Human Activity Recognition with smartphone sensors data using CNN-LSTM

Akriti Sharma
UIET
Panjab University
Chandigarh, India
akritisharma.pu503@gmail.com

Preeti Singh
UIET
Panjab University
Chandigarh, India
preeti_singh@pu.ac.in

Charu Madhu
UIET
Panjab University
Chandigarh, India
charunarula81@gmail.com

Nidhi Garg
UIET
Panjab University
Chandigarh, India
nidhi461@gmail.com

Garima Joshi
UIET
Panjab University
Chandigarh, India
joshi_garima5@yahoo.com

2022 IEEE Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI) | 978-1-6654-7719-2/22/$31.00 ©2022 IEEE | DOI: 10.1109/IATMSI56455.2022.10119372

Abstract— **Human activity recognition (HAR) utilizing wearable inertial sensors has nowadays become a new research hotspot due to various advancements in sensor technology. Recently, methods based on deep learning (DL) have been successfully used to evaluate time series data recorded by wearable sensors and smartphone to predict a variety of human activity. Furthermore, the majority of HAR methods relied on traditional feature engineering. In this study, a convolutional neural network along with, a long short-term memory network, that is deep learning architecture for activity recognition is proposed here (CNN-LSTM). With minimum data pre-processing, the proposed model CNN-LSTM network extracts feature from raw sensor data automatically. By using testing data, the trained model is then used for the recognition of various activity. The performance of the model is examined using the benchmark dataset WISDM. The results of the experiment show how the suggested approach outperforms alternative strategies and how adaptable it is to be implemented in sensor-based healthcare systems for recognition of human activity. The research findings show the proposed model outperforms the other approaches that were compared by achieving 98.04% accuracy and a F1 score of 98.04%, which is better than the similar existing models.**

Keywords— CNN-LSTM (Convolutional Neural Network – Long Short Term Memory), Smartphone, Smartphone sensor data, Human activity Recognition (HAR)

I. INTRODUCTION

The growing elderly population has put additional strain on healthcare systems around the world in terms of financial costs and resources. In order to lessen this burden and deliver quality healthcare services, the implementation of some IoT technology (Internet of Things) with wearable technology may prove promising. Through the use of these methods, the quality of life for the elderly population can be enhanced while the demand on the healthcare system is eased and its expenditures were also decreased [1]. The health industry is shifting from treatment to prevention as a result of this transformation. There are several different equipment in use, from smartphone to smart wristband, which are used for research and business applications [2]. Novel uses have been made possible by recent technological developments. Wearable technology provides continuous health monitoring is one of the possible applications. This is conceivable since there are over 335 wearable gadgets on market, with 55 of them to be used for medicinal reasons. With a little customization and examination, the data acquired from wearable technology like the Apple Watch as well as Fitbit can be clinically assessed [3].

The major objective of this technologies is to analyse the person's activity at some moment in time to help and assist the person in the areas like ambient assisted livings (AAL), wellbeing surveillance, sports injury detection, clinical applications, and in particular in elder care [2]. Healthcare, ubiquitous computing, smart homes, ambient assisted living, monitoring, and security were some of the applications of HAR. Particularly in cases of chronic illnesses like Alzheimer's disease (AD), visual impairment, Parkinson's disease (PD), the monitoring of elderly or disabled patients with their daily activities at home is a vital application in healthcare. Accurately detecting physical activity with HAR is another application [4].

The two main categories of human activity recognition technologies are HAR based on sensors and HAR based on video. sensor-based HAR analyses motion information from sophisticated sensors such an gyroscope, accelerometer, sound sensor, Bluetooth, and many more, while the video-based HAR studies video or images from the camera that feature human motions. With the advancement of sensor and ambient intelligence, sensor-based HAR has become more and more well-liked and widely used [5]. In order to identify activities utilizing signals from wearable sensor data, environmental sensor data, as well as vision-based systems, HAR technologies employ machine learning as well as deep learning models [2].

Over the past ten years, machine learning-based algorithms have successfully recognised HAR activities, but they frequently face challenges, such as a shortage of training data in multiclass activity detection. Second, adopting a manually developed or assembled feature, detecting arbitrary or complex features, and also distinguishing movements that are similar and not identical, like walking with climbing upward, and looking under its bed with falls. Machine learning-based approaches entirely rely on pre-processed data from raw signals that contains useful and noticeable properties that can improve classification algorithms' performance. All the above challenges can be resolved with the help of the Deep Learning model. It will reduce pre-processing of data and reduces the feature extraction phases also helps Reduce reliance on expertise and knowledge in feature extraction reduction in image-based recognition testing time high efficiency is achieved even when data is weakly labelled [2].

The remaining sections of the paper are arranged as follows. Section 2 showcases various activity recognition systems made with wearable sensors and smartphones that use various machine learning and deep learning algorithms. Section 3 details of Proposed CNN-LSTM architecture. Section 4 Proposed Methodology, dataset description, performance parameters considered in this study, and describe experimental results. Section 5 conclude proposed work done.

II. RELATED WORK

In the recent years, researchers have collected data from numerous smartphone sensors and wearable sensors to identify diverse human activity using a range of machine learning (ML) algorithms. Like Johan Wannenburg *et al*. [6] used several Machine Learning (ML) techniques for recognising physical activity utilising accelerometer data from smartphone sensors. The highest accuracy achieve with KNN and K-star algorithm. Smartphone is placed in the subject's pocket to capture data, and this is where a sizable quantity of data is utilized to test and train the algorithms. For physical activity recognition, multiple machine learning algorithms are applied, with KNN and Kstar achieving overall superior accuracy.

Although ML approaches performed reasonably well in HAR, there are still certain restrictions when utilizing them for human activity recognition. Like feature extraction, Data pre-processing and other manual tasks are quite manual when using ML-based techniques. Recent research has shown that Deep Learning-based algorithms perform exceptionally well in a number of areas, including object detection, natural language processing and speech recognition. Because deep learning frameworks can automatically learn features from vast volumes of data without the help and input of individuals. Hassan *et al*. [7] presented deep learning model in identifying human activity, and data from wearable and ambient sensors was collected. In this case, Deep Belief Network is the method utilised to recognise human activity. Comparison of DBN with the SVM and ANN based on accuracy and Mean Recognition rate. DBN achieves better results compared with previously existing techniques. Shaohua Wan *et al*. [8] constructed a deep learning framework for human activities. Utilizing a smartphone's accelerometer sensor for recognition. Design a smartphone-based inertial accelerometer Architecture for Real-time HAR with the proposed model is Convolutional neural network (CNN). Comparison of five different algorithms that is LSTM, CNN, BLSTM, SVM, and MLP on two publicly available datasets. Comparison is done in terms of Recall, Precision, F1 score, and Accuracy and the proposed model achieved better accuracy as compared with other algorithms.

Mohammad Mehedi Hassan *et al*. [9] Deep Belief Network (DBN) architecture and inputs from body worn sensors are used to recognise human activity. Sensor containing gyroscope and accelerometer is used to gather data. This DBN approach uses 40 hidden units for both hidden Layers to recognise human activities. Comparison is done on the basis of the accuracy with SVM model and DBN achieves better accuracy over SVM. Kun wang jun He *et al*. [10] Recognizing human activity with the use of attention-based CNN, using wearables sensor data. For processing the data, which consists of weakly labelled activity data, the attention-Based Human action Recognition model is suggested. For recognising human activity, attention-based CNNs (convolution neural networks) are employed. On the UCI HAR dataset, the suggested approach is contrasted with CNN, DeepConvLSTM. On weakly labelled data for activity recognition, the suggested model outperforms fundamental CNN, standard CNN, and DeepConvLSTM in terms of accuracy. Md. Zia Uddin *et al*. [11] Deep convolutional neural networks (CNN) and several body sensors are used for activity recognition. Examining the signals produced by bodily sensors such the accelerometer, ECG, magnetometer, and gyroscope. Utilize the publicly accessible mHealth dataset to train the model. Based on mean Accuracy, a comparison of ANN, deep CNN, and DBN. Compared to other techniques, Deep CNN produces accuracy that is higher. Zhenghua Chen *et al*. [12] Recognition of human activities using the sensors on a smartphone Here, a strategy for merging manually created features with those automatically learnt by deep learning models to recognise human behaviour is proposed. An method called maximum full a posterior (MFAP) is developed to enhance the effectiveness of human activity recognition as a result of changes in human behaviour. The performance of the proposed model is assessed using both publicly available and self-collected dataset.

Xiaokang Zhou *et al*. [13] To more precisely identify human activity, presented a semi-supervise deep learning technique to human activity recognition. It primarily consists of two modules: the auto labelling module and LSTM module built on a deep Q-network (DQN), which performs better with incompletely labelled data. Here, two publicly accessible datasets are used in conjunction with the DQN approach to recognize human activities. Using the Recall, Precision and F1 scores, the suggested method is compared to the RF, DNN, and SVM. Kun Xia *et al*. [14] using a deep neural networks model that combines an LSTM and a convolutional layer to recognize human activity. Mobile sensors equipped with two layers of LSTM and the convolutional layers are used to capture the data. On the basis of the F1-score using three publicly accessible datasets, the suggested model is evaluated against CNN and DeepConvLSTM using the LSTM-CNN architecture for HAR. Analysis of proposed model using three datasets and the F1-score.

Sravan Kumar Challa *et al*. [15] a hybrid convolutional neural network (CNN), along with bidirectional long-short term memory (Bi-LSTM) were utilized to create a model for human activity recognition. The three datasets employed by the model— UCI-HAR, WISDM and PAMAP2—capture both short- and long-term dependence on sequential data. The suggested model is compared to various deep learning-based models in terms of accuracy. The proposed model CNN-Bi-LSTM achieves better accuracy on all three datasets. Mohammad Mehedi Hassan *et al*. [16] A deep neural network (DNN) architecture that recognizes activities from temporal sparse data signals via passive sensing devices increases the average accuracy of HAR identification. A dataset from a clinical room is used to evaluate the created model. This dataset contains four separate actions performed by the hospitalized patient.

Satya P. Singh *et al*. [17] Current methods in this field make use of recurrent and convolutional models to identify human behavior by capturing relevant spatiotemporal characteristics from standard statistical data from various sensors. Here, researchers introduce the Deep ConvLSTM model Incorporating Self-Attention, a deep neural system architecture that not only collects the temporal characteristics of various sensor time information but also recognizes and learns important time points using a self-attention technique. Six publicly accessible datasets with various quantities of actions are used to evaluate the model. Andrey Ignatov [18] The authors introduced a DL-based architecture for the real-time detection of human activity. The authors used CNN with statistical features to keep knowledge about time-series data on a global scale. On two publicly accessible datasets with various numbers of activities, the model is examined here. The model's assessment parameters are accuracy and F1 score.

Wenbing shi *et al.* [19] built a HAR architecture based on data from wearable and smartphone sensors, and this architecture employs a sliding window on time series format. Effective multi-channel sensor data correlation requires and, in this work, CNN is created using a data augmentation method known as the AMC-CNN model. The proposed model has been tested on two publicly accessible datasets, MHEALTH and WISDM, and it is discovered that both single sensor and multi-sensor data show good performance from the model. Huaijun wang *et al.* [20] created a CNN-LSTM architecture for recognizing human activity here. The aim for LSTM would be to extract long-term dependencies among two or more activities with the goal of improving HAR identification rates work is done on the HAPT dataset. CNN is employed for extracting features from the raw data acquired by the sensors. Therefore, for our work, we decided to employ a distinct version of a CNN-LSTM model in HAR since CNN is strong at extracting features and LSTM is beneficial in identifying long-term connections between various actions [20], which ultimately is very valuable for better activity detection.

III. METHODOLOGY

A. *Pre-Processing*

Smartphone sensor signals are often continuous and time series in nature. These sensors collect activity data in a time series format. The first step in recognizing human activity is creating segments from sensor data. A sliding window method is used to divide the sensor data into fixed-size windows. The suggested model uses a moving window with such a size 128 (128 readings/window) and a 50% overlap for all datasets used. The dataset used in the suggested study is WISDM.

B. *Feature Extraction*

Smartphones and wearable sensors gather information on human actions in a time series. The time-series data shows a clear 1D structure, demonstrating how closely related variables are interconnected across time. It is essential to extract these traits as a result. CNN might recover local data features when there are local receptive fields present.

C. *Proposed Model*

The block diagram below presents our proposed CNN-LSTM technique for recognizing and identifying human activities.

The Keras API allows users to go from idea to result in the shortest amount of time possible, which is crucial for successful research and below fig.1, shows the complete layered Architecture that is going to be used here for human activity recognition from raw data as input with a TensorFlow backend, a Keras sequential model is developed.

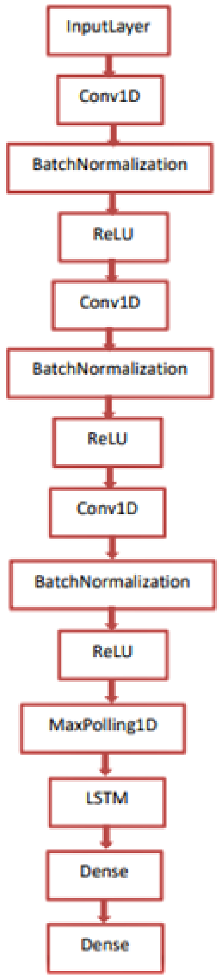

Fig 1: Flow diagram for proposed CNN-LSTM architecture

Firstly, Pre-processed input is fed into a 1-dimensional convolutional layer with the 32-filter size, followed by a BatchNormalisation layer. These layers employ a ReLu activation layer here as activation, and indeed the rest of the characteristics are left at default. Another 1-dimensional convolutional layer with the filter size of 64 was placed into the second layer, which was preceded by the BatchNormalization Layer. These layers employ a ReLu activation layer for activation in this case, and the remaining of the characteristics are kept at their default values. Following the BatchNormalization Layer, the third layer once more adds a further 1-dimensional convolutional layer with a filter size of 128. These layers once more employ a ReLu activation layer for activation, and the remaining parameters are left as default.

For dimensionality reduction, a 1-dimensional max-pooling layer with the pool size of two should then be added. The model is now assisted in detecting the long-term dependency of an input sequence by the addition of an LSTM layer. These layers' output was sent into a Dense layer, which normalized the output to have a zero mean and a uniform standard deviation. The final classification layer uses the final dense layer's normalized output to forecast the input class using the Softmax activation function.

IV. RESULTS AND DISCUSSION

A. Dataset description

Kwapisz *et al*. [21] produced the dataset and it includes six different human activities and data is recorded from 36 volunteers. The dataset covers the following activities: as standing, Sitting, Jogging, walking, Walking Downstairs, and Walking Upstairs shown table 1 shows the activities of the WISDM dataset along with their short names. The smartphone is placed inside the person's front leg pocket, and data is gathered using an accelerometer that has been integrated into the device with a sampling frequency of 20 Hz. For every activity, acceleration measured in the x, y, & z directions.

Table 1: Six different physical activities from the WISDM dataset and their short forms.

Name	Short form
Walking Downstairs	Down
Jogging	Jog
Sitting	Sit
Standing	Std
Walking Upstairs	Up
Walking	Walk

B. Performance Parameter:

The proposed technique performance is evaluated with mean accuracy along with Recall, Precision, and F1 – score, and below equations (1-4) show the formula to calculate these parameters.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

$$\text{F1 - score} = 2 \times \frac{\text{Precision x Recall}}{Precision+Recall} \quad (4)$$

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

Accuracy & Loss Plot: ln reaction to changes in accuracy rate and losses rate throughout the training of the neural network model. Every epoch will result in accuracy loss and value reduction. By displaying the accuracy as well as the loss diagram, the training of a network model may be clearly demonstrated. The trend can be used to determine how well and effectively the models has been trained, to spot temporal anomalies (such over or underfitting), and to consider making timely adjustments.

Unbalances commonly occur when obtaining data on human movement in natural settings [14]. The WISDM dataset that came before is imbalanced. If the classifier places every occurrence in the majority class that predicts and evaluates the model's efficacy by using overall accuracy, the results might be very accurate. Because of this, the overall accuracy is not really a trustworthy measure of performance. The total number of correctly identified samples determines the F1 score, which combines two metrics known in the data gathering world as accuracy and recall. It takes both false negatives and false positives into account. The F1 score is therefore often a more significant performance measure than accuracy. [14].

C. Model Implementation

The model was closely monitored throughout training. Weights and biases for each layer were originally set to values chosen at random. Categorical cross-entropy is used to measure the discrepancy between the probability distribution and the true distribution.

Table 2: Summarized selected Hyper Parameters

Phase	Hyper-Parameter		Value
Architecture	Conv1D	Filters	32
		Kernel size	3
	Conv1D	Filters	64
		Kernel size	3
	Conv1D	Filters	128
		Kernel size	3
	Maxpool1D	Pooling size	2
	LSTM		64
Training	Optimizer		Adam
	Learning rate		0.001
	Batch size		187
	Loss function		Categorical cross-entropy
	Number of epochs		150

The error between the predicted and observed values was calculated in this study using the cross-entropy loss function. Adam, an optimization technique that is rooted on a first-order gradient, served as the optimizer in this instance. During the training phase, 187 batch sizes with 150 epochs were employed to increase efficiency. In order to enhance fitting capability, a learning rate at 0.001 was also used, and also training feature's order were randomly shuffled to improve model robustness. A list of the selected hyper-parameters is shown in table 2.

D. Results

It is important to intelligently divide the complete dataset for training and testing in order to evaluate the outcomes of the suggested hybrid CNN-LSTM model. Arbitrarily separating train and test data with raw sensor data is not appropriate since this research relies on sequential Human Activity Recognition data. This is so that the classification model does not take into account the same human's activity in both train and test sets, which could lead to higher accuracy that does not correctly reflect the model's actual performance if the data split is done at random. As a result, grouping the HAR datasets by user ID would be the

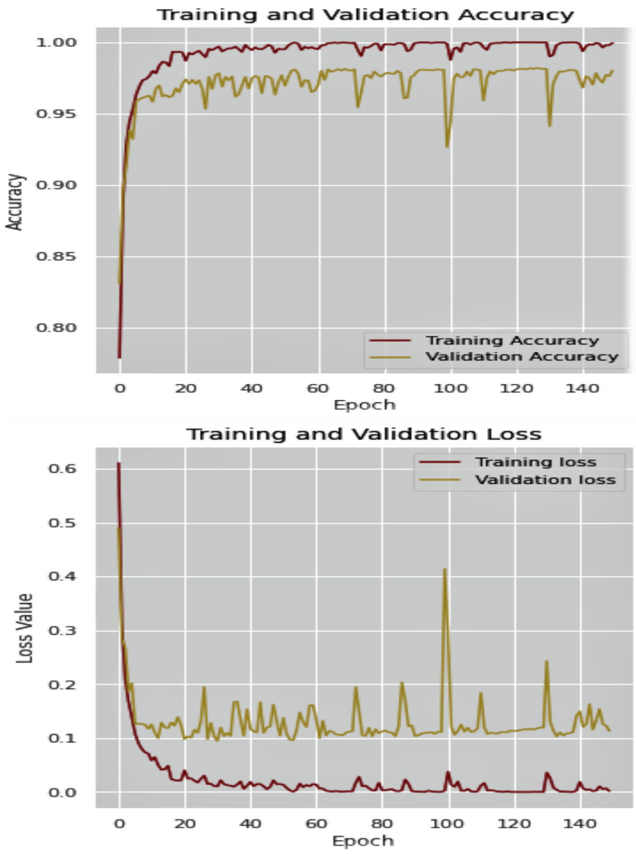

Fig 2: Experimental results of WISDM dataset

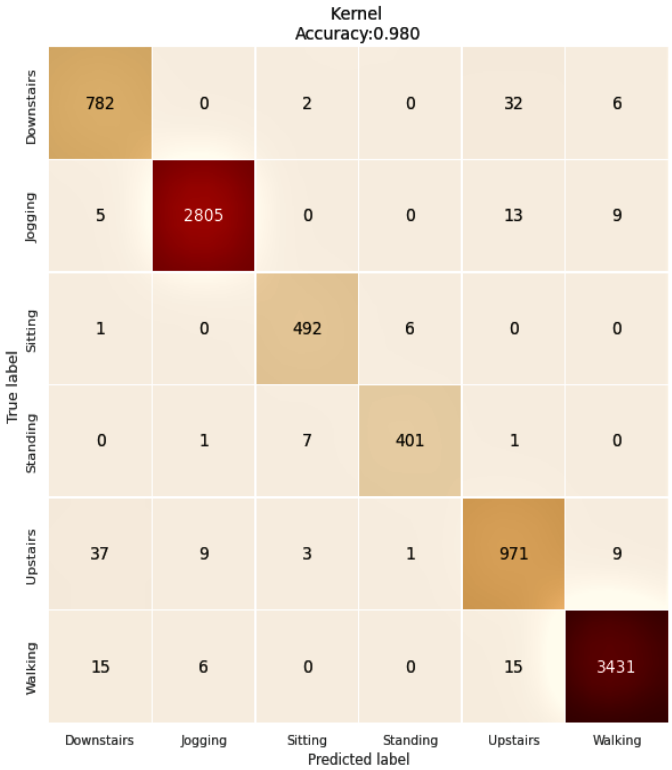

Fig 3: Confusion matrix from experimentation by using WISDM dataset for testing data with suggested model

best approach. To do this, train a model using data from a small number of people, then ask it to forecast the movements for unknown users. Here, the dataset WISDM is utilized in this investigation, with data separated for testing and training purposes according to user id.

The samples inside the WISDM dataset were typically divided by user-id for the purposes of training and testing the suggested approach and figure 2 shows performance of the suggested method on WISDM dataset during both training and testing. The proposed study method has a classification accuracy rate of about 98.04%.

The confusion matrix on testing samples of the WISDM dataset is presented in figure 3, table 3 demonstrates the evaluation outcomes for recall, precision, and F1 score from the experiment conducted on the dataset's testing samples.

Table 3: Evaluation of the proposed approach F1 score, recall, and precision performance

Activities name	Precision	Recall	f1-score
Downstairs	0.931	0.951	0.941
Jogging	0.994	0.990	0.992
Sitting	0.976	0.986	0.981
Standing	0.982	0.978	0.980
Upstairs	0.940	0.942	0.941
Walking	0.993	0.989	0.991

The accuracy and F1 score of the model presented in this research are compared to those of the current models as shown in table 4 and analyzing the performance of the already existing models [14, 15, 17, 18] with the model proposed in this study based on accuracy and F1 score values. The findings show that the suggested model outperformed the competing models by achieving about 98.04% accuracy and 98.04% of F1 score on testing data and below shown table 4 shows the comparison of the existing work with the proposed CNN-LSTM model and also the accuracy graph figure 4 shows the results.

Table 4: comparison of the proposed Approach and several DL-based models on WISDM dataset

Model name	Accuracy (%)	F1 score (%)
CNN[18]	93.32	-
LSTM-CNN[14]	95.75	-
Deep ConvLSTM[17]	90.41	86.88
CNN-BiLSTM[15]	96.05	96.04
CNN-LSTM	98.04	98.04

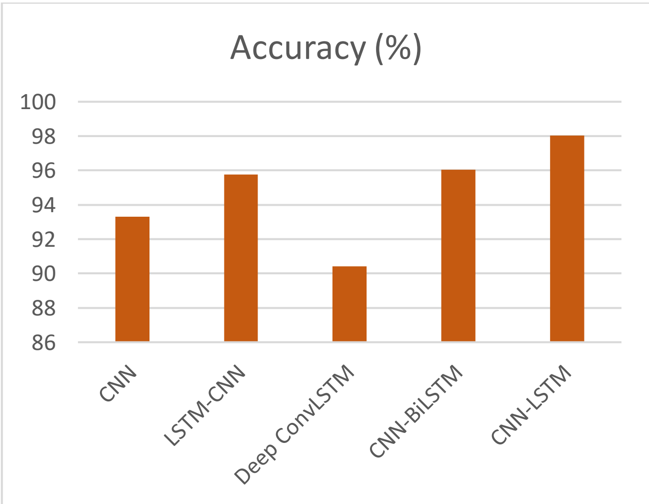

Fig 4: Five distinct models' performance on WISDM dataset

V. CONCLUSION AND FUTURE SCOPE

In this study, a hybrid CNN-LSTM architecture for HAR is suggested, which exclusively relies on unprocessed raw data obtained from wearable sensors or very minimal Preprocessing. By integrating the benefits both CNNs and LSTM, this model is able to extract both short-term and long-term relationships in sequential data. The recommended architecture is capable of reliably identifying activities like sitting, jogging and walking with good accuracy. It uses multiple convolutional filter size to optimise extraction of features and capture distinct local dependencies. Based upon the results, it is to be concluded that the proposed hybrid CNN-LSTM model effectively learns across the dataset. The proposed hybrid CNN-LSTM system was tested on the WISDM dataset and achieved an accuracy of 98.04% and an F1 score of 98.04%. The proposed CNN-LSTM model excelled over the existing HAR models, as per the experimental data. The technology can be used for cognitive assistance in smart healthcare to help people to live longer, more independent lives, especially elderly persons who live alone.

In Future work, we will be modified the model with different hyperparameters that as the batch size, learning rate, etc. so that more efficient work should be achieved on outdoor activities, and more complex activities, or even want to apply this model to postoral Transition activities.

Declarations

Conflict of Interest: We considered all the ethical concerns into considerations, to the best of our ability, followed all rules when writing the manuscript. There is no conflict of interest according to the authors.

REFERENCES

[1] Tun, Soe Ye Yint, Samaneh Madanian, and Farhaan Mirza. "Internet of things (IoT) applications for elderly care: a reflective review." Aging clinical and experimental research 33, no. 4 (2021): 855-867. https://doi.org/10.1007/s40520-020-01545-9

[2] Ramanujam, E., Thinagaran Perumal, and S. Padmavathi. "Human activity recognition with smartphone and wearable sensors using deep learning techniques: A review." IEEE Sensors Journal (2021). 10.1109/JSEN.2021.3069927

[3] Nguyen, Binh, Yves Coelho, Teodiano Bastos, and Sridhar Krishnan. "Trends in human activity recognition with a focus on machine learning and power requirements." Machine Learning with Applications 5 (2021): 100072. https://doi.org/10.1016/j.mlwa.2021.100072

[4] San-Segundo, Rubén, Henrik Blunck, José Moreno-Pimentel, Allan Stisen, and Manuel GilMartín. "Robust Human Activity Recognition using smartwatches and smartphones." Engineering Applications of Artificial Intelligence 72 (2018): 190-202. https://doi.org/10.1016/j.engappai.2018.04.002

[5] Wang, Jindong, Yiqiang Chen, Shuji Hao, Xiaohui Peng, and Lisha Hu. "Deep learning for sensor-based activity recognition: A survey."Pattern Recognition Letters 119 (2019): 3-11. https://doi.org/10.1016/j.patrec.2018.02.010

[6] Wannenburg, Johan, and Reza Malekian. "Physical activity recognition from smartphone accelerometer data for user context awareness sensing." IEEE Transactions on Systems, Man, and Cybernetics: Systems 47, no. 12 (2016): 3142-3149. 10.1109/TSMC.2016.2562509

[7] Hassan, Mohammed Mehedi, Md Zia Uddin, Amr Mohamed, and Ahmad Almogren. "A robust human activity recognition system using smartphone sensors and deep learning." Future Generation Computer Systems 81 (2018): 307-313. https://doi.org/10.1016/j.engappai.2018.04.002

[8] Wan, Shaohua, Lianyong Qi, Xiaolong Xu, Chao Tong, and Zonghua Gu. "Deep learning models for real-time human activity recognition with smartphones." Mobile Networks and Applications 25, no. 2 (2020): 743-755. https://doi.org/10.1007/s11036-019-01445-x

[9] Hassan, Mohammad Mehedi, Shamsul Huda, Md Zia Uddin, Ahmad Almogren, and Majed Alrubaian. "Human activity recognition from body sensor data using deep learning." Journal of medical systems 42, no. 6 (2018): 1-8. https://doi.org/10.1007/s10916-018-0948-z

[10] Wang, Kun, Jun He, and Lei Zhang. "Attention-based convolutional neural network for weakly labeled human activities' recognition with wearable sensors." IEEE Sensors Journal 19, no. 17 (2019): 7598-7604. 10.1109/JSEN.2019.2917225

[11] Uddin, Md Zia, and Mohammad Mehedi Hassan. "Activity recognition for cognitive assistance using body sensors data and deep convolutional neural network." IEEE Sensors Journal 19, no. 19 (2018): 8413-8419. 10.1109/JSEN.2018.2871203

[12] Chen, Zhenghua, Chaoyang Jiang, Shili Xiang, Jie Ding, Min Wu, and Xiaoli Li. "Smartphone sensor-based human activity recognition using feature fusion and maximum full a posteriori." IEEE Transactions on Instrumentation and Measurement 69, no. 7 (2019): 3992-4001. 10.1109/TIM.2019.2945467

[13] Zhou, Xiaokang, Wei Liang, I. Kevin, Kai Wang, Hao Wang, Laurence T. Yang, and Qun Jin. "Deep-learning-enhanced human activity recognition for Internet of healthcare things." IEEE Internet of Things Journal 7, no. 7 (2020): 6429-6438. 10.1109/JIOT.2020.2985082

[14] Xia, Kun, Jianguang Huang, and Hanyu Wang. "LSTM-CNN architecture for human activity recognition." IEEE Access 8 (2020): 56855-56866. 10.1109/ACCESS.2020.2982225

[15] Challa, Sravan Kumar, Akhilesh Kumar, and Vijay Bhaskar Semwal. "A multi-branch CNNBi-LSTM model for human activity recognition using wearable sensor data." The Visual Computer (2021): 1-15. https://doi.org/10.1007/s00371-021-02283-3

[16] Hassan, Mohammad Mehedi, Sana Ullah, M. Shamim Hossain, and Abdulhameed Alelaiwi. "An end-to-end deep learning model for human activity recognition from highly sparse body sensor data in the Internet of Medical Things environment." The Journal of Supercomputing 77, no. 3 (2021): 2237-2250. https://doi.org/10.1007/s11227-020-03361-4

[17] Singh, Satya P., Madan Kumar Sharma, Aimé Lay-Ekuakille, Deepak Gangwar, and Sukrit Gupta. "Deep ConvLSTM with self-attention for human activity decoding using wearable sensors." IEEE Sensors Journal 21, no. 6 (2020): 8575-8582. 10.1109/JSEN.2020.3045135

[18] Ignatov, Andrey. "Real-time human activity recognition from accelerometer data using Convolutional Neural Networks." Applied Soft Computing 62 (2018): 915-922. https://doi.org/10.1016/j.asoc.2017.09.027

[19] Shi, Wenbing, Xianjin Fang, Gaoming Yang, and Ji Huang. "Human Activity Recognition Based on Multichannel Convolutional Neural Network With Data Augmentation." IEEE Access 10 (2022): 76596-76606. 10.1109/ACCESS.2022.3192452

[20] Wang, Huaijun, Jing Zhao, Junhuai Li, Ling Tian, Pengjia Tu, Ting Cao, Yang An, Kan Wang, and Shancang Li. "Wearable sensor-based human activity recognition using hybrid deep learning techniques." Security and communication Networks 2020 (2020). https://doi.org/10.1155/2020/2132138

[21] Kwapisz, Jennifer R., Gary M. Weiss, and Samuel A. Moore. "Activity recognition using cell phone accelerometers." ACM SigKDD Explorations Newsletter 12, no. 2 (2011): 74-82. https://doi.org/10.1145/1964897.1964918