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Open Access Survey Paper

Development of Activity Recognition Model using LSTM-RNN Deep Learning Algorithm

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Abstract

This study analyses numerous human activities and also classifies the activities based on their trait of motion using wearable sensors data. As a part of the Human Activity Recognition Framework's development, the LSTM-RNN algorithm was implemented. We have considered ten types of motions for recognition and based on the duration of motions have classified those motions into repetitive and non-repetitive motions. The dataset utilized to evaluate the model's performance was recordings from Opportunity. The best trained model achieved an overall accuracy of 94% and The findings of the study stated that the LSTM-RNN model achieved greater accuracy of 91% pertaining to motions that are not repeating that means motions that are performed for short periods of time in comparison to the motions having long dependencies which achieved accuracy of 80%. The determination of performance has been done in terms of score of accuracy, score of precision and f1 score. In addition to this, a disparity analysis of the presented model with another devised model has also been done.

Keywords: Long Short Term Memory, Recurrent Neural Network, Human Activity Recognition, Sensor, Accuracy

1. Introduction

Identification of human behavior plays an essential part in developing interaction between people and in maintaining interpersonal relationships. It is quite difficult to extract as it contains details about a person's identity, personality, and psychological condition. Though analyzing human beings behavior has always been a challenging problem yet a solution is needed. As a consequence of which, significant research learnings has been carried out in the connection with Human Beings Behavior Recognition. Various algorithms that focused on ML have been applied for the purpose of identifying simple and complex activities. The HAR machine can be utilized for tracking elderly people’s movements [1]. Risky situations like falling are also detectable using HAR. Nowadays, the crime rate is rising sharply, and as a result it is required to maintain a track on the actions of people so that the rate of crime can be regulated and this can be attained by recognizing human activities [2]. Previous research on human activity detection can be classified into a group of several categories depending on the apparatuses, sensor methodologies, and data used to track activity information. The HAR system has its major utilisation in healthcare industries, for surveillance, sports tracking, smart homes, for supporting elderly people and so on. Former studies have considered into account usually common basic activities like sitting, standing, lying etc. for development of human activity recognition model and have also worked on multiple activities without considering the distinction in the characteristics of motions. This study makes contribution in the following ways:

- An extensive study of various human activities captured using the wearable sensor data was done.
- The model LSTM-RNN is trained and tested for ten activities categorized into repetitive and non-repetitive motions.
- Experiment is conducted with the goal of measuring the implied model's effectiveness for human activity recognition on Opportunity dataset.

The model's performance is evaluated in terms of accuracy score, precision score and F1 score and is also compared with other formerly developed models.

2. Literature Review

Murahari et al. developed an attention model for recognizing human activities. Model was created by incorporating an attention layer to the deep convolutional LSTM framework and after evaluation of the model on benchmark data-set, a significant enhancement in performance was noticed [3]. Subasi et al. created a Health-care intelligent framework for identification of human activities with the success of machine learning. The design was devised on two different datasets one is the mobile cell and another is wearable body sensors. Moreover, the study insinuated that using ML methods, human activities identification on sensor data is very challenging [4]. Singh et al. devised a system for detecting human activity on real world automated home datasets using (LSTM) Long Short Term Memory-Recurrent Neural Network (RNN). The applied strategy exceeded the existing approaches in terms of score of accuracy and performance also [5]. Murad et al. developed an activity recognition model capable of capturing input sequences of variable length having long range dependencies with the help of deep-recurrent neural networks (DRNNs). The framework was framed with the assistance of unidirectional, bidirectional and cascaded LSTM DRNNs structures and the results of the trial showed that the implied strategy outperformed conventional ML strategies such as k-nearest neighbors (KNN) and (SVM) Support Vector Machine. In fact it even performed quite well in comparison to other deep learning techniques like CNNs and Deep Believe Networks (DBNs) [6]. Hassan et al. developed a robust recognition model on smartphone inertial sensors. Firstly, the features such as mean, median, autoregressive coefficients etc. were derived from the unprocessed data then further processing of features was done using Kernel Principal Component Analysis-(KPCA) and (LDA) Linear Discriminant Analysis and finally the training of features was done using Deep-Belief Network

(DBN). The Experimental findings revealed that the implied method for feature processing and training outperformed traditional feature recognition approaches namely (ANN) Artificial Neural Network and SVM-Support Vector Machine [7]. A comparison analysis was conducted by Wang et al. on identification of human behavior using smartphone-inertial-sensors. As per the findings of the swotting more distinguished information can be obtained from a triaxial accelerometer in comparison to the information obtained from triaxial gyroscope. In addition the outcomes of the study also suggested that the fusion of triaxial-accelerometer and triaxial-gyroscope can result in better classification performance [8]. Taylor et al. developed a non-invasive intelligent real time human behavior recognition framework for the next generation of healthcare. The data set was made possible through the use of radio wave signal patterns which were acquired by using software-defined radios (SDR) to establish a test case of if the person is standing or sitting down. Using this dataset a machine learning model was created which achieved an accuracy of 96.70%. With the help of 10 fold cross validation, a Random Forest Algorithm (RFA) was utilized in construction of this model. Furthermore, the proposed dataset showed similar accuracy of nearly 90% with the wearable devices dataset [9]. Baldominos et al. compared various machine learning strategies for identification of human activities. An Activity recognition chain methodology comprised of sequence of steps from pre-processing, segmentation, feature extraction to classification of traditional machine learning approaches was applied. The data-set used was composed primarily of 13 activities from physical activities, common postures, working activities to leisure activities captured using two devices one was worn on wrist and other one was kept in pocket. As per this study the optimum outcome was obtained using randomized trees strategy on wrist data as well as identified that the DL models performance was not up to the point when compared to the suggested approach [10]. Guan et al. devised recognition model using collection of deep LSTM networks. The experimental determination was implemented on three benchmark datasets namely Opportunity, PAMAP2 and Skoda. Also, it was indicated that the group of various deep LSTM networks outperformed individual LSTM networks. The suggested strategy showed magnificent capability in recognizing activities and also has potential in recognizing real-time human activities [11]. Tüfek et al. developed action recognition system using accelerometer data and gyroscope data. The framework was build and assessed with the assistance of numerous techniques of deep learning strategies and ML approaches like CNN, LSTM. The highest accuracy attained was using 3 layer LSTM network [12]. Chen et al. proposed a recognition framework on WISDM public datasets employing LSTM network approach for extraction of features and the LSTM based approach achieved 92.1 percent accuracy [13]. Wang et al. conducted a survey on recent progresses on modality of sensor, deep model and applications. Also, found that DL accomplish better results by learning high-level representations of sensor data automatically [14]. Walse et al. evaluated the efficiency of several ML techniques for detecting human behavior on WISDM dataset. It was indicated that Random Forest Classifier achieved accuracy of 98.09% which was quite good in comparison to recognition done by other researchers using Multilayer Perceptron Classifier (MLP) and Random Forest Classifier as they achieved 91.7% accuracy and 75.9% on impersonal data respectively [15]. Cruciani et al. presented a case study where the pre-trained CNN feature extractor is assessed under real-world scenarios. Various parameters were analyzed in this study in order to identify the best designs for recognizing human activities [16]. Wan et al. developed architecture based on smartphone inertial accelerometer for Human Behavior Recognition with the help of CNN-LSTM. The study explored training of several deep learning strategies and noted that the suggested technique outperformed on two large public datasets [17]. Li et al. developed the human motion detection system based on the LSTM- Recurrent Neural Network algorithm. The developed model used a bottom-up approach in a way that at first place the human joints were identified and then the multiple joints were combined as a node for recognition of the body of a human in the image. As per the study the LSTM-Recurrent Neural Network achieved a higher recognition rate [26]. Albaba et al. developed the activities detection model using the Convolutional Neural Network and RNN-Long Short-Term memory model. The model was developed for identifying six activities which were walking, upstairs, jogging, downstairs, standing and sitting. The study found that the RNN-Long Short-Term memory approach achieved greater accuracy as compared to the model which was based on the Convolutional Neural Network [27]. Abbaspour et al. investigated the effectiveness of integrating Convolutional Neural Networks with RNNs on PAMAP2 dataset. The study found that integrating CNNs with RNNs results in higher accuracy rate in comparison to when the activities are recognized using RNN and Convolutional Neural Networks individually [28].

3. Benchmark Dataset

These benchmark datasets used contain various physical activities including repetitive motions, non- repetitive motions and postures. The opportunity dataset contain 113 signals which were recorded in a room. In-depth description of the data-set have been described below.

3.1. Opportunity Activity Recognition Dataset

The OPPORTUNITY Dataset from Wearable Sensors, Object Sensors, and Ambient Sensors to recognize Human Activity is a dataset that has been compiled to examine Algorithms like classification, automatic segmentation of data, fusion of sensors, feature extraction, etc. for recognizing human behavior. This dataset captured the difficulties faced by many other activity recognition scenarios. The dataset encompasses the motion sensor readings that were gathered while users performed typical daily activities in a room. The original dataset comprised of Body sensors which included 7 IMUs, four 3D coordinates from a localization system, 12 acceleration sensors (3D), Object Sensors which included 12 objects with wireless sensors capable of measuring three-dimensional acceleration and two-dimensional rate of turn and the Ambient sensors which included thirteen switches and 8 three dimensional acceleration sensors. Activities of 4 users were recorded, 6 runs per user out of which 5 were regular living Activity runs and the 6th run is the drill run in which a user executes a collection of scripted activities. ADL runs have large variations whereas drill runs have less variations.

4. Research Methodology

This segment explains the proposed approach which is composed of mainly four key modules. The initial module performs the data pre-processing. The second module describes about the benefits and drawbacks of Recurrent Network model. The third module talks about model of LSTM networks and the final module discuss about the design of LSTM-RNN that has been utilized in this swotting for the creation of human activity recognition model. Figure 1 is a description of the overall research methodology.

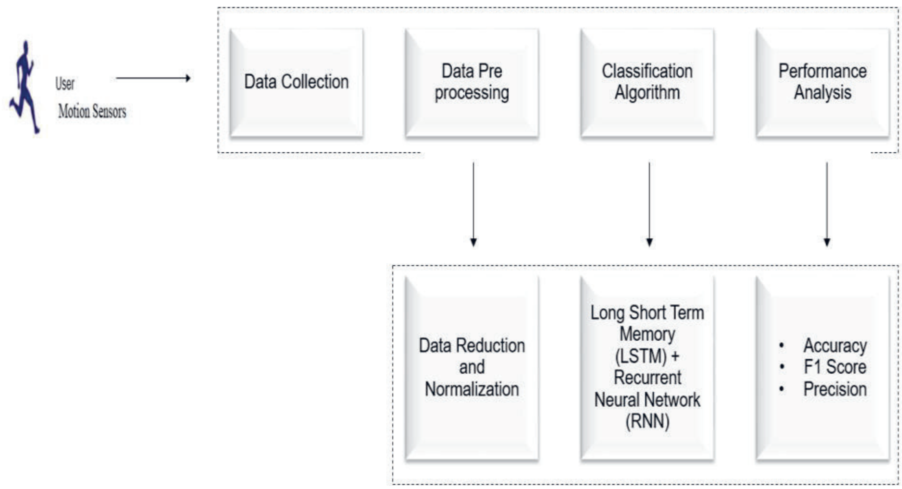

Figure 1. Overall Research Methodology

4.1. Data Pre-Processing

A huge volume of data is required to prepare a DL model. Mostly, messy data is gathered and since the deep learning models are extremely sensitive towards this. While preparing data, in order to acquire great outcome one must be wary. For this pre- processing of data need to be carried out [18]. In this study, for pre-processing of data innumerable python libraries like numpy, pandas, sklearn, keras and matplotlib were used. The data was segregated first into training, testing and cross validating data. Sensors were put to use to capture data and since continuous data was captured therefore the null values were eliminated with the sensor's previous value. After this feature scaling was done using normalization in which the values were scaled from zero to one and also least value was deducted from each feature and was divided by the range value ; maximum value – minimum value. Normalization was followed by labeling. Finally, the two dimensional data was converted to three dimensional data for long short term memory.

4.2. Recurrent Neural Network (RNN)

Artificial Neural Networks (ANNs) and Convolutional Neural Network are usually not capable of capturing time dependent information from sequential data. Feed-Forward Networks works quite well with sequential data but this network fails when it comes to dependency of the sequential data on time [19]. Same is the case with Convolutional Neural Network, they're effective with the images data but not with temporal information. Therefore, there is a need to have a model which will have a memory for storing time and RNN have the ability to capture temporal data this signifies that along with current stage input, the input of the prior state is also preserved [20]. Figure 2. Shows the expansion of folded RNN model into unfolded RNN model.

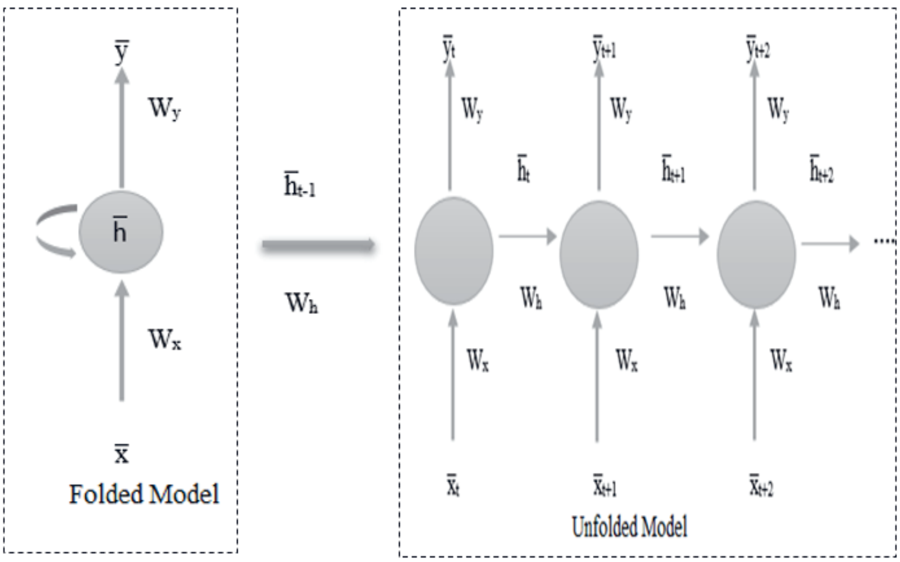

Figure 2. Folded and Unfolded RNN Models

So, in the RNN-model the output 'y' depends on two inputs one is previous input which is represented by 'h' and another is the current input denoted by 'x'. By applying activation function, it is possible to calculate input for hidden layer. The hidden layer's input in RNN is defined as follows:

$$\overline{h_t} = \emptyset\left(\overline{x}_t . W_x + \overline{h}_{t-1} \cdot W_h\right)$$

Where, $\overline{h}_t$ = previous input

$\overline{X}$ = current input

$\overline{y}$ = output

W_h = Weight for hidden layers

W_x = Weight for input layers
W_y = Weight for output layers.

The RNN's yield is defined as the state vector's product with the weight for output layer.

$$\overline{y}_t = \overline{h}_t \cdot W_y$$

In (RNN) recurrent neural network, sometimes weight become too small because of this factor the model becomes under-fit uncovered as the problem of vanishing gradients or occasionally the weights become too large because of which the model becomes over-fit known as the problem of exploding gradients [21]. This drawback constrain the ability of network to model long duration dependencies in-between the actions of human and the input observations. Because of this demerit of RNN we have developed human activity recognition model with the help of long short term memory (LSTM) based recurrent neural network (RNN).

4.3. Long Short Term Memory-(LSTM)

Recurrent Neural Network-RNN are not good at remembering the long duration activities. If the duration of activity is lengthy then the network won't be able to deliver the details from the recent steps to the next one. So, for prediction of durable activities crucial information may be left out by RNN from the beginning. While back propagating, the RNN faces vanishing gradient problem. Gradients are values used to update a neural networks weights. The problem of vanishing gradients arises when the gradient shrinks as it back propagates over time. When a gradient value falls below a certain threshold, it no longer contributes anything to learning. As a consequence of this the layers receiving small gradients stops learning and primarily these layers are the earlier layers. So, RNN might not be able to memorize the actions that has happened at the starting in the context of lengthy activities. Therefore there exists a requirement to resolve this issue and the solution to this is LSTM. LSTM contain gates that can manage the flow of information. There are mainly three gates in LSTM notably Input gate, Forget gate and Output gate. For making predictions relevant information can be passed down up to a long chain of sequence as the gates have capability to learn which information is important to keep and which information is to be thrown out.

Cell State in LSTM is responsible for carrying information throughout the processing in network. Consequently the past time steps information can be forwarded to the further time steps. The gates add into or take away data from the cell state as they only decide which information is supposed to be allowed to traverse the network and which information is to be left out. Operations performed inside the LSTM's cells are discussed below [22].

4.3.1. Sigmoid Activation

Sigmoid Activation compresses the value between 0 and 1. So, it becomes easy to filter out the irrelevant information. Any number when multiplied by 0 gives 0 that means the value is disappearing so this will help in forgetting the information and any number when multiplied by 1 gives the same number that indicates that value will remain unchanged so it will be kept. In this way the network would be capable of learning which information is crucial to keep and which can be forgotten.

4.3.2. Tanh Activation

Tanh Activation compresses the value between -1 and 1 which helps in regulating the output through network. Tanh ensures that the values remain in the boundaries otherwise the values can explode and become insignificant.

4.3.3. Forget Gate

Forget gate make out which information is supposed to be removed and which one is to be preserved. The information coming from prior hidden state as well as the information forthcoming from the present input state is moved through the sigmoid function then values that come out are in between 0 and 1. The value nearer to 0 means to forget and value nearer to 1 means to keep.

4.3.4. Input Gate

Input gate is utilized to update the cell state. First the preceding hidden state and present input state is pushed to the sigmoid function then the values measured will be in between one and zero. After this the prior hidden state and present input is also passed through the tanh function in order to compress the value between -1 and 1. Followed by multiplication of output from tanh function with output from sigmoid function and finally the sigmoid output will decide which information is important to keep from tanh output.

4.3.5. Cell State

After having enough information. Now we can calculate the cell state. For calculation, first the cell state gets multiplied point wise with the forget vector this may result in reduction of some of the values since the values can get multiplied with values close to 0. After this the cell state gets pointwise added with the values that are dispensed from input gate resulting in updation of cell state in to new values forming a new cell state.

4.3.6. Output Gate

The decision is made by the output gate for what state is hidden. For this, first the preceding hidden state and the present input are transferred to the sigmoid function.

Then the newly modified cell state is passed through the function tanh. Finally the tanh output is multiplied with the sigmoid output and the multiplication results in the information that will be carried out through the hidden state. The new hidden and cell state are then carried out to the next time step.

5. Experiments and Results

This section delves into the experiments that were implemented in this study on Opportunity dataset. The LSTM-RNN is trained on the Opportunity dataset. The dataset was categorized into training and testing dataset in ratio of 70:30. Sigmoid activation function is utilized for model's weights updation. The cost function employed to calculate the difference between the truth and predicted label was mean squared error. Hyper-parameter tuning was accomplished by choosing proper dropout, number of layers, window size, optimizing function, epochs etc. For updating parameters of model and for cost function minimization Adam optimizer was used. Models were cross validated and tested along with calculation of various evaluating parameters such as accuracy, precision score and F1 score.

Accuracy: Referred to as the ratio of total number of right predictions to total number of predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision Score: The ratio of number of rightly predicted positive observations to total number of predicted positive observations.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall: The ratio of total correctly expected positive observation to all the number of considerations.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1 Score: Defined as the weighted average of precision and Recall.

$$\text{F1- Score} = 2 * \frac{(\text{Recall} * \text{Precision})}{\text{Recall} + \text{Precision}}$$

Where TP = True Positive, TN = True Negative, FP = False Positive and FN = False Negative.

These performance metrics were evaluated on the Opportunity dataset. The Results are given below:

On Opportunity Dataset

For Non-Repeating motions: Dynamic isolated motions that are executed for a short period of time .These include like drinking coffee, opening drawers etc. Table 1. Displays the metrics for performance evaluation on opportunity dataset for non-repetitive motions.

Model	Accuracy	F1 score	Precision Score
RNN + LSTM	0.9165	0.9170	0.9179

Table 1. Performance Metrics for Non-Repetitive Motions

For Repeating Motions: Dynamic motions that are executed repeatedly over time like walking, sitting, standing etc. Table 2. Shows the performance metrics on opportunity dataset for repetitive motions.

Model	Accuracy	F1 score	Precision Score
RNN + LSTM	0.8031	0.8014	0.9179

Table 2. Performance Metrics for Repetitive Motions

The Experimental evaluation stated that LSTM - RNN achieved good accuracy for non- repetitive motions in comparison to repeating motions. An overall accuracy of 94% is achieved on the optimum trained model.

6. State-of-art

This segment possesses study on comparative analysis of the implied framework with formerly developed frameworks. The presented model is built up with the assistance of deep learning strategy and the previously developed models that have been taken into consideration for comparison, were built with the assistance of ML and deep learning strategies. The comparison was performed on the grounds of the attained accuracies and types of activity classes that were utilised during the development of human recognition model as described in Table 3.

Data-sets	**Number and Types of Activity Classes**	**Sensors**	**Model**		**Accuracy**			**Ref**
REALDISP(Realistic Sensor Displacement)	7 (Elliptical Bike, Cycling, Jogging, Jump-Up, Rowing, Running and Walking)	Body Sensors	SVM KNN ANN Naïve Bayes Random Forest CART C4.5 REPTree LADTree		99.43 98.92 99.33 93.97 99.19 98.71 98.83 98.25 84.05			[4]
	6 (Walking, Walking Upstairs, Walking Downstairs, Sitting, Standing and Laying)	Smartphone Sensors	SVM KNN ANN Naïve Bayes Random Forest CART C4.5 REPTree LADTree		98.91 97.66 56.26 76.79 98.61 93.76 94.84 93.42 88.06			
Publicly Available Sensor Dataset	House A (HA) House B (HB) House C (HC)	Smart Home Sensors (Raw Sensor Data)			HA	HB	HC	[5]
			Naïve Bayes		77.1±20.8	80.4±18.0	46.5±22.6	
			Hidden Markov Model		59.1±28.7	63.2±24.7	26.5±22.7	
			Hidden Semi Markov Model		59.5±29.0	63.8±24.2	31.2±24.6	
			Conditional Random Fields		89.8±8.5	78.0±25.9	46.3±25.5	
			Long Short Term Memory		89.8±8.2	85.7±14.3	64.22±21.9	
			CNNs	SVM	CNNs+RNNs	Proposed DRNNs		[6]
UCI HAD			95.2	96.0		96.7		
USC HAD			97.0			97.8		

Opportunity			88.3	84.7	91.5	92		
Daphnet FOG						93		
SKODA			91.7			92.6		
WISDM	6 (Jogging, Sitting, Standing, Walking, Upstairs and Downstairs)	Tri-axial Accelerometer	LSTM-RNN Deep Neural Network		Above 94			[23]
HASC Corpus Dataset	6 (Standing, Laying, Sitting, Walking Upstairs, Walking Downstairs and Walking)	Acceleration Sensors	Deep Recurrent Neural Network (DRNN)		95.42			[24]
ACTi Tracker(WISDM) and	7 (Jogging, Lying Down, Sitting, Stairs, Standing and Walking)	Accelerometer Sensors	Random Forest 89.7	KNN 90.1	DT 87.9	RNN 81.74	CNN 92.22	[25]
Sensor Activity Recognition (Shoaib SA)	7 (Biking, Downstairs, Jogging, Sitting, Standing, Upstairs and Walking)		95.7	97.6	90.5	95.65	99.12	
Opportunity	10(Repetitive Motions: walking, Sitting, Idle, Relax, Standing and Non-Repetitive Motions: Coffee Time, Early Morning, Clean up, sandwich time and Relaxing)	Motion Sensors	RNN + LSTM		For Repetitive Motions 80.31			
					For Non-Repetitive Motions 91.65			

Table 3. Comparative Analysis of proposed model in this study with previously developed models

7. Conclusion and Future Scope

The proposed model in this study has achieved an overall accuracy of 94% on the best trained model using long short term memory- based-recurrent neural networks. The approach was assessed and compared for motions that repeated over time and also for motions those are non-repetitive. This experimental study is being carried out on Opportunity Activity Recognition Dataset. An accuracy of 91% is achieved for movements that were performed for a short amount of time and an accuracy of 80% is achieved for the motions that are performed for a longer period of time. A comparative review of the presented model with other previously developed models is also done in terms of accuracies and activity classes in this study.

This work can be extended later for identifying long durable activities more efficiently. In this learning, the framework is set up using a fixed sliding window size architecture so in the forthcoming time a design of window having dynamic sliding could also be considered. Also, it can be outstretched to automatic classification of activities.

References

[1] Jobanputra, C., Bavishi, J., & Doshi, N. (2019). Human activity recognition: A survey. Procedia Computer Science, 155, 698-703.

[2] Wang, J., Chen, Y., Hao, S., Peng, X., & Hu, L. (2019). Deep learning for sensor-based activity recognition: A survey. Pattern Recognition Letters, 119, 3-11.

[3] Murahari, V. S., & Plötz, T. (2018, October). On attention models for human activity recognition. In Proceedings of the 2018 ACM International Symposium on Wearable Computers (pp. 100-103).

[4] Subasi, A., Khateeb, K., Brahimi, T., & Sarirete, A. (2020). Human activity recognition using machine learning methods in a smart healthcare environment. In Innovation in Health Informatics (pp. 123-144). Academic Press.

[5] Singh, D., Merdivan, E., Psychoula, I., Kropf, J., Hanke, S., Geist, M., & Holzinger, A. (2017, August). Human activity recognition using recurrent neural networks. In International cross-domain conference for machine learning and knowledge extraction (pp. 267-274). Springer, Cham.

[6] Murad, A., & Pyun, J. Y. (2017). Deep recurrent neural networks for human activity recognition. Sensors, 17(11), 2556.

[7] Hassan, M. M., Uddin, M. Z., Mohamed, A., & Almogren, A. (2018). A robust human activity recognition system using smartphone sensors and deep learning. Future Generation Computer Systems, 81, 307-313.

[8] Wang, A., Chen, G., Yang, J., Zhao, S., & Chang, C. Y. (2016). A comparative study on human activity recognition using inertial sensors in a smartphone. IEEE Sensors Journal, 16(11), 4566-4578.

[9] Taylor, W., Shah, S. A., Dashtipour, K., Zahid, A., Abbasi, Q. H., & Imran, M. A. (2020). An intelligent non-invasive real-time human activity recognition system for next-generation healthcare. Sensors, 20(9), 2653.

[10] Baldominos, A., Cervantes, A., Saez, Y., & Isasi, P. (2019). A comparison of machine learning and deep learning techniques for activity recognition using mobile devices. Sensors, 19(3), 521.

[11] 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.

[12] Tüfek, N., & Özkaya, O. (2019, April). A comparative research on human activity recognition using deep learning. In 2019 27th Signal Processing and Communications Applications Conference (SIU) (pp. 1-4). IEEE.

[13] 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 (pp. 50-53). Atlantis Press.

[14] Wang, J., Chen, Y., Hao, S., Peng, X., & Hu, L. (2019). Deep learning for sensor-based activity recognition: A survey. Pattern Recognition Letters, 119, 3-11.

[15] Walse, K. H., Dharaskar, R. V., & Thakare, V. M. (2016, March). Performance evaluation of classifiers on WISDM dataset for human activity recognition. In Proceedings of the Second International Conference on Information and Communication Technology for Competitive Strategies (pp. 1-7).

[16] Cruciani, F., Vafeiadis, A., Nugent, C., Cleland, I., McCullagh, P., Votis, K., ... & Hamzaoui, R. (2020). Feature learning for Human Activity Recognition using Convolutional Neural Networks. CCF Transactions on Pervasive Computing and Interaction, 2(1), 18-32.

[17] 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.

[18] https://www.marktechpost.com/2019/06/14/data-pre-processing-for-deep-learning-models-deep-learning-with-keras-part-2/.

[19] https://builtin.com/data-science/recurrent-neural-networks-and-lstm.

[20] Navamani, T. M. (2019). Efficient Deep Learning Approaches for Health Informatics. In Deep Learning and Parallel Computing Environment for Bioengineering Systems (pp. 123-137). Academic Press.

[21] https://www.superdatascience.com/blogs/recurrent-neural-networks-rnn-the-vanishing-gradient-problem.

[22] https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21.

[23] Pienaar, S. W., & Malekian, R. (2019, August). Human activity recognition using LSTM-RNN deep neural network architecture. In 2019 IEEE 2nd Wireless Africa Conference (WAC) (pp. 1-5). IEEE.

[24] Inoue, M., Inoue, S., & Nishida, T. (2018). Deep recurrent neural network for mobile human activity recognition with high throughput. Artificial Life and Robotics, 23(2), 173-185.

[25] Shakya, S. R., Zhang, C., & Zhou, Z. (2018). Comparative study of machine learning and deep learning architecture for human activity recognition using accelerometer data. Int. J. Mach. Learn. Comput, 8(6), 577-582.

[26] Cao, X. (2022). Human motion recognition information processing system based on LSTM Recurrent Neural Network Algorithm. Journal of Ambient Intelligence and Humanized Computing, 1-13.

[27] Albaba, M., Qassab, A., & YILMAZ, A. (2020). Human activity recognition and classification using of convolutional neural networks and recurrent neural networks. International Journal of Applied Mathematics Electronics and Computers, 8(4), 185-189.

[28] Abbaspour, S., Fotouhi, F., Sedaghatbaf, A., Fotouhi, H., Vahabi, M., & Linden, M. (2020). A comparative analysis of hybrid deep learning models for human activity recognition. Sensors, 20(19), 5707.