Activity Recognition for Cognitive Assistance Using Body Sensors Data and Deep Convolutional Neural Network

Md. Zia Uddin, *Senior Member, IEEE*, and Mohammad Mehedi Hassan, *Senior Member, IEEE*

***Abstract*— In this paper, we propose a robust activity recognition approach for smart healthcare using body sensors and deep convolutional neural network (CNN). We analyze signals from different body sensors for healthcare, such as ECG, magnetometer, accelerometer, and gyroscope sensors. After extracting salient features from the sensor data based on Gaussian kernel-based principal component analysis and Z-score normalization, a deep activity CNN is trained based on the features. Finally, the trained deep CNN is used for recognizing the activities in testing data. The proposed approach is applied to a publicly available standard data set and then compared with other conventional approaches. The experimental results show that the proposed approach is superior than others, indicating the robustness of the approach to be adopted for cognitive assistance in body sensor-based smart healthcare systems.**

***Index Terms*— Body sensors, deep CNN.**

I. Introduction

PEOPLES' health care at smart home is a matter of great concern if a person stays alone due to unforeseen circumstances that might occur. Hence, adopting technologies for independent living is promising to enhance the care in a reliable manner. The premise of smart home health care applications more often demands continuous monitoring of the environment and resident's behavior using an intelligent system. As a growing area of research, it is now essential to investigate distinguished approaches for developing a robust smart health care system for people to prolong their independent life. The total population of the world is growing rapidly, especially the elderly population is increasing faster than other age groups [1]. Hence, the trend of increasing the elderly population indicates the necessity of assisted healthcare technologies in smart homes to take care of people and help them to living independently.

Manuscript received August 29, 2018; accepted September 16, 2018. Date of publication September 20, 2018; date of current version September 5, 2019. This work was supported by the Deanship of Scientific Research at King Saud University through the Vice Deanship of Scientific Research Chairs. The associate editor coordinating the review of this paper and approving it for publication was Prof. Giancarlo Fortino. *(Corresponding author: Mohammad Mehedi Hassan.)*

M. Z. Uddin is with the Department of Informatics, University of Oslo, 0316 Oslo, Norway (e-mail: mdzu@ifi.uio.no).

M. M. Hassan is with the Chair of Pervasive and Mobile Computing and Information Systems Department, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia (e-mail: mmhassan@ksu.edu.sa).

Digital Object Identifier 10.1109/JSEN.2018.2871203

A. Related Works

Body sensors have been getting quite famous for various practical applications such as providing cognitive assistance to smart environments (e.g., smart home, office, and hospitals). They can be deeply explored to accurately model people's behavior in different healthcare applications. Hence, they can be used to ensure good and smart living environments. Thus, body sensors can be considered as promising to revolutionize people's lifestyle. Body sensors sometimes have been adopted in the form of emergency buttons to ask for serious help in emergencies [2]. These buttons can be called commercially successful as they have been commercially applied very much. However, one limitation using these buttons is that the user of the button should always be alert as well as physically fit to properly use the button.

From the research perspective, body sensors have attracted a lot of researchers for large amount of applications including monitoring vital signs and activities [3]. Regarding vital signs, the important health signs such as body temperature and heart rate are monitored with the help of body worn medical sensors. However, one important parameter to consider during the design process of body sensors is that, they should be light and comfortable to be worn. Body sensors can contribute to help in necessary treatments of people at home to observe or predict their critical conditions such as heart-attacks. In medical conditions of a patient, most of the physiological signals and physical activities of the patient can possibly be monitored with the help of body sensors. In addition, the body sensors can help in rehabilitation stage of a patient by providing him some feedbacks such as audio and virtual reality images. The overall body sensor-based monitoring system can be tuned to the requirement of the individual patient and can be remotely monitored by doctors and caregivers, if necessary [4].

For activity monitoring applications using body sensors, a large amount of research is done to develop different smart systems [5]–[7]. Due to their good success, the use of body sensors is increasing day by day for research and commercial purpose. For example, sensors in devices like smartwatches are getting a rapid growth. The body sensors seem to have a great impact in future healthcare technologies. For instance, they can substantially contribute in defining doctor-patient relationship and at the same time, saving healthcare cost. The rapid growth of body sensor technologies indicates opening of more research opportunities using them in many important applications related to healthcare. In addition to the above-mentioned research works, there have been many other works related to body sensors for many other smart home applications [8]–[23]. For instance, Hein *et al.* [11] adopted accelerometer sensors to analyze the activities of daily living where they applied a two-fold method. The authors conducted interviews of elderly people, their relatives, and caregivers in this work to analyze the feasibility of the sensors for them. Furthermore, considering the comments of the interviews, they experimented the system for different daily human activity modeling and recognition. Roy *et al.* [14] adopted accelerometer sensors along with some ambient sensors to model and recognize some daily activity recognition. To develop their proposed approach, they applied some possibility theories and combined with logic-based semantic modeling. Besides, they analyzed Gaussian mixture models, hidden Markov models, deep belief network for different human activity recognition. Sim *et al.* [15] adopted some wearable sensors with ambient sensors to apply mining correlated patterns in the sensors data for different activity pattern analysis in a smart home. In their work, they showed that the correlated activity pattern mining approach was able to achieve significant accuracy over typical frequent mining systems. Tolkiehn *et al.* [17] proposed a fall detection technique based on 3D accelerometers. They also focused on fall direction along with the fall detection. Technically, they adopted amplitude and angular features extracted from the accelerometer sensors. Based on their fall dataset, they obtained more than 89% accuracy of fall prediction. In addition to body sensors, ambient sensors were also applied in many works in combination with body sensors to characterize different events in different applications [24].

Artificial Neural Networks (ANNs) have been getting explored in enormous research works to model different pattern analysis applications in last several decades [25]–[27]. As a result of the continuous efforts based on ANNs, deep learning techniques have been getting lots of attention by pattern recognition and artificial intelligence researchers [25]. Deep Neural Network (DNN) (e.g., a big size typical ANN) was the first deep learning technique proposed for pattern analysis and recognition [18]. However, typical DNN consisted of two big disadvantages. Firstly, it generates overfitting problems and secondly, it very often consumes very long time during the process of training patterns. Afterward, Deep Belief Network (DBN) was proposed by Hinton *et al.* for deep learning with the help of Restricted Boltzmann Machines (RBMs) [26]. The main advantage in DBN is that usage of RBM makes the training process quite quicker than typical DNN. Furthermore, Convolutional Neural Networks (CNN) has become popular due to its improved discriminative power in comparison to DBN. CNNs have been mostly successful for visual pattern analysis. Basically, CNN is some sort of deep learning consisting of feature extractions in addition to some convolutions at each layer of the network to produce abstract features. The various significant elements of a CNN include convolution, pooling, tangent squashing, rectifier, and normalization [27]. CNN follows a hierarchical neural network where convolutional layers alternate with subsampling layers that finally follow a fully-connected layer.

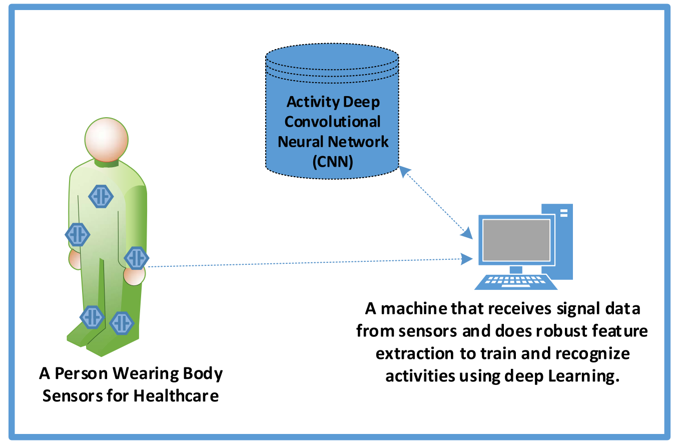


Fig. 1. A schematic setup for body sensor-based behavior recognition system.

Fully-connected layers are identical to typical multilayer perceptron-based neural network. CNN-based deep learning is mostly used to efficiently recognize the patterns in visual scenarios. With proper training, the convolutional layers of a CNN can learn important features and finally, the fully connected layer can perform classification task. CNNs can achieve an excellent classification performance even with the limited training data. CNN has already proven to be a very robust deep learning technique in the field of pattern recognition, mostly in image processing and computer vision-based applications. However, it can be actively investigated to apply on sensor data streams obtained from distinguished wearable sensors to achieve better accuracy of different applications such as human activities in smart environments. Thus, compare to the other deep learning structures, CNN often demonstrates higher recognition performance in machine learning and pattern classification applications due to its ability to extract and learn features based on convolution in different steps [27]. CNN also has one more major advantage of better utilizing bias and weight values compared to other deep learning approaches such as DBN. Even though CNN is an efficient deep learning approach, it has some limitations. Convolution operations are slow operations and hence, training steps in deep CNN can take very long time if the network is very deep. CNNs are comparatively computationally expensive than other typical deep learning approaches and hence, they sometimes require high performance computers for learning and testing data real time.

As deep CNN seems to be a good candidate for deep learning-based pattern analysis, it should be a suitable candidate to model and decode activity features in our bodies towards helping in cognitive help the people inside their homes to prolong their independent life.

B. Contributions

In the proposed body sensor-based human activity recognition system for cognitive assistance in a smart home, the multimodal sensor data is first processed with Gaussian kernel-based Principal Component Analysis (PCA) and Z-score normalization for robust feature extraction.

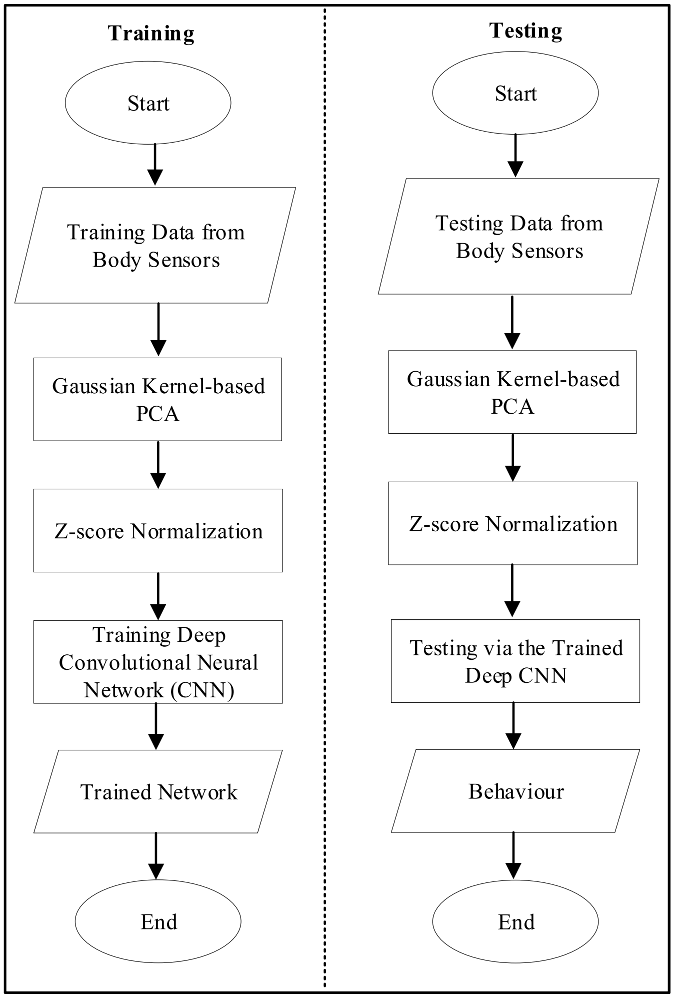


Fig. 2. Flowchart of the proposed activity recognition system using healthcare body sensors.

Then, the features go through the training and testing procedure via deep CNN. Fig. 1 demonstrates a schematic setup of a body sensor-based human behavior recognition system in a smart room where a person is wearing several healthcare body sensors. A machine collects the data and further process it for behavior modelling recognition, which can be used for cognitive assistance for the user of the smart home.

II. Methods

This section describes the methodology of the proposed approach. Fig. 2 depicts the basic architecture of the proposed system consisting of acquisition of data, feature extraction, normalization, training and testing procedure. In the training phase, the training data is obtained from the body sensors followed by feature extraction via Gaussian kernel-based PCA, normalization via Z-score, and training a deep CNN for all activities. On the other hand, testing phase includes testing data acquisition followed by PCA feature extraction, Z-score normalization, and applying the normalized features on the trained deep activity CNN for activity or behavior recognition from the testing data.

A. Data Processing

For this work, we rely on the set up of public Mhealth dataset [28]. The sensors were respectively placed on the subject's chest, right wrist and left ankle and attached by using elastic straps. The use of multiple sensors permits us to measure the motion experienced by diverse body parts, namely, the acceleration, the rate of turn and the magnetic field orientation, thus better capturing the body dynamics. Acceleration data from the chest sensor is obtained as

$$A_C = (C_x, C_y, C_z). \tag{1}$$

The ECG sensor is positioned on the chest. This information can be used, for example, basic heart monitoring. Electrocardiogram signals from ECG sensor lead 1 and z are obtained as

$$E = G_1 \| G_2. \tag{2}$$

Acceleration from the left-ankle accelerometer is obtained as

$$A_{LA} = (L_x, L_y, L_z). \tag{3}$$

Gyroscope sensor data from the left-ankle is obtained as

$$Y_{LA} = (R_x, R_y, R_z). \tag{4}$$

Sensor data from the left-ankle magnetometer sensor is obtained as

$$M_{LA} = (T_x, T_y, T_z). \tag{5}$$

Acceleration from the right wrist accelerometer is obtained as

$$A_{RW} = (I_x, I_y, I_z). \tag{6}$$

Gyroscope sensor data from the left-wrist gyroscope is obtained as

$$Y_{LW} = (S_x, S_y, S_z). \tag{7}$$

Gyroscope sensor data from the right-wrist is obtained as

$$Y_{RW} = (W_x, W_y, W_z). \tag{8}$$

Sensor data from the right-wrist magnetometer sensor is obtained as

$$G_{RW} = (E_x, E_y, E_z). \tag{9}$$

Furthermore, all the signals obtained from a signal of an event for a specific time-period of an activity are augmented as

$$M = A_C \| E \| A_{LA} \| Y_{LA} \| M_{LA} \| A_{RW} \| Y_{LW} \| Y_{RW} \| G_{RW}. \tag{10}$$

B. PCA Feature Extraction

The next step is to apply a Gaussian kernel-based PCA on the signal data obtained from the above-mentioned steps. PCA is a statistical approach used for approximating original data into a feature space with focusing on the direction of maximum covariance. It starts with eigenvalue and eigenvector computation of the covariance data or feature matrix. PCA has been the most popular approach in pattern analysis areas to reduce the dimension with focusing on most important directions of variance in data. As conventional PCA uses a linear structure to find out maximum directions with variations,

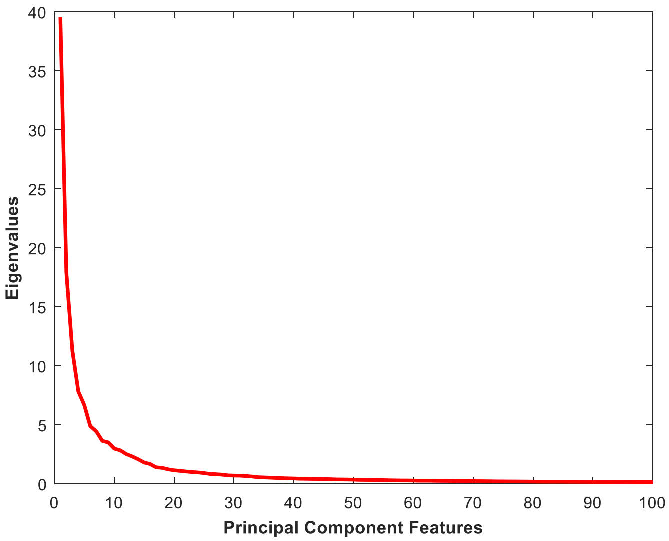


Fig. 3. Top 100 eigenvalues with respect to the principal component features.

it is a bit tough to characterize data if there are nonlinear structures in them. hence, a Gaussian kernel-based PCA can be adopted to solve the problem [29]. To do that, the input data is first transformed into a high-dimensional feature space using a Gaussian kernel followed by applying conventional eigenvalue decomposition there. Given the data signals of the sensors, the covariance matrix of the data is defined as

$$K = \frac{1}{N}\sum_{i=1}^{N}(\Omega(M_i).\Omega(M_i)^T), \quad (11)$$

$$\Omega(M_i) = \Xi(M_i) - \bar{\Xi}, \quad (12)$$

$$\bar{\Xi} = \frac{1}{N}\sum_{i=1}^{N}\Xi(M_i) \quad (13)$$

where N is the total number of events in the activity period and $\bar{\Xi}$ a Gaussian kernel. Now, the eigenvalue decomposition can be applied as

$$\alpha E = KE, \quad (14)$$

$$K = E^T \alpha E \quad (15)$$

where E represents the principal components and α eigenvalues. Then, the features for an event can be represented by means of projection on the principal components as

$$L = ME_m^T. \quad (16)$$

Fig. 3 shows the top 100 eigenvalues correspond to top 100 eigenvectors (i.e., principal components) where the first one represents the direction of maximum variation, the second one the second maximum variation and so on.

C. Normalization

The next step is to apply a normalization technique to normalize the features. To do that, we adopt Z-score-based normalization. A Z-score is basically a numerical measurement of how a number relates to the mean of the group numbers. Z-scores are typically expressed with the help of standard deviations of some numbers from their means. As a result, z-scores follow a distribution with 0 mean and 1 standard deviation. Zero Z-score represents that the score as identical to the mean score of the group. Besides, Z-scores can be positive or negative where the positive Z-scores indicate above the mean and negative scores below the mean. The basic Z-score formula for data X can be represented as

$$Z = \frac{(X - \mu)}{\sigma}. \quad (17)$$

where μ and σ are the mean and standard deviation of the data group, respectively.

In this activity recognition work, Z-score is applied on the PCA features of different activities based on their mean and standard deviation. Thus, we normalize the features L using Z-score value as

$$F_Z = \frac{(L - \bar{L})}{\sigma}. \quad (18)$$

where $\bar{L}$ represents the mean and σ standard deviation of the features. The values obtained via Z-score equation can be positive or negative. A positive Z-score basically means that the observed value greater than above the mean of the data. On the other hand, a negative Z-score means the observed value is lower than the mean of the data [30], [31].

D. Behavior Modeling

The robust normalized features are applied to deep Convolutional Neural Network (CNN) algorithm to model different activities. Fig. 4 depicts the basic structure of the deep CNN used in the proposed work. The convolution layer is derived as

$$Convolution\_Layer_y^{(i+1)}(u, v) = ReLU(x), \quad (19)$$

$$ReLU(x) = \sum\nolimits_{(g=1)}^{z}\Omega(u, (v - g + \frac{z+1}{2}))W_y^i(g) + \alpha_y^i \quad (20)$$

where $Convolution\_Layer_k^{(i+1)}(u, v)$ produces convolution results for *(u, v)* coordinates of $(i+1)^{\text{th}}$ layer with y^{th} convolution map. W_y^i represents s y^{th} convolution kernel for the i^{th} layer. α_y^i represents the y^{th} bias values for the i^{th} layer. Ω represents the map of the previous layer and z indicates the size of the convolution kernel. *ReLU* is basically the active function that does the summation of weights from the previous layer and passes them to the next layer for further calculation. The first convolution layer is basically followed by second layer i.e., first pooling layer *Pooling_Layer*$_1$. The pooling layer usually down samples down the results of the *Convolution_Layer*$_1$. In pooling, the maximum value is selected from the sliding windows applying them in the last map. Thus, the pooling results for the $(i+1)^{\text{th}}$ layer, kernel k, row u, and column v can be represented as

$$Pooling\_Layer_k^{i+1}(u, v) = \max_{1\le q\le s}(Convolution\_Layer_k^i(u, ((v-1)*q+s))) \quad (21)$$

where s represents the pooling window length. Adopting similar fashion, the second and third convolution layers apply

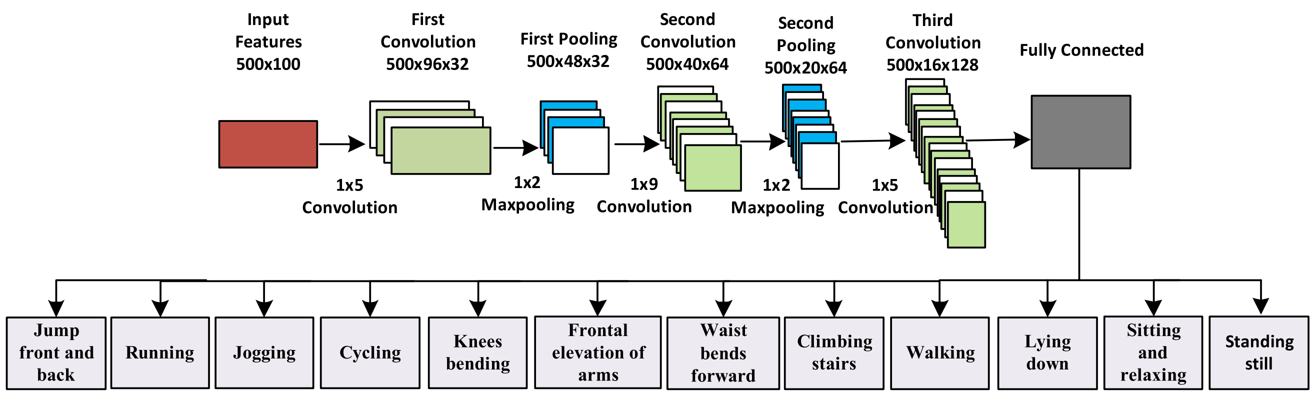


Fig. 4. Basic architecture of a deep CNN.

Algorithm1: Feature_Extraction()

1. **Begin**
2. Obtain ECG sensor data, C.
3. Obtain data from left-ankle accelerometer, L.
4. Obtain data from left-ankle gyroscope, G1.
5. Obtain data from left-ankle magneometer, M1.
6. Obtain data from right-wrist accelerometer, R.
7. Obtain data from left-wrist gyroscope, G2.
8. Obtain data from right-wrist gyroscope, G3.
9. Obtain data from right-wrist magnetometer, M2.
10. Augment all the sensor data, A=C||L||G1||M1|| R||G2|| G3||M2
11. Project A on Kernel PCA features E, K= A*E
13. Normalize E with Z-score, Z
14. Return Z
15. **End**

Fig. 5. Algorithm for feature extraction from the body sensor data.

Algorithm2: Activity_Training (Z)

1. **Begin**
2. Assign L= Number of Signal Segments in Z
3. **For** i:= 1 to L do
4. Obtain i^{th} segment, I_i.
5. Obtain features from I_i, U_i
6. **End for**
7. Augment all the features vertically, $V=U_1||U_2||...||U_L$.
8. Assign label For the signal Y.
8. Use all training features, V and activity labels, Y to train a Deep CNN.
10. **End**

Fig. 6. Algorithm for training activities.

64 kernels with the size 1×9 and 128 kernels with the size of 1×5, respectively. Figs. 5, 6, and 7 show the algorithms for features extraction, training and testing, respectively.

Regarding second pooling layer, it also applies 1×2 max-pooling just using the similar fashion of the first one. Finally, the fully connected layer for the classification task using is obtained as

$$Fully\_Connected_k^{(f+1)} = ReLU(\sum_i c_i^f W_{ik}^f + \alpha_k^f) \quad (22)$$

Algorithm3: Activity_Testing(T)

1. **Begin**
2. Assign N= Number of Signal Segments in T
3. **For** i:= 1 to N do
4. Obtain i^{th} segment, I_i.
5. Obtain features from I_i, U_i
6. **End for**
7. Augment all the features vertically, $S=U_1||U_2||...||U_L$.
8. Apply S on the trained CNN.
10. **End**

Fig. 7. Algorithm for testing activities.

TABLE I
MEAN ACCURACY USING THE PROPOSED APPROACH ON SUBJECT 1 TO 3 (%)

Activity	Subject 1	Subject 2	Subject 3
Standing still	94.01	93.18	94.63
Sitting and relaxing	93.54	94.42	93.17
Lying down	93.72	94.42	94.78
Walking	93.58	94.93	94.31
Climbing stairs	93.42	93.90	94.73
Waist bends forward	93.38	93.94	94.79
Frontal elevation of arms	94.78	92.21	94.70
Knees bending	94.49	94.73	93.51
Cycling	94.70	94.50	94.28
Jogging	93.49	83.96	94.06
Running	92.58	83.84	93.65
Jump front and back	92.10	93.79	93.02
Average	**93.65**	**92.32**	**94.14**

where W_{ik}^f represents a matrix holding the weight values from the i^{th} node of the f^{th} layer to the k^{th} node of the $(f+1)^{th}$ layer. c_i^f is the data of the i^{th} node of the f^{th} layer.

III. EXPERIMENTS AND RESULTS

The experiments were done on mHealth public dataset [28]. The dataset consists of data of vital signs and body motion recordings from ten volunteers for twelve human activities.

TABLE II
MEAN ACCURACY USING THE PROPOSED APPROACH ON SUBJECT 3 TO 6 (%)

Activity	Subject4	Subject5	Subject6
Standing still	93.55	94.38	94.07
Sitting and relaxing	94.55	94.05	94.28
Lying down	94.22	94.62	94.30
Walking	94.08	93.86	94.84
Climbing stairs	94.65	93.32	93.46
Waist bends forward	94.12	94.73	94.59
Frontal elevation of arms	94.44	93.21	92.27
Knees bending	93.50	94.75	94.08
Cycling	93.66	92.74	94.95
Jogging	94.22	93.99	94.50
Running	93.08	94.57	94.99
Jump front and back	90.19	94.43	93.01
Average	**93.69**	**94.05**	**94.11**

TABLE III
MEAN ACCURACY USING THE PROPOSED APPROACH ON SUBJECT 7 TO 10 (%)

Activity	Subject7	Subject8	Subject9	Subject10
Standing still	93.94	94.84	94.71	94.37
Sitting and relaxing	92.71	94.83	92.84	93.31
Lying down	94.89	94.96	94.91	94.21
Walking	94.75	93.81	94.39	94.39
Climbing stairs	94.42	93.54	93.47	94.68
Waist bends forward	94.64	94.96	94.64	93.23
Frontal elevation of arms	94.70	94.08	94.20	93.68
Knees bending	94.68	94.34	93.08	94.84
Cycling	94.84	94.37	93.39	94.92
Jogging	94.48	93.91	94.71	94.60
Running	94.49	93.80	94.41	94.60
Jump front and back	93.98	94.52	93.64	94.78
Average	**94.38**	**94.33**	**94.03**	**94.30**

The activities available in the dataset are Standing still, Sitting and relaxing, Lying down, Walking, Climbing stairs, Waist bends forward, Frontal elevation of arms, Knees bending, Cycling, Jogging, Running, Jump front and back. The sensors were installed mainly on the users' chest, left ankle, and right wrist. The sensors provided data representing some vital signs such as heart signals through the ECG sensors, acceleration through the accelerometers, turning rate through the gyroscopes, and orientation of the magnetic field through the magnetometers. The mean accuracy was used as the performance criteria.

The individual subject was focused on data collection and activity prediction in the data. The proposed CNN-based approach on subject1 achieved the average accuracy of 93.65%. For other subjects 2-10, the proposed approach achieved average accuracy of 92.32%, 94.14%, 93.69%,

TABLE IV
MEAN ACCURACY USING DIFFERENT APPROACHES (%)

Activity	ANN	DBN	Proposed Approach
Standing still	87.84	90.84	94.17
Sitting and relaxing	93.23	91.78	93.77
Lying down	84.69	90.73	94.50
Walking	89.78	92.27	94.29
Climbing stairs	85.53	87.93	93.96
Waist bends forward	90.93	91.45	94.30
Frontal elevation of arms	84.56	86.96	93.83
Knees bending	86.74	91.58	94.20
Cycling	92.28	90.64	94.24
Jogging	87.24	88.37	93.19
Running	89.53	90.43	93.00
Jump front and back	83.47	87.18	93.35
Average	**87.99**	**90.01**	**93.90**

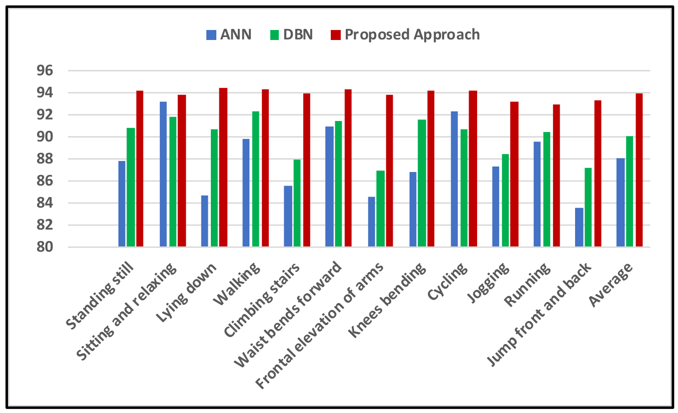


Fig. 8. Performances of different activity recognition approaches on mHealth dataset.

94.05%, 94.11%, 94.38%, 94.33%, 94.03%, and 94.30% respectively. The results for the subjects are reported from Tables I to III. Furthermore, to compare the proposed approach with other approaches, ANN and DBN-based experiments were done. The ANN and DBN-based approaches achieved the average accuracy of 87.99% and 90.01%, respectively. For all the subjects, the achieved average accuracy using the proposed approach was 93.90% as reported in Table IV. Fig. 8 also reports the superiority of the proposed approach over others by showing the highest performance.

IV. CONCLUSIONS

In this study, a novel approach has been proposed for human activity recognition using healthcare body sensors. The data extraction from the body sensor signals is followed by Gaussian kernel-based PCA and Z-score normalization to obtain robust activity features. Furthermore, the features are combined with deep learning technique, deep CNN for distinguished activity training and recognition. The proposed method was compared traditional approaches where it showed its superiority. The system can be adopted for cognitive assistance in smart home health care to prolong the independent life of the people, especially elderly people who are staying alone. In future, we will implement it in a real-life Smart Home environment using Cloud-based distributed platform.

REFERENCES

[1] *World Population Prospects: The 2017 Revision, Custom Data Acquired via Website*. United Nations, Dept. Econ. Social Affairs, Population Division, New York, NY, USA, 2017.

[2] K. Malhi, S. C. Mukhopadhyay, J. Schnepper, M. Haefke, and H. Ewald, "A Zigbee-based wearable physiological parameters monitoring system," *IEEE Sensors J.*, vol. 12, no. 3, pp. 423–430, Mar. 2012.

[3] P. Castillejo, J.-F. Martinez, R.-M. Jesus, and A. Cuerva, "Integration of wearable devices in a wireless sensor network for an E-health application," *IEEE Wireless Commun.*, vol. 20, no. 4, pp. 38–49, Aug. 2013.

[4] O. Aziz and S. N. Robinovitch, "An analysis of the accuracy of wearable sensors for classifying the causes of falls in humans," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 6, pp. 670–676, Dec. 2011.

[5] C. Ranhotigmage, "Human activities and posture recognition: Innovative algorithm for highly accurate detection rate," M.S. thesis, Dept. Eng. Electron. Comput. Syst. Eng., Massey Univ., Palmerston, New Zealand, 2013. [Online]. Available: http://mro.massey.ac.nz/handle/10179/4339

[6] T. Shany, S. J. Redmond, M. R. Narayanan, and N. H. Lovell, "Sensors-based wearable systems for monitoring of human movement and falls," *IEEE Sensors J.*, vol. 12, no. 3, pp. 658–670, Mar. 2012.

[7] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin-Perianu, and P. Havinga, "Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey," in *Proc. 23rd Int. Conf. Archit. Comput. Syst.*, Hannover, Germany, Feb. 2010, pp. 1–10.

[8] S. Bang, M. Kim, S. K. Song, and S. J. Park, "Toward real time detection of the basic living activity in home using a wearable sensor and smart home sensors," in *Proc. IEEE 30th Annu. Int. Conf. Eng. Med. Biol. Soc. (EMBS)*, Aug. 2008, pp. 5200–5203.

[9] F. Bianchi, S. J. Redmond, M. R. Narayanan, S. Cerutti, B. G. Celler, and N. H. Lovell, "Falls event detection using triaxial accelerometry and barometric pressure measurement," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Sep. 2009, pp. 6111–6114.

[10] Y. Cao, L. Tao, and G. Xu, "An event-driven context model in elderly health monitoring," in *Proc. Symposia Workshops Ubiquitous, Autonomic Trusted Comput.*, Jul. 2009, pp. 120–124.

[11] A. Hein *et al.*, "Monitoring systems for the support of home care," *Inform. Health Social Care*, vol. 35, nos. 3–4, pp. 157–176, 2010.

[12] H. Medjahed, D. Istrate, J. Boudy, and B. Dorizzi, "Human activities of daily living recognition using fuzzy logic for elderly home monitoring," in *Proc. IEEE Int. Conf. Fuzzy Syst.*, Aug. 2009, pp. 2001–2006.

[13] M. N. Nyan, F. E. H. Tay, A. W. Y. Tan, and K. H. W. Seah, "Distinguishing fall activities from normal activities by angular rate characteristics and high-speed camera characterization," *Med. Eng. Phys.*, vol. 28, no. 8, pp. 842–849, Oct. 2006.

[14] P. C. Roy, A. Bouzouane, S. Giroux, and B. Bouchard, "Possibilistic activity recognition in smart homes for cognitively impaired people," *Appl. Artif. Intell.*, vol. 25, no. 10, pp. 883–926, Nov. 2011.

[15] K. Sim, C. Phua, G.-E. Yap, J. Biswas, and M. Mokhtari, "Activity recognition using correlated pattern mining for people with dementia," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug./Sep. 2011, pp. 7593–7597.

[16] S. Srinivasan, J. Han, D. Lal, and A. Gacic, "Towards automatic detection of falls using wireless sensors," in *Proc. 29th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2007, pp. 1379–1382.

[17] M. Tolkiehn, L. Atallah, B. Lo, and G.-Z. Yang, "Direction sensitive fall detection using a triaxial accelerometer and a barometric pressure sensor," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., (EMBC)*, Aug. 2011, pp. 369–372.

[18] M. Cornacchia, K. Ozcan, Y. Zheng, and S. Velipasalar, "A survey on activity detection and classification using wearable sensors," *IEEE Sensors J.*, vol. 17, no. 2, pp. 386–403, Jan. 2017.

[19] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1192–1209, 3rd Quart., 2013.

[20] B. Bruno, F. Mastrogiovanni, A. Sgorbissa, T. Vernazza, and R. Zaccaria, "Analysis of human behavior recognition algorithms based on acceleration data," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Karlsruhe, Germany, May 2013, pp. 1602–1607.

[21] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu, "Elderly activities recognition and classification for applications in assisted living," *Expert Syst. Appl.*, vol. 40, no. 5, pp. 1662–1674, Apr. 2013.

[22] J. Windau and L. Itti, "Situation awareness via sensor-equipped eyeglasses," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Nov. 2013, pp. 5674–5679.

[23] J.-Y. Yang, J.-S. Wang, and Y.-P. Chen, "Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers," *Pattern Recognit. Lett.*, vol. 29, no. 16, pp. 2213–2220, Dec. 2008.

[24] M. Z. Uddin, W. Khaksar, and J. Torresen, "Ambient sensors for elderly care and independent living: A survey," *Sensors*, vol. 18, no. 7, p. 2027, 2018, doi: 10.3390/s18072027.

[25] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-time patient-specific ECG classification by 1-D convolutional neural networks," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 3, pp. 664–675, Mar. 2016.

[26] M. Z. Uddin, M. M. Hassan, A. Almogren, A. Alamri, M. Alrubaian, and G. Fortino, "Facial expression recognition utilizing local direction-based robust features and deep belief network," *IEEE Access*, vol. 5, pp. 4525–4536, 2017.

[27] M. Z. Uddin, W. J. Khaksar, and J. Torresen, "Facial expression recognition using salient features and convolutional neural network," *IEEE Access*, vol. 5, pp. 26146–26161, 2017.

[28] O. Banos *et al.*, "mHealthDroid: A novel framework for agile development of mobile health applications," in *Proc. Int. Workshop Ambient Assist. Living*, vol. 8868, Lecture Notes in Computer Science. Cham, Switzerland: Springer, 2014, pp. 91–98.

[29] X. Deng, X. Tian, S. Chen, and C. J. Harris, "Deep learning based nonlinear principal component analysis for industrial process fault detection," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Anchorage, AK, USA, May 2017, pp. 1237–1243.

[30] K. Cho, T. Yoon, S. Park, and D. Park, "Using standardization for fair data evaluation," in *Proc. 20th Int. Conf. Adv. Commun. Technol. (ICACT)*, Feb. 2018, pp. 585–589.

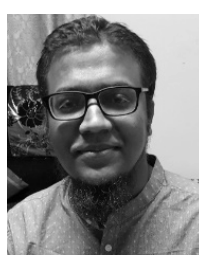
[31] K. Jaafar, N. Ismail, M. Tajjudin, R. Adnan, and M. H. F. Rahiman, "Z-score and feedforward neural network (FFNN) for flood modelling at Kuala Krai station," in *Proc. 7th IEEE Control Syst. Graduate Res. Colloq. (ICSGRC)*, Shah Alam, Malaysia, Aug. 2016, pp. 92–97.

[32] G. Fortino, R. Giannantonio, R. Gravina, P. Kuryloski, and R. Jafari, "Enabling effective programming and flexible management of efficient body sensor network applications," *IEEE Trans. Human-Mach. Syst.*, vol. 43, no. 1, pp. 115–133, Jan. 2013.

[33] M. M. Hassan, M. Z. Uddin, A. Mohamed, and A. Almogren, "A robust human activity recognition system using smartphone sensors and deep learning," *Future Gener. Comput. Syst.*, vol. 81, pp. 307–313, Apr. 2018.

[34] N. Raveendranathan *et al.*, "From modeling to implementation of virtual sensors in body sensor networks," *IEEE Sensors J.*, vol. 12, no. 3, pp. 583–593, Mar. 2012.

Md. Zia Uddin (SM'17) received the Ph.D. degree in biomedical engineering in 2011. He is currently a Post-Doctoral Research Fellow with the Robotics and Intelligent Systems Research Group, Department of Informatics, University of Oslo, Norway. His research interests are mainly focused on sensors, machine vision, robotics, machine learning, artificial intelligence, and pattern recognition. He got more than 90 research publications, including international journals, conferences, and book chapters.



Mohammad Mehedi Hassan (SM'18) received the Ph.D. degree in computer engineering from Kyung Hee University, South Korea, in 2011. He is currently an Associate Professor with the Information Systems Department, College of Computer and Information Sciences (CCIS), King Saud University (KSU), Riyadh, Saudi Arabia. He has published over 100 research papers in the journals and conferences of international repute. His research areas of interest are cloud federation, multimedia cloud, sensor-cloud, Internet of Things, big data, mobile cloud, body sensor network, pervasive healthcare, and deep learning. He received the Best Paper Award at the CloudComp Conference, China, in 2014, the Best Journal Paper Award from the IEEE SYSTEMS JOURNAL in 2018, and the Excellence in Research Award from CCIS, KSU, in 2015 and 2016, respectively. He was the guest editor of several international ISI-indexed journals.