IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

FALL DETECTION & DAILY LIVING ACTIVITY RECOGNITION USING CNN

S. Vyshali
Scholar, M.E. Computer Science and Engineering
KIT – KalaignarKarunanidhi Institute of Technology (Autonomous)
Coimbatore, TN, India

Dr. S. Raja Mohamed
Head of Department, Computer Science and Engineering
KIT – KalaignarKarunanidhi Institute of Technology (Autonomous)
Coimbatore, TN, India

Abstract-- The number of elder people in countries were increasing in number due to cultural life. Most of them prefer in be independent and leads in fall. Fall was often leads in serious and even severe injuries which leads in cause death for elder people. In address that problem, since must be essential to develop fall detection systems. In that project, developed a machine learning algorithm for fall detection and living activity recognition. Using acceleration with angular velocity data from public datasets are used in recognizing the 9 different activity which includes the falls and activity of daily living. From the angular velocity with acceleration frequency domain features, data, extracting time and providing a classification algorithms. The project proposes a machine learning algorithm for fall detecting and living activities recognizing, Convolution Neural Network was used in Classification. the first better contribution has been shown with the feature for fall detecting. More importantly, using the value of mean for triaxial acceleration and achieving the fall detecting accuracy and precision as best one. Even though, value of mean for triaxial acceleration was not shown a new feature since was used in previously proposals in classify ADLs, the value of mean of the triaxial acceleration is not utilizing as the features of classification the entire falls.

***Keywords:** elder fall detect, living activity recognition, convolutional neural network, dataset values.*

I. INTRODUCTION

Elder person who lives in all over the world faces much fall down was not only because of the faint. Elder person could experience the fear various types of the fall down violence in the public places.

Since happens on the workplaces, home, streets, public transport and parks, in public sanitation facility or in their own neighborhoods. Elder person adapts in assembling various groups of a adequate cause. Elder person often works over the national, the dedicated, the domineering, and the conceptual divides in motivate tranquility. the were all were in importance of elder person's security, but the would remember that would be well secured. Elder persons was not substantially muscular as dissimilarity in men; in cases, helping hand would be the relaxation for elder lives. The foremost way was in decreasing the possibility of violent crime (robbery, the fall down assault, the rape, and the domestic violence) was in discover and call on resources for helping out of the unsafe circumstances.

Artificial Intelligence, Machine Learning and Deep Learning was introduced better prediction by avoiding the noise and extracting the useful information for the datasets. These techniques was mainly used in removal of unwanted information for the datasets with applying dimensionality reduction techniques.

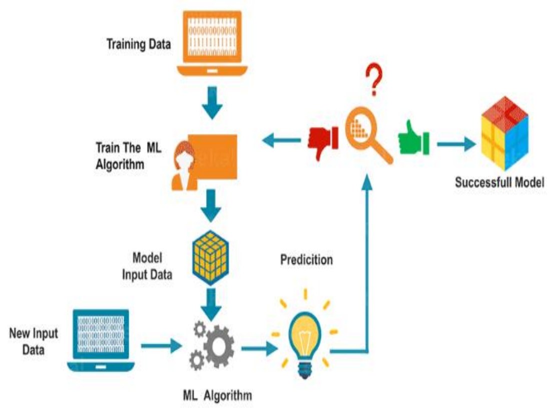

Fig 1a Work of ML (Reference)

The main contribution was related in features used in fall detection. More specifically, the were using the value of mean for triaxial acceleration and precision. Convolution Neural Network Classifier was used in find fall detection and living activity recognition.

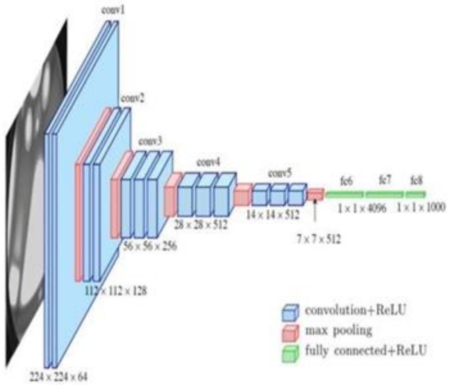

Fig 1b CNN Structure (Reference)

From literature survey, since was noticed that a few techniques proposed for recognizing daily activity and fall detection, []. Since was also noticed that though numerous methods and techniques proposed for that purpose, the need still better classifiers for the best prediction with highest prediction accuracy.

From the Literature Survey, since was noticed that there were still various intelligent techniques proposed namely pattern recognition, classification, and predictive methods for better cardiovascular problems prediction.

II. RELATED WORKS

Besides most research were concerning in the sketched in camera-based fall discovery used in simulate the datasets recorded on 2D Cameras, in best of the understanding the dataset were present practically: the datasets which was taken in Auvinet. [3] , the dataset which was taken in Charfi. [1].

Imen Charfi, J Miteran, Julien Dubois [1] was introduced the Support Vector Machine Based fall discovery system which were automatic approach in detecting the falls in the home environment and tried in achieve the better performance by using the single camera usage. the video segment ranged on 10 in 45s. About 190 of the video segment containing the fall incidents and 55 containing standard activity such as sit down, walking, stand up, and house keeping. In preferable since the real life activities, Charfi, consolidate some of provocation listed in [2] in the dataset such as modifications in light potency, penumbra and shaking the object. In further enhancements of the practicality for the datasets. Using a Support Vector Machine in categorizing each image.

All results with Support Vector Machine were obtained within a home-based software in the Support Vector Machine library. Experiment shows the best interchange in the middle of categorizing the demonstration on time handling result were acquired by incorporate the initial data within the foremost deviations. The global error rate was lesser than 3% & recall specificity and precision were high (respectively 0.97, 0.986, 0.953).

Rougier [12] has introduced "video surveillancing for fall discovery system. A Shape Matching technique was used. The falls were often detected in normal activity used in a Gaussian Mixture Model. The Shape matching were demonstrated by C++ with open CV library and the fall discovery system steps was demonstrated in Matrix laboratory by Network Laboratory for performing the Gaussian Mixture Model categorization. Technique was comparing with other 2D feature. The best categorizing error rate was less than 12% for each of the camera unaccompanied and dropping in 1.7% using weight of vote in the mean blending cost of the weight of vote given more than 92% correctness.

Rougier [12] obtaining global error rate was 3.4% However, these rates were not really compatible since testing protocol was different: Examinate the performance of the telecast surveillancing, in which was not really germane for the real world where the telecast was consumed on a uninterrupted manner, Comparatively, they pick the alignment of the camera of Rougier was not desirable in the attribution wrenching out. Rougier appraisal the algorithm using the database, and gaining a recall of 75% and global error rate of 6%, and the precision of 95.7%.

Auvinet [3] documented 20 video segment drawing from 30s in 4 minutes using 8 calibrated camera. The video segment contains 20 fall gatherings and 22 another event such as sleeping, sitting, and standing. Auvinet, using previous researchers for constructing realistic fall scenario.

Since those were adequately using on elder people and could show the own challenge whenever a fall occurs (e.g. peter rolls on the floor while the falls occurs), they must be including in both fall and non-fall structure.

Debard. [14] compared the demonstration of the state of picture fall discovery in the dataset of Auvinet. and the real world datasets. That practically implemented the need for more realistic dataset.

Although those 2D video-based fall discovery datasets, that there were few datasets demonstrated in which was recording for the Microsoft, which improves a colour image, such as the which dataset with Bogdan and Kepski [15], Anderson. [16] and the dataset with Gasparrini. [17]. further in the dataset there were also some steps to identify datasets demonstrated in which counting falls as the steps such as in which the in dataset from Kuehne. [18]. All the dataset as well as steps to identify dataset were moreover subjects in the similar imperfection as datasets such as very few fall and activity of daily living segments, fewer amount in fall scenario, non-realistic fall and no appliances, or a limited amount of appliances in room

III. A PUBLIC DOMAIN DATASET FOR HUMAN ACTIVITY RECOGNITION USING BY MOBILE PHONES

Human-centred computing was emerging research that aims in understanding the human behavioural and users and the social activity in computer applications. almost demanding, and favourable approach in that framework consists of sensing human body motion with help of mobile phones in acquire knowledge about elder lives activities.

In Paper, Chronicles the work in Activity recognizing database, built in the recorded of 32 suspects by Activity of Daily Living while switching a waist-in the saddle of mobile phones which immerse with inertial sensors, which was used in rescue the public province in well-being manner, acquired in the dataset with make the most of a multiclass Support Vector Machine, was also accomplishing. That the paper were presenting a publicly demonstrate dataset for Highway advisory ratio using mobile phones and recognizing some other results using by multiclass

SVM method. The multiclass Support vector machine deployed for the categorization in mobile phones inertial data demonstrated in a recollecting accomplish as much like foregoing paper that have using motivation sensors, therefore reinforce supplication of the devices for HAR more or less.

Since emphasized with increasing on the categorization presenting in the learned model used by that raw dataset among the previous version, which had in be decreased set for features. However, rooms for enhanced exist: while actuate activity can be sufficient categorization sincerely thank you in the newly present affection with the ejected dataset, non-actuate actions were present categorization overlaps. That needs foremost study of sufficient inputs and alteration for the

	WK	WU	WD	ST	SD	LD	**Recall**
Walking	**492**	1	3	0	0	0	99%
W. Upstairs	18	**451**	2	0	0	0	96%
W. Downstairs	4	6	**410**	0	0	0	98%
Sitting	0	2	0	**432**	57	0	88%
Standing	0	0	0	14	**518**	0	97%
Laying Down	0	0	0	0	0	**537**	100%
Precision	95%	96%	96%	95%	94%	100%	**95%**

HAR process pipeline articulate. Finally, computational entanglement aspects such as battery life and real time adapting of the application would be calculate on the forth upcoming works.

In HAR research, some datasets had been ejected in the public domain: where one of the liberty Project [10] were an example which have been evidenced a set of activity daily living in a sensor rich ambient using 70 ambient and body sensors. Similarly, on the other hand had allocating the public evidence, such as [11] and [13]. Publicly offered datasets provides a open source partible for data for dissimilar castigates and researchers.

Table 1: Confusion Matrix for the categorization results in the test data [5]

IV. DATASET FOR FALL EVENTS AND DAILY activity FROM INERTIAL SENSORS

Wearable sensors was being remodelled more relevant in exotic health monitoring since technology elevated and cost decrease. In which wearable sensors was agglomerate being used was falls monitoring. The elderly in foremost were endangered in falls and require uninterrupted monitoring. Indeed, many attempts, with inadequate success have been made towards perfect, universal falls and activity of Daily Living categorization. A major challenge in elaborating solutions for fall discovery was access in adequate large data sets. That paper presents a depiction for the data set and the demonstrated protocols sketched by the authors for the simulation of falls, near-falls and ADL. Forty-two foremost were employed in participate in an demonstration that involved a set of scripted protocols.

Four types of falls (onward, thrown off, lateral left and right) and several ADL were artificial. That data set was calculated for the appraisal of fall discovery algorithms by misspending daily activity and change over from one posture in another with falls. In the ahead of work, machine learning based fall discovery algorithms were sketched and appraised. That paper chronicles the data set imperturbable for artificial falls, near-falls and ADL. Protocols were sketched such that the data algometer were personation of the activity chance upon during real-life system use. they used that data set to the ahead of work in foremost machine learning based fall discovery algorithms.

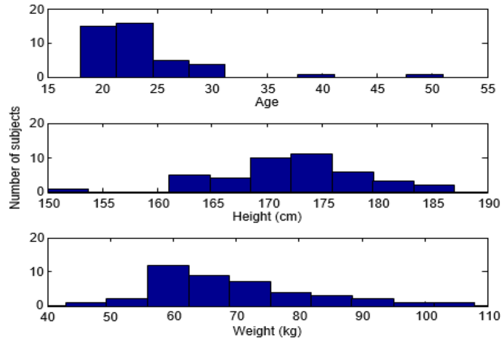

Fig 3: Subject’s Body profile dwastribution[6]

A. Protocol 1

Protocol 1 categorized four types of falls (front, back, left, right falls) and the set of activity for daily living (sleeping, walking, sitting, standing, jogging). In addition, Protocol 1 also counting loss of equilibrium and falls arguing by implementing the oblique force on the subjects. Near-falls were often get together that occurs in a result of spills, trips or accident on crosspiece, but do not intrude result in falls.

B. Protocol 2 →Ascending and dropping of stairs

Mounting a staircase was part of a normal daily activities, which was categorized in fast shifting for the limbs and demand to a high level of harmonize. since, was a assuredly vicious, and the exigent importunate task for a elderly persons [20]. Ascending and dropping in the elevator also describes higher peculiarity on glance amplitude like falls than static activity and may basis fall discovery algorithm on output false positives.

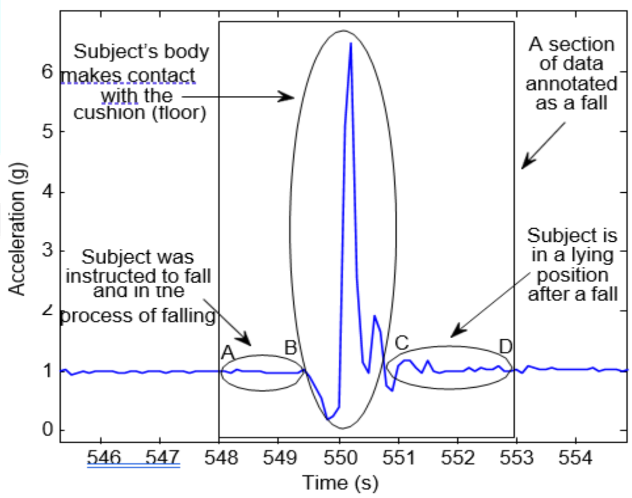

Fig 4: Fall annotation for a single fall event [6]

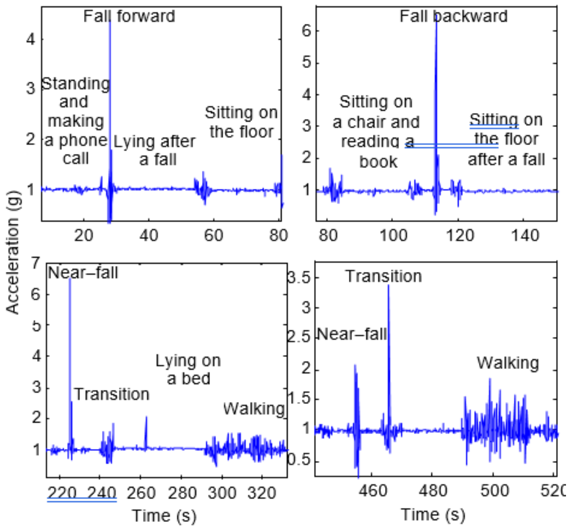

Fig 5: activities and events generated using data [6]

V. SISFALL

Researchers in the fall and daily living movement detecting with holdable devices had showed a compermising growth. However, there were kind of available datas that all recording with mobile phones, which were inadequate data for testing the papers published due in the truancy of aspiration population, paucity of performing the activities, and bounded information. Here, provisional a dataset of falls and activity of daily living consummate with a individual-developed device has two types for accelerometers and the one particular gyroscope.

Since list of 15 ADLs and 20 fall types. Those were performing by 25 young people, 17 daily living activity types performing by 20 healthy and individual participants over 70 years old lives, and data for one participants of 80 years old performing all activity of daily living and falls.

The data is obtained with an accelerometer makes on the body. among the dataset represented a 5 Hz fourth order filter that moves enough information for fall detection on independently elder lives to avoid severe injuries.

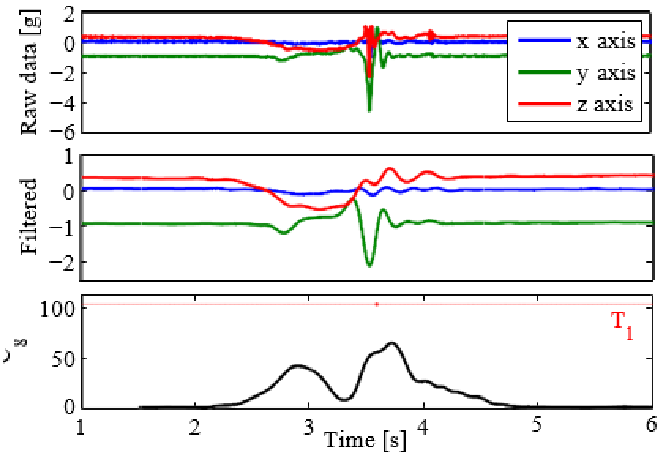

Fig 6: Activity of daily living [20]

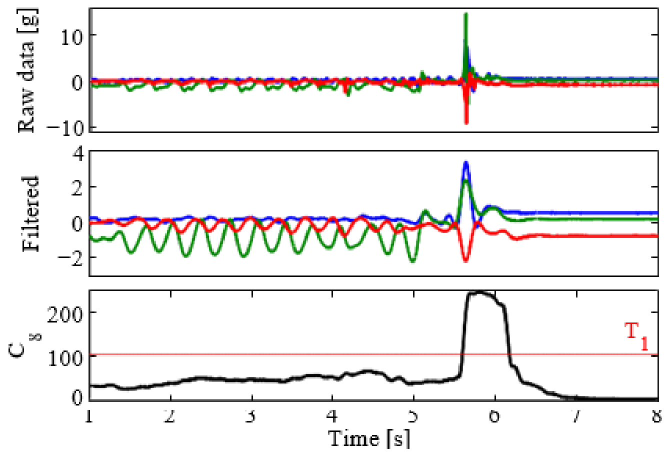

Fig 7: Fall trip and fall [20]

VI. EXPERIMENTAL SETUP

The proposed system were completed within 8 GB RAM, Windows 11 Operating System, Intel core i9 processor, 120 GB hard disc. That technique was implemented by the software IDE-Anaconda and notebook.

Primary packages were moving in the Pandas in work to data, NumPy with arrays, scikit-learn for building and evaluating the classifying models data split and imported all the primary packages in the python environment.

A. Performance Metrics

Accuracy

It is the ratio between total number of corretly predicted predictions to the total number of predictions to be made. ie sum of True Positive Prediction and Sum of True Negative Predictions to Total numbers of True Positive, True Negative, False Positive and False Negative.

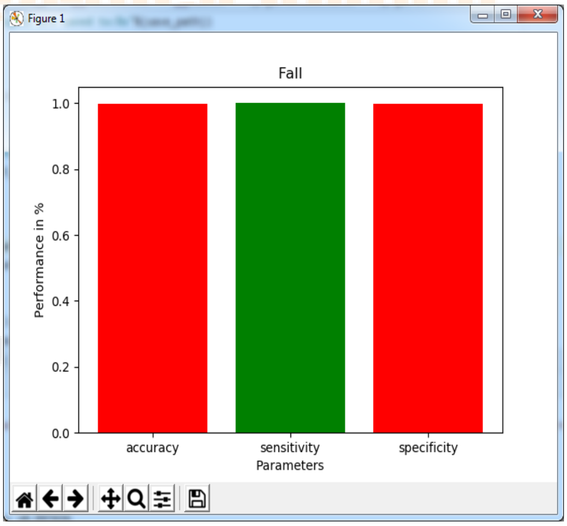

Fig 8 Performance graph for Fall

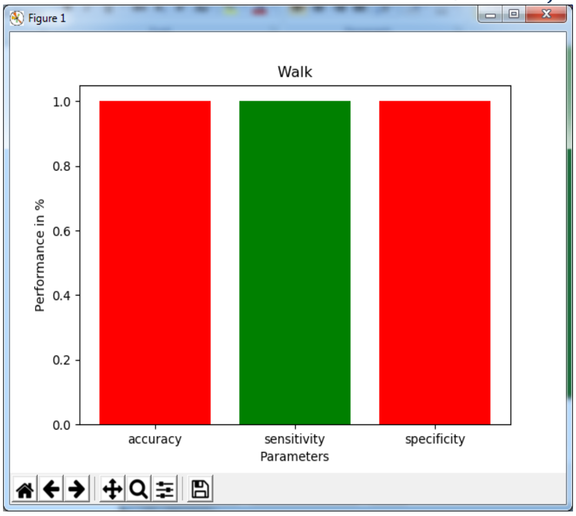

Fig 9 Performance graph of Walk

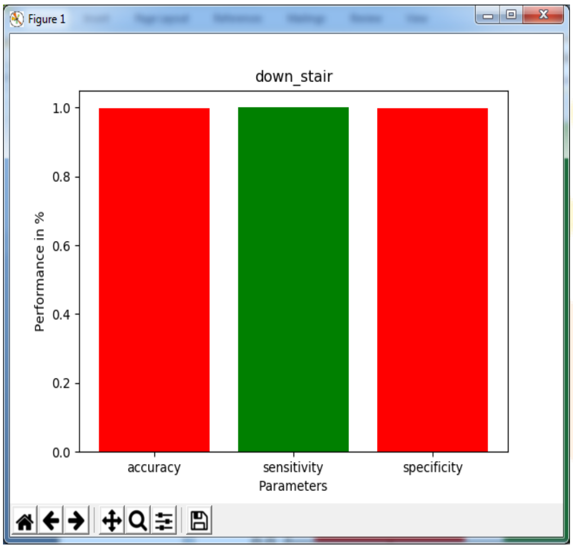

Fig 10 Performance graph of Downstairs

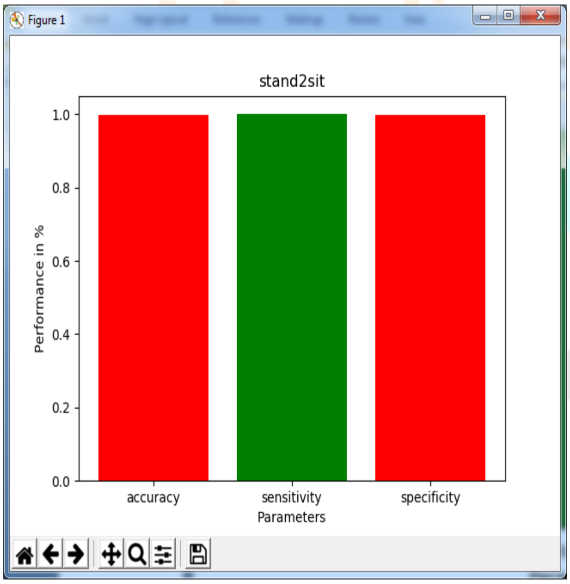

Fig 11 Performance graph of Stand2Sit

VII. CONCLUSION

A fall detection system are important in supporting the independent living of elder lives. From the proposals the get to know that most of the algorithms are used like SVM, KNN, and LIBSVM, HAR for detecting the daily living activity and almost achieved their prediction are performing well during Training and Testing Processes in form of Prediction Accuracy, Sensitivity, Specificity, Precision. By using SVM is not suitable for better prediction when Datasets have more different patterns with very less dissimilarities. To address this identified issues, this research work is planned to propose an Intelligent Classifier for better prediction.

REFERENCES

[1] I. Charfi, J. Miteran, J. Dubowas, M. Atri, and R. Tourki, “Definition and performance evaluation of a robust SVM based fall detection solution,” in 2012 Eighth International Conference on Signal Image Technology and Internet Based Systems. Naples, Italy: IEEE, Nov. 2012, pp. 218–224.

[2] Debard G., Karsmakers P., Deschodt M., *ET AL*.: ‘Camera-based fall detection on real world data, outdoor and large-scale real world scene analyswas’ (Springer, 2012), pp. 356–375

[3] Auvinet E., Multon F., Saint-Arnaud A., *ET AL*.: ‘Fall detection with multiple cameras: an occlusion reswastant method based on 3-D silhou- ette vertical dwastribution’, IEEE Trans. Inf. Technol. Biomed., 2011, 15, (2), pp. 290–300

[4] Medrano, C.; Igual, R.; Plaza, I.; Castro, M. Detecting Falls as Novelties in Acceleration Patterns Acquired with mobile phones . *PLoS ONE* **2014**, *9*, e94811.

[5] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, “A public domain dataset for human activity recognition using mobile phones ,” in European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, Bruges, Belgium, Apr. 2013, pp.24–26.

[6] O. Ojetola, E. Gaura, and J. Brusey, “Data set for fall events and daily activity from inertial sensors,” in 6th ACM Multimedia Systems Conference - MMSys ’15, Portland, OR, USA, Mar. 2015, pp. 243–248.

[7] Vavoulas, G.; Pediaditwas, M.; Chatzaki, C.; Spanakwas, E.; Tsiknakwas, M. The MobiFall Dataset: Fall Detectionand Classification with a Smartphone. *Int. J. Monit. Surveill. Technol. Res.* **2014**, *2*, 44–56.

[8] Frank, K.; Vera, M.J.; Robertson, P.; Pfeifer, T. Bayesian Recognition of Motion Related activity with Inertial Sensors. In Proceedings of the 12th ACM International Conference on Ubiquitous Computing (UbiComp), Copenhagen, Denmark, 26–29 September 2010; pp. 445–446.

[9] C. Cortes and V. Vapnik. Support-vector networks. Machine learning, 20(3):273–297, 1995.

[10] D. Roggen, A. Calatroni, M. Rossi, T. Holleczek, K. Förster, G. Tröster, P. Lukowicz, D. Bannach, G. Pirkl, and A. Ferscha. Collecting complex activity data sets in highly rich networked sensor envi- ronments. In Proceedings of the 7th International Conference on Networked Sensing Systems 2010, 2010.

[11] E.M. Tapia, S.S. Intille, L. Lopez, and K. Larson. The design of a portable ksince of wireless sensors for naturalwastic

data collection. In Proceedings of PERVASIVE 2006, pages 117–134, 2006.

[12] Caroline Rougier, Jean Meunier, Alain St- and Jacqueline "Robust Video Surveillance for Fall Detection Based on Human Shape Deformation" 2011

[13] S. Dernbach, B. Das, N.C. Krwashnan, B.L. Thomas, and D.J. Cook. Simple and complex activity recog-nition through smart phones. In *2012 8th International Conference on Intelligent Environments*, pages 214–221, 2012.

[14] Debard G., Mertens M., Deschodt M., *ET AL.*: 'Camera-based fall detection using real-world versus simulated data: how far were the from the solution?', *J. Ambient Intell. Smart Environ.*, 2015, In appear

[15] Bogdan K., Kepski M.: 'Human fall detection on embedded platform using depth maps and wireless accelerometer', *Comput.* Methods Programs Biomed., 2014, 117, (3), pp. 489–501

[16] Anderson D., Luke R.H., Keller J.M., *ET AL.*: 'Linguwastic summariza- tion of video for fall detection using voxel person and fuzzy logic', *Comput. Vwas. Image Underst.*, 2009, 113, (1), pp. 80–89

[17] Gasparrini S., Cippitelli E., Gambi E., *ET AL.*: 'Proposal and experimental evaluation of fall detection solution based on wearable and depth data fusion', ICT Innovations 2015, (Springer, Switzerland, 2015), pp. 99–108

[18] Kuehne H., Jhuang H., Garrote E., *ET AL.*: 'HMDB: a large video data-base for human motion recognition'. Proc. Int. Conf. on Computer Vwasion (ICCV), 2011, pp. 2556–2563

[19] Vilarinho, T.; Farshchian, B.; Bajer, D.G.; Dahl, O.H.; Egge, I.; Hegdal, S.S.; Lones, A.; Slettevold, J.N.; Weggersen, S.M. A combined smartphone and smartwatch fall detection system. In Proceedings of the IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing, Liverpool, UK, 26–28 October 2015.

[20] A. Sucerquia, J. D. L´opez, and J. F. Vargas-Bonilla, "SwasFall: A fall and movement dataset," Sensors, vol. 17, no. 1, pp. 1–14, Jan. 2017.