Human Activity Recognition Methods: A Review

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Abstract: The Human activity recognition (HAR) collects events to distinguish as the sequence of annotations to recognise the actions of subjects to determine the ecological situation. Humans have the ability to recognize an event from a single movement. It is the natural tendency of human beings gives more attention to dynamic objects than the static objects. Human motion analysis is currently one of the most active research topics in machine learning. In this analysis the machine learning techniques for human activity recognition provides detail issues, there has been an influx to the recent situation from that the effective extraction and learning from live datasets as information. The methodology differs from traditional algorithms to the present machine learning techniques uses hand-crafted heuristically derived features to the newly generate hierarchical based self-evolving features. Different types of quantitative and statistical tools are available for prediction and thus results are evaluated with various existing methods to get better results of recognition. These techniques are classified into statistical forecasting models, shallow machine learning models, ensemble learning models, deep learning models and other learning models. From the literature review this work produces depth analysis results of deep learning models which are found to provide improved accuracy when it is calculated RMSE values in recognising the routine activity.

Keywords: Human Activity Recognition, Human Motion Analysis, Deep Learning, Ensemble Learning, Machine Learning and Statistical methods.

1. Introduction

In today’s world, activity recognition involves interpretation of human actions using a series of image observations with respect to environmental conditions. Human Activity Recognition (HAR) refers toward the task of assessing a person's physical activity through the use of objective technology. Due to the scope and variety of human activities, this mission is highly challenging [1]. The medical research group has been a long-standing objective [2, 3]. Sometimes, external health sensors such as accelerometers have been used to monitor the operation [4]. The aim of the recognition of human activity is to infer the human brain's current actions and objectives through a collection of observations and analyses of human behavior and its environment [5]. HAR system has several applications in the field of automated surveillance [6], smart home [7], and health monitoring and elderly care system [8]. Currently, the activity recognition methods can be mainly summarized as two categories: [9]

1. Vision-based technique
2. Sensor-based technique

A vision-based technique is a policy failure for tracking and interpreting agents' actions through videos taken by different cameras. Computer vision is the main methodology employed.

In order to model a broad range of human activities, the sensor-based technique combines the evolving field of sensor networks with original information mining and machine learning techniques.

In human-to-human contact and relationships, the mechanism of acknowledgement of human behavior plays a critical role. It is difficult to distinguish because it provides data about the character of a person, their character, and mental state. The human capacity to perceive someone else's exercises is one of the principle subjects of investigation of the logical regions of computer vision and Artificial Intelligence (AI). Because of this exploration, the data of numerous applications include Camera frameworks for reconnaissance, human-computer communication, and mechanical technology for individual conduct portrayal, involve a various amount of movement with the acknowledgment framework. Time-series forecasting is one of the most challenging contemporary tasks that are being faced in different areas for HAR problem. Figure1 represents the process of activity recognition using training data and test data. The data acquisition with raw sensor data for preprocessing and feature selection by noise reduction, normalization and segmentation to extract valuable feature vectors for activity recognition.

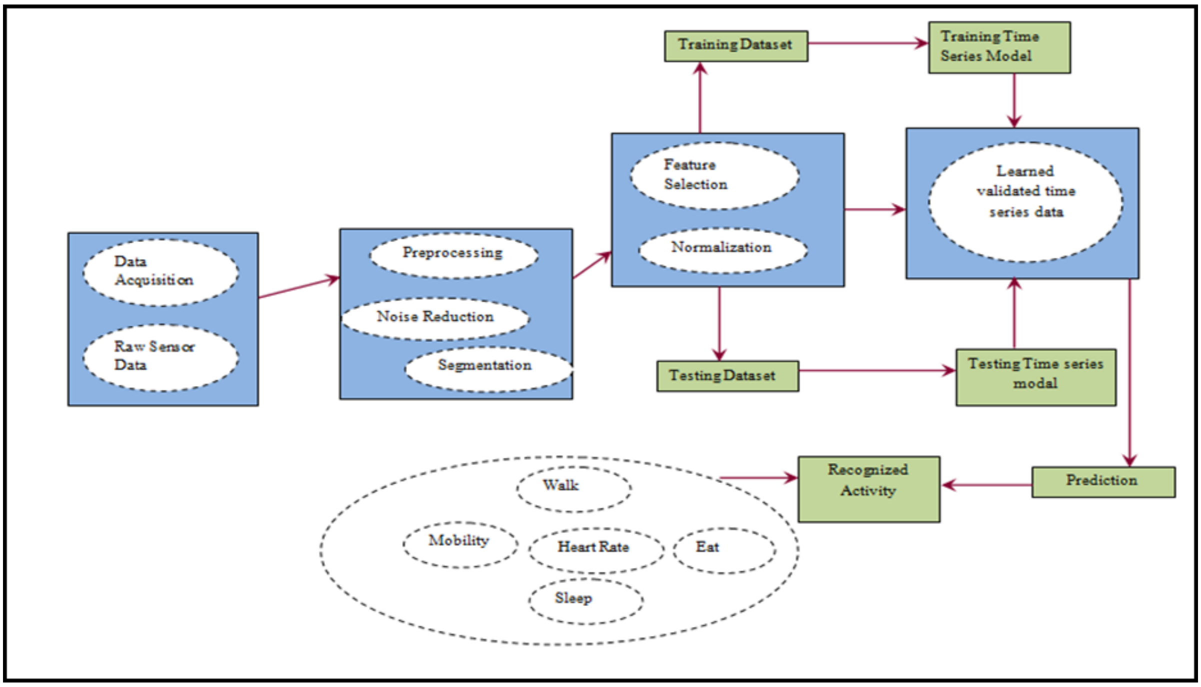

Figure 1 HAR Methods for Predicting Daily Activities

Table 1 refers Different types of datasets are used for each of the ways through which the data is obtained through various means, such as sensors, photographs, accelerometers, gyroscopes, etc., and the positioning of these instruments at different locations. [10].

TABLE 1: Different types of dataset for HAR

Ref	Dataset	Dataset Description
[11, 12]	Collected dataset	This dataset reflects environmental data obtained from volunteer residents in households. Data is constantly collected as residents carry out their daily routines.
[1 ,18]	PAMAP2 (Physical Activity Monitoring dataset)	The PAMAP2 dataset provides data from 18 separate physical activities undertaken by 9 participants wearing 3 inertial measuring units and a heart rate monitor.
[20]	OPPORTUNITY dataset	The OPPORTUNITY Dataset for Watch, Entity, and Ambient Sensor Recognition of Human Activity is a dataset designed to compare algorithms for HAR (automatic data segmentation, classification, sensor fusion, feature extraction, etc).
[26]	UCFSports dataset	The dataset contains motion sensor data from 19 everyday activities and sports activities, each performed for 5 minutes by 8 subjects in their own style.

[30]	MHEALTH(Mobile HEALTH) dataset	For ten volunteers with different profiles, the MHEALTH dataset contains body motion and vital signs recordings when performing multiple physical activities. Sensors mounted on the chest, right wrist and left ankle of the subject are used to measure the motion experienced by different parts of the body, including acceleration, rate of turn and direction of the magnetic field.
[32]	Heterogeneity dataset	The Heterogeneity Dataset for HAR Smartphone and Smart Watch Sensors consists of two datasets designed to analyze the effects of sensor heterogeneities on algorithms for human activity recognition (classification, automatic data segmentation, feature extraction, sensor fusion).

2. Review of Literature of Human Activity Recognition

The activities are recognized in several real-time domains the time series forecasting techniques has practical significance. The active research works are going on in predicting daily activity for the past decade. Many more worthy time series methods have been proposed in the literature for getting better the accuracy and competence of predicting activity recognition. The time series methods for predicting daily activity behaviour have been grouped as follows:

1. Statistical methods
2. Shallow machine learning methods
3. Ensemble learning methods
4. Deep learning methods

Statistical methods: Statistical forecasting models is the process of making future predictions based on past and current data and, most often, on trend analysis. It includes a correlation coefficient model [4], principal component analysis (PCA) model [10], Newton interpolation model [3], nonlinear regression model [3], and so on.

Shallow machine learning methods: Shallow machine learning model provides a method, the ability to learn and evolve automatically from experience without complex programming. This helps to predict new results that are based on recent results. In machine learning terms, this is also called supervised learning. These models include multilayer perceptron (MLP) [11], support vector machines [12], artificial neural networks [13], and the hybrid model employing two machine learning techniques, which could be a combination of clustering and classification techniques or fusion of two classification techniques.

Ensemble learning methods: Ensemble modeling is the approach used to run different analytical models and synthesize the outcome of score or spread to enhance the accuracy of prediction. Generally, researchers connected with one or more models to overcome overfitting issues. It includes BAGGing, or Bootstrap AGGregating [20] and Random forest model [21].

Deep learning methods: Deep learning models offer a lot of assurance for time arrangement determining, for example, the programmed learning of transient reliance and the programmed treatment of worldly structures like patterns and regularity. Deep learning models regularly utilized models are recurrent neural networks and its variations [22]. Long Short-Term Memory Unit, as a best in class model of RNN, was utilized in forecasting the air quality affecting factors [3]. Besides, manifold learning models and deep belief networks, deep uncertainty learning, and Encoder-Decoder model were likewise proposed [3].Table 2 refers the data information for each activity and algorithm used for human activity recognition.

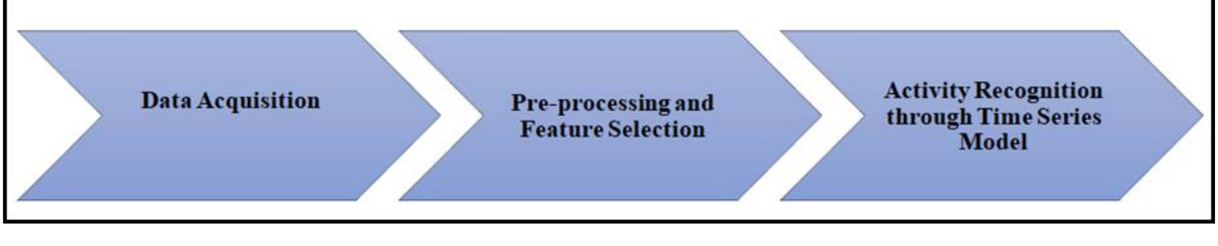

Figure 2 Process Flow of Literature Review

The figure 2 represents the flow of the survey in that the data acquisition collects various data from the multiple places to recognize the activity. Such collections generated huge volume of the data so that the preprocessing state filters the unwanted noises from the sensor collection and extract the exact feature to proceed with the next stage. The activity recognition always depend to the time series pattern, based on that the leaner of the system frequently learn the behaviour of the activity to produce accurate results to the output of the system. The table 2 represents the various data acquisition to recognize the activity using effective algorithm features to inference the activity.

TABLE 2: Data Acquisition

Ref	Data information	Activity	Algorithm	Features	Inference
[24]	Identifying a person's particular movement or behavior based on sensor data.	walking, talking, standing, and sitting.	Deep Belief Networks and Sparse coding, Convolutional Neural Network	32	In order to reduce memory consumption with 89% accuracy, the fusion exploits data protection act methods at the fully connected layer and convolutional kernel separation.
[37]	Effective and precise method for the combination of multiple classifiers	Lying, Sitting, Standing ,Walking, Running	Restricted Boltzmann Machine and Convolutional Neural Networks	15	Extrac invariant translation features and reduces instability with 93% during training data.
[45]	Supported Function Fusion	Car driving, Cycling, Vacuum cleaning, Ironing	Deep learning ensemble algorithm	24	The fusion of different deep learning enables 91% for high model diversification and output generalization.
[48]	Achieving high diversity, increasing prediction reliability and generalization of output using bias and inconsistency of each base classifier. The techniques allow precise identification of fine and coarse grain operations.	Ascending stairs, Descending stairs, Rope jumping, Playing	Convolutional NeuralNetwork (CNN)	24	The fusion of the two discriminative models is valid for multimodal and multi-sensor based human activity detection of 89 %. Furthermore, to detect complex and simultaneous activities and to learn spatial-temporal features from raw sensor data, algorithms are essential.
[52]	Capacities to have adaptability in conduct for nonlinear space dissemination acknowledgment dataset.	Watching TV , Computer work	Gated Recurrent Unit (GRU), Convolutional Neural Network	32	For efficient production on mobile devices, the Gated Recurrent Unit has compact parameters and simple terms to minimize network complexity.

[56]	Input feature manipulation	walking upstairs , walking downstairs, sitting, standing ,laying	Long Short Term Memory (LSTM)	17	The fusion of different deep learning enables high model diversification and generalization of results with 94% accuracy..

Table 3 refers the various pre-processing stages from that it extracts the feature selection methods to infer the daily activities of human behavior.

TABLE 3: Pre-processing and Feature Selection

S.No	Author	Year	Title of the paper	Preprocessing	Feature Selection methods	Inference
1.	Zhang, Y	2021	Deep unsupervised multi-modal fusion network for detecting driver distraction	Segmentation	Filter and wrapper methods - LASSO regression - RIDGE regression	Multi-task learning (MTL) aims to increase the efficiency of supervised regression or classification generalization by simultaneously learning many similar tasks to classify the activity.
2.	Alawneh, L	2020	Enhancing human activity recognition using deep learning and time series augmented data	Dimensionality reduction	Filter method - feature weighting algorithms - subset search algorithms	Generalized linear models with high-dimensional data to enhance the activity
3.	Ullah, M	2019	Stacked LSTM Network for Human Activity Recognition Using Smartphone Data	Missing data	Embedded method - LSTM algorithm	Using sensor information fusion strategy to unravel the relationship between on-body, environmental and emotional data

Table 4 represents different types of effective time series models and techniques used to recognize the human activity.

TABLE 4: Different types of Time series model

S.No	Author	Title of the paper	Time Series Model	Techniques used	Inference

1.	Wanru Xu	A Hierarchical Spatio-Temporal Model for HumanActivity Recognition	Statistical model	PCA transformation and K-means clustering	Recognition of behavior by simultaneously modeling spatial limits and temporal constraints.
2.	Qingchang Zhu	Smartphone-based Human Activity Recognition inBuildings Using Locality-constrained Linear Coding	Statistical model	Data partitioning	Develop numerous theories to achieve diversity and robustness of high production. Data partitioning also helps reduce ambiguity and vulnerability to data.
3.	Jozsef	Efficiency Investigation from Shallow to Deep Neural Network Techniques in Human Activity Recognition	Shallow machine learning model	Support Vector Machine (SVM)	Improved the performance of secure computation.
4.	Zhenghua Chen	A Novel Ensemble ELM for Human Activity Recognition Using Smartphone Sensors	Ensemble learning model	Random Forest	Ensemble learning aims to incorporate several core learners in order to increase results. It is capable of stabilizing the outcome and reducing the chance of trapping in the optimum local
5.	Yin Tang	Layer-wise training convolutional neural networks with smaller filters for human activity recognition using wearable sensors	Deep learning model	CNN	multiple sensor nodes, indicate a novel Lego CNN with local loss can greatly reduce memory and computation cost over CNN, while achieving higher accuracy

3.Conclusion

In this work produces the detail study of the proposed model review. In that analysis various time series methods deeply analysed to correctly identify the daily activity effectible. From the review, it was observed that, statistical forecasting models and ensemble learning models are the phenomenon models and that are able to provide improved accuracy results even when the input data had noises. It was also observed that from all other models the deep learning models were found to provide improved accuracy results with reduced RMSE values from the real-time readings. Finally, such effective method works accurate even high noise and outliers.

References

1. Sanguannarm, P., Elbasani, E., Kim, B., Kim, E. H., & Kim, J. D. (2021). Experimentation of Human Activity Recognition by Using Accelerometer Data Based on LSTM. In Advanced Multimedia and Ubiquitous Engineering (pp. 83-89). Springer, Singapore.
2. Alawneh, L., Alsarhan, T., Al-Zinati, M., Al-Ayyoub, M., Jararweh, Y., & Lu, H. (2018)Enhancing human activity recognition using deep learning and time series augmented data. Journal of Ambient Intelligence and Humanized Computing, 1-16.
3. Kim, S., Nam, H., Park, H., Lee, Y. T., & Yoon, Y. (2021). Activity-Recognition Model for Violence Behavior Using LSTM. In Advances in Computer Science and Ubiquitous Computing (pp. 529-535). Springer, Singapore.
4. Pattamaset, S., & Choi, J. S. (2021). Efficient Data Aggregation for Human Activity Detection with Smart Home Sensor Network Using K-Means Clustering Algorithm. In Advances in Computer Science and Ubiquitous Computing (pp. 9-15). Springer, Singapore.
5. Zhang, Y., Chen, Y., & Gao, C. (2021). Deep unsupervised multi-modal fusion network for detecting driver distraction. Neurocomputing, 421, 26-38.
6. Alawneh, L., Alsarhan, T., Al-Zinati, M., Al-Ayyoub, M., Jararweh, Y., & Lu, H. (2020) Enhancing human activity recognition using deep learning and time series augmented data. Journal of Ambient Intelligence and Humanized Computing, 1-16.
7. Langroodi, A. K., Vahdatikhaki, F., & Doree, A. (2020). Activity recognition of construction equipment using fractional random forest. Automation in Construction, 122, 103465.
8. Zhao, P., & Wang, M. (2021). Mobile behavior trusted certification based on multivariate behavior sequences. Neurocomputing, 419, 203-214.
9. Cvitić, I., Peraković, D., Periša, M., & Gupta, B.(2019) Ensemble machine learning approach for classification of IoT devices in smart home. International Journal of Machine Learning and Cybernetics, 1-24.
10. Yahaya, S. W., Lotfi, A., & Mahmud, M. (2021). Detecting Anomaly and Its Sources in Activities of Daily Living. SN Computer Science, 2(1), 1-18.
11. Porwal, K., Gupta, R., Naik, T. G., & Vijayarajan, V. (2020, September). Recognition of Human Activities in a Controlled Environment using CNN. In 2020 International Conference on Smart Electronics and Communication (ICOSEC) (pp. 291-296). IEEE.
12. Jegham, I., Khalifa, A. B., Alouani, I., & Mahjoub, M. A. (2020). Vision-based human action recognition: An overview and real world challenges. Forensic Science International: Digital Investigation, 32, 200901.
13. Clua, E. E., Linnell, J. D., Planes, S., & Meyer, C. G. (2020). Selective removal of problem individuals as an environmentally responsible approach for managing shark bites on humans. Ocean & Coastal Management, 194, 105266.
14. Vishwakarma, D. K., & Dhiman, C. (2019). A unified model for human activity recognition using spatial distribution of gradients and difference of Gaussian kernel. The Visual Computer, 35(11), 1595-1613.
15. Langroodi, A. K., Vahdatikhaki, F., & Doree, A. (2021). Activity recognition of construction equipment using fractional random forest. Automation in Construction, 122, 103465.
16. Conti, V., Militello, C., Rundo, L., & Vitabile, S. (2020). A Novel Bio-Inspired Approach for High-Performance Management in Service-Oriented Networks. IEEE Transactions on Emerging Topics in Computing.
17. Plötz, T., & Guan, Y. (2018). Deep learning for human activity recognition in mobile computing. Computer, 51(5), 50-59.
18. Ullah, M., Ullah, H., Khan, S. D., & Cheikh, F. A. (2019, October). Stacked Lstm Network for Human Activity Recognition Using Smartphone Data. In 2019 8th European Workshop on Visual Information Processing (EUVIP) (pp. 175-180). IEEE.
19. Abdel-Salam, R., Mostafa, R., & Hadhood, M. (2021). Human Activity Recognition using Wearable Sensors: Review, Challenges, Evaluation Benchmark. arXiv preprint arXiv:2101.01665.
20. Lawal, I. A., & Bano, S. (2020). Deep Human Activity Recognition With Localisation of Wearable Sensors. IEEE Access, 8, 155060-155070.
21. Qin, Z., Zhang, Y., Meng, S., Qin, Z., & Choo, K. K. R. (2020). Imaging and fusing time series for wearable sensor-based human activity recognition. Information Fusion, 53, 80-87.
22. Jung, M., & Chi, S. (2020). Human activity classification based on sound recognition and residual convolutional neural network. Automation in Construction, 114, 103177.
23. Wan, S., Qi, L., Xu, X., Tong, C., & Gu, Z. (2020). Deep learning models for real-time human activity recognition with smartphones. Mobile Networks and Applications, 25(2), 743-755.
24. Wang, Y., Cang, S., & Yu, H. (2019). A survey on wearable sensor modality centred human activity recognition in health care. Expert Systems with Applications, 137, 167-190.

25. Brady, K., Gwon, Y., Khorrami, P., Godoy, E., Campbell, W., Dagli, C., & Huang, T. S. (2016, October). Multi-modal audio, video and physiological sensor learning for continuous emotion prediction. In Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge (pp. 97-104).

26. Ichino, H., Kaji, K., Sakurada, K., Hiroi, K., & Kawaguchi, N. (2016, September). HASC-PAC2016: large scale human pedestrian activity corpus and its baseline recognition. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct (pp. 705-714).

27. Mughal, F. T. (2018). Latest trends in human activity recognition and behavioral analysis using different types of sensors. Int. J. Adv. Electron. Comput. Sci, 5, 2393-2835.

28. Chen, Y., & Shen, C. (2017). Performance analysis of smartphone-sensor behavior for human activity recognition. Ieee Access, 5, 3095-3110.

29. Nurhanim, K., Elamvazuthi, I., Izhar, L. I., & Ganesan, T. (2017, September). Classification of human activity based on smartphone inertial sensor using support vector machine. In 2017 ieee 3rd international symposium in robotics and manufacturing automation (roma) (pp. 1-5). IEEE.

30. Chen, Z., Zhu, Q., Soh, Y. C., & Zhang, L. (2017). Robust human activity recognition using smartphone sensors via CT-PCA and online SVM. IEEE Transactions on Industrial Informatics, 13(6), 3070-3080.

31. Ching, Y. T., Cheng, C. C., He, G. W., & Yang, Y. J. (2017, September). Full model for sensors placement and activities recognition. In Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers (pp. 17-20).

32. Münzner, S., Schmidt, P., Reiss, A., Hanselmann, M., Stiefelhagen, R., & Dürichen, R. (2017, September). CNN-based sensor fusion techniques for multimodal human activity recognition. In Proceedings of the 2017 ACM International Symposium on Wearable Computers (pp. 158-165).

33. Tran, D. N., & Phan, D. D. (2016, January). Human activities recognition in android smartphone using support vector machine. In 2016 7th international conference on intelligent systems, modelling and simulation (isms) (pp. 64-68). IEEE.

34. Kanjo, E., Younis, E. M., & Sherkat, N. (2018). Towards unravelling the relationship between on-body, environmental and emotion data using sensor information fusion approach. Information Fusion, 40, 18-31.

35. Xie, B., & Wu, Q. (2012, October). Hmm-based tri-training algorithm in human activity recognition with smartphone. In 2012 IEEE 2nd International Conference on Cloud Computing and Intelligence Systems (Vol. 1, pp. 109-113). IEEE.

36. Zhan, Y., & Kuroda, T. (2014). Wearable sensor-based human activity recognition from environmental background sounds. Journal of Ambient Intelligence and Humanized Computing, 5(1), 77-89.

37. Murao, K., Mogari, H., Terada, T., & Tsukamoto, M. (2013, September). Evaluation function of sensor position for activity recognition considering wearability. In Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication (pp. 623-632).

38. Li, C. Y., Chen, Y. C., Chen, W. J., Huang, P., & Chu, H. H. (2013, September). Sensor-embedded teeth for oral activity recognition. In Proceedings of the 2013 international symposium on wearable computers (pp. 41-44).

39. Luštrek, M., Cvetković, B., Mirchevska, V., Kafalı, Ö., Romero, A. E., & Stathis, K. (2015, May). Recognising lifestyle activities of diabetic patients with a smartphone. In 2015 9th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) (pp. 317-324). IEEE.

40. Jiang, W., & Yin, Z. (2015, October). Human activity recognition using wearable sensors by deep convolutional neural networks. In Proceedings of the 23rd ACM international conference on Multimedia (pp. 1307-1310).

41. Stisen, A., Blunck, H., Bhattacharya, S., Prentow, T. S., Kjærgaard, M. B., Dey, A., ... & Jensen, M. M. (2015, November). Smart devices are different: Assessing and mitigatingmobile sensing heterogeneities for activity recognition. In Proceedings of the 13th ACM conference on embedded networked sensor systems (pp. 127-140).

42. Zhu, Q., Chen, Z., & Soh, Y. C. (2015, June). Smartphone-based human activity recognition in buildings using locality-constrained linear coding. In 2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA) (pp. 214-219). IEEE.

43. Kakarla, M., & Reddy, G. R. M. (2014, May). A real time facial emotion recognition using depth sensor and interfacing with Second Life based Virtual 3D avatar. In International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014) (pp. 1-7). IEEE.

44. Ghosh, A., & Riccardi, G. (2014, November). Recognizing human activities from smartphone sensor signals. In Proceedings of the 22nd ACM international conference on Multimedia (pp. 865-868).

45. Hinton, G. E., Osindero, S., & Teh, Y. W. (2006). A fast learning algorithm for deep beliefnets. Neural computation, 18(7), 1527-1554.

46. Raja, S. Kanaga Suba, and T. Jebarajan. "Reliable and secured data transmission in wireless body area networks (WBAN)." European Journal of Scientific Research 82, no. 2 (2012): 173-184.

47. Alsheikh, M. A., Selim, A., Niyato, D., Doyle, L., Lin, S., & Tan, H. P. (2015). Deep activity recognition models with triaxial accelerometers. arXiv preprint arXiv:1511.04664.
48. Bhattacharya, S., & Lane, N. D. (2016, March). From smart to deep: Robust activity recognition on smartwatches using deep learning. In 2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops) (pp. 1-6). IEEE.
49. Rifai, S., Vincent, P., Muller, X., Glorot, X., & Bengio, Y. (2011, January). Contractive auto-encoders: Explicit invariance during feature extraction. In Icml.
50. Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y., Manzagol, P. A., & Bottou, L. (2010). Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. Journal of machine learning research, 11(12).
51. Schulz, H., Cho, K., Raiko, T., & Behnke, S. (2015). Two-layer contractive encodings for learning stable nonlinear features. Neural Networks, 64, 4-11.
52. Harandi, M. T., Sanderson, C., Hartley, R., & Lovell, B. C. (2012, October). Sparse coding and dictionary learning for symmetric positive definite matrices: A kernel approach. In European Conference on Computer Vision (pp. 216-229). Springer, Berlin, Heidelberg.
53. He, Y., Kavukcuoglu, K., Wang, Y., Szlam, A., & Qi, Y. (2014, April). Unsupervised feature learning by deep sparse coding. In Proceedings of the 2014 SIAM international conference on data mining (pp. 902-910). Society for Industrial and Applied Mathematics.
54. Bhattacharya, S., Nurmi, P., Hammerla, N., & Plötz, T. (2014). Using unlabeled data in a sparse-coding framework for human activity recognition. Pervasive and Mobile Computing, 15, 242-262.
55. Guo, J., Xie, X., Bie, R., & Sun, L. (2014). Structural health monitoring by using a sparse coding-based deep learning algorithm with wireless sensor networks. Personal and ubiquitous computing, 18(8), 1977-1987.
56. Ravi, D., Wong, C., Lo, B., & Yang, G. Z. (2016). A deep learning approach to on-node sensor data analytics for mobile or wearable devices. IEEE journal of biomedical and health informatics, 21(1), 56-64.
57. Ronao, C. A., & Cho, S. B. (2016). Human activity recognition with smartphone sensors using deep learning neural networks. Expert systems with applications, 59, 235-244.
58. Chen, Y., Zhong, K., Zhang, J., Sun, Q., & Zhao, X. (2016, January). Lstm networks for mobile human activity recognition. In 2016 International Conference on Artificial Intelligence: Technologies and Applications. Atlantis Press.
59. Guan, Y., & Plötz, T. (2017). Ensembles of deep lstm learners for activity recognition using wearables. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1(2), 1-28.
60. Zhang, J., & Wu, Y. (2018). Automatic sleep stage classification of single-channel EEG by using complex-valued convolutional neural network. Biomedical Engineering/Biomedizinische Technik, 63(2), 177-190.