Comparing model performances applied to fall detection*

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***Abstract*— This study focuses on the comparison of techniques for modelling and classifying data gathered from wearable sensors, in order to detect fall events of elderly people. Although the vast majority of studies concerning fall detection place the sensory on the waist, in this research the wearable device must be placed on the wrist because it's usability. A first pre-processing stage is carried out as stated in [1], [2]; this stage detects the most relevant points to label. This study analyses the suitability of different models in solving this classification problem: a feed-forward Neural Network and a decision tree based on C5.0. A discussion about the results and the deployment issues is performed according to whether the models are to be exploited in edge/cloud computing or in the wearable device.**

I. INTRODUCTION

Fall Detection (FD) is a very active research area, with many applications to healthcare, work safety, etc. Even though there are plenty of commercial products, the best rated products only reach a 80% of success[3]. There are basically two types of FD systems: contex-aware systems and wearable devices [4]. FD has been widely studied using context-aware systems, i.e. video systems [5]; nevertheless, the use of wearable devices is crucial because the high percentage of elderly people and their desire to live autonomously in their own house [6].

Wearables-based solutions include, mainly, tri-axial accelerometers (3DACC) either alone or combined with other sensors. Several solutions incorporate more than one sensory element; for instance, Sorvala et al [7] proposed two sets of a 3DACC and a gyroscope, one on the wrist and another on the ankle, detecting the fall events with two defined thresholds. The use of 3DACC and a barometer in a necklace was also reported in [8]; similar approaches have been developed in several commercial products.

Several solutions using wearable devices combining 3DACC have been reported, i.e., identifying the fall events using Support Vector Machines [9]. In [10] several classifiers are compared using the 3DACC and the inertial sensor within a smartphone to sample the data. A similar solution is proposed in [11], using some different transformations of the 3DACC signal. A main characteristic in all these solutions is that the wearable devices are placed on the wrist. The reason of this location is that it is by far much easier to detect a fall using the sensory system in this placement. Nevertheless, this type of devices lacks in usability and the people trend to dismiss them in the bedside table. Thus, this research limits itself to use a single sensor -a marketed smartwatch- placed on the wrist in order to promote its usability.

Interestingly, the previous studies do not focus on the specific dynamics of a falling event: although some of the proposals report good performances, they are just machine learning applied to the focused problem. There are studies concerned with the dynamics in a fall event [12], [13], establishing the taxonomy and the time periods for each sequence. Additionally, Abbate et al proposed the use of these dynamics as the basis of the FD algorithm [1]. A very interesting point of this approach is that the computational constraints are kept moderate, although this solution includes a high number of thresholds to tune. In citekhojaste-HAIS2018, this solution was analysed with data gathered from sensors placed on the wrist, using the Abate solution plus a SMOTE balancing stage and a feed-forward Neural Network. In this research, an alternative based on decision trees and C5.0 is proposed.

II. ADAPTING FALL DETECTION TO A WRIST-BASED SOLUTION

Abate et al [1] proposed the following scheme to detect a candidate event as a fall event (refer to Fig. 1). A time t corresponds to a **peak time** (point 1) if the magnitude of the acceleration a is higher than $th_1 = 3 \times g, g = 9.8m/s$. After a peak time there must be a period of 2500 ms with relatively calm (no other a value higher than th_1). The **impact end** (point 2) denotes the end of the fall event; it is the last time for which the a value is higher than $th_2 = 1.5 \times g$. Finally, the **impact start** (point 3) denotes the starting time of the fall event, computed as the time of the first sequence of an $a <= th_3$ ($th_3 = 0.8 \times g$) followed by a value of $a >= th_2$. The impact start must belong to the interval $[impact\ end - 1200\ ms, peak\ time]$. If no impact end is found, then it is fixed to peak time plus 1000 ms. If no impact start is found, it is fixed to peak time.

Whenever a peak time is found, the following transformations should be computed:

- Average Absolute Acceleration Magnitude Variation, $AAMV = \sum_{t=is}^{ie} \frac{|a_{t+1} - a_t|}{N}$, with is being the impact start, ie the impact end, and N the number of samples in the interval.

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- Impact Duration Index, $IDI = impact\ end - impact\ start$. Alternatively, it could be computed as the number of samples.
- Maximum Peak Index, $MPI = max_{t\in[is,ie]}(a_t)$.
- Minimum Valley Index, $MVI = min_{t\in[is-500,ie]}(a_t)$.
- Peak Duration Index, $PDI = peak\ end - peak\ start$, with peak start defined as the time of the last magnitude sample below $th_{PDI} = 1.8 \times g$ occurred before peak time, and peak end is defined as the time of the first magnitude sample below $th_{PDI} = 1.8 \times g$ occurred after peak time.
- Activity Ratio Index, ARI, measuring the activity level in an interval of 700 ms centred at the middle time between impact start and impact end. The activity level is calculated as the ratio between the number of samples not in $[th_{ARIlow}0.85 \times g, th_{ARIIhigh} = 1.3 \times g]$ and the total number of samples in the 700 ms interval.
- Free Fall Index, FFI, computed as follows. Firstly, search for an acceleration sample below $th_{FFI} = 0.8 \times g$ occurring up to 200 ms before peak time; if found, the sample time represents the end of the interval, otherwise the end of the interval is set 200 ms before peak time. Secondly, the start of the interval is simply set to 200 ms before its end. FFI is defined as the average acceleration magnitude evaluated within the interval.
- Step Count Index, SCI, measured as the number of peaks in the interval $[peak\ time - 2200, peak\ time]$. SCI is the step count evaluated 2200 ms before peak time. The number of valleys are counted, defining a valley as a region with acceleration magnitude below $th_{SCIlow} = 1 \times g$ for at least 80 ms, followed by a magnitude higher than $th_{SCIhigh}1.6 \times g$ during the next 200 ms. Some ideas on computing the time between peaks [14] were used when implementing this feature.

Evaluating this approach was proposed as follows. The time series of acceleration magnitude values are analysed searching for peaks that marks where a fall event candidate appears. When it happens to occur, the *impact end* and the *impact start* are determined, and thus the remaining features. As long as this fall events are detected when walking or running, for instance, a Neural Network (NN) model is obtained to classify the set of features extracted.

In order to train the NN, the authors made use of an Activities of Daily Living (ADL) and FD dataset, where each file contains a Time Series of 3DACC values corresponding to an activity or to a fall event. Therefore, each dataset including a fall event or a similar activity -for instance, running can perform similarly to falling- will generate a set of transformation values. Thus, for a dataset file we will detect something similar to a falling, producing a row of the transformations computed for each of the detected events within the file. If nothing is detected within the file, no row is produced. With this strategy, the Abbate et al obtained the training and testing dataset to learn the NN.

A. The modifications on the algorithm

As stated in [15], [16], the solutions to this type of problems must be ergonomic: the users must feel comfortable using them. We considered that placing a device on the waist is not comfortable, for instance, it is not valid for women using dresses. When working with elder people, this issue is of main relevance. Therefore, in this study, we placed the wearable device on the wrist. This is not a simple change: the vast majority of the literature reports solutions for FD using waist based solutions. Moreover, according to [17] the calculations should be performed on the smartwatches to extend the battery life by reducing the communications. Therefore, these calculations should be kept as simple as possible.

A second modification is focused on the training of the NN. The original strategy for the generation of the training and testing dataset produced a highly imbalanced dataset: up to 81% of the obtained samples belong to the class FD, while the remaining belong to the different ADL similar to a fall event.

To solve this problem a normalization stage is applied to the generated imbalanced dataset, followed by a SMOTE balancing stage [18]. This balancing stage will produce a 60%(FALL)-40%(no FALL) dataset, which would allow to avoid the over-fitting of the NN models. As usual, there is a compromise between the balancing of the dataset and the synthetic data samples introduced in the dataset.

These above mentioned changes have already been studied in [2]. In this research we proposed to analyse the performance of decision trees in this context: the decision trees represent very simple models that can be easily deployed in wearable devices and with a very reduced computational complexity. Therefore, they could represent a very interesting improvement, either if they work similarly to the NN or just similarly to them.

III. Experiments and results

A ADL and FD dataset is needed to evaluate the adaptation, so it contains time series sample from ADL and for falls. This research made use of the UMA-FALL dataset [19] among the publicly available datasets. This dataset includes data for several participants carrying on with different activities and performing forward, backward and lateral falls. Actually, this falls are not real falls -demonstrative videos have been also published-, but they can represent the initial step for evaluating the adapted solution problem. Interestingly, this dataset includes multiple sensors; therefore, the researcher can evaluate the approach using sensors placed on different parts of the body.

The thresholds used in this study are exactly the same as those mentioned in the original paper. All the code was implemented in R[20] and caret[21]. The parameters for SMOTE were perc.over set to 300 and perc.under set to 200 -that is, 3 minority class samples are generated per original sample while keeping 2 samples from the majority class- . These parameters produces a balanced dataset that moves from a distribution of 47 samples from the minority class and

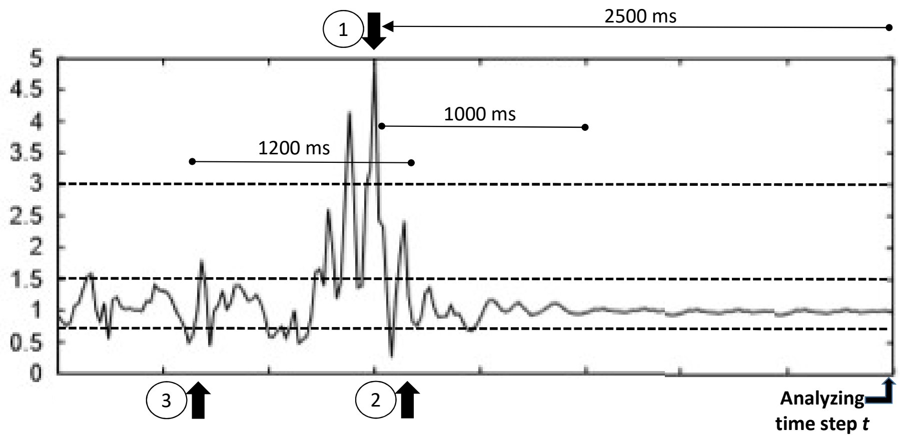

Fig. 1. Evolution of the magnitude of the acceleration -y-axis, extracted from [1]

200 from the majority class to a 188 minority class versus 282 majority class (40%/60% of balance).

To obtain the parameters for the NN a grid search was performed; the final values were size set to 20, decay set to 10^{-3} and maximum number of iterations 500, the absolute and relative tolerances set to 4×10^{-6} and 10^{-10}, respectively. In this research, we use the C5.0 implementation of the C4.5 that is included in the R package to obtain the decision trees. The parameters found optimum for this classification problem are cf set to 0.25, bands set to 2, the fuzzy Threshold parameter set to TRUE, the number of trials set to 15, and winnow set to FALSE.

Both 5x2 cross validation (cv) and 10-fold cv were performed to analysed the robustness of the solution. The latter cv would allow us to compare with existing solutions, while the former shows the performance of the system with an increase in the number of unseen samples. The results are shown in Table I and Table II for 10-fold cv and 5x2 cv, respectively. The boxplots for the statistical measurements Accuracy, Kappa factor, Sensitivity, Specificity, Precision and Recall are shown in Fig. 2 for 10-fold cv and Fig. 3 for 5x2 cv, respectively.

A. *Discussion on the results*

From the tables it can be seen that both modelling techniques perform exceptionally well once the SMOTE is performed and using test folds from 10-fold cv: the models even perform ideally for several folds. And more importantly, the two models are interchangeable with no apparent loss in the performance. Actually, these results are rather similar to those published in the original work [1]. However, when using 5x2 cv the results diverts from those previously mentioned.

With 5x2 cv, the size of the train and test datasets are of similar number of samples, producing a worse training and, what is more interesting, introduces more variability in the test dataset. Therefore, the results are worse. The point is that these results suggest the task is not solved yet as the number of false alarms increased unexpectedly.

This problem is important because in this experimentation we used the UMA-Fall dataset [19]. This dataset used was generated with young participants using a very deterministic protocol of activities. The falls were performed with the participants standing still and letting them fall in the forward/backward/lateral direction. Therefore, the differences with real falls might be relevant; even if they are not so different, the variability that might be introduced will severely punish the performance of the obtained models.

There are more publicly available datasets, the majority of these datasets have been gathered with healthy volunteers [22], [23]. However, a real-world fall and activity of daily living dataset is published in [24], where a comparison of the different methods published so far is also included. Therefore, the method described in this study needs to be validated with more datasets, more specifically, with data from real fall events.

In apart, the solution proposed analysed and extended in this work includes far too many thresholds. These thresholds have been manually set by the authors for the sensory system placed on the waist; consequently, these values must be tuned for the sensor in a different location as long as the acceleration values are not the same. Even if the thresholds are valid, perhaps the classification models must be specific for groups of people according to their movement characteristics [25], [26].

Besides, the eHealth and wearable applications deployment issues have been study in the literature [17]. According to the published results, there is a trade off between the mobile computation and the communication acts to extend the battery charge as long as possible. Consequently, it has been found that moving all the pre-processing and modelling issues to the mobile part could be advantageous provided the computational complexity of the solution is kept low. The consequences of these findings shall be reflected in the transformations and in the models, reducing complex floating point operations as much as possible [27], [26].

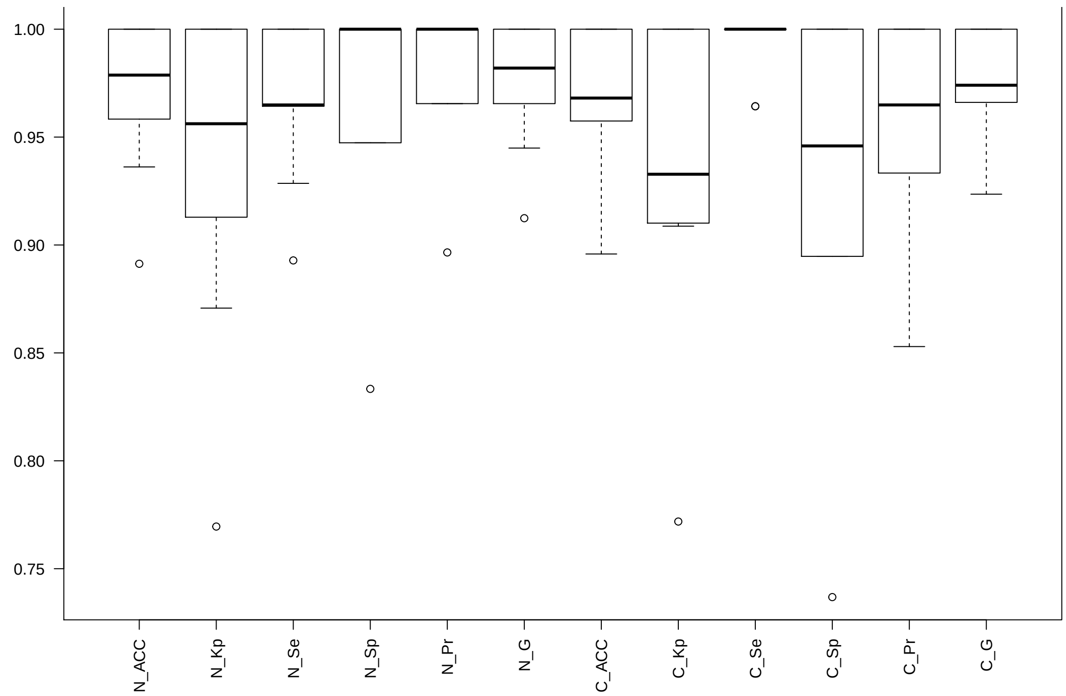

Fig. 2. 10 fold cv Boxplot for the different measurements -Accuracy (Acc), Kappa (Kp), Sensitivity (Se) and Specificity (Sp), Precision (Pr) and the geometric mean of the Acc and Pr, $G = \sqrt[2]{Pr \times Acc}$-, both for the feed-forward NN (six boxplots to the left, with the N_ prefix) and C5.0 (six boxplots to the right, with the C_ prefix).

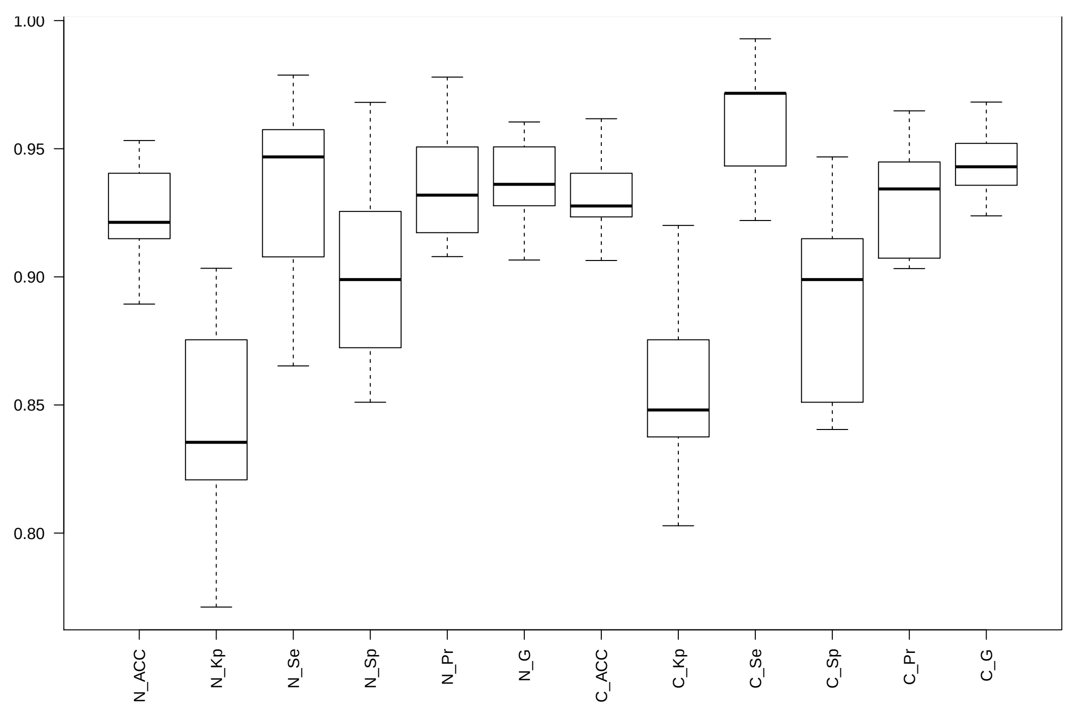

Fig. 3. 5x2 cv Boxplot for the different measurements -Accuracy (Acc), Kappa (Kp), Sensitivity (Se) and Specificity (Sp), Precision (Pr) and the geometric mean of the Acc and Pr, $G = \sqrt[2]{Pr \times Acc}$-, both for the feed-forward NN (six boxplots to the left, with the N_ prefix) and C5.0 (six boxplots to the right, with the C_ prefix).

Fold	Feed forward NN Acc	Kp	Se	Sp	Pr	G	C5.0 decision tree Acc	Kp	Se	Sp	Pr	G
1	0.97872	0.95620	0.9643	1.00000	1.00000	0.98198	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
2	1.00000	1.00000	1.0000	1.00000	1.00000	1.00000	0.95745	0.91013	1.00000	0.89474	0.93333	0.96609
3	0.97872	0.95620	0.9643	1.00000	1.00000	0.98198	0.97872	0.95620	0.96429	1.00000	1.00000	0.98198
4	0.95833	0.91289	0.9655	0.94737	0.96552	0.96552	0.89583	0.77186	1.00000	0.73684	0.85294	0.92355
5	0.93617	0.87076	0.8929	1.00000	1.00000	0.94491	0.95745	0.91013	1.00000	0.89474	0.93333	0.96609
6	1.00000	1.00000	1.0000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
7	1.00000	1.00000	1.0000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
8	0.89130	0.76954	0.9286	0.83333	0.89655	0.91242	0.95652	0.90873	0.96429	0.94444	0.96429	0.96429
9	0.97872	0.95545	1.0000	0.94737	0.96552	0.98261	0.95745	0.91013	1.00000	0.89474	0.93333	0.96609
10	0.97872	0.95620	0.9643	1.00000	1.00000	0.98198	0.97872	0.95545	1.00000	0.94737	0.96552	0.98261
mean	0.97007	0.93772	0.9680	0.97281	0.98276	0.97514	0.96821	0.93226	0.99286	0.93129	0.95827	0.97507
median	0.97872	0.95620	0.9649	1.00000	1.00000	0.98198	0.96809	0.93279	1.00000	0.94591	0.96490	0.97404
std	0.03412	0.07177	0.0355	0.05367	0.03351	0.02787	0.03158	0.06882	0.01506	0.08242	0.04716	0.02353

TABLE I

10 fold cv results obtained for hte NN and C5.0. From left to right, the main statistical measurements are shown: accuracy (Acc), Kappa factor (Kp, sensitivity (Se), the specificity (Sp), the precision (Pr) and the geometric mean of the Acc and Pr, $G = \sqrt[2]{Pr \times Acc}$.

Fold	Feed forward NN Acc	Kp	Se	Sp	Pr	G	C5.0 decision tree Acc	Kp	Se	Sp	Pr	G
1	0.92766	0.84740	0.9645	0.87234	0.91892	0.9415	0.92340	0.83755	0.97163	0.85106	0.90728	0.93891
2	0.95319	0.90334	0.9433	0.96809	0.97794	0.9604	0.92340	0.84155	0.92199	0.92553	0.94891	0.93535
3	0.91489	0.82079	0.9504	0.86170	0.91156	0.9308	0.90638	0.80287	0.94326	0.85106	0.90476	0.92381
4	0.88936	0.77113	0.8936	0.88298	0.91971	0.9066	0.93191	0.85455	0.99291	0.84043	0.90323	0.94701
5	0.89362	0.78336	0.8652	0.93617	0.95312	0.9081	0.96170	0.92007	0.97163	0.94681	0.96479	0.96820
6	0.94468	0.88455	0.9574	0.92553	0.95070	0.9541	0.94043	0.87544	0.95745	0.91489	0.94406	0.95073
7	0.92766	0.84629	0.9787	0.85106	0.90789	0.9426	0.94043	0.87410	0.97872	0.88298	0.92617	0.95209
8	0.91489	0.82143	0.9433	0.87234	0.91724	0.9302	0.92340	0.83755	0.97163	0.85106	0.90728	0.93891
9	0.91489	0.82456	0.9078	0.92553	0.94815	0.9278	0.92340	0.84099	0.92908	0.91489	0.94245	0.93574
10	0.94043	0.87544	0.9574	0.91489	0.94406	0.9507	0.94894	0.89286	0.97163	0.91489	0.94483	0.95814
mean	0.92213	0.83783	0.9362	0.90106	0.93493	0.9353	0.93234	0.85775	0.96099	0.88936	0.92938	0.94489
median	0.92128	0.83543	0.9468	0.89894	0.93188	0.9361	0.92766	0.84805	0.97163	0.89894	0.93431	0.94296
std	0.02085	0.04243	0.0357	0.03821	0.02301	0.0182	0.01585	0.03346	0.02274	0.03859	0.02245	0.01291

TABLE II

5x2 cv results obtained for hte NN and C5.0. From left to right, the main statistical measurements are shown: accuracy (Acc), Kappa factor (Kp, sensitivity (Se), the specificity (Sp), the precision (Pr) and the geometric mean of the Acc and Pr, $G = \sqrt[2]{Pr \times Acc}$.

IV. Conclusions

This study compares the performances of two classification techniques when tackling the problem fall detection with data gathered from accelerometers located on one wrist. The original proposal detected fall events and performed a feature extraction which was classified with a feed-forward NN. A SMOTE stage is included to balance the transformed dataset previous modelling. Two different techniques are compared: the feed-forward NN and C5.0 decision trees. A publicly available dataset with falls has been used in evaluating the proposal. Interestingly, the two modelling techniques performed similarly, which suggest that in real world applications with the solution embedded in smartwatches perhaps the decision tree is more likely to be used.

Although exceptional results have been found using 10 fold cv, the 5x2 cv results suggest that still a high number of false alarms is obtained. Although the percentages are better that those reported for commercial devices, some design aspects must be analyzed in depth: the robustness to the variability in the behaviour of the user, or the tuning of the threshold to fit specific populations like the elderly.

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References

[1] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini, and AlessioVecchio, "A smartphone-based fall detection system," *Pervasive and Mobile Computing*, vol. 8, no. 6, pp. 883–899, Dec. 2012.

[2] S. B. Khojasteh, J. R. Villar, E. de la Cal, V. M. González, J. Sedano, and H. R. YAZĞAN, *submitted to the 13th International Conference on Soft Computing Models in Industrial and Environmental Applications*, 2018, ch. Evaluation of a Wrist-based Wearable Fall Detection Method.

[3] Purch.com, "Top ten reviews for fall detection of seniors," http://www.toptenreviews.com/health/senior-care/best-fall-detection-sensors/, 2018.

[4] R. Igual, C. Medrano, and I. Plaza, "Challenges, issues and trends in fall detection systems," *BioMedical Engineering OnLine*, vol. 12, no. 66, 2013. [Online]. Available: http://www.biomedical-engineering-online.com/content/12/1/66

[5] S. Zhang, Z. Wei, J. Nie, L. Huang, S. Wang, , and Z. Li, "A review on human activity recognition using vision-based method," *Journal of Healthcare Engineering*, vol. 2017, 2017.

[6] P. Kumari, L. Mathew, and P. Syal, "Increasing trend of wearables and multimodal interface for human activity monitoring: A review," *Biosensors and Bioelectronics*, vol. 90, no. 15, pp. 298–307, Apr. 2017.

[7] A. Sorvala, E. Alasaarela, H. Sorvoja, and R. Myllyla, "A two-threshold fall detection algorithm for reducing false alarms," in *Proceedings of 2012 6th International Symposium on Medical Information and Communication Technology (ISMICT)*, 2012.

[8] F. Bianchi, S. J. Redmond, M. R. Narayanan, S. Cerutti, and N. H. Lovell, "Barometric pressure and triaxial accelerometry-based falls event detection," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 6, pp. 619–627, 2010.

[9] T. Zhang, J. Wang, L. Xu, and P. Liu, "Fall detection by wearable sensor and one-class svm algorithm," in *Intelligent Computing in Signal Processing and Pattern Recognition*, ser. Lecture Notes in Control and Information Systems, I. G. Huang DS., Li K., Ed. Springer Berlin Heidelberg, 2006, vol. 345, pp. 858–863.

[10] A. Hakim, M. S. Huq, S. Shanta, and B. Ibrahim, "Smartphone based data mining for fall detection: Analysis and design," *Procedia Computer Science*, vol. 105, pp. 46–51, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050917302065

[11] F. Wu, H. Zhao, Y. Zhao, and H. Zhong, "Development of a wearable-sensor-based fall detection system," *International Journal of Telemedicine and Applications*, vol. 2015, p. 11, 2015. [Online]. Available: https://www.hindawi.com/journals/ijta/2015/576364/

[12] S. Abbate, M. Avvenuti, P. Corsini, J. Light, and A. Vecchio, *Wireless Sensor Networks: Application - Centric Design*. Intech, 2010, ch. Monitoring of human movements for fall detection and activities recognition in elderly care using wireless sensor network: a survey, p. 22.

[13] Y. S. Delahoz and M. A. Labrador, "Survey on fall detection and fall prevention using wearable and external sensors," *Sensors*, vol. 14, no. 10, pp. 19 806–19 842, 2014. [Online]. Available: http://www.mdpi.com/1424-8220/14/10/19806/htm

[14] J. R. Villar, S. González, J. Sedano, C. Chira, and J. M. Trejo-Gabriel-Galán, "Improving human activity recognition and its application in early stroke diagnosis," *International Journal of Neural Systems*, vol. 25, no. 4, pp. 1 450 036–1 450 055, 2015.

[15] S. González, J. Sedano, J. R. Villar, E. Corchado, Á. Herrero, and B. Baruque, "Features and models for human activity recognition," *Neurocomputing*, vol. in press, 2015.

[16] J. R. Villar, S. González, J. Sedano, C. Chira, and J. M. Trejo, "Human activity recognition and feature selection for stroke early diagnosis," in *Hybrid Artificial Intelligent Systems*, ser. Lecture Notes in Computer Science, J.-S. Pan, M. M. Polycarpou, M. Wozniak, A. de Carvalho, H. Quintián, and E. Corchado, Eds. Springer Berlin Heidelberg, 2013, vol. 8073.

[17] P. M. Vergara, E. de la Cal, J. R. Villar, V. M. González, and J. Sedano, "An iot platform for epilepsy monitoring and supervising," *Journal of Sensors*, vol. 2017, p. 18, 2017.

[18] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "Smote: synthetic minority over-sampling technique," *Journal of artificial intelligence research*, pp. 321–357, 2002.

[19] E. Casilari, J. A. Santoyo-Ramn, and J. M. Cano-Garca, "Umafall: A multisensor dataset for the research on automatic fall detection," *Procedia Computer Science*, vol. 110, no. Supplement C, pp. 32 – 39, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050917312899

[20] R Development Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2008, ISBN 3-900051-07-0. [Online]. Available: http://www.R-project.org

[21] M. Kuhn, "The caret package," http://topepo.github.io/caret/index.html, 2017, last checked 15-1-2018.

[22] R. Igual, C. Medrano, and I. Plaza, "A comparison of public datasets for acceleration-based fall detection," *Medical Engineering and Physics*, vol. 37, no. 9, pp. 870–878, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1350453315001575

[23] S. S. Khan and JesseHoey, "Review of fall detection techniques: A data availability perspective," *Medical Engineering and Physics*, vol. 39, pp. 12–22, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1350453316302600

[24] F. Bagala, C. Becker, A. Cappello, L. Chiari, K. Aminian, J. M. Hausdorff, W. Zijlstra, and J. Klenk, "Evaluation of accelerometer-based fall detection algorithms on real-world falls," *PLoS ONE*, vol. 7, no. 5, p. e37062, 2012.

[25] S. González, J. R. Villar, J. Sedano, J. Terán, M. L. Alonso-Álvarez, and J. González, "Heuristics for apnea episodes recognition," in *accepted for Proceedings of the International Conference on Soft Computing Models in Industrial and Environmental Applications*. Springer, 2015.

[26] J. R. Villar, M. Menéndez, E. de la Cal, V. M. González, and J. Sedano, "Identification of abnormal movements with 3d accelerometer sensors for its application to seizure recognition," *accepted for publication, International Journal of Applied Logic*, 2016.

[27] J. R. Villar, P. Vergara, M. Menéndez, E. de la Cal, V. M. González, and J. Sedano, "Generalized models for the classification of abnormal movements in daily life and its applicability to epilepsy convulsion recognition," *accepted for publication, International Journal of Neural Systems*, 2016.