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WEARABLE SENSOR BASED HUMAN BEHAVIOUR AND PATTERN RECOGNITION APPLYING DEEP LEARNING TECHNIQUE

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ABSTRACT

Activity recognition is an important field that influences different applications related to healthcare. In the current work, we have used a triaxial accelerometer IMU sensor to record the activity of 30 different subjects having a diverse age range of 10 to 45 which consisted of 11 females and 19 males. Subjects were asked to perform 5 different activities for 20 seconds and the sensor was placed at the umbilical region. Further, this data is pre-processed with different filtering algorithms and fed to deep learning models to discretely identify different activities. Activities are specifically chosen that have a very close resemblance to each other and the performances of different deep learning models are observed on the data. The classification accuracy of two models reported 86% and 90 % for CNN and CNN-LSTM respectively.

Keywords: **Human activity recognition, IMU Sensor, Deep learning, Classification, Convolution neural network, Long Short Term Memory.**

1. INTRODUCTION

Human activity recognition (HAR) is an important research field for human computer interaction and ubiquitous computing. Activity recognition [1-2] is deeply rooted in health care applications that monitor a person's daily routine and keep a check on them. Because of its broad range of human-centric applications, human activity recognition has received attention, recently. One key application area is to monitor everyday activities because modern lifestyles are leading to a rise in diseases of human such as diabetes, obesity, high blood pressure, insomnia and cardiovascular problems [3-5]. Such patients needs to engage in regular activities like- walking, riding, jogging, running, push-ups, and sit-ups.For the subject to assess their daily success, accurate information about the length of certain activities is critical. As a result, activity recognition determines whether the person has trouble sticking to their everyday routines. Activity recognition may also be used as part of an elder-care support system, as it allows family members to monitor the behaviours of their elderly relatives or residents while they are away from home. Home security, surveillance, home automation, workplaces, IoT & smart cities, electrical energy saving systems, object detection, bipedal robot walking [6-7], and pedestrian navigation all such activities are strictly depends on recognition of activity. HAR problem which is a problem of pattern recognition and for HAR we have two types of solution i.e. wearable sensor based and vision sensor based. The main focus of wearable sensor-based HAR is on the belief that a particular body movement can be translated into a distinct sensor signal pattern, which can then be further analysed by using a machine learning method to classify. Deep learning techniques have recently outperformed many traditional machine learning approaches, reflecting a significant research trend in HAR. Deep learning [8-10] has the advantage of being able to extract features automatically based on the task requirements.

This research paper attempts to resolve many of the issues associated with capturing human behaviour using wearable sensors. The study of five distinct walk related activity patterns was thoroughly presented in the research work. The paper also describes the creation of two deep learning-based HAR models-CNN and CNN-LSTM [11-12], for the classification of five different activities. Finally, the work includes a comparison of all the models based on their output matrices. The classification models are validated using data sets of 30 subjects from various age groups, sexes, and health conditions. In terms of data collection and classification, the proposed solution is unique.

Literature Review

Deep learning is mostly used in wearable based HAR, especially CNN is one of the well-studied deep learning techniques for extracting features and detecting hidden or unknown behaviour patterns from raw time series sensor data. Various researchers have done significant work on activity recognition using machine learning techniques and other related work [13-19], some of which are listed below in Table I.

Table I
Literature review

Author's / Cite	Subjects		Activities performed	Model accuracy in percentage %	Methods			
	Number	Diversity		Model	Smartphone / Sensor's	Segmentation	Features	Algorithms
D. Anguita [1]	30	Age range 19-48	06 activities, walk, sit, stand, upstairs, downstairs, lie down	89	Smartphone, acceleration	2.56 s overlapping windows	Basic statistics, FFT	SVM
T. Brezmes [2]			06 activities, walk, sit, stand, upstairs, downstairs, Fall	80	Many	windows	Raw data	kNN
S. Dernbach [3]	10	UG Students	08 activities, walk, sit, stand, run, upstairs, lie down, cycle, drive	93	Smartphone, acceleration, gyroscope	Overlapping windows	Basic statistics	Decision trees, neural networks, k-star
Z. He [6]	11	09 Male,02 female	04 activities Walk, stand, run, Jump	97	Custom accelerometer	5s overlapping windows	Discrete cosine transform (DCT)	SVM
M. Han [7]	03	Graduate students	05 activities walk, sit, stand, run, drive	90	Smartphone, acceleration, gyroscope, GPS			Adaptive Bayes
M Kastner	30	Age	06 activities,	98	Smartpho	2.5 s	561	Learnin

[9]		range 19-48	walk, sit, stand, upstairs,		ne, accelerati on	overlapping windows	given features	g vector quantiza tion
			downstairs, lie down					
J.R Kwapisz [11]	29	UG Students	06 activities, walk, sit, stand, run, upstairs, downstairs,	92	Smartpho ne, accelerati on	10 s windows	Basic statistics	Decisio n trees, neural network s, kNN
A.M Khan [8]	40	26 Male,16 females Age range 18-50	06 activities, Walk, stand run, upstairs, downstairs, jump	90	Smartpho ne, accelerati on	3s windows	Advanc ed statistics , FFT, DCT	Neural network s
N.D Lane [10]	120	--	06 activities walk, sit-stand, run, upstairs, down stairs, skip	85	Smartpho ne, accelerati on, micropho ne, GPS		Basic statistics , FFT	Naïve Bayes with update
A. Reiss [19]	30		06 activities walk, sit, stand, upstairs, downstairs, lie down	98	Smartpho ne, accelerati on,		Basic statistics , FFT	Decisio n tree, adaboos t
X. Qi [20]	8	5 Male,03 Female	06 activities walk, sit, stand, run, lie down, cycle	87	Smartpho ne, accelerati on,	1s windows	Basic statistics	SVM
P. Sirtolla [21]	7	Healthy subject age group 24-34	05 activities walk, sit-stand, run, cycle, drive	100	Smartpho ne, accelerati on,	7.5 s overlapping windows	Basic statistics	Decisio n trees
B.Yuan [22]	8	Graduat e students	03 walk, run, upstairs-downstairs	95	Smartpho ne, accelerati on, gyroscope , body accelerati on	1s overlapping windows	Basic statistics	NB, decision trees, Neural network s, kNN
Federico Cruciani	--	UCI Dataset used for IMU and DCASE	05 walking, sitting, lying, running, cycling	93	IMU, accelerati on, Audio signals	2.56 s overlapping windows	Basic statistics , FFT	CNN, Multi-CNN

		2017 for audio						

2. PROPOSED METHODOLOGY

This experiment aims to develop a better classification modelling technique to recognize different activities performed by a human being. We handpicked 5 activities that closely resemble and recorded them with 30 subjects. These 30 subjects have age in a range of 10 to 45 years. It consists of 11 females and 19 males. When an activity is performed repeatedly it generates a particular type of acceleration due to different muscle memory that is inherently built by the body over time [2-4]. For instance when we look at figure 3 and figure 5 walk on the toe and normal walk are seemingly similar activities but still, the specific difference can easily be observed in the graph of both activities. Each activity has its phases as which inherently differ from one another and this is the reason for such differences in these patterns. We tend to exploit these patterns in the data to accurately classify them. In this experimental setup, only one IMU sensor [20-22] is used to mimic the data that a smartphone user may generate. More than one sensor may easily produce better results but it may not apply to the normal life of users that carry only one smart device. Fig. 1 depicts the proposed human activity recognition task.

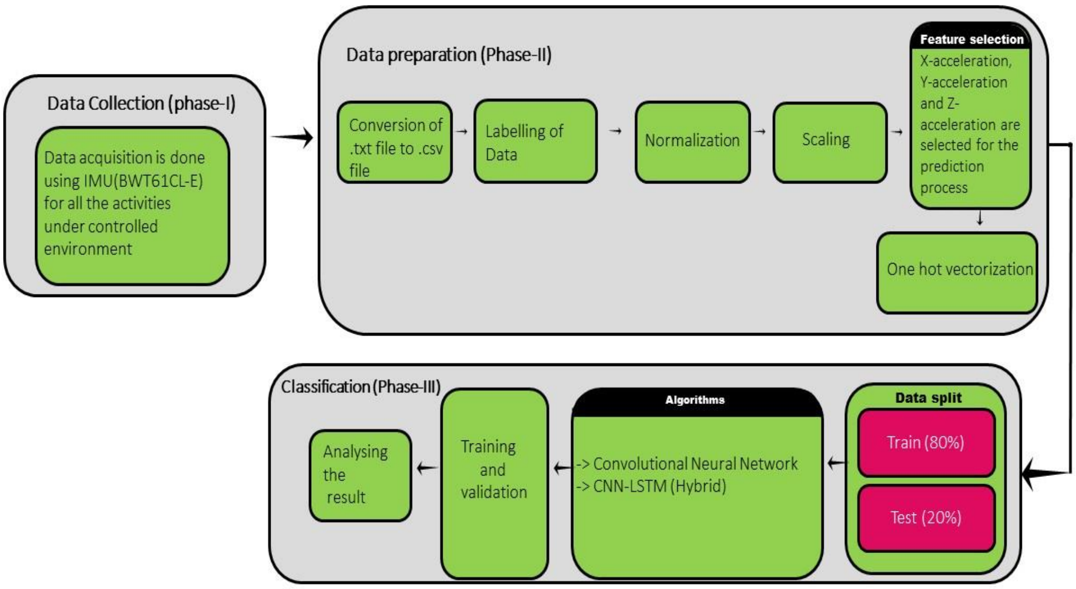

Fig. 1 Flow chart of the proposed work on HAR

The Subjects performed 5 different activities [7-9] namely 'normal walk', 'walk on the toe', 'jogging', sit-ups', and 'walking downstairs' repeatedly, and there accelerometer reading is recorded using BWT61 IMU Sensor which was placed on subjects umbilical region, due to human center of mass lies there. Afterward, this data is pre-processed and fed to a neural network for training. CNN and CNN-LSTM are used for training of the data. Fig.2 shows the different subject of diverse age range were used for data collection. UID (user id of the subject), timestamp, operation, x, y and z accelerations are the five features considered as input to the learning algorithm in the proposed approach.

Each sample is given a label, which is used to process the data. The acceleration is normalized and scaled, and then a hot vectorization is performed.

Fig.2 Three different subjects with IMU placed on Umbilical region (centre of mass of the human body) and IMU sensor

Figure3, 4,5,6,7 are the trajectories of 5 different activities performed by the subjects. The trajectories are based on 3-D accelerometer data taken from IMU sensor. We may also and take the magnetometer reading, angular velocity, acceleration due to gravity or fusion of these data as a feature for our analysis.

CNN

The convolution neural network [23-25] is well known for its pattern recognition property. It splits up the data using different filters and chooses the best features to classify the activity. The data is split up into frames and then filters are applied to it that creates a volume of frames that contain different features. These features are finally used for classification.

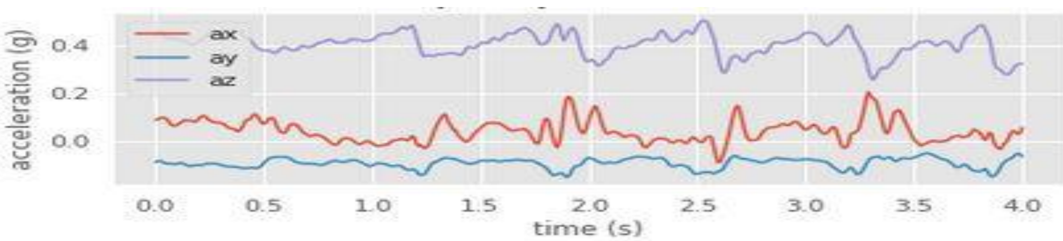

Fig.3 Subject trajectory of Walk on toe

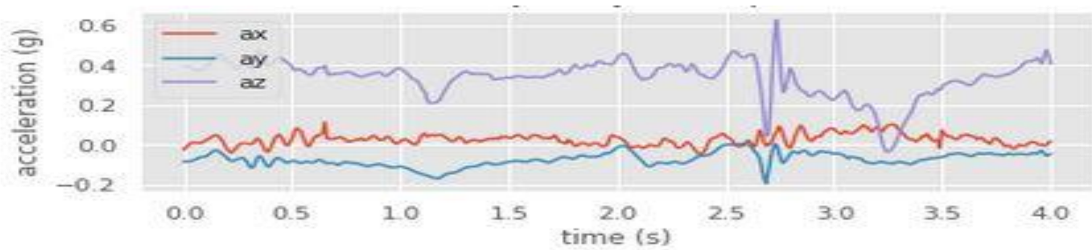

Fig.4 Subject trajectory of Sit-ups

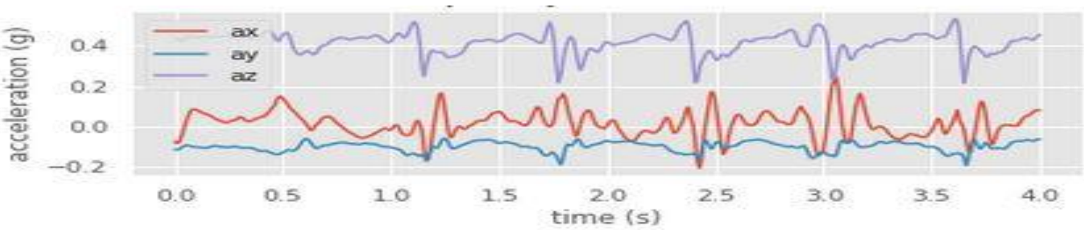

Fig.5 Subject trajectory of normal walk

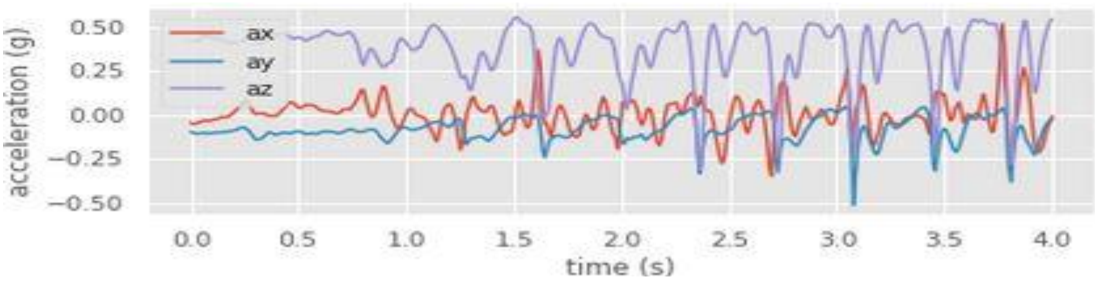

Fig.6 Subject trajectory of Jogging

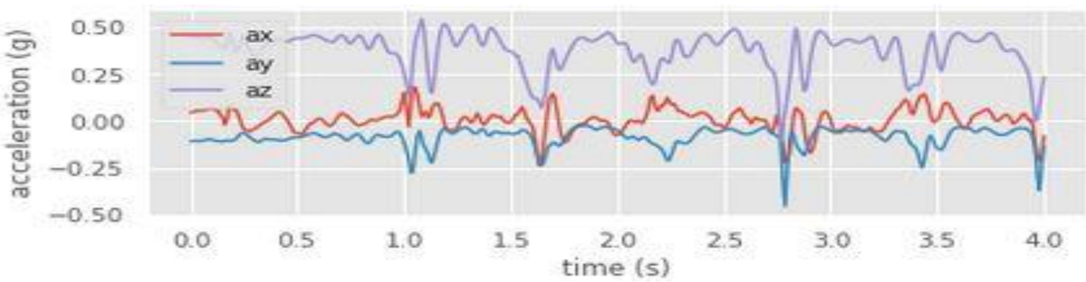

Fig.7 Subject trajectory of downstairs

CNN-LSTM

CNN is profound for its feature extraction property. Time-series data is processed using long and short term memory. A combination of both produces boosting up of results as CNN extracts the features and then LSTM is employed for the learning of these features. We can see a significant difference in the accuracies of CNN and CNN-LSTM [26] architectures.

3. RESULTS AND DISCUSSION

The CNN model obtained an accuracy of 87% while CNN-LSTM was able to boost it up to 90 %. The difference in the values of recall, precision and F-score are depicted in figure 11. As we look up to the figure 9 and figure 10 we can see most errors are made between normal walk and walk on the toe as both have a very close resemblance. CNN miss classified 30 normal walks to be a walk on the toe and 22 similar errors are made by CNN-LSTM model. Some small errors are seen between jogging and normal walk. Fig.8 demonstrates the model accuracy and loss plot for CNN-LSTM. We see that after first 20 epochs the training and test data both have the saturated and stable values i.e accuracy almost in the range of 1. In fig. 9 and 10 the confusion matrix shows very nice accuracy and there is no such activity is there in which the model is unable to distinct the activity. This is also shown that using hybrid deep learning model CNN-LSTM, we have achieved more accuracy than only CNN.

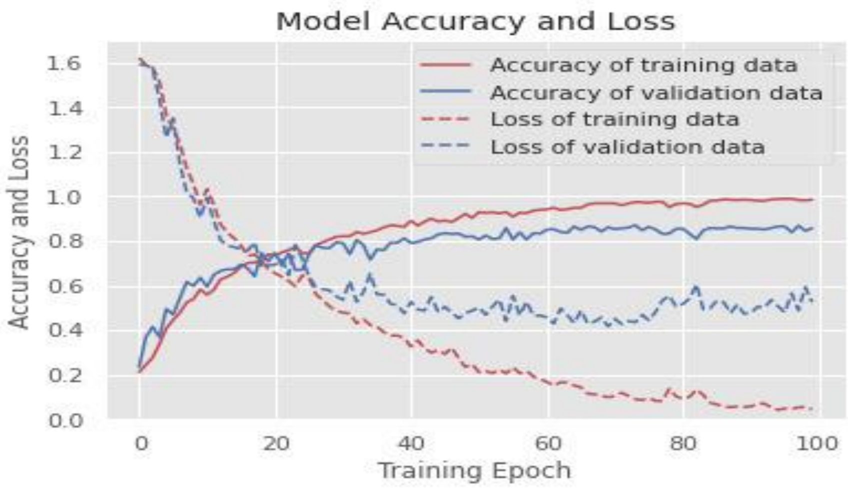

Fig.8 Accuracy and loss plot for CNN-

Fig.9. Confusion matrix of CNN-LSTM model

Fig.10. Confusion matrix for CNN

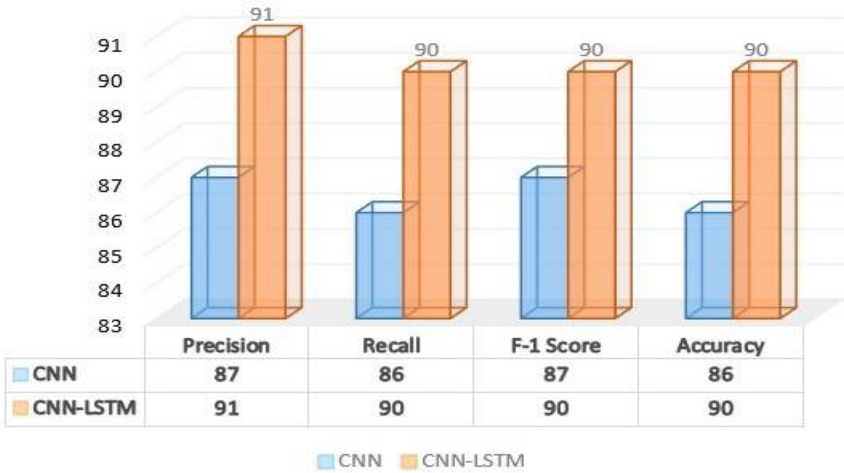

Fig.11 Comparison between CNN and CNN-LSTM

4. CONCLUSION

CNN model performed profoundly well for the classification of different activities and it is evident from the data presented in figure 11 that CNN-LSTM shows a significant increase in the efficacy of the classification task. In current work, we have included 5 activities with close resemblance and both models showed satisfying performance. Both precision and recall of the models are high which depicts the reliability of the technique employed. Currently, data is taken from 30 different subjects. Reaching such good accuracies with this amount of sampling data implies models used have high competency. Present work can be explored for diverse human performances in future. The Microsoft Kinect sensor can also utilized for the purpose. The computer vision-based multi-sensor and multi-view HAR system will be developed in future study. In the multi-view environment, the Microsoft

Kinect v2 sensor will be used for HAR and GAIT analysis. The data collection for 30 topics has been made publicly available online for use by the science and academic communities.

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