Radar for assisted living in the context of Internet of Things for Health and beyond

Julien Le Kernec[1,2*], *Senior Member, IEEE*, Francesco Fioranelli[1], Member, IEEE,
Shufan Yang[1], *Member, IEEE*, Jordane Lorandel[3], *Member, IEEE*, Olivier Romain[3], *Member, IEEE*

[1]*Communication, Sensing and Imaging group, School of Engineering, University of Glasgow, Glasgow, UK*
[2]*School of Information and Electronics, Univ. of Electronic Science and Technology of China, Chengdu, China*
[3]*ETIS-ASTRE, Université Cergy-Pontoise, Cergy-Pontoise, France*

Abstract—**This paper discusses the place of radar for assisted living in the context of IoT for Health and beyond. First, the context of assisted living and the urgency to address the problem is described. The second part gives a literature review of existing sensing modalities for assisted living and explains why radar is an upcoming preferred modality to address this issue. The third section presents developments in machine learning that helps improve performances in classification especially with deep learning with a reflection on lessons learned from it. The fourth section introduces recent published work from our research group in the area that shows promise with multimodal sensor fusion for classification and long short-term memory applied to early stages in the radar signal processing chain. Finally, we conclude with open challenges still to be addressed in the area and open to future research directions in animal welfare.**

Index Terms—**Human activity classification, fall detection, ambient assisted living, inertial sensors, magnetic sensors, radar sensors, multisensory data fusion, feature selection, machine learning, micro-Doppler signatures, feature extraction.**

I. INTRODUCTION

Internet of Things (IoT) in healthcare was evaluated at $60 billion and will reach $136 billion by 2021 [1]. IoT comprises intermediary components, such as devices, network connectivity, electronic systems, and software. It is networked smart electronic devices sharing information autonomously leveraging machine learning. In healthcare, this technology will facilitate managing and mining patient data and resources.
Life expectancy is increasing and poses challenges for health services as it comes with medical issues (chronic illnesses, multi-morbidity) and an alarming rise in the population over 60 predicted to reach 30% by 2050 worldwide [1-2]. This trend is not new but accelerating especially in developed countries.
In 2016, signal processing magazine had a special issue on assisted living [3–8]. It covered a range of technologies such as inertial measurement units, wearables, ambient sensors (pyroelectric infrared (PIR), vibration sensors, accelerometers, cameras, depth sensors and microphones) and radio waves with existing infrastructure (Wifi) present on site or active devices such as radar. For all sensing modalities, enhancing accuracy,

lowering computational complexity, reducing power consumption, exploiting multiple domains and modalities for complementarity and robustness, are crucial in developing technology enabled self-dependent living in-home care.

II. EXISTING SENSING MODALITIES

Many systems have been proposed to tackle this problem [5,8-9] including radar sensors or a combination of these systems, whereby their information is used concurrently and fused at different levels to optimize the overall performance.

Monitoring people in their daily life poses a privacy issue; there is a correlation between the perceived privacy and richness of information collected by sensors [9]. Video provides very rich information but is perceived as intrusive; PIR sensors are not perceived as invasive but provide little information.

A review of healthcare using mobile wireless technologies shows major challenges (data acquisition, processing data locally, wireless data, quality of service over cellular network, cloud storage, security, user interface and platforms) before being feasible [11]. It also suffers from integration problems where a lot has to come together before it is practical to use and requires the lifting of technological barriers as well.

Wearable sensors despite giving good classification results [12] greater than 98%, suffer from several major problems [13]:
- require user compliance as they need to be worn or to think about it if you wake during the night to go to the washroom.
- easily broken if dropped, crushed while sitting or falling.

In [14], [15], entire apartments have been fitted with sensors PIR motion sensors, stove sensors, floor sensors,… and provide good density maps for activities of daily living at the macro level. However, they cannot provide a finer granularity for gait analysis change detection as well as requiring transformations in a persons living environment.

An extensive review [16] of RGB cameras, depth sensors and radar technologies for assisted living highlighting open challenges for deployment in residences or specialized homes:
- For cameras, the main challenges are occlusions, working at night, dead zones in 3D, accuracy, precision, resolution and respecting privacy.

- For radar systems, the presence of strong scatterers and clutter in indoor environments may generate multipath and ghost targets which is comparable to occlusion in cameras. The compliance of radar system with emission regulations limits.

The technological challenges are greater for radar technology, but the fact there are no judicial issues regarding rights to image and plain images are not recorded, thus respecting privacy, facilitating acceptance of end users and investors. For these reasons, the radar sensing modality is an interesting research trend however still underutilized in specialized homes.

Radar is attractive due to reliability, low power emissions for indoor use (similar to WiFi), safety, which brings it at the frontier of indoor monitoring modalities rivaling video cameras and wearable devices for health. Radar can be used for fall detection, gait analysis and activities of daily living (ADL) to provide supplemental information to detect early signs of deteriorating physical/cognitive health. It would allow greater healthcare coverage, better quality of provision through 24/7 monitoring of the elderly well-being while respecting privacy.

Furthermore, the elderly may suffer from reduced cognitive capabilities and memory loss. To enable assistive technologies to help them to deal with ADL and monitoring their condition, a system requiring no intervention from their part is more suited.

Existing radar systems can be used to monitor activities [12,16–20], but it could create a paradigm shift in health monitoring moving from reactive technologies to preventive. If they are made smart enough to learn the daily activity pattern of an end user, and identify deviations/anomalies linked to declining health, they could foresee the occurrence of possible critical events (e.g. falls, strokes).

Radar will enable prompt emergency responses following critical events (reactive), continuous in-home health monitoring for medical professionals to improve diagnostics and develop precision medicine for individuals (predictive). It would also enable persuasive feedback to individuals to advise/influence behaviours for safer and better practice, when variations in their routine are identified (prevention & assistance).

III. MACHINE LEARNING PERSPECTIVE

Machine learning is becoming an integral part of technology development given the advantages it provides, radar system applications are also leveraging machine learning for enhanced performances and accuracy in activity classification.

Generally, to classify activities, radar micro-Doppler (mD) signatures are used as a base. The relative motion of limbs and head with respect to the torso generates unique signatures in the time-frequency domain of the radar returns. Different activities create uniquely identifiable features in mD signatures used for classification. A comprehensive coverage of the subject can be found in [21-22]. Spectrograms are then processed to extract features [23] followed by different classifiers [24-25].

Here is a non-exhaustive list of machine learning techniques for classification: Fisher Discriminant Analysis [26-27], K-nearest neighbors [28-29], Naïve Bayes [30], Ensembles (e.g. Bagging [31]) and Support Vector Machine (SVM) [32].

A review classifiers for activity classification [16] advise to use multiple sensors to enhance classification accuracy by covering multiple aspect angles and combat occlusions. Another way to improve accuracy is to fuse data and select the most salient features [12,18,33-34]. Many classifiers are used in activity classification of which SVM is the most common [35]. The choice of classifier is important, but choosing the most salient features has a greater impact on accuracy than the classifier [36]. There is a wealth of contributions trying to extract features and classify activities from mD signatures [16].

Beyond machine learning lies deep learning thanks to advances in computational power (GPUs). Feature extraction is an expert-knowledge based task. Deep learning techniques however can figure out relevant features for classification, sparse representations and time-dependencies through several layers of neurons with activation functions e.g. recognize faces with convolutional neural networks [37]. Another class of deep learning algorithms used for speech recognition are Recurrent Neural Networks (RNN) with Gated Recurrent Units [38], [39] and Long Short-Term Memory (LSTM) [40].

A general belief is that deep learning requires "Big Data" to be effective; but small datasets also produce good results [41-42] via data augmentation and transfer learning.

Figure 1 summarizes the research on activity classification using deep learning for enhanced accuracy [43–57] yielding precisions from 80 to almost 100%.
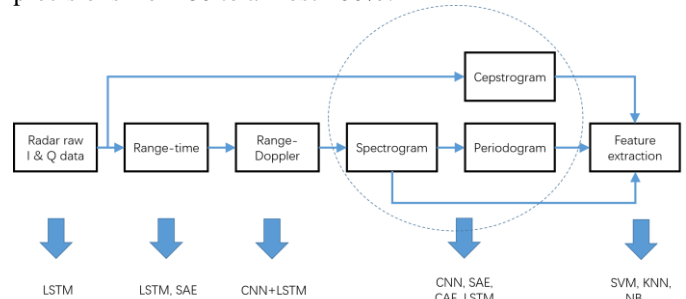

Figure 1: typical radar signal processing chain and associated machine/deep learning method from the state of the art (SAE: stacked Autoencoders, CAE: convolutional autoencoders, LSTM: Long Short-Term Memory, CNN: Convolutional Neural Network)

It is hard to assess the different performances since all the deep learning algorithms are ad hoc and the size and the nature of datasets vary. Because the intra class variance for similar activities is smaller than for different ones, therefore advertised accuracy varies in meaning. Deep learning is already showing better performance than expertly pre-trained models [58].

The problematic of multiple people in the field of view [47, 54, 56, 59] is rarely studied as they mostly consider only one person. In [16, 19, 24, 25, 60–63], the multi-static radar approach is utilized for classification from spectrograms using feature extraction. The difficulty in research with multi-static radar is the synchronization requirement between radar units and they are not commercially available. Aspect angle dependence in classification is rarely discussed although it has a large effect on accuracy [36, 53, 60]; most studies adopt actions happening in the radial direction of the radar.

Generally, the activities are looked at different activity snapshots and not in a continuum like in [51] for wearables.

The lessons from the literature are that CNN can recognize elaborate features from signals/images for particular snapshots at a given time where RNN of which LSTM is the leading technique takes into consideration time dependencies between snapshots. [51] shows a combination of CNN and LSTM for wearables and [49] presents a multimodal CNN multi-stream in parallel with LSTM with fusion; showing new ways to think about classifying data as a continuum.

Great efforts should go on preparing datasets, neural network architectures, training/optimizing to avoid overfitting, bias and ensure the model generalizes the activities to recognize unseen data or people accurately even with small datasets.

IV. RECENT RESULTS FROM THE COMMUNICATIONS, SENSING AND IMAGING GROUP AT UNIVERSITY OF GLASGOW

Now we have gone around the state of the art and the context, it is time to present some results from our recent studies.

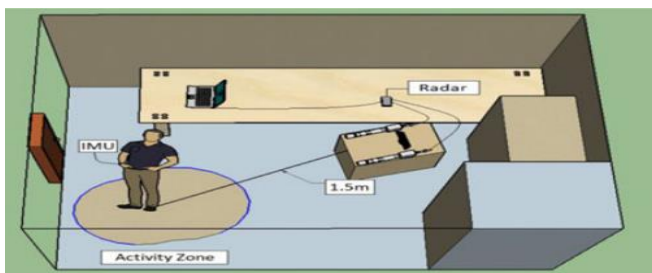### A. Multisensor approach for remote health monitoring of older people [12], [18]

Figure 2: Experimental setup with radar and inertial motion unit (accelerometer, gyroscope, magnetometer, inertial) [12]

The experimental setup (Figure 2) shows the placement of the radar and the wearable sensor. The activities (walk, walk while carrying an object, sit down, stand up, pick up an object, crouch to tie shoe laces, drink, answer the phone, frontal fall, check under a piece of furniture) were measured with 9 volunteers giving 270 samples in total. 177 features were extracted using the inertial sensor in time and frequency domains and 28 features from spectrograms using radar.

The classifiers were quadratic kernel SVM and 10-NN trained using 10-folds randomly (9 for training and 1 for testing). The results in Table I are the result of the average of 10 folds. Notice, radar underperforms compared to wearables.

Feature selection (Fscore [64], ReliefF [65], SFS [64]) on single modality significantly increases classification accuracy.

Table I: Classification accuracy using a single sensor [12]

Classification Accuracy (%)	SVM	KNN
Accelerometer	85.2	79.6
Gyroscope	84.1	79.6
Magnetometer	80.4	69.6
Inertial	89.3	85.2
Radar	77.9	70.7

Table II: Improvements wit feature selection methods for IMU and radar in terms of accuracy and number of features

Method	IMU		Radar	
	Accuracy(%)	Features #	Accuracy(%)	Features #
Fscore SVM	90.7	73	78.8	17
Fscore KNN	88.2	76	74.1	17
ReliefF SVM	91.1	164	74	20
ReliefF KNN	89.3	58	67	18
SFS SVM	95.6	35	85.6	20
SFS KNN	88.25	69	79.8	19

Table II shows 5-9% improvement for both sensors. So "less is more": having more features does not improve accuracy but using/identifying the salient features does.

To increase accuracy, it is interesting to explore the benefit of using multimodal fusion at various levels (signal, feature and decision) [66–68] (Table III).

Table III: classification accuracy improvement with fusion

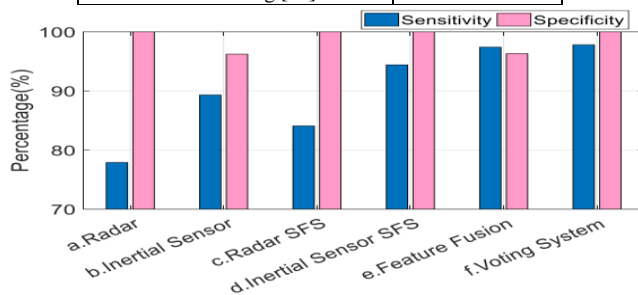| Fusion method	Accuracy (%)
Feature level	97.4
Decision level logP [69]	96.7
Decision level fuzzy logic [66]	94.8
Decision level voting [12]	97.8

Figure 3: sensitivity and specificity for the fall action using various classifications methods [12]

Figure 3 shows an improvement overall without affecting fall specificity (reaching 100% with voting) by applying suitable feature selection and fusion.

B. Activity Classification Using Raw Range and I & Q Radar Data With Long Short Term Memory Layers [70]

LSTM are used to classify directly from raw data and range maps for binary classification every 0.5 s of action recorded. 5 subjects contributed, actions were recorded continuously for 60s giving 19 recordings (10 'walk' and 9 'sitting & standing').

For both, 2,280 samples were obtained by dividing the recording in 0.5s snapshots and the data is presented to the LSTM as described in Table IV and Figure 4.
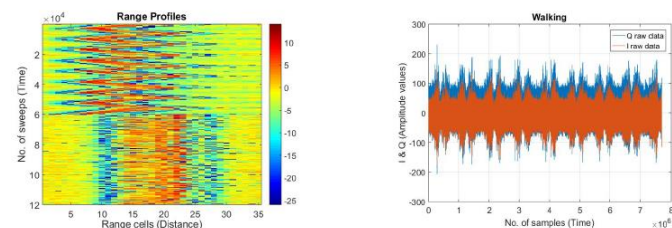

Figure IV: left) Range profiles for walking (60s) and sitting&standing movements (60s). right) illustrate I & Q data for walking movement. The time patterns that exist in the signals are exploited through the LSTM layers. [70]

Table IV: LSTM data parameters for classification

LSTM data	Number of time samples	Number of features
I&Q	64000	2
Range profiles	500	35

Table V: results of preliminary binary classification and metrics

Metrics	I&Q data	Range Profiles
LSTM units	4	35

Mean test Accuracy	97.67%	94.16%
Standard deviation	1.14%	2.02%
optimizer	RMSprop	RMSprop
Learning rate	0.001	0.001
Batch size	1	1
epochs	10	50
Layers	2	2
Prediction time	2s	2ms

The samples were shuffled in a stratified manner (80% for training and 20% for testing) under the 5-fold scheme. Table V shows that I&Q data yields better accuracy than range profiles and LSTM are able to process backscattered data as time series. The drawback is the time for an estimation is 2s for raw data and 2ms for range profiles for 0.5s of a data continuum.

V. CONCLUSION

From the literature and our recent work, the radar community is very active in the development of robust classification algorithms for elderly care using a range of algorithms and modalities. The advent of deep learning will certainly help improve algorithms gradually. Still some very important open challenges remain in this area such as how much data is enough data? how to teach a network to learn fast? what about community data sharing regulations? how to get relevant data and moving from detection to prediction?. The linchpin challenge is the real-time implementation of those algorithms on hardware while maintaining the accuracy obtained with offline processing.

Furthermore, IoT can be extended to animal welfare applications where the dairy industry, farm animals (sheep, cattle, pigs) and horses (Thoroughbreds and leisure) can benefit for lameness assessment [33], [34] and connected farms with IoT will improve significantly productivity and animal monitoring for better yield for our growing needs.

REFERENCES

[1] Mohd. Adnan Malik, "Internet of Things (IoT) Healthcare Market by Component (Implantable Sensor Devices, Wearable Sensor Devices, System and Software), Application (Patient Monitoring, Clinical Operation and Workflow Optimization, Clinical Imaging, Fitness and Wellness Measu," 2016.

[2] WHO, "Ageing," *WHO*, 2016. .

[3] P. D. United Nations, Department of Economic and Social Affairs, "World Population Prospects The 2017 Revision Key Findings and Advance Tables," *World Popul. Prospect. 2017*, pp. 1–46, 2017.

[4] M. G. Amin, Y. D. Zhang, F. Ahmad, and K. C. D. Ho, "Radar signal processing for elderly fall detection: The future for in-home monitoring," *IEEE Signal Process. Mag.*, vol. 33, no. 2, pp. 71–80, 2016.

[5] T. R. Bennett, J. Wu, N. Kehtarnavaz, and R. Jafari, "Inertial Measurement Unit-Based Wearable Computers for Assisted Living Applications: A signal processing perspective," *IEEE Signal Process. Mag.*, vol. 33, no. 2, pp. 28–35, 2016.

[6] F. Erden, S. Velipasalar, A. Z. Alkar, and A. E. Cetin, "Sensors in Assisted Living," *IEEE Signal Process. Mag.*, no. March, pp. 36–44, 2016.

[7] S. Savazzi, S. Sigg, and M. Nicoli, "Device-Free Radio Vision for Assisted Living," *IEEE Signal Process. Mag.*, vol. 33, no. 2, pp. 45–58, 2016.

[8] K. Witrisal *et al.*, "High - Accuracy Localization for Assisted Living," *IEEE Signal Process. Mag.*, vol. 33, no. 2, pp. 59–70, 2016.

[9] C. Debes, A. Merentitis, S. Sukhanov, M. Niessen, N. Frangiadakis, and A. Bauer, "Monitoring Activities of Daily Living in Smart Homes: Understanding human behavior," *IEEE Signal Process. Mag.*, vol. 33, no. 2, pp. 81–94, 2016.

[10] R. Igual, C. Medrano, and I. Plaza, "Challenges, issues and trends in fall detection systems," *BioMedical Engineering Online*, vol. 12, no. 1. 2013.

[11] G. Chiarini, P. Ray, S. Akter, C. Masella, and A. Ganz, "MHealth technologies for chronic diseases and elders: A systematic review," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 9, pp. 6–18, 2013.

[12] H. Li, A. Shrestha, H. Heidari, J. L. Kernec, and F. Fioranelli, "A Multisensory Approach for Remote Health Monitoring of Older People," *IEEE J. Electromagn. RF Microwaves Med. Biol.*, vol. 2, no. 2, pp. 102–108, 2018.

[13] H. Aykan, "Report to Congress: Aging Services Technology Study," Washington, 2012.

[14] P. Calyam, I. Jahnke, A. Mishra, R. B. Antequera, D. Chemodanov, and M. Skubic, "Toward an ElderCare Living Lab for Sensor-Based Health Assessment and Physical Therapy," *IEEE Cloud Comput.*, vol. 4, no. 3, pp. 30–39, 2017.

[15] S. Wang, M. Skubic, and Y. Zhu, "Activity density map visualization and dissimilarity comparison for eldercare monitoring," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 4, pp. 607–614, 2012.

[16] E. Cippitelli, F. Fioranelli, E. Gambi, and S. Spinsante, "Radar and RGB-depth sensors for fall detection: A review," *IEEE Sensors Journal*, vol. 17, no. 12. pp. 3585–3604, 2017.

[17] A. Shrestha, J. Le Kernec, F. Fioranelli, E. Cippitellii, E. Gambi, and S. Spinsante, "Feature diversity for fall detection and human indoor activities classification using radar systems," in *International Conference on Radar Systems (Radar 2017)*, 2017, pp. 1–6.

[18] H. Li *et al.*, "Multisensor data fusion for human activities classification and fall detection," in *2017 IEEE SENSORS*, 2017, pp. 1–3.

[19] F. Fioranelli, M. Ritchie, S. Z. Gürbüz, and H. Griffiths, "Feature Diversity for Optimized Human Micro-Doppler Classification Using Multistatic Radar," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 53, no. 2, pp. 640–654, 2017.

[20] L. Yang, G. Li, M. Ritchie, F. Fioranelli, and H. Griffiths, "Gait classification based on micro-Doppler features," in *2016 CIE International Conference on Radar, RADAR 2016*, 2017.

[21] D. Tahmoush, "Review of micro-Doppler signatures," *IET Radar, Sonar Navig.*, vol. 9, no. 9, pp. 1140–1146, 2015.

[22] V. C. Chen, D. Tahmoush, and W. J. Miceli, "Radar Micro-Doppler signatures: processing and applications," in *Micro-Doppler signatures - Review, challenges, and Perspectives*, The Institute of Engineering and Technology, 2014.

[23] S. Björklund, H. Petersson, and G. Hendeby, "Features for micro-Doppler based activity classification," *IET Radar, Sonar Navig.*, vol. 9, no. 9, pp. 1181–1187, 2015.

[24] F. Fioranelli, M. Ritchie, and H. Griffiths, "Performance analysis of centroid and SVD features for personnel recognition using multistatic micro-Doppler," *IEEE Geosci. Remote Sens. Lett.*, vol. 13, no. 5, pp. 725–729, 2016.

[25] F. Fioranelli, M. Ritchie, and H. Griffiths, "Multistatic human micro-Doppler classification of armed/unarmed personnel," *IET Radar, Sonar Navig.*, vol. 9, no. 7, pp. 857–865, 2015.

[26] J. Ye, R. Janardan, and Q. Li, "Two-Dimensional Linear Discriminant Analysis," in *Advances in Neural Information Processing Systems*, 2005, pp. 1569–1576.

[27] S. Mika, G. Ratsch, J. Weston, B. Schölkopf, and K.-R. Muller, "Fisher discriminant analysis with kernels," *Ieee*, pp. 41–48, 1999.

[28] P. Cunningham and S. J. Delany, "K -Nearest Neighbour Classifiers," *Mult. Classif. Syst.*, pp. 1–17, 2007.

[29] J. M. Kraus, L. Lausser, and H. A. Kestler, "Exhaustive k-nearest-neighbour subspace clustering," *J. Stat. Comput. Simul.*, vol. 85, no. 1, pp. 30–46, 2015.

[30] S.-B. Kim, K.-S. Han, H.-C. Rim, and S. H. Myaeng, "Some Effective Techniques for Naive Bayes Text Classification," *IEEE Trans. Knowl. Data Eng.*, vol. 18, no. 11, pp. 1457–1466, 2006.

[31] T. K. Ho, "A data complexity analysis of comparative advantages of decision forest constructors," *Pattern Anal. Appl.*, vol. 5, no. 2, pp. 102–112, 2002.

[32] S. Tong and D. Koller, "Support vector machine active learning with applications to text classification," *J. Mach. Learn. Res.*, vol. 2, pp. 45–66, 2002.

[33] A. Shrestha, J. Le Kernec, F. Fioranelli, J. F. Marshall, and L. Voute, "Gait analysis of horses for lameness detection with radar sensors," in *International Conference on Radar Systems (Radar 2017)*, 2017, pp. 1–6.

[34] A. Shrestha *et al.*, "Animal Lameness Detection With Radar Sensing," *IEEE Geosci. Remote Sens. Lett.*, pp. 1–5, 2018.

[35] Y. Kim and H. Ling, "Human activity classification based on micro-doppler signatures using a support vector machine," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 5, pp. 1328–1337, 2009.

[36] B. Çağlıyan and S. Z. Gürbüz, "Micro-Doppler-Based Human Activity Classification Using the Mote-Scale BumbleBee Radar," *IEEE Geosci. Remote Sens. Lett.*, vol. 12, no. 10, pp. 2135–2139, 2015.

[37] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[38] K. Cho, B. Van Merrienboer, D. Bahdanau, and Y. Bengio, "On the Properties of Neural Machine Translation : Encoder – Decoder Approaches," *Ssst-2014*, pp. 103–111, 2014.

[39] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," in *NIPS 2014 Workshop on Deep Learning*, 2014.

[40] S. Hochreiter and J. J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1–32, 1997.

[41] Q. Wu, Y. D. Zhang, W. Tao, and M. G. Amin, "Radar-based fall detection based on Doppler time–frequency signatures for assisted living," *IET Radar, Sonar Navig.*, vol. 9, no. 2, pp. 164–172, 2015.

[42] Y. Sawada and K. Kozuka, "Transfer learning method using multi-prediction deep Boltzmann machines for a small scale dataset," in *2015 14th IAPR International Conference on Machine Vision Applications (MVA)*, 2015, pp. 110–113.

[43] B. Jokanovic and M. Amin, "Fall Detection Using Deep Learning in Range-Doppler Radars," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 54, no. 1, pp. 180–189, 2018.

[44] Y. Shao, S. Guo, L. Sun, and W. Chen, "Human Motion Classification Based on Range Information with Deep Convolutional Neural Network," in *2017 4th International Conference on Information Science and Control Engineering (ICISCE)*, 2017, pp. 1519–1523.

[45] B. Chikhaoui and F. Gouineau, "Towards Automatic Feature Extraction for Activity Recognition from Wearable Sensors: A Deep Learning Approach," in *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*, 2017, pp. 693–702.

[46] M. Z. Uddin, W. Khaksar, and J. Torresen, "Human activity recognition using robust spatiotemporal features and convolutional neural network," in *2017 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, 2017, pp. 144–149.

[47] Y. Zhang *et al.*, "Poster Abstract: CAR - A Deep Learning Structure for Concurrent Activity Recognition," in *2017 16th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN)*, 2017, pp. 299–300.

[48] T. Zebin, P. J. Scully, and K. B. Ozanyan, "Human activity recognition with inertial sensors using a deep learning approach," in *2016 IEEE SENSORS*, 2016, pp. 1–3.

[49] S. Song *et al.*, "Multimodal Multi-Stream Deep Learning for Egocentric Activity Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2016, pp. 378–385.

[50] R. Saeedi, S. Norgaard, and A. H. Gebremedhin, "A closed-loop deep learning architecture for robust activity recognition using wearable sensors," in *2017 IEEE International Conference on Big Data (Big Data)*, 2017, pp. 473–479.

[51] J. F. Ordóñez and D. Roggen, "Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition," *Sensors*, vol. 16, no. 1. 2016.

[52] M. S. Seyfioglu, A. M. Ozbayoglu, and S. Z. Gurbuz, "Deep Convolutional Autoencoder for Radar-Based Classification of Similar Aided and Unaided Human Activities," *IEEE Transactions on Aerospace and Electronic Systems*, 2018.

[53] Y. Kim and B. Toomajian, "Hand Gesture Recognition Using Micro-Doppler Signatures With Convolutional Neural Network," *IEEE Access*, vol. 4, pp. 7125–7130, 2016.

[54] R. P. Trommel, R. I. A. Harmanny, L. Cifola, and J. N. Driessen, "Multi-target human gait classification using deep convolutional neural networks on micro-doppler spectrograms," in *2016 European Radar Conference (EuRAD)*, 2016, pp. 81–84.

[55] Y. Kim and T. Moon, "Human Detection and Activity Classification Based on Micro-Doppler Signatures Using Deep Convolutional Neural Networks," *IEEE Geosci. Remote Sens. Lett.*, vol. 13, no. 1, pp. 8–12, 2016.

[56] G. Klarenbeek, R. I. A. Harmanny, and L. Cifola, "Multi-target human gait classification using LSTM recurrent neural networks applied to micro-Doppler," in *2017 European Radar Conference (EURAD)*, 2017, pp. 167–170.

[57] M. Gochoo, T. H. Tan, S. C. Huang, S. H. Liu, and F. S. Alnajjar, "DCNN-based elderly activity recognition using binary sensors," in *2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA)*, 2017, pp. 1–5.

[58] S. Cao and R. Nevatia, "Exploring deep learning based solutions in fine grained activity recognition in the wild," in *2016 23rd International Conference on Pattern Recognition (ICPR)*, 2016, pp. 384–389.

[59] F. Adib, Z. Kabelac, and D. Katabi, "Multi-Person Localization via {RF} Body Reflections," in *12th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 15)*, 2015, pp. 279–292.

[60] F. Fioranelli, M. Ritchie, and H. Griffiths, "Aspect angle dependence and multistatic data fusion for micro-Doppler classification of armed/unarmed personnel," *IET Radar, Sonar Navig.*, vol. 9, no. 9, pp. 1231–1239, 2015.

[61] F. Fioranelli, M. Ritchie, and H. Griffiths, "Classification of Unarmed/Armed Personnel Using the NetRAD Multistatic Radar for Micro-Doppler and Singular Value Decomposition Features," *IEEE Geosci. Remote Sens. Lett.*, vol. 12, no. 9, pp. 1933–1937, 2015.

[62] F. Fioranelli, M. Ritchie, and H. Griffiths, "Bistatic human micro-Doppler signatures for classification of indoor activities," in *2017 IEEE Radar Conference (RadarConf)*, 2017, pp. 610–615.

[63] J. S. Patel, F. Fioranelli, M. Ritchie, and H. Griffiths, "Multistatic radar classification of armed vs unarmed personnel using neural networks," *Evol. Syst.*, vol. 9, no. 2, pp. 135–144, 2018.

[64] S. Z. Gürbüz, B. Erol, B. Çağlıyan, and B. Tekeli, "Operational assessment and adaptive selection of micro-Doppler features," *IET Radar, Sonar Navig.*, vol. 9, no. 9, pp. 1196–1204, 2015.

[65] R. Durgabai and Y. Ravi Bhushan, "Feature selection using reliefF algorithm," *Int. J. Adv. Res. Comput. Commun. Eng.*, vol. 3, no. 10, pp. 8215–8218, 2014.

[66] R. C. King, E. Villeneuve, R. J. White, R. S. Sherratt, W. Holderbaum, and W. S. Harwin, "Application of data fusion techniques and technologies for wearable health monitoring," *Med. Eng. Phys.*, vol. 42, pp. 1–12, 2017.

[67] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proc. IEEE*, vol. 85, no. 1, pp. 6–23, 1997.

[68] F. CasA Review of Data Fusion Techniquestanedo, "A Review of Data Fusion Techniques," *Sci. World J.*, vol. 2013, 2013.

[69] C. Chen, R. Jafari, and N. Kehtarnavaz, "A Real-Time Human Action Recognition System Using Depth and Inertial Sensor Fusion," *IEEE Sens. J.*, vol. 16, no. 3, pp. 773–781, 2016.

[70] C. Loukas, F. Fioranelli, J. Le Kernec, and S. Yang, "Activity Classification Using Raw Range and I & Q Radar Data With Long Short Term Memory Layers," in *Cyber Science and technology congress*, 2018, pp. 1–5.