Sensor based Human Activity Recognition

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Abstract: Human activity recognition (HAR) is to recognize another person's activities and it is one of the active research areas in the computer field. The goal of this System is to understand people's actions and interactions. We proposed a method of Human Activity is by predicting the person's activity, their personality, and their psychological state like Human activity recognition (HAR). We propose a recurrent neural network of deep learning architecture. The critical factor of RNN includes bidirectional connection that is simply called from the input node, the information only flows in forwarding direction after that it passthrough so many hidden layers to reach the output.. This system is to design the six different activities of a human. The final model should use as a good source of information about human's daily activities. The dataset has taken from UCI Machine Learning Repository. Our system accuracy is higher than the previous results.

Keywords: Long short-term memory, RNN, Activity.

I. INTRODUCTION

To predict people's reciprocal action on the external environment and circumstance it plays an essential thing in Artificial intelligent systems to deliver the foreseen calculation to the end-user and the activity is sensed by various sensors. It identifies anonymous behaviour that impacts on an object or person, the way we built HAR for ambient assistance living systems and so on.

Human activity recognition system is used in many applications such as video surveillance systems, Homecare for elderly people and children to prompt timely assistance, Human-Computer Interaction, video retrieval, virtual reality, computer gaming, and many other fields.

Since 1870 a huge growth in human life expectancy. This growth was expand in the whole world principally due to the great achievements in the healthcare field. As a result, the elderly people is rapidly increasing. Aging people is generally lives in isolated conditions. In addition to that some of them are not capable of living normally and take advantages from health care facilities services. Building remote monitoring systems for elderly patients who live alone or without permanent caretaking will improve their quality of life. For better decision making these remote monitoring systems needs some regular and trustful information about patients.

Human activity recognition possesses knowledge of context-aware information accurately measured via deep learning algorithms and sensors. So it helps in various applications. Let us see a simple example for HAR janitor activity and reporting what specific things affect the external circumstance have automatically given acknowledgment to the concerned person, and another usage field are hospital zone and military defense protection.

II. LITERATURE REVIEW

A survey on human activity recognition has explored in this paper, some concentrated upon real-time processing, and some of the approaches use offline processing.

Bayat et al. studied on human activity recognition with accelerator signals [1]. Attal et al. tried to classify activity depending on wearable multiple gyroscope and accelerometers [2]. Ronao et al. structured a convolutional artificial neural network in order to recognize user activity using smart phones accelerometer and gyroscope [3]. Kozina et al. worked on fall detection using an accelerometer [4]. Muhammad Shoaib et. al review the studies done so far that implement activity recognition systems on mobile phones and use only their onboard sensors [5]. Subhas Chandra Mukhopadhyay has reviewed the reported literature on wearable sensors and devices for monitoring human activities [6]. Davide Anguita et al. presented a novel energy efficient approach for the classification of Activities of Daily Living using smart phones [7]. Jie Yin, Qiang Yang proposed a novel approach for detecting a user's abnormal activities from body worn sensors [8].

III. METHODS

A. Basic Approach

The activity recognition module has four main steps there are data collection, data sensing, feature extraction, classification.
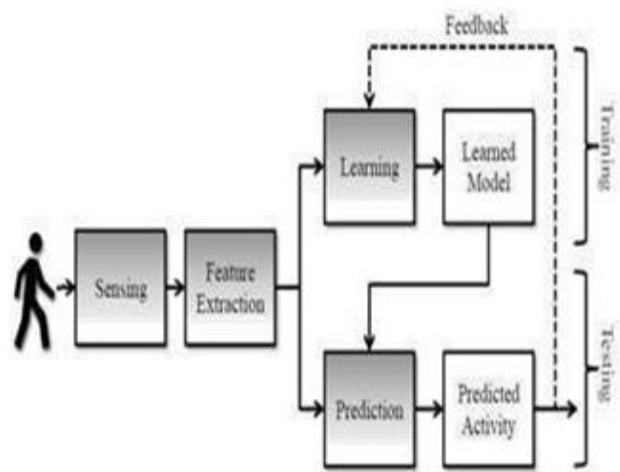

Fig 1 Four Main Blocks

Sensor based Human Activity Recognition

A. Data Sensing

In this era, the mobile phone comes with a variety of sensors that contain unique features; it is also useful to record data for every second of their active life. Our objective of Human Activity Recognition research is to monitor human activities. We constructed the database that has taken from recordings of 30 subjects carry-out day to day activity. That includes hand gestures and movements on our body like sit, stand, run, inert motions these are executed by attached waist-mounted smartphones with embedded inertial sensors on a person.

When the subjects were taken out with Thirty volunteers with an age limit between 19-45 years, our experiments collaborated with six activities. The six activities performed are:

- Walking
- Walking Upstairs
- Walking Downstairs
- Sitting
- Standing
- Laying

The data recorded was the x, y, and z accelerometer and gyroscope sensors from the Smartphone. The Observations were recorded at 50 Hz (i.e. 50 data points per second). Each subject performed the sequence of activities twice; once with the device on their left-side and once with the device on their right-side.

B. Data Pre-processing

Data Pre-processing is an integral step in Machine Learning to increase the quality of data. It refers to the transformations applied to our data before feeding it to the algorithm. Preprocessing the data is a technique that is used to transform the raw data into a clean data set. The dataset has been taken from UCI ML Repository.

Fig 2 Preprocessing the data

C. Data Splitting

Splitting a dataset into the train (70%) and test (30%) sets based on data for subjects, i.e., 21 subjects for train and nine for the test.

Table I: Splitting of Data

Class Division	Walking	Walking Upstairs	Walking Downstairs	Sitting	Standing	Laying	Total
Train	1226	1073	986	1286	1374	1407	7352
Test	496	471	420	491	532	537	2947

D. Feature Extraction

Signal Processing is to remove the noises with the corner frequency of 20Hz in the features. The Feature selection will reduce the processing cost by remove irrelevant and redundant features, whereas ensuring the accuracy of recognition. These frequency domain Signals were then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window). 561 features was obtained from each sampled window by calculating variables from the time and frequency domain. Accidentally, it may drop samples due to the instability of sensor in a smartphone. interpolation is applied to fill the gaps. To analyze the human activities in a short period, we group every 256 samples in a window, which corresponds to 5.12-sec length of data. When applying Fast Fourier Transformation, the choice of 256, which is a power of two, is a preferred size 31 features are extracted of each sample window in both the time domain and frequency domain, as shown in the above table. All the other features are generated for directions in x, y and z axis except the resultant acceleration.
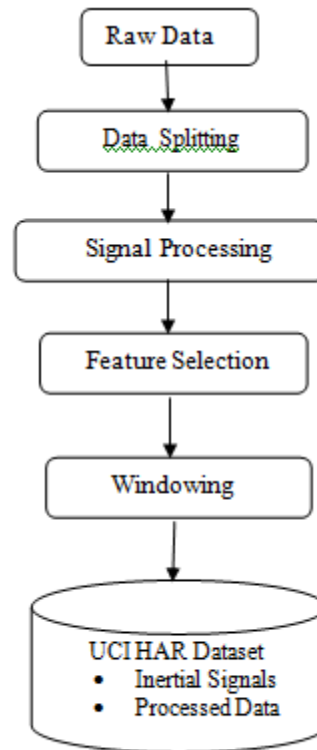
Time Domain
Variance
Mean
Median
25% Percentile
75% Percentile
Correlation between axis
Average resultant acceleration
Frequency Domain
Energy
Entropy
Centroid Frequency
Peak Frequency

Fig 3 Feature Generation

When the window is filled, classification phase will starts, and average, minimum, maximum, standard deviation values of the data in the window are calculated ,and these values are compared one by one with the values in the compact training sets which were created during the pre-processing steps.

IV. IMPLEMENTATION

A. Data labels

In Dataset, labels are represented as numbers from C1 to C6 as their identifiers.

Table- III: Labelling the dataset

S.NO	CLASS LABEL	ACTION DESCRIPTION
1	C1	Walking
2	C2	Walking Upstairs
3	C3	Walking Downstairs
4	C4	Sitting
5	C5	Standing
6	C6	Laying

70% of the volunteers readings were taken as training data and remaining 30% subject's recordings were taken for test data.

B. Neural Network

Neural networks are the most important blocks of deep learning systems. It contains a real-life biological neural network that is connected to our nervous system — this network is made up of number of interconnected nerve cells and it have the graph structure.

While there are many, many different NN architectures, the most common architecture is the feedforward network.
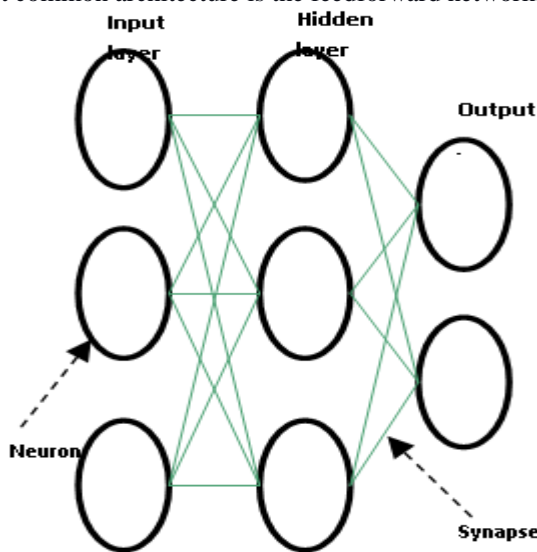

Fig 4 Neural Network Architecture

From fig 2 layer 1 is the input layer which we feed the input into our model , layer 2 is the hidden layer is take the set of inputs to produce an output through activated function and the layer 3 is the output or visible layer.

C. Recurrent Neural Network(RNN)

Recurrent Neural Network(RNN) is composed of internal memory. While RNN saving the output of a layer and feeding back to the input to predict the output of the layer. It also performs the same function for every data input while the output of the current input depends on the past computation. After producing the output, it sent back into the RNN. For prediction, it considers the current input and the output which was learn from the previous input. In this paper, we proposed a RNN model is to recognize the activities of the human from the raw Inertial Signals instead of using Featured Engineered data.
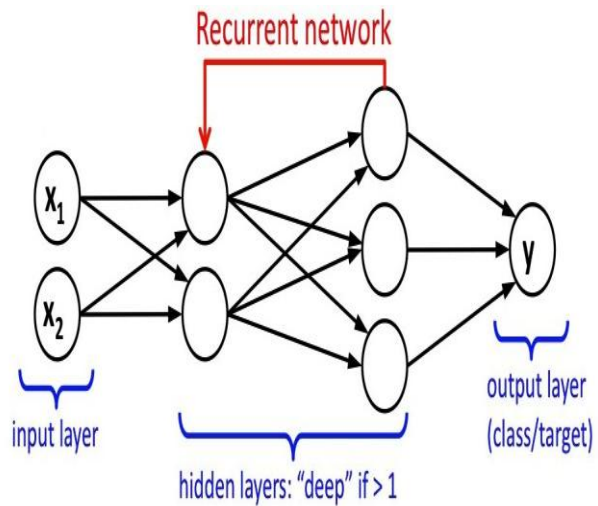

Fig 5 Recurrent Neural Network

D. Confusion Matrix

A confusion matrix is a Performance measurement on Machine Learning problems. The usage of the confusion matrix to evaluate the quality of the output of a classifier on the iris data set. The elements present in the diagonal are correctly classified and the element presents out of the diagonals are misclassified. Most of the performance measures are computed from the confusion matrix.

- True Positives (TP) is the result of our model in class a is correctly predicted as class a.
- True Negative (TN) is the result of our model in class a is correctly predicted as class b.
- False Positives (FP) is the result of our model in class b is incorrectly predicted as class a.
- False Negatives (FN) is the result of our model in class a is incorrectly predicted as class b.

Fig 6 Confusion Matrix

Table-IV: Confusion Matrix For RNN model

PRE/TRUE	Walking	Walking Upstairs	Walking Downstairs	Sitting	Standing	Laying
Walking	441	14	41	0	0	0
Walking Upstairs	127	279	55	2	3	5
Walking Downstairs	104	41	275	0	0	0
Sitting	17	5	0	369	97	3
Standing	0	0	0	65	461	0

In the above table, the precision of the model is high in Laying(C6) ,Sitting (C4), Standing(C5) and Walking(C1).The model has problem for Clearly identifying upstairs(C2) and Downstairs(C3).The class name C2 accuracy is low due to overlapping of C1,C2 and C3.And the class name C6 is high because it is different from other classes.

E. Performance Analysis

The plot of model performance from the confusion matrix and this is to determine the behavior of our model.
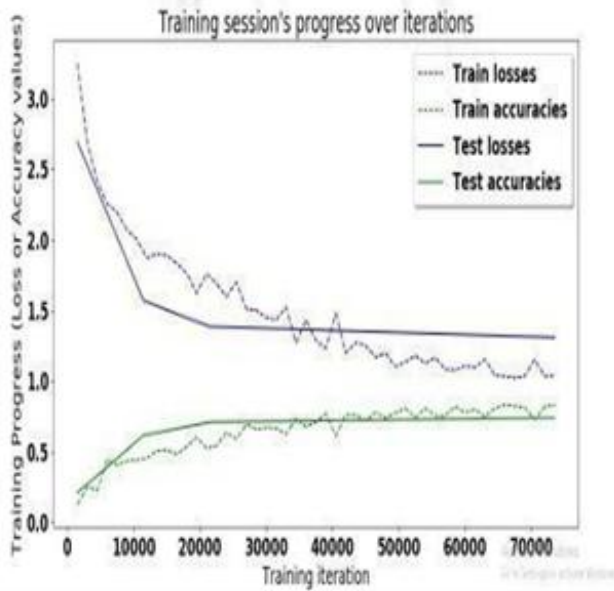

Fig 7 Training Progress over iteration

To verify the performance, the training the testing were conducted with maximum iteration as 70000.The above fig has shown the plot of losses and accuracies during training and testing phases.

F. Performance Metrics

Total Samples (N) is the number of elements present in each row.

Correctly Classified Samples (Nc) are the elements which are present in the diagonals.

Misclassified Samples (Nm) are the elements presents the rest of the diagonals. It denotes the number of elements that are wrongly classified. It is the difference between the total samples and the correctly classified samples.

Misclassified Samples = Total samples - Correctly classified samples

Accuracy is to evaluate the performance of our models. It is the ratio of the number of correct predictions to the total samples. To get our model accuracy in percentage(%), then the fraction is multiplied by 100.

$$\text{Accuracy(Acc)} = \frac{Number\ of\ correct\ predictions(Nc)}{Total\ samples(N)} * 100$$

Error Rate is the process of determining the misclassification of our model. It is the ratio of Misclassified Samples to the total samples.

$$\text{Error Rate} = \frac{Misclassified\ Samples\ (Nm)}{Total\ samples\ (N)}$$

Table-IV: Performance Metrics of RNN model

Class Name	Total Samples(N)	Correctly Classified Samples(Nc)	Misclassified Samples(Nm)	Accuracy(%)	Error Rate
C1	496	441	55	88.91	0.11
C2	469	279	190	59.68	0.4
C3	420	275	145	65.47	0.37

C4	491	369	122	75.15	0.24
C5	532	461	71	86.65	0.13
C6	537	519	18	96.64	0.03

Table-V: Observed Accuracy of the model

Algorithm	Data	Model fit
RNN	Classify features With Raw series data	Used Tensor flow and Keras to build models and Tuned Hyperparameters with Hyperas.

V. CONCLUSION

The model runs well and the observed average testing accuracy for RNN is 79.5%. Due to Overlapping of classes, RNN testing accuracy is low.

Human activity recognition has a broader application such as scientific research and Computer vision. In our paper, we have proposed a working model for human activity based recognition system that is monitoring six human activities. These actions can be monitored by mounting the smartphone on the waist of the human body. This collected time-series signals using an accelerometer and gyroscope in a smartphone. Thirty-one features in the time and frequency domain are generated, and then it reduced the dimensionality of the features for the performance improvement.

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