Identification of Abnormal Behavior in Activities of Daily Life Using Novelty Detection

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Abstract. The world population is aging at a rapid pace. According to the WHO (World Health Organization), from 2015 to 2050, the proportion of elderly people will practically double, from 12 to 22%, representing 2.1 billion people. From the individual's point of view, aging brings a series of challenges, mainly related to health conditions. Although, seniors can experience opposing health profiles. With advancing age, cognitive functions tend to degrade, and conditions that affect the physical and mental health of the elderly are disabilities or deficiencies that affect Activities of Daily Living (ADL). The difficulty of carrying out these activities within the domestic context prevents the individual from living independently in their home. Abnormal behaviors in these activities may represent a decline in health status and the need for intervention by family members or caregivers. This work proposes the identification of anomalies in the ADL of the elderly in the domestic context through Machine Learning algorithms using the Novelty Detection method. The focus is on using available ADL data to create a baseline of behavior and using new data to classify them as normal or abnormal daily. The results obtained using the E-Health Monitoring database, using different Novelty Detection algorithms, have an accuracy of 91% and an F1-Score of 90%.

Keywords: Novelty Detection · Anomaly Detection · Activities of Daily Living · Machine Learning · One-Class Support Vector Machine (OC-SVM) · Local Outlier Factor (LOF)

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1 Introduction

The world population is aging at a rapid pace. According to the WHO, from 2015 to 2050. The proportion of people over 60 will practically double, from 12% to 22% of the population, representing 2.1 billion people. The number of people over 80 is expected to triple and reach 526 million [24].

From the individual's point of view, aging brings a series of challenges, mainly related to health conditions. Although seniors can experience opposite health profiles, several conditions are common at this stage of life [25]. The most common are chronic diseases affecting 80% of the elderly, such as hypertension, heart disease, heart failure, ischemic heart disease/coronary diabetes, chronic obstructive pulmonary disease, depression, Alzheimer's disease, and dementia [26].

Other conditions that affect the physical and mental health of the elderly are disabilities or impairments, which affect activities of daily living (ADL) [9]. It is estimated that more than 56% of the elderly suffer from moderate to severe disability, representing more than 256 million people [27]. The difficulty of carrying out these activities within the domestic context and which prevent the individual from living independently in their own home are minimized through Ambient Assisted Living (AAL) technologies.

AAL technologies aim to develop personal health and remote monitoring systems [8]. Thus, monitoring the ADL is essential to identify abnormalities in activities [2, 11]. It is because significant changes in the elderly's routine can represent a decline in physical or mental health. This detection allows family members and caregivers to be aware of the need for intervention [19]. The recognition of ADL is done by Human Activity Recognition (HAR) techniques [1, 14]. Recognizing these activities in a period defines a pattern of typical behavior, and, from this pattern, abnormalities can be detected [3, 22, 23].

In this context, the Novelty Detection technique can be used to identify abnormalities in ADL. Novelty Detection is a Machine Learning technique for the classification task. It is used when the target class is well characterized in the training data, and the data of the other class has few samples or is not well defined. This technique is also known as a class classification, and its use is related to identifying rare events and anomalies in [18]. Among the novelty detection algorithms are One-Class Support Vector Machine (OC-SVM) [12] and Local Outlier Factor (LOF) [5]. These algorithms were selected for this experiment because they are used in similar works.

OC-SVM is a powerful machine learning algorithm that can be used to build a model from only available normal data to learn its normal behavior. OC-SVM classifies any deviation from this normal behavior as anomalous [5, 36]. OC-SVM is very sensitive to the initial values of its hyperparameters [32, 33, 37] and this affects its generalization performance.

LOF is a density-based technique, that can be considered as a classical local outlier detection algorithm, widely used in network intrusion detection and processing of classification benchmark data [5, 38].

The main objective of this work is to identify ADL abnormalities in the elderly using the Novelty Detection technique. Where available, ADL data represent the individual's normal behavior, and subsequent data are analyzed to identify abnormal behaviors. This means predicting whether the newly observed data is within the pattern learned by the model, normal class, or is out of this pattern, characterizing an abnormality or, in the context of Novelty Detection, a novelty [18].

Although the focus and objective of the research carried out and the results obtained have no focus and relationship with the treatment of patient data privacy, we based our work on different works [6, 13, 15, 16, 34, 35]. These works present research and useful contributions to data privacy management in different concepts and scenarios.

The rest of the article is structured as follows: Sect. 2 shows the related works, Sect. 3 presents the methodology, Sect. 4 the results found, and Sect. 5 concludes the article.

2 Related Work

Through the search in the literature, four related works were identified. They all present the use of Machine Learning in conjunction with several algorithms for detecting anomalies in Activities of Daily Living. Also, one to three databases are used for analysis in conjunction with the algorithms.

Yahaya, Lofti, and Mahmud [23] used an ensemble of one-class support vector machine, isolation forest, robust covariance estimator and local outlier factor is utilized for the anomaly detection achieving an accuracy of 98%. Bozdog et al. [4] used five algorithms and two databases, one generated synthetically. The results were based on three quantities, each with an algorithm obtaining a better result.

Erfanmanesh, Tahayori, and Visconti [7] use four algorithms to detect and predict user actions and one to detect anomalies. The AdaBoost learning algorithm had the best performance and was used for detecting the anomalies and modeling normal/abnormal behavior. In conjunction with only one database, it obtained an accuracy of 100% and an approximate recall value of 83% in detecting abnormalities.

Finally, Fouquet, Faraut, and Lesage [10] use only one algorithm and database. The results were determined based on three scenarios: the inhabitant is in good health, lacks appetite, and has a urinary tract infection.

3 Methodology

The proposed workflow to identify ADL abnormalities is shown in Fig. 1. The steps presented in Fig. 1, are described below. The initial set of daily ADL data, which represents the baseline behavior of the elderly, is used to train the model. This model uses the following daily data to identify deviant daily routines that constitute an abnormality. The result for each new day observed is considered normal (1) or abnormal (−1).

This work has secondary objectives: (i) to identify the predictive attribute that presents the best model generalization analyzing activities' duration and duration/frequency attributes. (ii) identify the minimum number of weeks to obtain an accuracy above 85%; (iii) identify and select among the OC-SVM and LOF algorithms the one with the best performance; (iv) select the predictive parameter, training weeks, and the algorithm for the proposed anomaly identification model.

Among the ADL databases found in the literature [20, 21, 28–31], the eHealth Monitoring Open Data Project [28] was selected. This presents monitoring the elderly's ADL activity in the domestic context, where 21 activities are observed in one year. Each observation includes the day of the observation, the activity, and the start and end times. Activities include Eating, Laundry, Sleep, making coffee, Watching TV, and Cell Use, among others. On this basis, the monitoringP1HRversion dataset was selected. It contains 14297 records and presents the monitoring of the elderly's ADL on the one dependency profile of SMAF (Functional Autonomy Measurement System). This profile corresponds to an autonomous individual with some level of supervision and helps needed [17].

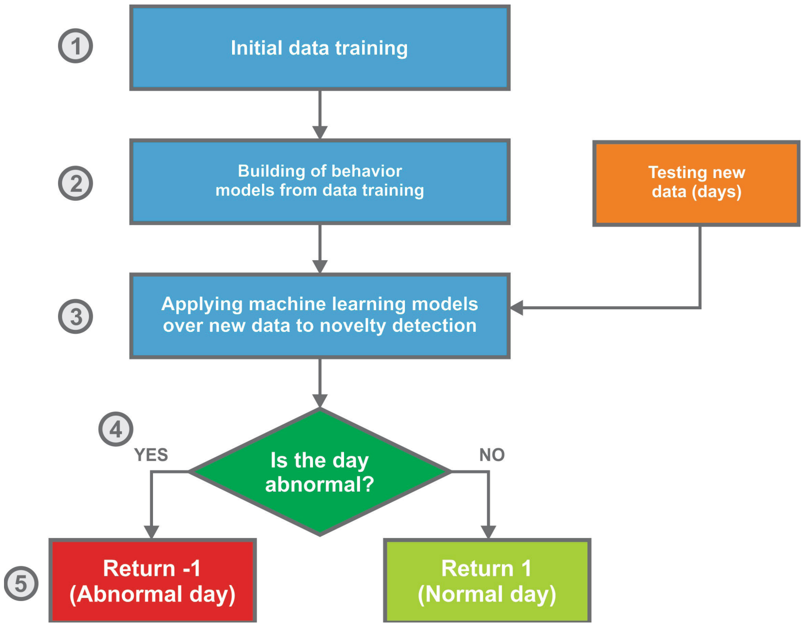

Fig. 1. Workflow to identify ADL abnormalities.

The development and pre-processing of data were done using the Python 3.10.7 programming language, using the Machine Learning library Scikit Learn 1.1.2.

3.1 Pre-processing

To use the E-Health monitoringP1HRversion dataset, it was necessary two steps to pre-processing data. Table 1 shows the dataset partially in raw format. In the first stage, the data were organized into a CSV file, presenting the same information as the original file, adding the duration of each activity (Table 2).

Table 1. Original dataset [28]

day_begin	day_end	begin_time	end_time	begin_time_seconds	end_time_seconds	activity_name	activity_number
1	1	08:03:32	08:22:40	29012	30160	Washing (take shower)	3
1	1	08:23:46	08:26:53	30226	30413	Hair dray	5
1	1	08:28:50	08:38:39	30530	31119	Change clothes	2
1	1	08:40:37	08:50:24	31237	31824	Toileting	7
1	1	08:52:12	08:55:38	31932	32138	Washing hand/face	4

Table 2. Pre-processing First Stage

day	activity_number	activity_name	duration	frequency	duration/frequency
1	1	Eating	73.450000	2	36.725000
1	2	Change clothes	21.983333	3	7.327778
1	3	Washing (take shower)	19.133333	1	19.133333
1	4	Washing hand/face	49.516667	10	4.951667
1	5	Hair dray	3.116667	1	3.116667

The second pre-processing stage included the creation of two distinct datasets using pivoting the dataset resulting from the second pre-processing stage. Both use activities as predictive attributes (columns), the first using the duration attribute as content (Table 3) and the second duration/frequency (Table 4). In both, the day of the task was kept. The creation of these two datasets is necessary for the generalization evaluation of the duration and duration/frequency predictive attributes. Nine activities were selected arbitrarily for this work to facilitate experiments and analysis. The selected activities were Change clothes, Eating, Make hot food, Sleep, Take M., Toileting, Take shower, Washing hand/face, Watching TV.

Table 3. Pre-processing result with the Duration predictive attribute

Activities									
day	Change clothes	Eating	Make hot food	Sleep	Take M	Toileting	Take shower	Washing hand/face	Watching TV
1	21.98	73.45	44.73	415.65	2.80	47.33	19.13	49.52	172.77
2	20.70	123.48	78.50	786.10	2.50	32.28	19.28	44.32	94.65
3	25.22	64.08	102.88	726.72	2.10	46.67	12.65	39.32	184.33
4	15.98	116.83	97.00	620.42	3.07	40.02	10.87	47.70	206.72
5	15.78	133.78	97.05	734.07	3.42	23.82	11.08	17.77	181.07

Table 4. Pre-processing result with the Duration/Frequency predictive attribute

Activities									
day	Change clothes	Eating	Make hot food	Sleep	Take M	Toileting	Take shower	Washing hand/face	Watching TV
1	7.33	36.73	44.73	207.83	2.80	7.89	19.13	4.96	86.38
2	6.90	41.16	39.25	262.03	2.50	8.07	19.28	4.43	47.33
3	8.41	32.04	51.44	242.24	2.10	6.67	12.65	4.91	36.87
4	7.99	38.94	48.50	206.81	3.07	8.00	10.87	4.34	68.91
5	7.89	44.59	48.53	244.69	3.42	7.94	11.08	4.44	36.21

3.2 Machine Learning for Novelty Detection

The novelty detection step predicts whether a given day is normal or abnormal. The OC-SVM and LOF algorithms were applied to the datasets resulting from the last pre-processing step. In both datasets, the data were separated into training, validation, and testing. For training data, the first 20 weeks of observations were selected. For validation data, the next eight weeks were determined. The same validation data were used for the training data, adding abnormalities. This addition obeyed the following rules: in the first 4 weeks, 1 to 9 activities were selected, in 50% of the data an increase from 20% to 200% was applied, and in the remaining 50% a decrease from 20% to 200%. Both the selection of activities and the changes in values were done randomly. In the remaining 4 weeks, no changes were applied to the data, maintaining the proportion of 50% between days with and without abnormalities. In this process, negative values were imputed, replacing them with zero. It is important to say that expansion and decreased values follow a normal error distribution Fig. 2 shows the graph of fluctuations applied to the dataset that uses the predictive attribute duration. Similarly, Fig. 3 shows the dataset that uses the duration/frequency predictive attribute.

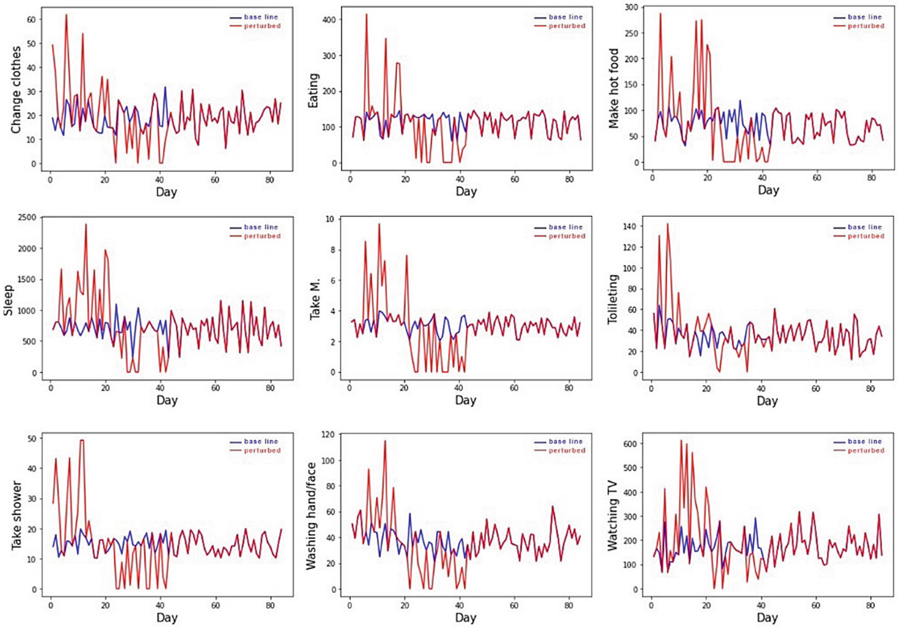

Fig. 2. Validation and test data with predictive attribute: duration.

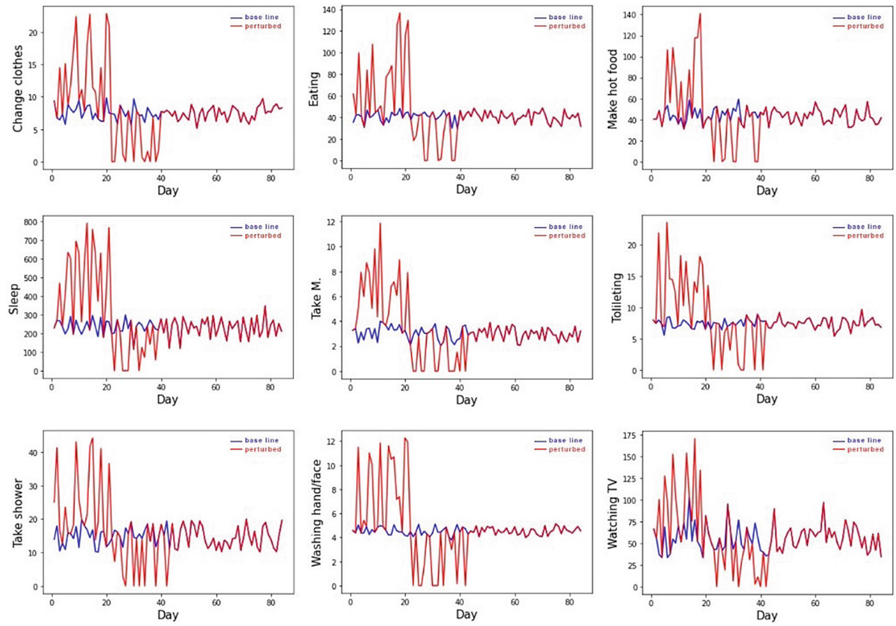

Fig. 3. Validation and test data with predictive attribute: duration/frequency.

Before applying the OC-SVM and LOF algorithms to the data, normalization was applied to the training, validation, and test data. Training data were used to adjust the normalization model.

4 Results

The performance of the LOF and OC-SVM algorithms can be seen in the graph presented in Fig. 4. It is observed that the LOF showed better results in using the predictive attribute duration and the attribute duration/frequency, reaching 100% accuracy and F1-score. While OC-SVM achieved 84% accuracy and 86% F1-score. However, it is observed that the predictive attribute duration/frequency presented better generalization using LOF, while the attribute duration was in OC-SVM. Regarding the number of weeks for training, the LOF showed accuracy above 80% from the 2nd week and the OC-SVM only from the 9th week. Another issue is that the OC-SVM presented a more unstable behavior in the generalization than the LOF. The values of the metrics can be seen in Table 5.

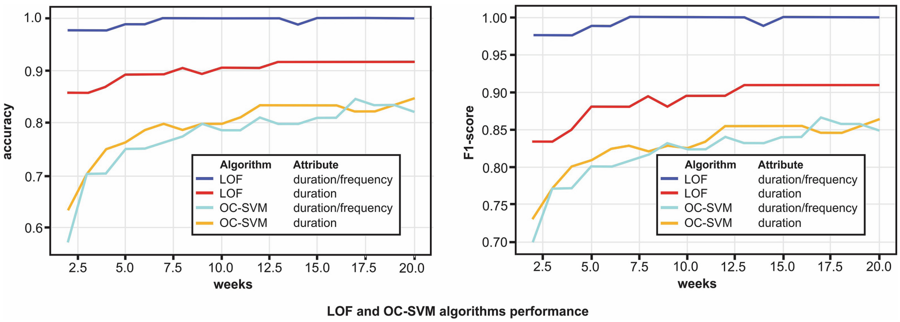

Fig. 4. Performance of the LOF and OC-SVM algorithms.

Considering the results presented in the previous section, the following were selected for the proposed model: the LOF algorithm, for having demonstrated a better performance than the OC-SVM; set the predictive attribute duration/frequency, for achieving a better generalization of the model; and two weeks for the minimum number of training data. Table 6 presents the metrics achieved by the model. The proposed model achieved 98% accuracy and F1-score, using two weeks of ADL data for training, using the duration/frequency predictive attribute.

Table 5. Performance of the LOF and OC-SVM algorithms by predictive attributes.

LOF				OC-SVM			
duration		duration/frequency		duration		duration/frequency	
accuracy	F1score	accuracy	F1score	accuracy	F1score	accuracy	F1score
0.857	0.833	0.976	0.976	0.631	0.73	0.571	0.7
0.857	0.833	0.976	0.976	0.702	0.771	0.702	0.771
0.869	0.849	0.976	0.976	0.75	0.8	0.702	0.771
0.893	0.88	0.988	0.988	0.762	0.808	0.75	0.8
0.893	0.88	0.988	0.988	0.786	0.824	0.75	0.8
0.893	0.88	1	1	0.798	0.828	0.762	0.808
0.905	0.895	1	1	0.786	0.82	0.774	0.816
0.893	0.88	1	1	0.798	0.828	0.798	0.832
0.905	0.895	1	1	0.798	0.825	0.786	0.824
0.905	0.895	1	1	0.81	0.833	0.786	0.824
0.905	0.895	1	1	0.833	0.854	0.81	0.84
0.917	0.909	1	1	0.833	0.854	0.798	0.832
0.917	0.909	0.988	0.988	0.833	0.854	0.798	0.832
0.917	0.909	1	1	0.833	0.854	0.81	0.84
0.917	0.909	1	1	0.833	0.854	0.81	0.84
0.917	0.909	1	1	0.821	0.845	0.845	0.866
0.917	0.909	1	1	0.821	0.845	0.833	0.857
0.917	0.909	1	1	0.833	0.854	0.833	0.857
0.917	0.909	1	1	0.845	0.863	0.821	0.848

Table 6. Proposed method performance for the evaluated metrics.

True Positive	True Negative	False Positive	False Negative	Accuracy	Precision	Recall	F1-score
40	42	2	0	0.976	0.952	1	0.976

5 Conclusion

This work proposed a model to identify abnormalities in the Activities of Daily Living of the Elderly using the Novelty Detection method. And it had as sub-objectives: to evaluate the LOF and OC-SVM algorithms; identify the predictive attribute with the best generalization, considering the duration and duration/frequency attributes; determine the minimum number of training weeks to obtain an accuracy greater than or equal to 85%; and select the best configuration for the proposed model based on the results.

The E-Heath database was used to train the model. The first 20 weeks were used as training data and the subsequent 8 weeks for validation and test data. In addition, over 50% of the test data, 1 to 9 activities were selected, adding variations from 20 to 200% for plus and minus, maintaining the 50% ratio between data with and without variances.

The novelty detection algorithms OC-SVM and LOF were used and evaluated in the detection of anomalies. As a result, the LOF performed better, with an F1-score accuracy of 97% from the second week onwards and 100% from the seventh week onwards. The OC-SVM presented its highest accuracy and F1-Score in the twentieth week, respectively 84% and 86%. However, OC-SVM presented better generalization with the use of the duration predictive attribute, and the LOF with the duration/frequency attribute.

Considering the results presented, the following were selected for the predictive model: the LOF algorithm, for achieving a better performance in relation to the OC-SVM; the predictive attribute duration/frequency, for presenting a greater generalization with the LOF; and two weeks for model training data. The proposed model achieved an accuracy and F1-Score of 98%.

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References

1. Abdulhussein, A.A., Hassen, O.A., Gupta, C., Virmani, D., Nair, A., Rani, P.: Health monitoring catalogue based on human activity classification using machine learning. Int. J. Electr. Comput. Eng. **12**(4), 3970 (2022)
2. Acuña, S.A., Tyler, M.E., Danilov, Y.P., Thelen, D.G.: Abnormal muscle activation patterns are associated with chronic gait deficits following traumatic brain injury. Gait Posture **62**, 510–517 (2018). https://doi.org/10.1016/j.gaitpost.2018.04.012
3. Arifoglu, D., Bouchachia, A.: Detection of abnormal behaviour for dementia sufferers using Convolutional Neural Networks. Artif. Intell. Med. **94**, 88–95 (2019)
4. Bozdog, I.A., et al.: Human behavior and anomaly detection using machine learning and wearable sensors. In: 2021 IEEE 17th International Conference on Intelligent Computer Communication and Processing (ICCP), pp. 383–390. IEEE (2021)

5. Budiarto, E.H., Permanasari, A.E., Fauziati, S.: Unsupervised anomaly detection using K-means, local outlier factor and one class SVM. In: 2019 5th International Conference on Science and Technology (ICST), pp. 1–5. IEEE (2019)
6. Cesconetto, J., Augusto Silva, L., Bortoluzzi, F., Navarro-Cáceres, M., Zeferino, C.A., Leithardt, V.R.Q.: PRIPRO—privacy profiles: user profiling management for smart environments. Electronics **9**, 1519 (2020). https://doi.org/10.3390/electronics9091519
7. Erfanmanesh, M., Tahayori, H., Visconti, A.: Elderly action prediction and anomalous activity detection in smart homes through profiling residents' behavior. Mod. Care J. **16**(3), e94661 (2019). https://doi.org/10.5812/modernc.94661
8. Ferreira, J.M., et al.: Activities of daily living and environment recognition using mobile devices: a comparative study. Electronics **9**, 180 (2020). https://doi.org/10.3390/electron-ics9010180
9. Foti, D., Koketsu, J.S.: Activities of daily living. Pedretti's Occup. Ther. Pract. Skills Phys. Dysfunction **7**, 157–232 (2013)
10. Fouquet, K., Faraut, G., Lesage, J.-J.: Model-based approach for anomaly detection in smart home inhabitant daily life. In: 2021 American Control Conference (ACC), pp. 3596–3601. IEEE (2021)
11. Guo, J., Zhou, X., Sun, Y., Ping, G., Zhao, G., Li, Z.: Smartphone-based patients' activity recognition by using a self-learning scheme for medical monitoring. J. Med. Syst. **40**(6), 1–14 (2016). https://doi.org/10.1007/s10916-016-0497-2
12. Jin, B., Chen, Y., Li, D., Poolla, K., Sangiovanni-Vincentelli, A.: A one-class support vector machine calibration method for time series change point detection. In: 2019 IEEE International Conference on Prognostics and Health Management (ICPHM), pp. 1–5. IEEE (2019)
13. Leithardt, V., et al.: A privacy taxonomy for the management of ubiquitous environments. J. Commun. Comput. **10**, 1529–1553 (2013)
14. Leithardt, V.R., et al.: Mobile architecture for identifying users in ubiquitous environments focused on Percontrol. In: The Seventh International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies, UBICOMM, pp. 145–151 (2013)
15. Leithardt, V.R., et al.: Mechanism for privacy management based on data history (UbiPri-His). J. Ubiquit. Syst. Pervasive Netw. **10**, 11–19 (2018)
16. Leithardt, V.R., Nunes, D., Rossetto, A.G., Rolim, C.O., Geyer, C.F., Silva, J.S.: Privacy management solution in ubiquitous environments using percontrol. J. Ubiquit. Syst. Pervasive Netw. **5**, 21–28 (2014)
17. Mshali, H., Lemlouma, T., Magoni, D.: Analysis of dependency evaluation models for eHealth services. In: 2014 IEEE Global Communications Conference, Austin, TX, USA, pp. 2429–2435. IEEE (2014)
18. Ouafae, B., Oumaima, L., Mariam, R., Abdelouahid, L.: Novelty detection review state of art and discussion of new innovations in the main application domains. In: 2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), pp. 1–7. IEEE (2020)
19. Pires, I.M., et al.: Mobile 5P-medicine approach for cardiovascular patients. Sensors **21**, 6986 (2021). https://doi.org/10.3390/s21216986
20. Pires, I.M., Garcia, N.M., Zdravevski, E., Lameski, P.: Activities of daily living with motion: a dataset with accelerometer, magnetometer and gyroscope data from mobile devices. Data Brief **33**, 106628 (2020). https://doi.org/10.1016/j.dib.2020.106628
21. Pires, I.M., Garcia, N.M., Zdravevski, E., Lameski, P.: Daily motionless activities: a dataset with accelerometer, magnetometer, gyroscope, environment, and GPS data. Sci Data **9**, 105 (2022). https://doi.org/10.1038/s41597-022-01213-9
22. Saha, S.S., Rahman, S., Rasna, M.J., Mahfuzul Islam, A.K.M., Rahman Ahad, Md.A.: DU-MD: an open-source human action dataset for ubiquitous wearable sensors. In: 2018 Joint

7th International Conference on Informatics, Electronics & Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision & Pattern Recognition (icIVPR), Kitakyushu, Japan, pp. 567–572. IEEE (2018)
23. Yahaya, S.W., Lotfi, A., Mahmud, M.: Detecting anomaly and its sources in activities of daily living. SN Comput. Sci. **2**(1), 14 (2020). https://doi.org/10.1007/s42979-020-00418-2
24. Ageing and health. https://www.who.int/news-room/fact-sheets/detail/ageing-and-health. Accessed 5 Aug 2020
25. 10 facts on ageing and health. https://www.who.int/news-room/fact-sheets/detail/10-facts-on-ageing-and-health. Accessed 2 Sept 2022
26. The Top 10 Most Common Chronic Diseases for Older Adults. https://www.ncoa.org/article/the-top-10-most-common-chronic-conditions-in-older-adults. Accessed 2 Sept 2022
27. Ageing and disability: United Nations Enable. https://www.un.org/development/desa/disabilities/disability-and-ageing.html. Accessed 2 Sept 2022
28. eHealth Monitoring Open Data Project. SourceForge. https://sourceforge.net/projects/ehealthmonitoringproject/. Accessed 2 Sept 2022
29. Welcome to CASAS. http://casas.wsu.edu/datasets/. Accessed 2 Sept 2022
30. DaLiAc: Daily Life Activities. https://www.mad.tf.fau.de/research/activitynet/daliacdaily-life-activities/. Accessed 2 Sept 2022
31. UCI Machine Learning Repository: Activities of Daily Living (ADLs) Recognition Using Binary Sensors Data Set. https://archive.ics.uci.edu/ml/datasets/Activities+of+Daily+Living+(ADLs)+Recognition+Using+Binary+Sensors. Accessed 2 Sept 2022
32. Xiao, Y., Wang, H., Xu, W.: Parameter selection of Gaussian kernel for one-class SVM. IEEE Trans. Cybern. **45**(5), 941–953 (2015)
33. Zou, X., Cao, J., Guo, Q., Wen, T.: A novel network security algorithm based on improved support vector machine from smart city perspective. Comput. Electr. Eng. **65**, 67–78 (2018)
34. Silva, L.A., Leithardt, V.R.Q., Rolim, C.O., González, G.V., Geyer, C.F.R., Silva, J.S.: PRISER: managing notification in multiples devices with data privacy support. Sensors **19**(14), 3098 (2019). https://doi.org/10.3390/s19143098
35. Apolinário, V.A., Dal Bianco, G., Duarte, D., Leithardt, V.R.Q.: Exploring feature extraction to vulnerability prediction problem. In: de la Iglesia, D.H., de Paz, J.F., Santana, A.J., Rivero, L. (eds.) New Trends in Disruptive Technologies, Tech Ethics and Artificial Intelligence: The DITTET 2022 Collection, pp. 79–90. Springer, Cham (2023). https://doi.org/10.1007/978-3-031-14859-0_7
36. Klikowski, J., Woźniak, M.: Employing one-class SVM classifier ensemble for imbalanced data stream classification. In: Krzhizhanovskaya, V.V., et al. (eds.) ICCS 2020. LNCS, vol. 12140, pp. 117–127. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-50423-6_9
37. Khraisat, A., Gondal, I., Vamplew, P., Kamruzzaman, J., Alazab, A.: Hybrid intrusion detection system based on the stacking ensemble of C5 decision tree classifier and one class support vector machine. Electronics **9**(1), 173 (2020). https://doi.org/10.3390/electronics9010173
38. Alghushairy, O., Alsini, R., Soule, T., Ma, X.: A review of local outlier factor algorithms for outlier detection in big data streams. Big Data Cogn. Comput. **5**, 1 (2021). https://doi.org/10.3390/bdcc5010001