



HUMAN ACTIVITY RECOGNITION USING LSTM MODEL

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Abstract—Detecting the physical body movements of a human is called Human Activity Recognition . HAR is a time series classifying work, means it can be used in different fields, domains and varieties of application. Sensor data are used. The Movements here are often regular activities like walking, jogging, standing and sitting. In general deep learning architecture manages HAR job with a distinct result.

Long Short Term Memory (LSTM) neural architecture which is a deep learning model can be designate as a distinct sort of recurrent neural network model this is able to gaining knowledge of long time dependencies in data. The LSTM neural network model comprises a merger of four layers that interact with each other.

We have used Long Short Term Memory neural architecture in UCI HAR dataset to identify the type of activity or movement the person is doing. We saw that after the network completes training, optimization and accuracy is found to be 87% to 90% also a graph and confusion matrix has been used to show the losses, accuracies, training iteration, etc.

Keywords—HAR, LSTM, UCI HAR, dataset.

I. INTRODUCTION

Human activity recognition (HAR) is also an extensive studied computer vision problem. Applications of Human activity recognition manifest video vigilance, between human-computer interaction and health care, because the imaging technique has progressed and also the camera device enhances, innovative approaches for Human activity recognition constantly emerge [1]. With several phenomenal successes within the development of ANN model an accordingly advancement of process performance, by different deep learning systems, namely convolutional neural network and recurrent neural network, demonstrate a vigorous way to extract options from different variety of knowledge, square measure currently taking part as a vital role in several studies of ML, along with natural language process (NLP) and computer version (CV) and it is much beneficial to the uses of sensible devices in day-to-day life square measure oftentimes give update of those efficient algorithms embedded within the core of every appliance [3].

The HAR (Human Activity Recognition Systems) is competent of distinguishing some of the physical activeness such as eating, sleeping, running, playing and many such activities. The detection of the physical activeness by entirely distinct such sensors and recognition approach is a main topic of study of research, survey and analysis in mobile computing, wireless and smartphones. Human Activity Recognition Systems is in a position to perform totally peculiar tasks and recognize the multi day to day behaviours execute by individual which can be either direct activities like sleeping or the advance movement like eating and running [2].

- HAR Task

Human Activity Recognition task are:

- walking,
- walking-upstairs,
- walking-downstairs,
- sitting,
- standing,
- laying.

In our study we have used UCI HAR dataset and have used 7352 training series, 2947 testing series, 128-time step per series, 9 input parameters per time step.

Here in LSTM neural network 32 hidden layer number of features and 6 total classes were used and other parameters are also used.

The parameter learning rate is used here in this project. We can see that while making headway to a minimal of a loss function, generally it is found that the learning rate in ML is an integrated specification of an optimization algorithm which finally decide the step size at every iteration. The learning rate which is considered to be a parameter that is often used to train the different neural networks which has a very small positive range of values that is from 0.0 to 1.0 [4]. By the learning rate we can have a control of how fast the neural network model is fitted to the problem. Learning rates which are smaller they need added training epochs when it is given that the smaller reversal were pulled off to the weights after every update it has gone through, although greater; training epochs. It is found that learning rate which is greater can lead neural network architecture to assemble too fast to a



substandard result, on the other hand learning rate which is very small can cause the model to get stuck [4].

The activation function is liable for reconstruct the aggregated weighted input which is taken from the nodule toward the nodule of the activation.

Here Rectified Linear Units (ReLU), activation function, used in this project. In 2011, ReLU was demonstrated to made an improvement in training of deep neural networks model [5].

ReLU activation function formula is given by:

$$f(x) = \max(0, x)$$

- deep learning algorithm

In this section we are going to cover an outline of Deep Learning algorithms that have been used in this project work. LSTM is the basic algorithm in this project for constructing the HAR system.

Deep Learning can be explained as a function of AI which generally replicates function of an individual brain for preparing different types of data and constructing patterns that is to be used in choice building. Deep Learning which is a subdivision of ML in computing which has different networks and is capable of how to learn from unsupervised knowledge that which is not structured or untagged or unlabeled. It can also be called as Deep Neural network or Deep Neural Learning [6].

Nowadays, Artificial Neural Network has become a budding algorithm in ML, that is also an important branch of Artificial Intelligence.

In deep learning, learning is a job looking for weights that create the neural network to arrive at desired proposes. To learning with correctness, deep learning is built supported many neurons and layers moreover as special affiliation fashions in step with varied sensible issues.

- Artificial Neural Network

An ANN is motivated by the human brain's cerebral cortex structure and also ANN can be defined as a data process arrangement that consists of a huge quantity of straightforward highly interrelated artificial neurons. [8]

Neurons or nodes are generally huge number of extremely interconnected process elements in Artificial Neural Network. Each and every neuron is connected with new neuron by connection network. All connection network is associated with different weights which contains instruction of the input signal. This instruction is used by neural network to determine a distinct problem.

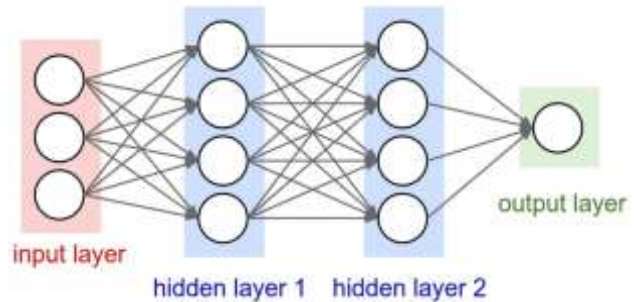


Fig.1. Artificial Neural Network [9].

When an ANN begins to learn that the weights in between the neurons are altering and hence the connection strength also. Every dataset and even every task have different set of weights. Prediction of the weight values in advance is not possible, but the neural network need to learn and this process is known as training [7].

- Characteristics of Neural Network
- The Neural Networks has mapping effective which means it has the power to map different input patterning's to their related output patterning's.
- The Neural Network is feasible to trained with examples that are known, aforetime it is tested for its inference effectiveness on not known reason of the problem.
- The Neural Network has the capability to process information at a high speed in distributed and parallel way.
- The Neural Networks are robust in nature and has fault tolerance capability. So it is use to recall full patterns which starts from incomplete, noisy or different partial patterns.

FEEDFORWARD NETWORK

The first and simplest category of ANN is the feed forward network. Such network, the instruction always advances generally in forward way i.e. it starts from the input nodes, then it enters the hidden nodes and finally it moves to the output nodes.

- Single Feed forward Network

The input layer and output layer are present in Single Feed forward Network. Here we find that the input signals are received by input neurons and similarly the output signals are receiving by output layer neurons. All input neuron which carry the weights are mostly connected to the o/p neuron. Hence it's called feed forward which is not cyclic in nature. The only output layer performs the operation so the term single layer is introduced for this network and is also known as Single Feedback Network.

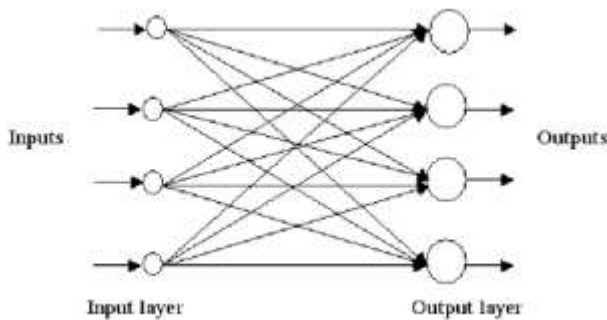


Fig. 2. Single Layer Feed forward Network [12].

• Multilayer Feed forward Network

This network has input layer, output layer & the middle layers which is referred as hidden layers, it has some computational element referred as neurons. The intermediate computation takes place ahead of the input to the output layer. The neurons which are found in the input layer are associated with the neurons which are found in the hidden layers and they have weights in them which is referred to as input hidden layer weights. Further, the neurons in hidden layer are associated with the neurons of the output layer and hence the weights are mentioned as hidden-output layer weights. A multilayer feed forward network with 1 input neurons, m1 neurons within the first hidden layer, m2 neurons within the second hidden layer, and n output neurons within the output layer is written as 1-m1-m2-n [8].

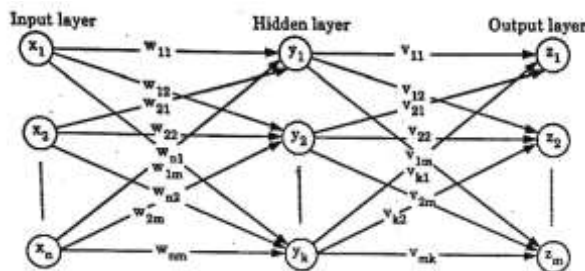


Fig.3. Multilayer Feedforward network [13].

• WHY RECURRENT NEURAL NETWORK FAIL

Recurrent Neural Networks (RNN) are class of neural network which consists of cyclic links and has a memory or a feedback loop which accomplish them a more robust tool to model such sequence data than any other feedforward network. RNNs are used to predict task which are language modeling [10] and handwriting recognition and also in acoustic modeling [11].

RNN fail because of the Gradient problem as well as it cannot process very long sequence if the activation function used is ReLU. A gradient is a partial derivative with respect to their input. When the value of the gradient is small and

hence the resultant model takes a bit long time than usual or the learning is stop, then vanishing gradient occurs.

Earlier in the 1990s, this vanishing gradient used to be a major issue, to overcome this issue, the LSTM model came into the picture by two scientists Juergen Schmidhuber & Sepp Hochreiter.

• LSTM NEURAL NETWORK

LSTM networks are the higher form of RNN, where it remembers the previous information or data in its memory. In this project we have use LSTM neural network for the Human Activity Recognition.

LSTM has revolutionize the fields in neuro-computing as well as ML. Even LSTM model has upgraded both speech recognition of Google, and Amazon's Alexa answer. This LSTM neural system is also employed by Facebook. This LSTM model has become famous because it can overcome to handle the vanishing and exploding gradient problem. [14]

LSTM uses the method of back propagation to train the model. LSTM network generally has 3 gates.

(a) **Forget Gate:** To begin with, the gate that is used first is the forget gate. Here Forget gate will take the decision what type of information should stay or what to move away out. The information which is passed from the past hidden layer and information originating out of the present input layer takes place by the sigmoid function. Values come in the range of 0 and 1. The values which come nearer to Zero is forgotten and the values which come nearer to 1 is to keep [15].

(b) **Input Gate:** Update the cell status. Firstly, the previous hidden state is passed and present input position toward a sigmoid function and then decision is taken which values need to be updated by reorienting the values between 0 & 1. Here the value 0 signifies it is insignificant and the value 1 signifies it is significant [15].

We conjointly pass the hidden state and current input into the tanh perform to compress values starting from -1 to 1 to help regulate the network. subsequently tanh output is increased with the sigmoid output. The sigmoid output than take call that info is important to remain from the output of tanh [15].

(c) **Output Gate:** The output gate decides what is supposed to be the coming hidden layer and it always consists of previous input information.

Previous input information from the hidden layer is carried toward the sigmoid function. Recently reformed cell status is pass to the tanh. The hidden layer will carry what kind of observation after the tanh output function is multiplied with the sigmoidal output function. The output becomes the



hidden layer now. The new hidden layer is then put forward to the next step [15].

II. PROPOSED PROBLEM

- This project we have use LSTM model for Human Activity Recognition using UCI HAR datasets. Here we found that, LSTM is slow
- Training time as well as memory requirement of LSTM is more during training data.
- Over fitting are easily occurring in LSTM
- It is very sensitive for different random weights.
- Dropout is much harder to implement in LSTMs
- Implementation and result analysis

Here, I have construct the HAR model using UCI HAR dataset.



Fig. 4. UCI HAR dataset

- Experimental Configuration

TABLE I: PARAMETERS SETTING IN TRAINING LSTM (LONG SHORT TERM MEMORY) MODEL

Parameters	LSTM model
batch size	1500
number of Labels	6
learning_rate	0.0025
lambda_loss_amount	0.0015
display_iter	3000
optimizer	Adam Optimizer

In this research, all experimentation was executed with the help of Tensor Flow, an open-source for machine learning also using Keras, a deep learning framework. The operating system used is Windows 10, Python 3, programming language used in implementing deep learning algorithms, and Jupyter notebook is the operational environment for coding.

TABLE II: TRAINING ITERATION, BATCH LOSS AND ACCURACY

Training iteration	Batch loss	Performance on Test Set	
		Accuracy	Batch loss Accuracy
1500	0.1746666		
	2.71227	72945022	2.53019094
	0	58	4671631
30000	1.37610	0.68866661	4.94131320
	9	41712188	6675415
		7	756851196
60000	1.28134	0.70533331	3.69470230
	3	52088928	8685608
		2	970115662
90000	1.08161	0.80466661	2.12021580
	7	38374328	92791748
		6	493545532
120000	1.05188	0.80866661	1.12542593
	0	46480560	4791565
		3	562408447
150000	0.89154	0.88200001	1.05654394
	4	29087066	62661743
		7	244865417
180000	0.99522	0.81266661	0.05553174
	7	54586792	01885986
			822662354
210000	0.84914	0.87666660	0.99526870
	8	65077209	2507019
		5	071723938
240000	0.82432	0.86933331	0.27365422
	4	26816558	24884033
		8	417816162
270000	0.67469	0.97066660	0.94756007
	1	46957397	19451904
		5	02130127
300000	0.64251	0.96133330	0.89796149
	2	34445953	73068237
		4	115280151
330000	0.66257	0.95933330	0.90070259
	7	60195159	57107544
		9	273796082
360000	0.65471	0.95133330	0.88143056
			0.8944689



0	43982696	63108826	631462097
	5		
390000	0.66303	0.94066660	928216040.8676620
	9	75567627	01344299 125770569
420000	0.60205	0.95399990	866662260.8822531
	7	96185302	38702393 10408783
	7		
450000	0.59612	0.94333330	832086020.8890396
	2	27770233	66685486 952629089
	2		
480000	0.62416	0.92933330	838425510.8941296
	1	29200744	70822144 339035034
	6		
510000	0.57186	0.94800000	845685950.8761452
	6	13828277	88623047 436447144
	6		
540000	0.64617	0.90200000	861445420.8656260
	9	10013580	6940918 371208191
	3		
570000	0.79109	0.88599990	911540380.8483203
	7	77588653	90609741 053474426
	6		
600000	0.65379	0.88133330	793090400.8805565
	4	51135253	30799866 237998962
	9		
630000	0.59314	0.95933330	901339820.8473023
	5	60195159	89680481 176193237
	9		
660000	0.53092	0.96666660	803773520.8764845
	3	38851165	23770142 728874207
	8		
690000	0.48010	0.98533330	748867150.8903970
	4	23478698	41213989 122337341
	7		
720000	0.54292	0.95333330	770225880.8903970
	3	1823349	25302124 122337341
750000	0.54727	0.94199990	779521940.8920936
	1	71866607	21386719 584472656
	7		
780000	0.45869	0.96799990	772324620.8924329
	6	94754791	16773987 876899719

3

The training stopped after an optimization is reached and hence,

FINAL RESULT: Batch Loss = 0.6116480827331543, Accuracy = 0.8788598775863647

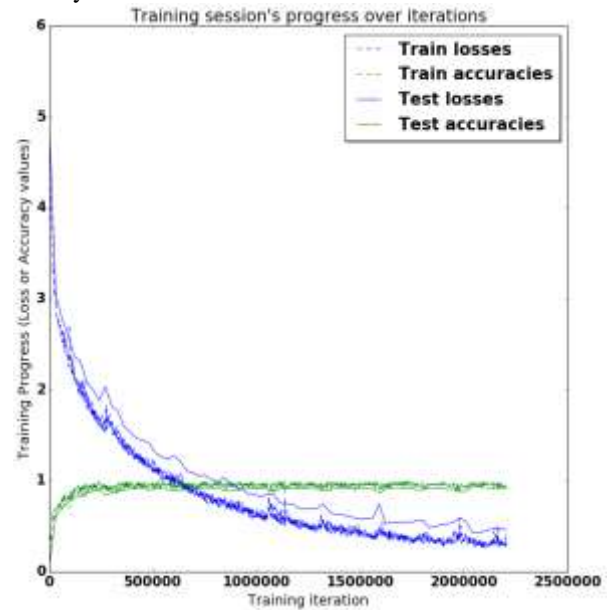


Fig. 5. Graph showing train and test losses and accuracies

• Experimental Evaluation

To determine the performance of different task on the UCI HAR dataset using the LSTM model the following performance on testing accuracy, Precision, Recall, F1_score is as shown in Table III

TABLE III. Testing Accuracy, Precision, Recall, F1_score

Testing Accuracy	Precision	Recall	F1_score
87.885987758	88.78194982	87.885985	87.942815539
63647%	2189%	74821853	49016%

TABLE IV. HAR classification Confusion Matrix

	WALKI NG	UPSTAI RS	DOWNST AIRS	SITTI NG	LAY NDINING G
WALKI NG	491	2	1	0	2
UPSTAI RS	101	364	2	0	4
DOWNST AIRS	48	14	358	0	0
SITTI NG	0	4	0	407	78
LAY NDINING G				2	



STANDI NG	0	0	71	460	0
LAYIN G	0	27	0	0	510

TABLE V. Confusion Matrix

	WALKI NG	UPSTA AIRS	DOWNSTAI RS	SITTI NG	STAND ING	LAY ING
WALKI NG	16.66	0.067	0.033	0	0.067	0
UPSTA IRS	3.427	12.35	0.067	0	0.135	0
DOWN STAIR S	1.628	0.475	12.147	0	0	0
SITTI NG	0	0.135	0	13.81	2.64	0.067
STAN DING	0.0339	0	0	2.40	15.60	0
LAYIN G	0	0.91	0	0	0	17.30

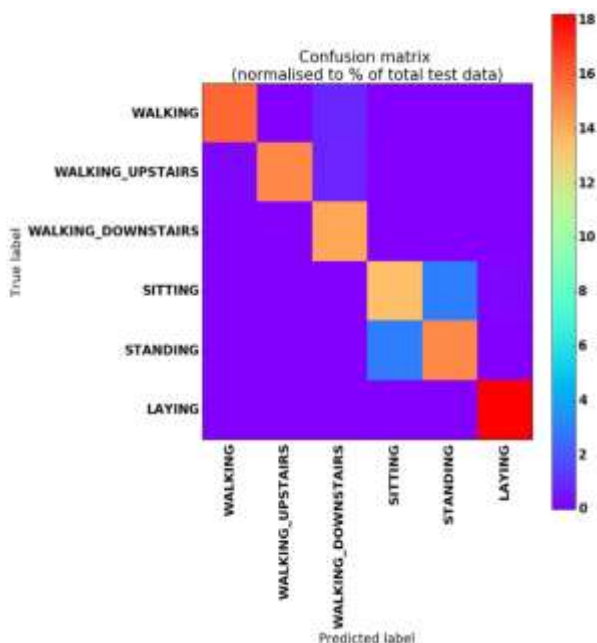


Fig.6. Heat map Confusion Matrix on test data.

The prediction biases is found to be low. The prediction is high in classes like WALKING and LAYING. While prediction is low in WALKING_DOWNSTAIRS, SITTING_DOWNSTAIRS

III. CONCLUSION & FUTURE WORK

Here LSTM model and Adam optimizer are used for HAR task by applying some time series datasets. After designing LSTM model to accelerate the method of statistical feature

extraction then validate this concept based on this LSTM model with UCI HAR dataset.

Here I have developed a confusion matrix, to get a better idea of model performance.

Hereafter performing the training, the final accuracy is 87% and sometimes it can vary to 91% relies upon what means the neural network weights are introduced randomly at the beginning of the training.

Because of their similarity some obstacles are found while trying to differentiate them, such activities which create the obstacles are walking, downstairs and upstairs.

In future work, different models like CNN, Bi-LSTM, and also taking different datasets can be taken to find out finding more accuracy, training time, and also transfer learning method can be used to get a better idea of this model.

IV. REFERENCES

- [1]. S.Zhang, Z. Wei, et.al., "A Review on Human Activity Recognition Using Vision-Based Method", Journal of Healthcare Engineering, Vol. 2017, Article ID 3090343, 20 July, 2017.
- [2]. Shikha, R. Kumar, Aggarwal and S. Jain, "Human Activity Recognition", International Journal of Innovative Technology and Exploring Engineering (IJITEE), Vol.-9 Issue-7, May 2020.
- [3]. J. Pang, "Human Activity Recognition Based on Transfer Learning", Scholar CommonUSF, July 2018.
- [4]. J. Nicole, "Understand the Impact of Learning rate on Neural Network Performance," machinelearningmastery.com, Sept 12, 2020 [online]. Available:<https://machinelearningmastery.com/understand-the-dynamics-of-learning-rate-on-deep-learning-neural-networks/>
- [5]. A. F.M. Agarap, "Deep Learning Using Rectified Linear Units (ReLU)", arXiv:1803.08375vol.2 [cs.NE] 7 Feb 2019
- [6]. M. Hargrave, "Deep Learning", investopedia.com, May 17, 2021 [online]. Available: <https://www.investopedia.com/terms/d/deep-learning.asp>
- [7]. A. Oppermann, "What is Deep Learning and How does it work ?", towardsdatascience.com, Nov 13, 2019 [online]. Available: <https://towardsdatascience.com/what-is-deep-learning-and-how-does-it-work-2ce44bb692ac>
- [8]. S. Rajasekaran, G.A. VijayaLakshmi Pai, "Neural Networks, Fuzzy Logic and Genetic Algorithms Synthesis and Applications ", PHI Learning Private Limited, July 2011
- [9]. C. Dabakoglu, "Artificial Neural Network with Keras ", kaggle.com 2017. Available: <https://www.kaggle.com/cdabakoglu/artificial-neural-network-with-keras>.



- [10]. H. Sak, A. Senior, F. Beaufays, “Long Short-Term Memory Recurrent Neural Network Architectures for Large Scale Acoustic Modeling”, Google, USA 2014.
- [11]. [T. Zia &U. Zahid, “Long Short-Term Memory Recurrent Neural Network Architectures for Urdu Acoustic Modeling”, International Journal of Speech Technology, 22, 21-30(2019).
- [12]. M. H. Sazil, “A brief review of feed-forward neural networks,” Commun. Fac. Sci. Univ. Ank. Series A2-A3 V.50(1) pp 11-17 (2006)
- [13]. Asquero, “Different Types of Neural Network Architecture”, asquero.com, Aug 23, 2020 [online] Available: <https://www.asquero.com/article/different-types-of-neural-network-architecture/>
- [14]. V. Houdt, G., Mosquera, C.& Napoles, “A review on the long short-term memory model”, Artificial Intelligence Review53, 5929-5955 (2020). May,2020.
- [15]. M. Phi, “Illustrated Guide to LSTM’s and GRU’s. A step by step explanation”, towardsdatascience.com, Sep 24, 2018 [online]. Available: <https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21>