Hybrid model featuring CNN and LSTM architecture for Human Activity Recognition on smartphone sensor data

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***Abstract*—The traditional methods of recognizing human activities involve typical machine learning (ML) algorithms which uses heuristic engineered features. Human activities are dynamic in nature and are encoded with a sequence of actions. ML methods are able to perform activity recognition tasks but may not exploit the temporal correlations of the input data. Therefore, in this paper, we proposed and showed the effectiveness of employing a new combination of deep learning (DL) methods for human activity recognition (HAR). DL methods are capable of extracting discriminative features automatically from the raw sensor data. Specifically, in this paper, we proposed a hybrid architecture which features a combination of Convolutional neural networks (CNN) and Long short-term Memory (LSTM) networks for HAR task. The model is tested on UCI_HAR_dataset which is a benchmark dataset and comprises of accelerometer and gyroscope data obtained from a smartphone. Our experimental results showed that our proposed method outperformed the recent results which used pure LSTM and bidirectional LSTM networks on the same dataset.**

***Index Terms*—Activity recognition, neural network, deep learning, CNN, LSTM and Hybrid model.**

I. Introduction

The proliferation of smartphones with various embedded sensors have eased the method of gathering human activity data in recent time. With the development of unprecedented characteristics of sensors such as accelerometer and gyroscope, sensor based human activity recognition (HAR) has received extensive concerns [1]. HAR is applicable to many real-world applications such as nursing care, anomaly detection and surveillance systems. The shortage of health-care workers and increase in nursing-care abuse have also increased the demand of HAR systems. HAR systems are broadly categorised into wearable-based [2] and non-wearable based [3] HAR systems. Non-wearable based are further categorised into vision-based [4] and device free-based [5] HAR. In wearable based HAR, sensors or other external devices are attached to human body. In contrast, sensors or external devices are placed in occupants' environment in non-wearable HAR based systems.

HAR is a method of predicting activities from the data obtained from sensors. The process involves extracting motion features and classifying the activities in different categories. Various machine learning algorithms have been used for activity recognition task. Traditional machine learning often requires domain knowledge and extensive training [6]. It uses heuristic hand crafted features for training the model. The data collected from the sensors are sequence of time series data and traditional machine learning algorithms may not exploit the temporal correlations of input data. Current research on HAR using deep learning methods have outperformed traditional machine learning methods [7]. Deep learning methods have managed to mitigate some issues of traditional machine learning in recent time. It has ability to automatically extract the discriminative features and prevent dependence on hand-crafted features. Convolutional neural networks (CNNs) and Long short-term Memory (LSTM) are some popular deep learning methods that are widely used in HAR [8]. CNNs are capable of learning complex activities and LSTM networks are effective in capturing temporal information from time series data.

Recognising human activities from sensor data is challenging because the activities performed by the human are dynamic in nature. Each action performed by human may not be performed again in similar manner or different activities performed may have similar data patterns. Therefore, this work majorly focus on two parameters. First is to enhance the activity recognition score and second is to avoid dependence on hand-crafted features to address ever increasing complex human activities problems.

Inspired by the architecture of CNN-LSTM used for precipitation nowcasting [9] and voice search tasks [10], we also use combination of CNN and LSTM architecture for predicting human activities on UCI_HAR_dataset [11]. Hybrid models have emerged as a popular technique which is applicable to several area of research. Hybrid models are reported to produce better recognition scores than pure CNN or LSTM networks [12]. In this paper, we use combination of CNN and LSTM for HAR. Furthermore, we also apply LSTM for activity recognition task in the same dataset and compare the results with CNN-LSTM model. In summary, the main contributions of our work are as follows:

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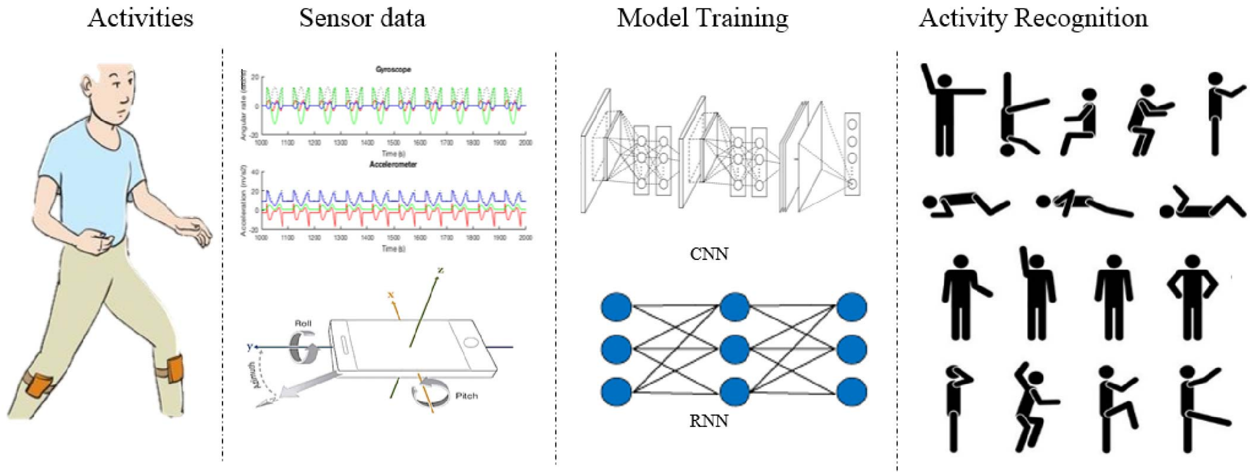

Fig. 1. Schematic diagram of smartphone data based human activity recognition using hybrid model

1) We show the effectiveness of using hybrid architecture on time series data that combines CNN and LSTM networks for HAR task.
2) The hybrid model leverages the dependence on hand-crafted features and extracts discriminative features automatically.
3) We demonstrate that combination of CNN and LSTM networks yield better recognition scores than recently used methods such as pure LSTM and bidirectional LSTM in UCI_HAR_dataset.

The rest of the paper is as follows: Section 2 provide an overview of related work in hybrid model based HAR systems. Section 3 discuss the CNN-LSTM architecture used in our work. Section 4 outline the research methodology, sources of data and research approach. Section 5 discuss the experimental results. Lastly in section 6, we provide conclusion, suggestions and future work.

II. Related Work

Various methods such as machine learning models, deep learning models, and hybrid models [12] [13] have been proposed in the literature for HAR. Traditional machine learning methods have achieved good recognition scores. However, it uses heuristic hand-crafted features and requires domain expert for training the model. In recent time, deep learning models have gained popularity and outperformed traditional machine learning methods [7]. It does not require manual filtering and feature extraction like traditional algorithms. With the recent success of deep learning models, a trend of using hybrid model has accelerated for HAR and several other area of research. Hybrid models are combination of two or more deep learning models. Hybrid models are reported to produce better recognition scores than pure CNN or LSTM networks [12].

Wang et al. [14] have proposed a framework in which they combined 3D CNN with LSTM for to identify actions from video. They applied Saliency-aware methods to generate video and input was fed to the 3D CNN and then sent to LSTM to explore temporal correlation among video clips. Wu et al. [15] have proposed a deep hybrid model that feature CNN and LSTM for video classification. They have used two convolution layers for feature extraction and then combined the extracted features for classification. The LSTM layer is stacked on the top of the two CNN layers to provide longer term temporal clues. Similarly, Shi et al. [16] used combination of CNN and LSTM for action recognition from video. They used CNN-RNN network to learn an effective representation for long-term motion. The actions are then identified from video using three-stream framework.

Davis et al. [17] proposed a hybrid model using Support Vector Machine (SVM) and Hidden Markov Model (HMM) for activity recognition. The experimental results of hybrid model featuring SVM and HMM achieved higher recognition scores than pure SVM and Artificial Neural Networks ANN. Similarly, Vishwakarma et al. [18] have proposed a hybrid model that feature SVM and 1-NN model for identification of human activities from video. The experimental results showed better accuracy compared to the similar state-of-the art methods. However, the proposed system is compromised when the person to be identified is occluded.

From our literature review, we observed that most of the CNN-LSTM based activity recognition is done in the area of computer vision. The combination of CNN and LSTM model is still in nascent stage for time series sensor data. Combination of CNN and LSTM networks have achieved good recognition scores in the area of image processing and video-based HAR. Inspired by the success of hybrid architecture for HAR using images and videos, we also decide to use hybrid architecture for predicting human activities from sensor data. To the best of our knowledge, there have been no work on sensor data (accelerometer and gyroscope) using hybrid CNN-LSTM model on UCI_HAR dataset. In this work, we apply LSTM and hybrid CNN-LSTM networks for HAR. We also compare our results with recent work on different forms of LSTM models used on sensor data for HAR.

III. CNN-LSTM Architecture

Hybrid models are often referred as the combination of two or more deep learning models [19]. In hybrid models, each layers process the output of previous layers. The order of the proposed CNN-LSTM networks are as follows: 1D Convolution layer, 1D Convolution layer, Dropout layer, 1D Maxpool layer, Time Distributed Layer, Flatten layer, LSTM layer, Dropout Layer, Dense layer and Output Layer.

Convolutional neural networks (CNNs) are multilayered deep neural networks. It has the ability of extracting complex features automatically [20]. CNNs comprise of multi convolutional layers that create hierarchy of the operations being performed. The output from each previous convolutional layers in the CNN architecture is fed as an input to the following convolutional layers. CNNs have been largely used in computer vision, autonomous vehicles and image processing. Long-short-term memory (LSTM) are type of recurrent neural networks (RNN) which comprise of memory cells to capture temporal information from time series data [21]. LSTM are designed to handle long-term time dependencies problems [22].

A. Convolutional Neural Network (CNN)

In this work, we have implemented two consecutive blocks of 1D convolutional layers. 1D CNN is effective in extracting discriminative features from a dataset of fixed window-length. We have decided to use 1D CNN layers because the dataset which we have used in this work has fixed window length of 128. Each 1D convolutional layer includes ReLu activation, Kernel size and number of filters. The consecutive 1D CNN layers are followed by max-pooling layers to avoid data overfit and to minimize complexity of the output data. We chose a pool size of 2 in this network.

B. Long-short-term memory (LSTM)

The end of CNN pipeline in the CNN-LSTM network is followed by LSTM network. We use one LSTM network with 100 units where each layer is producing hidden cell information. The output data from the previous 1D convolutional layer is passed through LSTM layers as the input. The LSTM layer is followed by dense layer, hyperbolic tangent activation (tanh) and softmax layer at the end. The output is generated for one of the six classes at the end of this network

C. Hybrid CNN and LSTM Model (CNN-LSTM)

Inspired from the architecture proposed in [9] [10], we decided to stack convolutional and LSTM layer for the activity recognition task. The schematic diagram of our CNN-LSTM model is as shown in the figure 2. The preliminary results did not show any significant accuracy improvement after adding more number of layers. The adding of additional layers only increased the computational cost. Therefore, we decided to keep our model simple by using only two 1D convolutional layers and one LSTM layer for activity recognition.

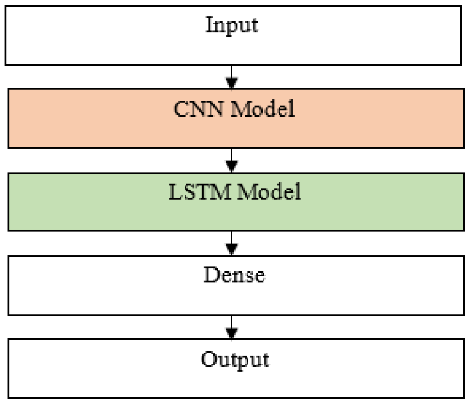

Fig. 2. Architecture of CNN-LSTM networks

IV. Implementation

A. Dataset

In order to evaluate the effectiveness of the CNN-LSTM model, we perform experiment on UCI_HAR dataset. The dataset consist of time series data collected from from 30 volunteers of 19-48 age-group. Each volunteer performed six activities (*walking, walking-upstairs, walking-downstairs, sitting, standing, laying*) with a smartphone attached to their waist. The 3-axial linear acceleration (tAcc-XYZ) from accelerometer, and 3-axial angular velocity (tGyro-XYZ) from gyroscope data were collected. The data were collected with a constant sampling rate of 50Hz. The activities were video-recorded for ground truth and data were manually labelled. The dataset is randomly divided into 70% training and 30% testing data.

The obtained signals were pre-processed applying noise filters. The filtered signals were sampled at 2.56 sec fixed-width sliding windows with 128 readings/window. Butterworth low-pass filter was used to separate gravitational and body motion components from acceleration signal. A feature vector is obtained from each window by calculating variables from time and frequency domain. The data is engineered very well. The description of UCI_HAR dataset is presented in table 1.

TABLE I
DESCRIPTION OF UCI HAR DATASET

Dataset	UCI-HAR [11]
Number of Subjects	30
Number of Activities	6
Sensors	2 (accelerometer and gyroscope)
Training Window Length	128
Sampling Rate	50 Hz

B. Experimental setup

We conducted the experiments on Windows PC with i7-6700 CPU and 16 GB RAM. The experiments were smooth and took less time to generate the output. The use of GPU was not felt essential. Thus, the computational cost of CNN-LSTM architecture used in this work is comparatively low. The idea is to propose a computationally less expensive model without compromising the accuracy level. We first checked for any imbalance data before conducting the activity recognition experiments. The experimental results showed that the publicly available UCI_HAR dataset is carefully engineered and are well balanced.

The idea is to pass the data through the hybrid model that combines CNN-LSTM architecture. In this hybrid architecture, we use convolutional layer followed by LSTM layer. The data collected were measured in three axis x, y, z - total acceleration, body acceleration and angular acceleration. These data resulted in 9 files. Each files have samples of 128 time steps. The data from the resulted 9 files were combined and then converted into a shape of no. of samples X time steps X no. features. The shape for training data is 7352 X 128 X 9.

The next step is to pass the data through the CNN layers for which the data is transformed into 4D matrix. The data is converted into the format of no. of samples X length X width X channels to pass through CNN. The dataset is converted into 7352 X 4 X 64 X 9. For each sample, 128 points are divided into 64 batch size and an epochs of 100 was used on this data. We used 1D convolutional layers in this experiment because it works well for time series sensor data. The goal is to pass the output data from 1D convolutional layer to LSTM layers as the input in this architecture to predict activities from one of the six classes.

The input size for one sub-sequence will be 1 X 1 X 64 X 9. The input is then passed through two 1D convolutional layers. We decided to use 1D CNN layers because the dataset which we have used in this work has fixed window length of 128. Each 1D convolutional layer includes ReLu activation, Kernel size and number of filters. We used kernel size of 6 and and number of filters 128 for both the convolutional layers. The output data size is then passed through dropout layer. The dropout layer functions as regularization in this architecture to prevent over-fitting. The data is then passed through maxpool layer to minimize complexity of the output data. We chose a pool size of 2 in this network. Finally, it is passed through flatten layer which ends the usage of CNN networks in this hybrid model. The flatten layer transformed the data into a single matrix of size 1 X 1 X 1664 which is 3 dimension (length, width and channels) data. This output data is further used to pass through the LSTM layer.

The output 3D data is then fed to LSTM layer. The LSTM layer is used in this hybrid architecture because it works well with the time series data and is designed to handle time dependence problems. Each LSTM layer in this architecture produces hidden cell information. The LSTM layer is followed by dense layer, hyperbolic tangent activation (tanh) and softmax layer at the end. It is then passed through dense layer with hyperbolic tangent activation (tanh) and used Adam optimizer which ends the LSTM networks in this hybrid model. Finally, the output is generated for one of the six classes.

V. Results and Discussions

We used UCI_HAR benchmark dataset that comprise of accelerometer and gyroscope data collected from a smartphone for human activity recognition. The experiments were conducted on the dataset to recognise six different human activities using pure LSTM model and combination of CNN and LSTM model (CNN-LSTM). We conducted experiments on very carefully engineered data from UCI_HAR dataset which is publicly available. We first conducted the following two tests on the dataset to check for the imbalance data:

1) activity by each test subject
2) count of each activity

From the figures 3 and 4, we can infer that the classes are very well balanced. This shows that features are very carefully engineered by domain experts.

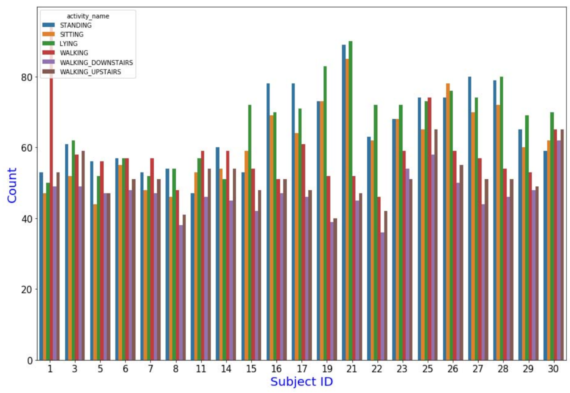

Fig. 3. Activity by each test subject

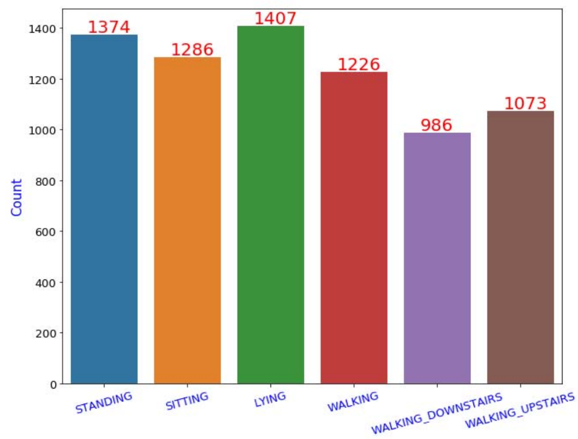

Fig. 4. Count of each activity

In the first experiment, we used only LSTM model to predict human activities. We used pure LSTM because human activities are sequence of actions and LSTM are considered good for time series sensor data. It is capable of capturing temporal dependencies from time series sensor data. The experimental results showed the accuracy of 92.98% using only LSTM model. Figure 5 and 6 show the training and validation loss, and confusion matrix of the LSTM model respectively.

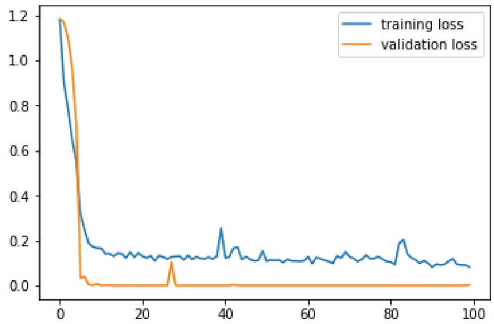

Fig. 5. training and validation loss of LSTM

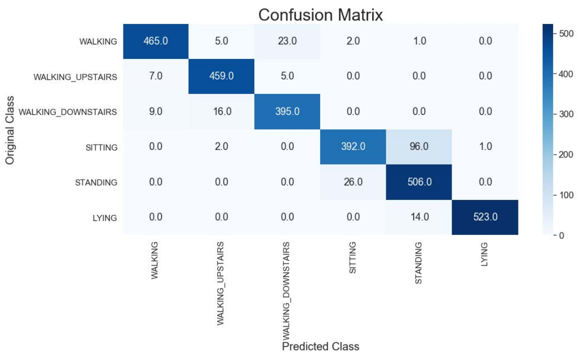

Fig. 6. Confusion matrix using LSTM architecture

In the second experiment, we used CNN-LSTM network to predict human activities. The recent success of hybrid models motivated us to use combination of two highly popular deep learning models for our sensor based activity recognition task. CNN models works well with images and computer vision domains. CNN model is widely used deep learning model. It has the ability to extract discriminative features automatically. LSTM works well with time series data and are capable of capturing temporal information. It has the memory cell which are basically designed to address time dependencies problems. Therefore, we decided to take advantages of both highly popular deep learning models by combining them into one model (CNN-LSTM).

We converted the time series data collected from smartphone sensors into 4D matrix shape in order to pass through CNN architecture of our CNN-LSTM model. After preliminary tests with different epochs and batch size, we decided to use an epochs of 100 and batch size of 64 to conduct this experiment. We used two 1D convolutional layers with ReLu activations and maxpooling layers. The output from the first 1D convolutional layers is passed through the next 1D convolutional layers. The output from the second 1D convolutional layer is then passed through LSTM layers to generated output for one of the six classes.

We conducted experiments using different optimizer such as stochastic gradient descent (SGD), Adagrad [23], RMSprop [24] and Adam [25]. We decided to use Adam as an optimizer based on our preliminary results. Experimental results showed the accuracy of 93.4% which outperformed different forms of LSTM models used in this dataset. The adding of additional layers did not show any significant accuracy improvement but only increased the computational cost. Therefore, we decided to keep our CNN-LSTM model simple by keeping two 1D convolutional layers and one LSTM network. The experimental results showed the advantages of using hybrid model over pure and other forms of LSTM models. Figure 7 show the training and validation loss of our CNN-LSTM model. Figure 8 shows the confusion matrix of our CNN-LSTM model. We also compared our results with state-of-the-art LSTM models proposed on same dataset. The comparison of performance of other LSTM models on UCI_HAR dataset is given in the table 2.

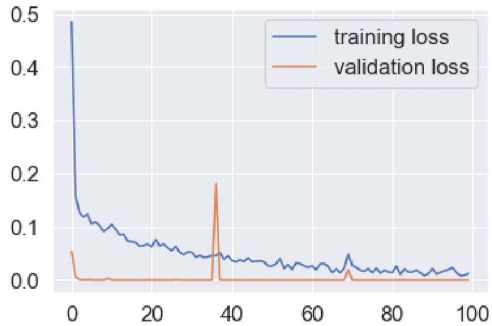

Fig. 7. training and validation loss of CNN-LSTM

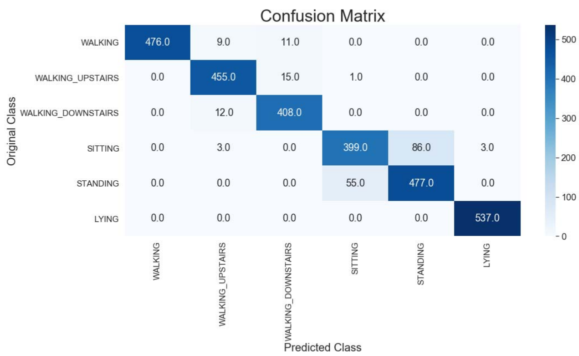

Fig. 8. Confusion matrix using CNN-LSTM architecture

The performance comparison table shows the effectiveness of our CNN-LSTM model compared to state-of-the-art methods used for LSTM, Bidirectional LSTM, Res-LSTM and Baseline LSTM model on same UCI_HAR dataset. The

TABLE II
PERFORMANCE COMPARISON ON UCI HAR DATASET

Model	Accuracy
CNN-LSTM	**93.40 %**
LSTM	92.98 %
Bidirectional LSTM [26]	92.67 %
Res-LSTM [27]	91.60 %
Baseline LSTM [27]	90.80 %

CNN-LSTM model yield better recognition score than applied LSTM model and also outperformed other forms of LSTM used for activity recognition in the same dataset.

VI. CONCLUSION

The hybrid model featuring CNN and LSTM architectures have exhibited optimum performances in several domain such as speech recognition and image processing. However, combination of CNN and LSTM models have not been used on sensor data (accelerometer and gyroscope) for HAR. In this work, we have proposed a combination of CNN and LSTM model for HAR on smartphone sensor data. We also conducted experiment on same dataset using only LSTM model. CNN-LSTM model resulted higher accuracy than LSTM model. The experimental results also demonstrated the effectiveness of using CNN-LSTM model compared to state-of-the-art methods on the same dataset which used different forms of LSTM. The proposed architecture take advantages of CNN and LSTM model for recognising human activities. Human activities are a sequence of actions where temporal information is crucial. CNN are useful to extract discriminative features automatically by convolutional operations and LSTM are useful to capture temporal information and avoid time dependencies problems.

The proposed architecture showed significant recognition score in predicting simple and limited activities performed by a single person. However, the model may not achieve similar accuracy when multi activity is being performed by more than one person. In future, we aim to evaluate our model for multi people activity recognition. We also aim to identify complex human activities in future.

REFERENCES

[1] C. V. San Buenaventura and N. M. C. Tiglao, "Basic human activity recognition based on sensor fusion in smartphones," in *2017 IFIP/IEEE Symposium on Integrated Network and Service Management (IM)*. IEEE, 2017, pp. 1182–1185.

[2] F. Li, K. Shirahama, M. A. Nisar, L. Köping, and M. Grzegorzek, "Comparison of feature learning methods for human activity recognition using wearable sensors," *Sensors*, vol. 18, no. 2, p. 679, 2018.

[3] I. Lillo, J. C. Niebles, and A. Soto, "Sparse composition of body poses and atomic actions for human activity recognition in rgb-d videos," *Image and Vision Computing*, vol. 59, pp. 63–75, 2017.

[4] A. Jalal, Y.-H. Kim, Y.-J. Kim, S. Kamal, and D. Kim, "Robust human activity recognition from depth video using spatiotemporal multi-fused features," *Pattern recognition*, vol. 61, pp. 295–308, 2017.

[5] Y. Wang, K. Wu, and L. M. Ni, "Wifall: Device-free fall detection by wireless networks," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 581–594, 2017.

[6] M. I. Razzak, S. Naz, and A. Zaib, "Deep learning for medical image processing: Overview, challenges and the future," in *Classification in BioApps*. Springer, 2018, pp. 323–350.

[7] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1–9.

[8] S. Ramasamy Ramamurthy and N. Roy, "Recent trends in machine learning for human activity recognitiona survey," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 8, no. 4, p. e1254, 2018.

[9] S. Xingjian, Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-c. Woo, "Convolutional lstm network: A machine learning approach for precipitation nowcasting," in *Advances in neural information processing systems*, 2015, pp. 802–810.

[10] T. N. Sainath, O. Vinyals, A. Senior, and H. Sak, "Convolutional, long short-term memory, fully connected deep neural networks," in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2015, pp. 4580–4584.

[11] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "A public domain dataset for human activity recognition using smartphones." in *Esann*, 2013.

[12] F. Ordóñez and D. Roggen, "Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition," *Sensors*, vol. 16, no. 1, p. 115, 2016.

[13] S. Yao, S. Hu, Y. Zhao, A. Zhang, and T. Abdelzaher, "Deepsense: A unified deep learning framework for time-series mobile sensing data processing," in *Proceedings of the 26th International Conference on World Wide Web*. International World Wide Web Conferences Steering Committee, 2017, pp. 351–360.

[14] X. Wang, L. Gao, J. Song, and H. Shen, "Beyond frame-level cnn: saliency-aware 3-d cnn with lstm for video action recognition," *IEEE Signal Processing Letters*, vol. 24, no. 4, pp. 510–514, 2016.

[15] Z. Wu, X. Wang, Y.-G. Jiang, H. Ye, and X. Xue, "Modeling spatial-temporal clues in a hybrid deep learning framework for video classification," in *Proceedings of the 23rd ACM international conference on Multimedia*. ACM, 2015, pp. 461–470.

[16] Y. Shi, Y. Tian, Y. Wang, and T. Huang, "Sequential deep trajectory descriptor for action recognition with three-stream cnn," *IEEE Transactions on Multimedia*, vol. 19, no. 7, pp. 1510–1520, 2017.

[17] K. Davis, E. Owusu, V. Bastani, L. Marcenaro, J. Hu, C. Regazzoni, and L. Feijs, "Activity recognition based on inertial sensors for ambient assisted living," in *2016 19th international conference on information fusion (fusion)*. IEEE, 2016, pp. 371–378.

[18] D. K. Vishwakarma and R. Kapoor, "Hybrid classifier based human activity recognition using the silhouette and cells," *Expert Systems with Applications*, vol. 42, no. 20, pp. 6957–6965, 2015.

[19] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, "Deep learning for sensor-based activity recognition: A survey," *Pattern Recognition Letters*, vol. 119, pp. 3–11, 2019.

[20] O. Ghorbanzadeh, T. Blaschke, K. Gholamnia, S. R. Meena, D. Tiede, and J. Aryal, "Evaluation of different machine learning methods and deep-learning convolutional neural networks for landslide detection," *Remote Sensing*, vol. 11, no. 2, p. 196, 2019.

[21] M. S. Ibrahim, S. Muralidharan, Z. Deng, A. Vahdat, and G. Mori, "A hierarchical deep temporal model for group activity recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, pp. 1971–1980.

[22] M. Abdel-Nasser and K. Mahmoud, "Accurate photovoltaic power forecasting models using deep lstm-rnn," *Neural Computing and Applications*, pp. 1–14, 2017.

[23] J. Duchi, E. Hazan, and Y. Singer, "Adaptive subgradient methods for online learning and stochastic optimization," *Journal of Machine Learning Research*, vol. 12, no. Jul, pp. 2121–2159, 2011.

[24] T. Tieleman and G. Hinton, "Rmsprop: Divide the gradient by a running average of its recent magnitude. coursera: Neural networks for machine learning," *Tech. Rep., Technical report*, p. 31, 2012.

[25] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[26] F. Hernández, L. F. Suárez, J. Villamizar, and M. Altuve, "Human activity recognition on smartphones using a bidirectional lstm network," in *2019 XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA)*. IEEE, 2019, pp. 1–5.

[27] Y. Zhao, R. Yang, G. Chevalier, X. Xu, and Z. Zhang, "Deep residual bidir-lstm for human activity recognition using wearable sensors," *Mathematical Problems in Engineering*, vol. 2018, 2018.