework for the recognition of ADL previously presented in [4-6], there are several modules for the creation of the final method, such as data acquisition, data processing, data fusion, and classification methods. Assuming that the data acquired from all sensors is fulfilled, the data processing module is

ACCEPTED MANUSCRIPT

composed by data cleaning and feature extraction methods. After that, the data fusion method will be applied for further classification of the data. In the Figure 1, a simplified schema for the development of a framework for the identification of ADL is presented.

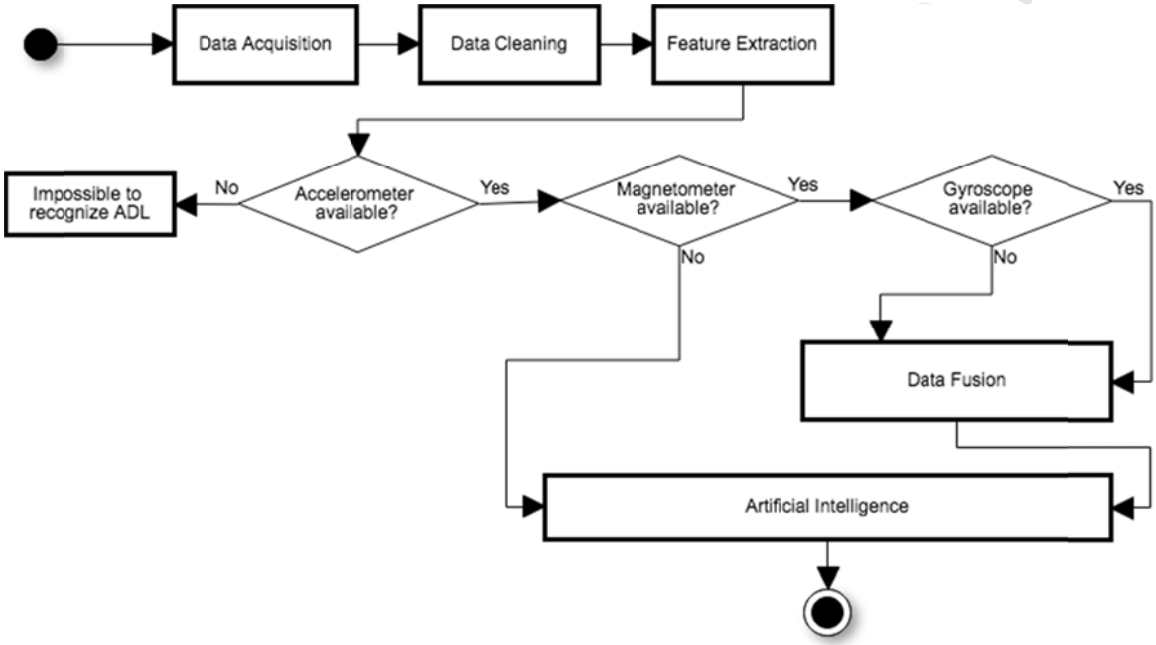



*Figure 1 - Simplified diagram for the framework for the identification of ADL.*

Section 3.1 presents the methodology for the data acquisition. Data processing methods are presented in the section 3.2 and, finally, in the section 3.3, the data fusion and classification methods are presented.

### 3.1. Data Acquisition

A mobile application developed for Android devices [43, 44] was installed in the *BQ Aquaris* 5.7 smartphone, which it has a Quad Core CPU and 16GB of internal memory [45] for the acquisition of the sensors' data, saving the data captured from the accelerometer, magnetometer, and gyroscope sensors into text files. The mobile application captures the data in 5 seconds slots every 5 minutes, where the frequency of the data acquisition is around 10ms per sample. For the definition of the experiments, 25 individuals aged between 16 and 60 years old were selected. The individuals selected had distinct lifestyles, being 10 individuals mainly active and the remaining 15 individuals, mainly sedentary. During the data acquisition, the mobile device was in the front pocket of the user's trousers, and using the data collection application, the user manually defined a label of the ADL performed in each of the 5 seconds of data captured. Based on the ADL that are the most identified in the previous research studies [4-6,

ACCEPTED MANUSCRIPT

15], the selected ADL for this study in the mobile application are: running, walking, going upstairs, going downstairs, and standing.

After the selection of the individuals for the experimental study and the definition of the main rules previously discussed, the environment of the data acquisition needs to be characterized. The environment is strictly defined for the different types of ADL performed, where the walking and running activities are performed in outdoor environments (*e.g.* street) at different times of the day, the standing activity is performed in the living room at different times of the day, and the going upstairs and going downstairs activities are performed in indoor environments at different times of the day. In total, there are around 36 hours of captures for each activity, resulting in 2000 captures with 5 seconds of raw sensors' data.

By default, without user selection, the mobile application will label the acquired data as unknown activity, therefore, before starting the data acquisition, the user must select in the mobile application the ADL that will be performed during a certain time for completion of the classification method. After this selection the user must put the mobile device is front pocket of the trousers. The unlabeled data is not stored in the final dataset for the creation of the classification method. Nevertheless, all the data used in this research is publicly available at the ALLab MediaWiki [46].

One of the problems related to the data acquisition is the battery lifetime and power processing capabilities of the mobile device, already described in [47], verifying that the acquisition of 5 seconds of raw data every 5 minutes using the oldest tested devices has possible for a minimum of 16 hours with a normal use of the mobile device. As the mobile devices usually require a daily recharge, it is possible to consider that the acquisition of the sensors' data with this method can be implemented in a real-life scenario. The performance of the mobile device is also not significantly affected during the data acquisition. In conclusion, the acquisition of small datasets sampled in a defined time interval allows the use of this method, but it only characterizes the data acquired on each interval, discarding the activities performed during the time where the data acquisition is in standby (the 5 minutes every 5 seconds). It will be probably sufficient for the characterization of lifestyles, but it may miss some important events that may not be identified, including other activities *e.g.* users' falls, that are out of the scope of this research. The development of a method that implements a more significant sampling strategy without

ACCEPTED MANUSCRIPT

decreasing the performance and the availability of resources at the mobile device requires additional research.

### 3.2. Data Processing

The data processing is the second step of the method for the recognition of ADL, which is executed after the data acquisition. Data cleaning methods are executed for noise reduction, as presented in section 3.2.1. After cleaning the data, the features were extracted for further analysis, as discussed in section 3.2.2.

#### 3.2.1. Data Cleaning

Data cleaning is a process to filter the data acquired from the accelerometer, magnetometer, and gyroscope sensors, in order to remove the noise. The data cleaning method should be selected according to the types of sensors used, nevertheless, the low-pass filter is the best method for the data acquired from the sensors used in this study [48], removing the noise and allowing the correct extraction of the selected features.

#### 3.2.2. Feature Extraction

After the data cleaning, and based on the features most commonly extracted in previous research studies [4-6, 15] (see Table 2), several features were extracted from the accelerometer, magnetometer, and gyroscope sensors. These are the five greatest distances between the maximum peaks, the average, standard deviation, variance and median of the maximum peaks, and the standard deviation, average, maximum value, minimum value, variance and median of the raw signal.

The feature extraction process starts with the calculation of the maximum peaks of the 5 seconds of data acquired related to each sensor used. After the calculation of the maximum peaks, the distance between the different peaks (in milliseconds) is calculated, using the five highest distances between the highest peaks. After that, the remaining features related to the maximum peaks are calculated, including the average, standard deviation, variance and median. Finally, the standard deviation, average, maximum value, minimum value, variance and median are calculated from the original acquired data. These features will be used in the different datasets presented in section 3.3.

### 3.3. Identification of Activities of Daily Living with Data Fusion

ACCEPTED MANUSCRIPT

Extending a previous study [15] that used only the accelerometer sensor, this study fuses the features extracted from the accelerometer and magnetometer sensors (section 3.3.1), and the features extracted from the accelerometer, gyroscope and magnetometer sensors (section 3.3.2). Finally, the classification methods for the identification of ADL are presented in the section 3.3.3.

### 3.3.1. Data Fusion with Accelerometer and Magnetometer sensors

Regarding the features extracted from each ADL, five datasets have been constructed with features extracted from the data acquired from the accelerometer and magnetometer during the performance of the five ADL, resulting in 2000 records from each ADL. The datasets defined are:

- **Dataset 5:** Composed by the average, and the standard deviation of the raw signal extracted from both accelerometer and magnetometer sensors;
- **Dataset 4:** Composed by the features of the Dataset 5 plus the variance and the median of the raw signal extracted from both accelerometer and magnetometer sensors;
- **Dataset 3:** Composed by the features of the Dataset 4 plus the maximum and the minimum values of the raw signal extracted from both accelerometer and magnetometer sensors;
- **Dataset 2:** Composed by the features of the Dataset 3 plus the average, the standard deviation, the variance and the median of the maximum peaks obtained from the raw signal extracted from both accelerometer and magnetometer sensors;
- **Dataset 1:** Composed by the features of the Dataset 2 plus the five greatest distances between the maximum peaks obtained from the raw signal extracted from both accelerometer and magnetometer sensor.

### 3.3.2. Data Fusion with Accelerometer, Magnetometer and Gyroscope sensors

Regarding the features extracted from each ADL, five datasets have been similarly constructed with features extracted from the data captured from the accelerometer, magnetometer and gyroscope, again resulting in 2000 records from each ADL. The datasets defined are:

- **Dataset 5:** Composed by the average, and the standard deviation of the raw signal extracted from both accelerometer, magnetometer and gyroscope sensors;
- **Dataset 4:** Composed by the features of the Dataset 5 plus the variance and the median of the raw signal extracted from both accelerometer, magnetometer and gyroscope sensors;

ACCEPTED MANUSCRIPT

- **Dataset 3:** Composed by the features of the Dataset 4 plus the maximum and the minimum values of the raw signal extracted from both accelerometer, magnetometer and gyroscope sensors;
- **Dataset 2:** Composed by the features of the Dataset 3 plus the average, the standard deviation, the variance and the median of the maximum peaks obtained from the raw signal extracted from both accelerometer, magnetometer and gyroscope sensors;
- **Dataset 1:** Composed by the features of the Dataset 2 plus the five greatest distances between the maximum peaks obtained from the raw signal extracted from both accelerometer, magnetometer and gyroscope sensors.

#### 3.3.3. Classification

Based on the results reported by the literature review presented in the section 2, one of the most used methods for the recognition of ADL based on the use of the mobiles' sensors is the ANN, and this method reports a better accuracy than SVM, KNN, Random Forest, and Naïve Bayes.

Following the datasets defined in the sections 3.3.1 and 3.3.2, this study implements three implementations of ANN, such as MLP, FNN, and DNN, in order to identify the best ANN for the recognition of ADL, these are:

- MLP method with Backpropagation, applied with the Neuroph framework [16];
- FNN method with Backpropagation, applied with the Encog framework [17];
- DNN method, applied with the DeepLearning4j framework [18].

The configurations between the three implementations of ANN methods used are presented in Table 4, where it is visible that the Sigmoid as activation function and backpropagation parameters are implemented in all methods. The used of more efficient activation functions, resulting in a better energy efficiency of the proposed method, will be subject to additional research.

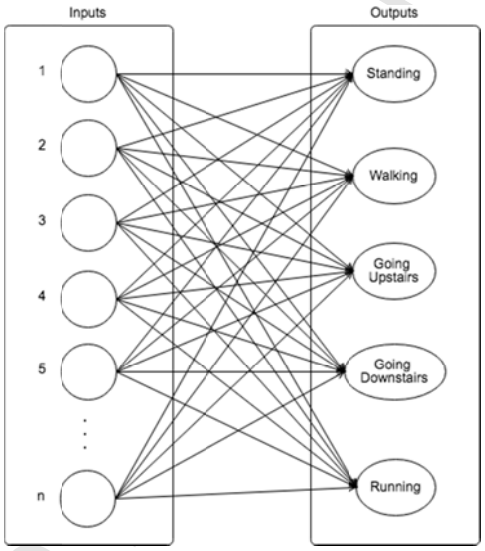
ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

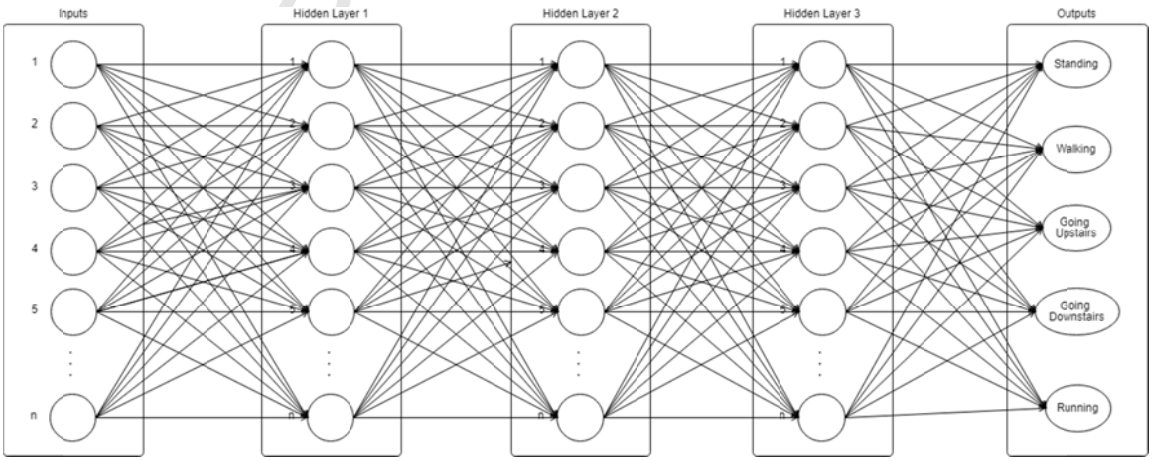
*Table 4 - Configurations of the ANN methods implemented.*

| **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 | $L_2$ |

Based on the parameters of the three implementations of ANN presented in the Table 4, the architecture of the MLP and the FNN methods is presented in the Figure 2-a and the architecture of the DNN method is presented in the Figure 2-b.




a)




b)

*Figure 2 – Schema of the architecture of the different implementations of ANN used in this study. The Figure a) shows the architecture related to the MLP and FNN methods. The Figure b) shows the architecture of the DNN method.*

ACCEPTED MANUSCRIPT

In order to improve the results obtained by the ANN, the MIN/MAX normalizer [49] was applied to the defined datasets, implementing the MLP method with Backpropagation, and the FNN method with Backpropagation with normalized and non-normalized at different stages.

Before the application of the DNN method, the $L_2$ regularization [50] was applied to the defined datasets. After the application of the $L_2$ regularization, the normalization with mean and standard deviation [51] was applied to the datasets, implementing the DNN method with normalized and non-normalized data at different stages.

The number of training iterations may influence the results of the ANN, defining the maximum number of $10^6$, $2x10^6$ and $4x10^6$ iterations, in order to identify the best number of training iterations with best results.

After this research, the methods that should be implemented in the framework for the recognition of ADL defined in [4-6] are a function of the number of sensors available in the off-the-shelf mobile device. According to the results available in [15], if the mobile device has only the accelerometer sensor, the method that should be implemented is the DNN method, verifying with this research the best methods for the use of the datasets defined in the sections 3.3.1 and 3.3.2.

## 4. Results

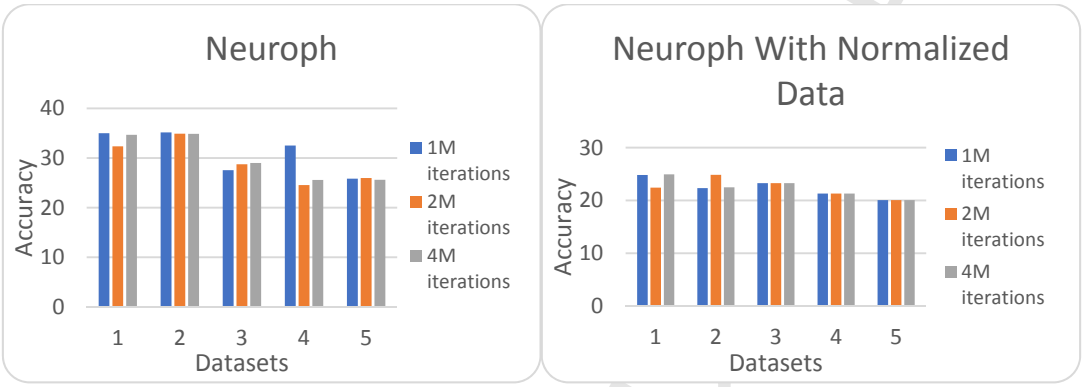
This research consists in the creation of two different methods for the recognition of ADL with different number of sensors. Firstly, the results of the creation of a method with accelerometer and magnetometer sensors are presented in the section 4.1. Finally, the results of the creation of a method with accelerometer, magnetometer, and gyroscope sensors are presented in the section 4.2.

### 4.1. Identification of Activities of Daily Living with Accelerometer and Magnetometer sensors

Based on the datasets defined in the section 3.3.1, the three implementations of ANN proposed in the section 3.3.3 are implemented with the frameworks proposed, these are the MLP method with Backpropagation, the FNN method with Backpropagation, and the DNN method. The defined training dataset has 10000 records, where each ADL has 2000 records.

ACCEPTED MANUSCRIPT

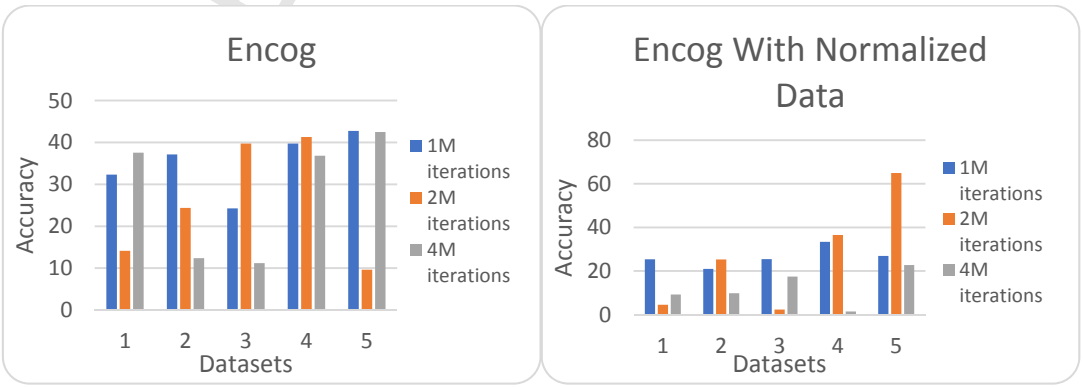
Firstly, the results of the implementation of the MLP method with Backpropagation using the Neuroph framework are presented in the Figure 3, verifying that the results have very low accuracy with all datasets, achieving values between 20% and 40% with non-normalized data (Figure 3-a), and values between 20% and 30% with normalized data (Figure 3-b).




a) b)

*Figure 3 –Results obtained with the Neuroph framework for the different datasets of accelerometer and magnetometer sensors (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.*

Secondly, the results of the implementation of the FNN method with Backpropagation using the Encog framework are presented in the Figure 4. In general, this implementation of ANN achieves low accuracy results with both non-normalized and normalized data, reporting the maximum results around 40%. With non-normalized data (Figure 4-a), the ANN reports results above 30% with the dataset 1 trained over $10^6$ and $4x10^6$ iterations, the dataset 2 trained over $10^6$ iterations, the dataset 3 trained over $2x10^6$ iterations, the dataset 4 trained over $10^6$, $2x10^6$ and $4x10^6$ iterations, and the dataset 5 trained over $10^6$ and $4x10^6$ iterations. With normalized data (Figure 4-b), the results reported are lower than 40%, with an exception for the ANN trained over $2x10^6$ iterations with the dataset 5 that reports results higher than 60%.

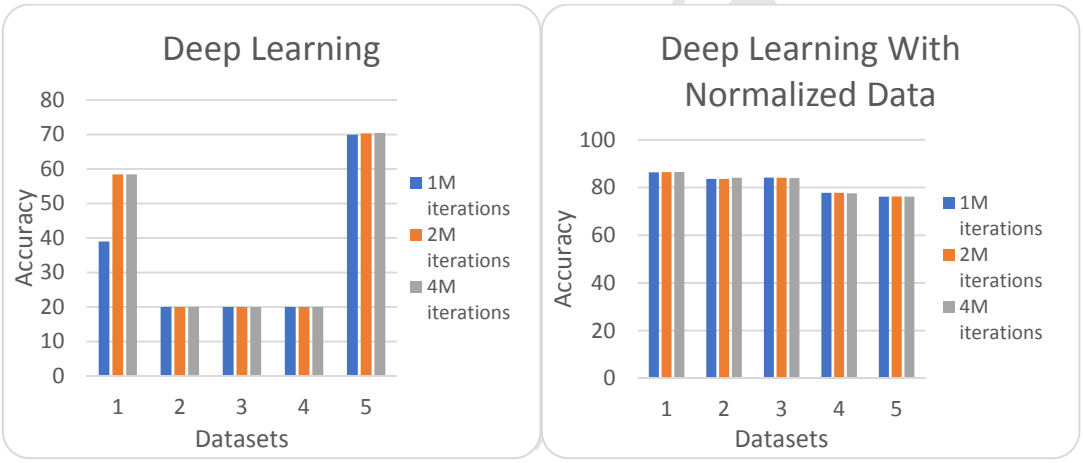



a) b)

ACCEPTED MANUSCRIPT

*Figure 4 –Results obtained with the Encog framework for the different datasets of accelerometer and magnetometer sensors (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.*

Finally, the results of the implementation of the DNN method with the DeepLearning4j framework are presented in the Figure 5. With non-normalized data (Figure 5-a), the results obtained are below the expectations (around 20%) for the datasets 2, 3 and 4, and the results obtained with dataset 5 are around 70%. On the other hand, with normalized data (Figure 5-b), the results reported are always higher than 70%, achieving better results with the dataset 1, decreasing with the reduction of the number of features in the dataset.




a) b)

*Figure 5 –Results obtained with DeepLearning4j framework for the different datasets of accelerometer and magnetometer sensors (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.*

In Table 5, the maximum accuracies achieved with the different implementations of ANN are presented with the relation of the different datasets used for accelerometer and magnetometer data, and the computational complexity [52] and the maximum number of iterations, verifying that the use of the DNN method with normalized data reports better results than others. The computational complexity taken in account in this study consists on the absolute value of the lower bounds of time complexity calculated with Big-Oh [52].

*Table 5 - Best accuracies obtained with the different frameworks, datasets and number of iterations.*

| | FRAMEWORK | ABSOLUTE VALUE OF THE LOWER BOUND OF THE TIME COMPLEXITY | DATASET | ITERATIONS NEEDED FOR TRAINING | BEST ACCURACY ACHIEVED (%) |
|---|---|---|---|---|---|
| NOT NORMALIZED DATA | NEUROPH | $9.53674 \times 10^{-27}$ | 2 | $10^6$ | 35.15 |
| | ENCOG | 0.00390625 | 5 | $10^6$ | 42.75 |

ACCEPTED MANUSCRIPT

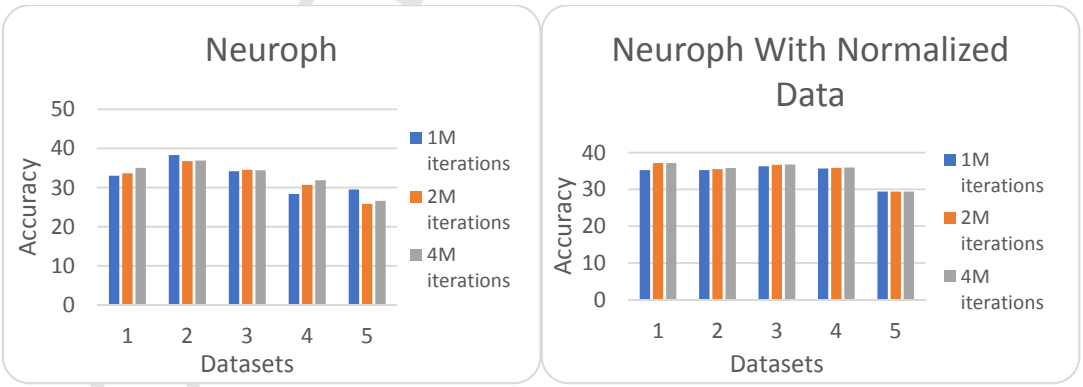
| | | | | | |
|---|---|---|---|---|---|
| | **DEEP LEARNING** | 4 | 5 | $4x10^6$ | 70.43 |
| **NORMALIZED DATA** | **NEUROPH** | $4.85694x10^{-45}$ | 1 | $4x10^6$ | 24.93 |
| | **ENCOG** | 0.00390625 | 5 | $2x10^6$ | 64.94 |
| | **DEEP LEARNING** | 4 | 1 | $4x10^6$ | 86.49 |

Regarding the results obtained, in the case of the use of accelerometer and magnetometer sensors in the framework for the identification of ADL, the implementation of ANN that should be used is the DNN method with normalized data, because the results obtained are always higher than 80%.

### 4.2. Identification of Activities of Daily Living with Accelerometer, Magnetometer and Gyroscope sensors

Based on the datasets defined in the section 3.3.2, the three implementations of ANN proposed in the section 3.3.3 are implemented with the frameworks proposed, these are the MLP method with Backpropagation, the FNN method with Backpropagation, and the DNN method. The defined training dataset has 10000 records, where each ADL has 2000 records.

Firstly, the results of the implementation of the MLP method with Backpropagation using the Neuroph framework are presented in the Figure 6, verifying that the results have very low accuracy with all datasets. With non-normalized data (Figure 6-a), the results achieved are between 20% and 40%, where the better accuracy was achieved with the dataset 2. And, with normalized data (Figure 6-b), the results obtained are between 30% and 40%, with lower results for the dataset 5.



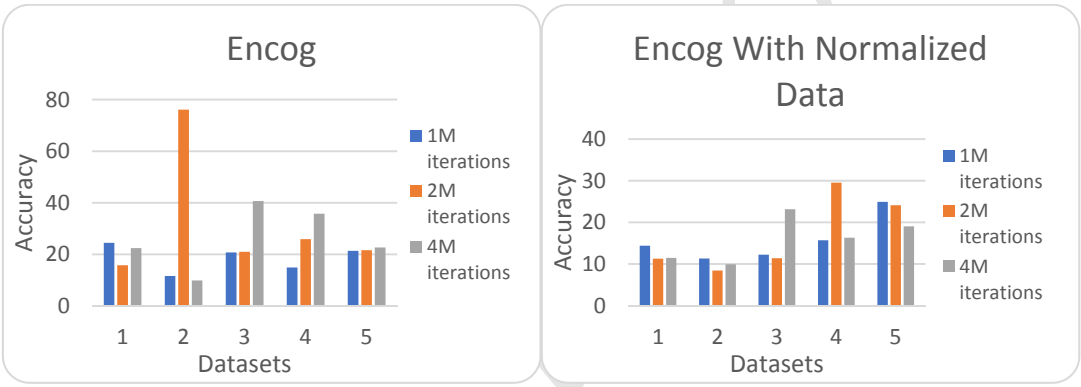

a) b)

*Figure 6 –Results obtained with the Neuroph framework for the different datasets of accelerometer, magnetometer and gyroscope sensors (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.*

Secondly, the results of the implementation of the FNN method with Backpropagation using the Encog framework are presented in the Figure 7. In general, this implementation of ANN achieves low

ACCEPTED MANUSCRIPT

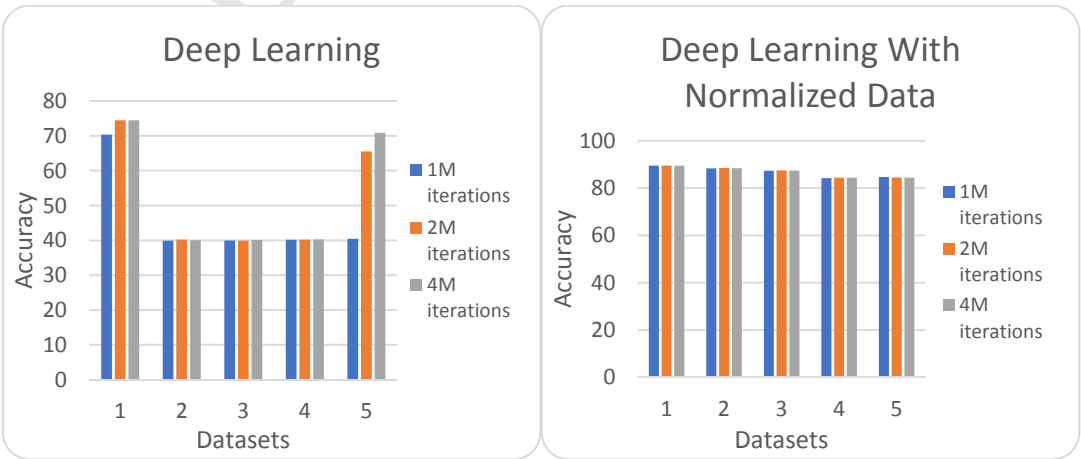
accuracy results with non-normalized and normalized data, reporting the maximum results around 40%. With non-normalized data (Figure 7-a), the ANN reports results above 30% with the dataset 2 trained over $2x10^6$ iterations, the dataset 3 trained over $4x10^6$ iterations, and the dataset 4 trained over $4x10^6$ iterations, reporting an accuracy higher than 70% with the dataset 2 trained over $2x10^6$ iterations. With normalized data (Figure 7-b), the results reported are lower than 20%, with an exception for the ANN with the dataset 3 trained over $4x10^6$ iterations, the dataset 4 trained over $2x10^6$ iterations, and the dataset 5 trained over $10^6$ and $2x10^6$ iterations.




a)¶ b)

*Figure 7 –Results obtained with the Encog framework for the different datasets of accelerometer, magnetometer and gyroscope sensors (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.*

Finally, the results of the implementation of the DNN method with the DeepLearning4j framework are presented in the Figure 8. With non-normalized data (Figure 8-a), the results obtained are below the expectations (around 40%) for the datasets 2, 3 and 4, and the results obtained with datasets 1 and 5 are around 70%. On the other hand, with normalized data (Figure 8-b), the results reported are always higher than 80%, achieving better results with the dataset 1, decreasing with the reduction of the number of features in the dataset.



ACCEPTED MANUSCRIPT

a) b)

*Figure 8 –Results obtained with the DeepLearning4j framework for the different datasets of accelerometer, magnetometer and gyroscope sensors (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.*

In Table 6, the maximum accuracies achieved with the different implementations of ANN are presented with the relation of the different datasets used for the accelerometer, magnetometer and gyroscope data, and the computational complexity [52] and the maximum number of iterations, verifying that the use of the DNN method with normalized data reports better results than others. The computational complexity taken in account in this study consists on the absolute value of the lower bounds of time complexity calculated with Big-Oh [52].

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

| | FRAMEWORK | ABSOLUTE VALUE OF THE LOWER BOUND OF THE TIME COMPLEXITY | DATASETS | ITERATIONS NEEDED FOR TRAINING | BEST ACCURACY ACHIEVED (%) |
|---|---|---|---|---|---|
| NOT NORMALIZED DATA | NEUROPH | $4.85694 \times 10^{-45}$ | 2 | $10^6$ | 38.32 |
| | ENCOG | $4.85694 \times 10^{-45}$ | 2 | $2 \times 10^6$ | 76.13 |
| | DEEP LEARNING | 4 | 1 | $2 \times 10^6$ | 74.47 |
| NORMALIZED DATA | NEUROPH | $4.03122 \times 10^{-75}$ | 1 | $2 \times 10^6$ | 37.13 |
| | ENCOG | $1.12157 \times 10^{-13}$ | 4 | $2 \times 10^6$ | 29.54 |
| | DEEP LEARNING | 4 | 1 | $4 \times 10^6$ | 89.51 |

Regarding the results obtained, in the case of the use of accelerometer, magnetometer and gyroscope sensors in the framework for the identification of ADL, the implementation of ANN that should be used is the DNN method with normalized data, because the results obtained are always higher than 80%, and the best result was achieved with dataset 1 that was equals to 89.51%.

## 5. Discussion

Based on the previous studies available in the literature, there are only 3 studies in the literature that focus on the use of the accelerometer, the gyroscope and the magnetometer sensors, but datasets and detailed specifications of the methods implemented are not available. In line with this, and due to the absence of previous studies focused on the proposed topology, we compared the use of three Java frameworks with different implementations of ANN, *i.e.,* MLP method with Backpropagation, FNN method with Backpropagation and DNN method. The main goal is to research on the most efficient

ACCEPTED MANUSCRIPT

implementation for the recognition of the ADL, in order to may provide both the sequence of the steps used for the recognition of ADL and the comparison based on the accuracy of the recognition of ADL.

Following the research for the development of a framework for the identification of the ADL using motion and magnetic sensors, presented in [4-6], there are several modules, such as data acquisition, data cleaning, feature extraction, data fusion, and classification methods. The choice of the methods for data fusion, and classification modules, depends on the number of sensors available on the mobile device, aiming to use the maximum number of sensors available on the mobile device, in order to increase the reliability of the method.

According to the previous study based only in the use of the accelerometer sensor for the recognition of ADL, presented in [15], the best results achieved for each implementation of ANN are presented in the Table 7, verifying that the best method is the DNN method with normalized data, reporting an accuracy of 85.89%. In the case of the mobile device only has the accelerometer sensor available, DNN method with normalized data should be implemented in the framework for the recognition of ADL, removing the data fusion, as presented in the Figure 1.

*Table 7 –Best accuracies achieved by the method using only the accelerometer sensor.*

| | FRAMEWORK | BEST ACCURACY ACHIEVED (%) |
|---|---|---|
| NOT NORMALIZED DATA | NEUROPH | 34.76 |
| | ENCOG | 74.45 |
| | DEEP LEARNING | 80.35 |
| NORMALIZED DATA | NEUROPH | 24.03 |
| | ENCOG | 37.07 |
| | DEEP LEARNING | 85.89 |

Based on results obtained with the use of accelerometer and magnetometer sensors, presented in the section 4.1, the comparison of the results between the use of the accelerometer sensor, and the use of accelerometer and magnetometer sensors is presented in the Table 8. In general, the accuracy increases with the use of normalized data, and decreases with the use of non-normalized data, where the highest difference was verified with the use of the accelerometer and magnetometer sensors with the implementation of FNN method with Backpropagation using the Encog framework, reporting a difference of 27.87%. However, the DNN method continues to report the best results with an accuracy

ACCEPTED MANUSCRIPT

of 86.49%. In the case of the mobile device only having the accelerometer and magnetometer sensors available, the DNN method with normalized data should be implemented in the framework for the recognition of ADL.

*Table 8 - Comparison between the best results achieved only using the accelerometer sensor, and using the accelerometer and magnetometer sensors.*

| | | BEST ACCURACY ACHIEVED (%) | | DIFFERENCE (%) |
|---|---|---|---|---|
| | FRAMEWORK | ACCELEROMETER | ACCELEROMETER MAGNETOMETER | |
| NOT NORMALIZED DATA | NEUROPH | 34.76 | 35.15 | +0.39 |
| | ENCOG | 74.45 | 42.75 | -31.70 |
| | DEEP LEARNING | 80.35 | 70.43 | -9.92 |
| NORMALIZED DATA | NEUROPH | 24.03 | 24.93 | +0.90 |
| | ENCOG | 37.07 | 64.94 | +27.87 |
| | DEEP LEARNING | 85.89 | 86.49 | +0.60 |

Based on results obtained with the use of accelerometer, magnetometer and gyroscope sensors, presented in the section 4.2, the comparison of the results between the use of the accelerometer sensor, and the use of accelerometer, magnetometer and gyroscope sensors is presented in the Table 9. In general, the accuracy increases, except in the cases of the use of the DNN method with non-normalized data and the FNN method with Backpropagation using the Encog framework with normalized data. The highest difference in the accuracy is verified with the use of MLP method with Backpropagation using the Neuroph framework, where the accuracy results increased 13.1% with normalized data, but the DNN method achieves better results with an accuracy of 89.51%. However, the computational complexity of the DNN method is higher than the MLP and FNN methods, but the results obtained are significantly higher than the others in the recognition of the proposed ADL.

*Table 9 - Comparison between the best results achieved only using the accelerometer sensor, and using the accelerometer, magnetometer and gyroscope sensors.*

| | | BEST ACCURACY ACHIEVED (%) | | DIFFERENCE (%) |
|---|---|---|---|---|
| | FRAMEWORK | ACCELEROMETER | ACCELEROMETER MAGNETOMETER GYROSCOPE | |
| NOT NORMALIZED DATA | NEUROPH | 34.76 | 38.32 | +3.56 |
| | ENCOG | 74.45 | 76.13 | +1.46 |

ACCEPTED MANUSCRIPT

| | | | | |
|---|---|---|---|---|
| | **DEEP LEARNING** | 80.35 | 74.47 | -5.88 |
| **NORMALIZED DATA** | **NEUROPH** | 24.03 | 37.13 | +13.10 |
| | **ENCOG** | 37.07 | 29.54 | -7.53 |
| | **DEEP LEARNING** | 85.89 | 89.51 | +3.62 |

Based on results obtained with the use of accelerometer, magnetometer and gyroscope sensors, presented in the section 4.2, and the results obtained with the use of accelerometer and magnetometer sensors, presented in the section 4.1, the comparison between these results is presented in the Table 10. In general, the accuracy increases, except in the case of the use of the FNN method with Backpropagation using the Encog framework with normalized data. The highest difference in the accuracy is verified with the use of the FNN method with Backpropagation using the Encog framework with non-normalized data, where the accuracy results increased 33.38% with non-normalized data, but the DNN method continues achieving the better results with an accuracy of 89.51%. Thus, in the case of the mobile device has the accelerometer, magnetometer and gyroscope sensors available, the DNN method with normalized data should be implemented in the framework for the recognition of ADL.

*Table 10 - Comparison between the best results achieved only using the accelerometer and magnetometer sensors, and using the accelerometer, magnetometer and gyroscope sensors*

| | | **BEST ACCURACY ACHIEVED (%)** | | **DIFFERENCE (%)** |
|---|---|---|---|---|
| | **FRAMEWORK** | **ACCELEROMETER MAGNETOMETER** | **ACCELEROMETER MAGNETOMETER GYROSCOPE** | |
| **NOT NORMALIZED DATA** | **NEUROPH** | 35.15 | 38.32 | +3.17 |
| | **ENCOG** | 42.75 | 76.13 | +33.38 |
| | **DEEP LEARNING** | 70.43 | 74.47 | +4.04 |
| **NORMALIZED DATA** | **NEUROPH** | 24.93 | 37.13 | +12.20 |
| | **ENCOG** | 64.94 | 29.54 | -35.40 |
| | **DEEP LEARNING** | 86.49 | 89.51 | +3.02 |

In conclusion, when compared with MLP method with Backpropagation using the Neuroph framework and FNN method with Backpropagation using the Encog framework, the DNN method with normalized data achieves better results for the recognition of the ADL with accuracies between 85% and 90% with the different datasets.

ACCEPTED MANUSCRIPT

The fusion of the data acquired from the sensors available in the mobile device requires the acquisition, processing, fusion and classification of the different sensors' data as defined in the schema of the framework proposed (see Figure 1). The energy consumptions for the different sensors is very different, being the accelerometer consumption range of one order of magnitude, the magnetometer in the range of two orders of magnitude, and the gyroscope in the range of three orders of magnitude, unbalancing and increasing the resources (*e.g.,* battery and power processing capabilities) needed for the execution of the framework. However, as presented in [47], with the method proposed in this study the effects are minimized and only a daily recharge is needed for the execution of the framework with the three sensors. The devices used in [47] were used to study different combinations of sensors both in number and type, including a configuration where the oldest devices had only the accelerometer sensor, and the remaining devices were used for other configurations. Regarding the use of only the accelerometer and the use of the fusion of one accelerometer and one magnetometer, the accuracy has a marginal improvement (+0.60%), but it increases the reliability of the framework and reduces the problems with the possible failures of one of the sensors during data acquisition. Finally, the use of the three sensors improves the accuracy of the framework in 3.02%, the main problem consisting in the fact that some commercially available devices do not integrate the set comprising the gyroscope, magnetometer and accelerometer sensors. In conclusion, data fusion increases the reliability of the framework, proving the viability of the use of the proposed framework.

## 6. Conclusions

The sensors that are available in the mobile devices, including accelerometer, gyroscope, and magnetometer sensors, allow the capture of data that can be used to the recognition of ADL [2]. This study focused on the architecture defined in [4-6], composed by data acquisition, data cleaning, feature extraction, data fusion and classification methods. Based on the literature review, the proposed ADL for the recognition with motion and magnetic sensors are running, walking, going upstairs, going downstairs, and standing.

Based on the data acquired, several features must be extracted from the sensors' signal, such as the five greatest distances between the maximum peaks, the average, standard deviation, variance, and median of the maximum peaks, plus the average, the standard deviation, the variance, the median, and

ACCEPTED MANUSCRIPT

the minimum, the maximum of the raw signal have been extracted from the accelerometer, magnetometer and/or gyroscope sensors available on the off-the-shelf mobile device. The fusion of the features implemented in the framework for the recognition of ADL should be a function of the number of sensors available. The method implemented in the framework for the recognition of ADL should also adapted with the software and hardware limitations of the mobile devices, including the number of sensors available and the low memory and power processing capabilities.

For the development of the framework for the recognition of the ADL, three implementations of ANN were created in order to identify the best framework and implementation of ANN for the development of each step of the framework for the recognition of ADL, such as the MLP method with Backpropagation using the Neuroph framework [16], the FNN method with Backpropagation using the Encog framework [17], and the DNN method using DeepLearning4j framework [18], verifying that the DNN method achieves better results than others.

Due to the limitations of mobile devices and regarding the results obtained with the method for the recognition of ADL with the accelerometer previously performed, presented in [15], it was verified that the best results were obtained with the DNN method with $L_2$ regularization and normalized data with an accuracy of 85.89%.

Related to the development of a method for the recognition of ADL, this study proves that the best accuracy are always achieved with the DNN method with $L_2$ regularization and normalized data, and the data fusion increases the accuracy of the method, reporting an accuracy of 86.49% with the fusion of the data acquired from two sensors (*i.e.,* accelerometer and magnetometer), and 89.51% with the fusion of the data acquired from three sensors (*i.e.,* accelerometer, magnetometer and gyroscope).

On the other hand, the MLP method with Backpropagation and the FNN method with Backpropagation achieve low accuracies, because the networks are overfitting, and this problem may be solved with several strategies, these being 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 implemented.

As future work, the methods for the recognition of ADL presented in this study should be implemented during the development of the framework for the identification of ADL, adapting the

ACCEPTED MANUSCRIPT

method to the number of sensors available on the mobile device, but the method that should be implemented is the DNN method. The data related to this research is available in a free repository [46].

**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

[1] L. H. A. Salazar, T. Lacerda, J. V. Nunes, and C. Gresse von Wangenheim, "A Systematic Literature Review on Usability Heuristics for Mobile Phones," *International Journal of Mobile Human Computer Interaction,* vol. 5, pp. 50-61, 2013. doi: 10.4018/jmhci.2013040103

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

[3] N. M. Garcia, "A Roadmap to the Design of a Personal Digital Life Coach," in *ICT Innovations 2015*, ed: Springer, 2016.

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

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

[6] I. M. Pires, N. M. Garcia, N. Pombo, and F. Flórez-Revuelta, "Identification of Activities of Daily Living Using Sensors Available in off-the-shelf Mobile Devices: Research and Hypothesis," in *Ambient Intelligence-Software and Applications–7th International Symposium on Ambient Intelligence (ISAmI 2016)*, 2016, pp. 121-130.

[7] O. Banos, M. Damas, H. Pomares, and I. Rojas, "On the use of sensor fusion to reduce the impact of rotational and additive noise in human activity recognition," *Sensors (Basel),* vol. 12, pp. 8039-54, 2012. doi: 10.3390/s120608039

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

[9] P. Paul and T. George, "An Effective Approach for Human Activity Recognition on Smartphone," *2015 Ieee International Conference on Engineering and Technology (Icetech),* pp. 45-47, 2015. doi: 10.1109/icetech.2015.7275024

[10] Y.-W. Hsu, K.-H. Chen, J.-J. Yang, and F.-S. Jaw, "Smartphone-based fall detection algorithm using feature extraction," in *2016 9th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, Datong, China, 2016, pp. 1535-1540.

[11] S. Dernbach, B. Das, N. C. Krishnan, B. L. Thomas, and D. J. Cook, "Simple and Complex Activity Recognition through Smart Phones," in *2012 8th International Conference on Intelligent Environments (IE)*, Guanajuato, Mexico, 2012, pp. 214-221.

[12] C. Shen, Y. F. Chen, and G. S. Yang, "On Motion-Sensor Behavior Analysis for Human-Activity Recognition via Smartphones," in *2016 Ieee International Conference on Identity, Security and Behavior Analysis (Isba)*, Sendai, Japan, 2016, pp. 1-6.

[13] D. Wang, "Pattern recognition: neural networks in perspective," *IEEE Expert,* vol. 8, pp. 52-60, 1993. doi: 10.1109/64.223991

[14] K. Doya and D. Wang, "Exciting Time for Neural Networks," *Neural Networks,* vol. 61, pp. xv-xvi, 2015. doi: 10.1016/s0893-6080(14)00260-3

ACCEPTED MANUSCRIPT


[15] I. M. Pires, N. M. Garcia, N. Pombo, F. Flórez-Revuelta, and S. Spinsante, "Pattern Recognition Techniques for the Identification of Activities of Daily Living using Mobile Device Accelerometer," ed: arXiv:1711.00096, 2017 (In Review).

[16] Neuroph. (2017, 2 Sep. 2017). *Java Neural Network Framework Neuroph*. Available: http://neuroph.sourceforge.net/

[17] H. Research. (2017, 2 Sep. 2017). *Encog Machine Learning Framework*. Available: http://www.heatonresearch.com/encog/

[18] A. Chris Nicholson. (2017, 2 Sep. 2017). *Deeplearning4j: Open-source, Distributed Deep Learning for the JVM*. Available: https://deeplearning4j.org/

[19] Q. Guo, B. Liu, and C. W. Chen, "A Two-layer and Multi-strategy Framework for Human Activity Recognition using smartphone," *2016 Ieee International Conference on Communications (Icc),* pp. 1-6, 2016. doi: 10.1109/icc.2016.7511487

[20] M. Shoaib, H. Scholten, and P. J. M. Havinga, "Towards Physical Activity Recognition Using Smartphone Sensors," *2013 Ieee 10th International Conference on and 10th International Conference on Autonomic and Trusted Computing (Uic/Atc) Ubiquitous Intelligence and Computing,* pp. 80-87, 2013. doi: 10.1109/Uic-Atc.2013.43

[21] M. Elhoushi, J. Georgy, A. Wahdan, M. Korenberg, and A. Noureldin, "Using Portable Device Sensors to Recognize Height Changing Modes of Motion," *2014 Ieee International Instrumentation and Measurement Technology Conference (I2mtc) Proceedings,* pp. 477-481, 2014. doi: 10.1109/i2mtc.2014.6860791

[22] C. A. Ronao and S. B. Cho, "Human Activity Recognition Using Smartphone Sensors With Two-Stage Continuous Hidden Markov Models," *2014 10th International Conference on Natural Computation (Icnc),* pp. 681-686, 2014. doi: 10.1109/icnc.2014.6975918

[23] Y. Y. Liu, F. Zhao, W. H. Shao, and H. Y. Luo, "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),* pp. 223-229, 2016. doi: 10.1109/upinlbs.2016.7809976

[24] W. C. Hung, F. Shen, Y. L. Wu, M. K. Hor, and C. Y. Tang, "Activity Recognition with Sensors on Mobile Devices," *Proceedings of 2014 International Conference on Machine Learning and Cybernetics (Icmlc), Vol 2,* pp. 449-454, 2014. doi: 10.1109/icmlc.2014.7009650

[25] M. B. Rasheed, N. Javaid, T. A. Alghamdi, S. Mukhtar, U. Qasim, Z. A. Khan*, et al.*, "Evaluation of Human Activity Recognition and Fall Detection Using Android Phone," *2015 IEEE 29th International Conference on Advanced Information Networking and Applications (IEEE AINA 2015),* pp. 163-170, 2015. doi: 10.1109/Aina.2015.181

[26] F. Kawsar, M. K. Hasan, R. Love, and S. I. Ahamed, "A Novel Activity Detection System Using Plantar Pressure Sensors and Smartphone," *39th Annual IEEE Computers, Software and Applications Conference (COMPSAC 2015), Vol 1,* pp. 44-49, 2015. doi: 10.1109/Compsac.2015.201

[27] V. Simonetti, W. Baccinelli, M. Bulgheroni, and E. d'Amico, "Free context smartphone based application for motor activity levels recognition," *2016 Ieee 2nd International Forum on Research and Technologies for Society and Industry Leveraging a Better Tomorrow (Rtsi),* pp. 292-295, 2016. doi: 10.1109/rtsi.2016.7740601

[28] Y. F. Chen and C. Shen, "Performance Analysis of Smartphone-Sensor Behavior for Human Activity Recognition," *Ieee Access,* vol. 5, pp. 3095-3110, 2017. doi: 10.1109/access.2017.2676168

[29] Y. Tian and W. J. Chen, "MEMS-based Human Activity Recognition Using Smartphone," *Proceedings of the 35th Chinese Control Conference 2016,* pp. 3984-3989, 2016. doi: 10.1109/ChiCC.2016.7553975

[30] P. Vallabh, R. Malekian, N. Ye, and D. C. Bogatinoska, "Fall Detection Using Machine Learning Algorithms," *2016 24th International Conference on Software, Telecommunications and Computer Networks (Softcom),* pp. 51-59, 2016. doi: 10.1109/softcom.2016.7772142

[31] C. X. Tang and V. V. Phoha, "An Empirical Evaluation of Activities and Classifiers for User Identification on Smartphones," *2016 Ieee 8th International Conference on Biometrics Theory, Applications and Systems (Btas),* pp. 1-8, 2016. doi: 10.1109/btas.2016.7791159

[32] T. H. Sanders and M. A. Clements, "Multimodal monitoring for neurological disorders," *2014 40th Annual Northeast Bioengineering Conference (Nebec),* pp. 1-2, 2014. doi: 10.1109/nebec.2014.6972928

ACCEPTED MANUSCRIPT


[33] A. Bajpai, V. Jilla, V. N. Tiwari, S. M. Venkatesan, and R. Narayanan, "Quantifiable fitness tracking using wearable devices," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2015, pp. 1633-7, Aug 2015. doi: 10.1109/EMBC.2015.7318688

[34] F. De Cillisy, F. De Simioy, F. Guidoy, R. A. Incalzi, and R. Setolay, "Fall-detection solution for mobile platforms using accelerometer and gyroscope data," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2015, pp. 3727-30, Aug 2015. doi: 10.1109/EMBC.2015.7319203

[35] Q. C. Zhu, Z. H. Chen, and Y. C. Soh, "Smartphone-based Human Activity Recognition in Buildings Using Locality-constrained Linear Coding," *Proceedings of the 2015 10th Ieee Conference on Industrial Electronics and Applications,* pp. 214-219, 2015. doi: 10.1109/iciea.2015.7334113

[36] Y. Y. Fan, L. Xie, Y. F. Yin, and S. L. Lu, "A Context Aware Energy-Saving Scheme for Smart Camera Phones based on Activity Sensing," *2015 IEEE 12th International Conference on Mobile Ad Hoc and Sensor Systems (MASS),* pp. 64-72, 2015. doi: 10.1109/Mass.2015.17

[37] P. Li, Y. Wang, Y. Tian, T. S. Zhou, and J. S. Li, "An Automatic User-Adapted Physical Activity Classification Method Using Smartphones," *IEEE Trans Biomed Eng,* vol. 64, pp. 706-714, Mar 2017. doi: 10.1109/TBME.2016.2573045

[38] M. T. Uddin, M. M. Billah, and M. F. Hossain, "Random Forests based Recognition of Human Activities and Postural Transitions on Smartphone," *2016 5th International Conference on Informatics, Electronics and Vision (Iciev),* pp. 250-255, 2016. doi: 10.1109/iciev.2016.7760005

[39] L. Fang, S. Yishui, and C. Wei, "Up and down buses activity recognition using smartphone accelerometer," in *2016 IEEE Information Technology, Networking, Electronic and Automation Control Conference*, 2016, pp. 761-765.

[40] M. Altini, R. Vullers, C. Van Hoof, M. van Dort, and O. Amft, "Self-Calibration of Walking Speed Estimations Using Smartphone Sensors," *2014 Ieee International Conference on Pervasive Computing and Communications Workshops (Percom Workshops),* pp. 10-18, 2014. doi: 10.1109/PerComW.2014.6815158

[41] J. Windau and L. Itti, "Situation awareness via sensor-equipped eyeglasses," *2013 Ieee/Rsj International Conference on Intelligent Robots and Systems (Iros),* pp. 5674-5679, 2013. doi: 10.1109/iros.2013.6697178

[42] G. Vavoulas, C. Chatzaki, T. Malliotakis, M. Pediaditis, and M. Tsiknakis, "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),* pp. 143-151, 2016. doi: 10.5220/0005792401430151

[43] H. Bojinov, Y. Michalevsky, G. Nakibly, and D. Boneh, "Mobile device identification via sensor fingerprinting," *arXiv preprint arXiv:1408.1416,* 2014

[44] K. Katevas, H. Haddadi, and L. Tokarchuk, "Sensingkit: Evaluating the sensor power consumption in ios devices," in *Intelligent Environments (IE), 2016 12th International Conference on*, 2016, pp. 222-225.

[45] Bq.com. (2017, 2 Sep. 2017). *Smartphones BQ Aquaris | BQ Portugal*. Available: https://www.bq.com/pt/smartphones

[46] ALLab. (2017, September 2nd). *August 2017- Multi-sensor data fusion in mobile devices for the identification of activities of daily living - ALLab Signals*. Available: 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

[47] I. M. Pires, N. M. Garcia, N. Pombo, and F. Flórez-Revuelta, "Limitations of the Use of Mobile Devices and Smart Environments for the Monitoring of Ageing People," in *ICT4AWE 2018 4th International Conference on Information and Communication Technologies for Ageing Well and e-Health*, Madeira, Portugal, 2018.

[48] V. Graizer, "Effect of low-pass filtering and re-sampling on spectral and peak ground acceleration in strong-motion records," in *Proc. 15th World Conference of Earthquake Engineering, Lisbon, Portugal*, 2012, pp. 24-28.

[49] A. Jain, K. Nandakumar, and A. Ross, "Score normalization in multimodal biometric systems," *Pattern Recognition,* vol. 38, pp. 2270-2285, Dec 2005. doi: 10.1016/j.patcog.2005.01.012

[50] A. Y. Ng, "Feature selection, L 1 vs. L 2 regularization, and rotational invariance," in *Proceedings of the twenty-first international conference on Machine learning*, 2004, p. 78.

ACCEPTED MANUSCRIPT

[51] L. Brocca, F. Melone, T. Moramarco, W. Wagner, V. Naeimi, Z. Bartalis*, et al.*, "Improving runoff prediction through the assimilation of the ASCAT soil moisture product," *Hydrology and Earth System Sciences,* vol. 14, pp. 1881-1893, 2010. doi: 10.5194/hess-14-1881-2010

[52] M. Bianchini and F. Scarselli, "On the complexity of shallow and deep neural network classifiers," in *ESANN*, 2014.

ACCEPTED MANUSCRIPT