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HUMAN ACTIVITY RECOGNITION USING **DEEP NEURAL NETWORKS**

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Abstract: In this paper, our goal was to minimize the process of Human Activity Recognition in terms of the methodology as well as the physical equipment used for the same. The research was carried out using some tri-axis accelerometers and use of adaptive learning approaches like deep neural networks. The observed output and the response were better than the previously carried out experiments both in terms of accuracy and time.

IndexTerms - accelerometer, deep neural network, style, styling, insert.

I. INTRODUCTION

Human activity recognition is the method to find out accurate information about people's activity. It is an active and effective method in the field of medical, military, and tracking activities of old age people. HAR framework can be isolated into a few modules, detecting, division, highlight extraction, grouping, and post preprocessing. There is a fair amount of methods like artificial neural networks (ANN) [1, 4], movelets, support vector machine (SVM) [5, 6], a combination of methods [7] for automated activity and step classification. HAR is reflected as a significant component in several fields like as Surveillance Systems, Humancomputer interaction, anti-terrorists, anti-crime securities, Healthcare as well as life logging and assistance, etc.

Type of Neural Network:

A). Artificial Neural Network (ANN): ANN a brain-inspired system in which the flow of information takes place and models are trained and then operating itself after being trained without any human interaction.

B). C-NN (Convolution Neural Network): A Convolutional Neural Network (Conv Net/CNN) is a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

C). R-NN (Recurrent Neural Network): Recurrent Neural Networks (RNNs) add an interesting turn to essential neural systems because it has a memory which remembers everything that has happened previously without increasing the complexity of the neural network.

II. RESEARCH METHODOLOGY

As we know activity recognition is not easy, we have to train our model with an enormous amount of data for better accuracy and better results. It's a fact that the more we train our model, the probability of getting higher accuracy increases. But before reaching results, several issues arose in almost every phase during human activity recognition which are listed below:

- Choice of attributes and sensors 1.
- 2. Inadequate or insufficient Training Set
- 3. Data collection protocol under realistic conditions
- 4. Daily monitoring and recognition performance
- 5. Different people have different motions at a particular time.
- 6. Data Processing and flexibility
- 7. High consumption of energy
- 8. Re-training the model
- 9. Designing of feature extraction

The greatest qualification between tri-axial acceleration data and picture information is the distinction of the size of their information. The length and width of pictures can fluctuate, yet the width of the tri-axial accelerometer speeding up information is fixed to 3, which speaks to the x, y and z parts individually. Here we will use the tri-axial accelerometer.

A) Data Collection:

The basic module for gathering human activity information is a movement sensor. In this project, live data is collected from an accelerometer which is a movement sensor that is attached to a microcontroller, and a separate power supply is given and transmission of data is done for further evaluation.

B) Feature Extraction:

It has been demonstrated that many sign-handling strategies help separate highlights for HAR, including time-domain highlights, recurrence space highlights, and some others. Time- area highlights incorporate mean, change brief time vitality. *C) Choosing Model:*

Choosing a model for problem-solving is a challenging task for researchers is the target of model determination is to discover the system design with the best speculation properties, which will be, what limits the mistake on the choose the selected instances of the data set (the selection error). There are two groups of model determination algorithms order selection and input selection D) *Training and Evaluation:*

In this step, a researcher uses data to improve model ability and collected data will be fed into a neural network model for training purposes, and architecture of the neural network will consist of neurons that have weight assigned to them which will change according to the applied optimizer to produce desired results. Then, trained data and live data will be compared and computation will be performed for best-fit activity.

E) Evaluation:

In this phase, we check our model is good. This step allows testing our model against data that has never been used for training and how the model might perform against data that it has not yet seen.

F) Deployment:

If it fits into the desired and optimized output deployment of the model is done.

III. PROPOSED MODEL

Figure 1 depicts the functional block diagram of the working model. The system comprises 8-Bit MCU based Hardware connected with 5 tri-axial accelerometers. The data of accelerometers is sent over a serial channel using Bluetooth or an equivalent device to the main computing system. The main computing system comprises a data-capturing unit that captures and filters the received data and then converts it into the Data Frame. The Data Frame is then used to train the Model and later on the same data collection process and identify the activity done by the user by implementing the trained model.





Fig. 1: Functional Block Diagram of Proposed Model

IV. WORKING

It includes static activities and transitional activities which are fed into the system by using a Bluetooth device now data that is transferred in the system is in byte code so we have to decode collected live data into accelerometer values and arrange data in tables after removing garbage values and splitting data into test and train division after that create a sequential neural network model by adding dense layers with input dimension as the number of features then set output layer equal to six and adding dropout layers and NN layer which will be compiled with optimizer, then supervised learning is done and finding accuracy of the model during training and evaluation of results is done.

An activation function is significant for an Artificial Neural Network so, in this project, the Relu activation function is used to solve the complex network by adding some non-linearity properties, permitting models to learn quicker and perform better and optimizers like Adam are used to minimize the loss and acquire the optimized desired result.

V. ALGORITHMS

- A) Data collection
- Step 1: Power ON the device
- Step 2: Accelerometer collects data and sends serially
- Step 3: Data collected, decoded and filtered
- Step 4: Generating data tables with labels
- Step 5: Saving Data



B) Training Model

Step 1: Read Data from Files

Step 2: Split the data in two parts, i.e. training and testing

Step 3: Building the model with all the parameters tuned

Step 4: Performing the training on created model

C) Model Evaluation & *Deployment*

Step 1: Performing model evaluation with during the epochs Step 2: Considering early stopping in case of non-improvements Step 3: Deploying the model in case of satisfactory results Step 4: Obtaining Results

VI. HARDWARE SETUP

HAR system can be made up of using different kinds of sensors for collecting raw data. Here we have used ADXL345 Accelerometers along with an 8-Bit AVR Microcontroller (ATMega328) based Arduino Prototyping Development board. The Customized PCB was fabricated and a Bluetooth module was used to send data serially over the channel. Although the system is plug and play, a push button is also deployed on the PCB to control the data transmission effectively. The circuit is powered through a +5V DC supply or by an adaptor or SMPS of up-to +12Volt 1 Amp, which is further regulated and lowered to +5V 1Amp by the on-board voltage regulators.



Fig. 4 : Hardware Model

VII. RESULT

The Signals fetched by sensors for various activities are plotted in figure 5. The Accuracy Curve and Loss Curves are shown in the figure 6. The Confusion matrix is shown in the figure 7. And lastly, the results table is drawn and depicted in table 1. The proposed model is compared with other standard Machine Learning Approaches. The model shows an average accuracy score above 98%. Here are graphs of different activities which is used in these experiments.





Figure 5: Accelerometer Signals for Each Activity

In all the above graphs x-axis depicts the time in 100ms and the y-axis depicts global acceleration in x, y and z directions. The Proposed System shows a high level of accuracy within 7-8 iterations (epochs) performed during its neural network process. The following figures depict the Accuracy and loss curves of the proposed model.



Figure 6 shows the model accuracy and losses during training and testing the value of loss decreases by increasing the epoch, and the accuracy increases by the number of epochs

Method	Activity	Precision	Recall	FI-Score	Support	Score		
Proposed Model	Static	1.0	1.0	1.0	4182	0.98		
	Transitional	0.9	0.83	0.9	918			
ANN (Adadelta)	Static	0.89	0.89	0.89	4182	0.07		
	Transitional	0.85	0.85	0.85	918	0.97		
Random Forest	Static	0.98	0.98	0.98	4182	0.07		
Classifier	Transitional	0.92	0.8	0.9	918	0.97		
Support Vector Classifier	Static	0.98	0.75	0.85	4182	0.75		
	Transitional	0.77	0.54	0.49	918	0.75		
Logistic Regression	Static	0.96	0.99	0.97	4182	0.04		
	Transitional	0.71	0.51	0.58	918	0.94		

Table 1: Different Algorithms Comparison

lying_left ·	619	0	0	0	0	0	0	0	0	0	- 6	00
lying_right -	0	605	0	0	0	0	0	0	0	0	- 5	00
lying_straight -	0	0	601	0	0	0	0	1	0	0		
sitting_chair ·	0	0	0	586	0	0	0	0	0	0	- 4	00
sitting_crossleg -	0	0	0	0	578	0	0	0	0	0		
sitting_legfold -	0	0	0	0	0	574	0	0	0	0	- 3	00
standing -	0	0	0	0	0	0	609	0	0	9	- 2	00
transition_lyeSitStandWalk ·	0	0	0	0	0	1	1	211	9	37		
transition_sit_stand ·	0	0	0	0	0	0	0	5	48	12	- 1	00
walking -	0	0	0	0	0	0	4	0	1	589		
	lying_left -	lying_right -	lying_straight -	sitting_chair -	sitting_crossleg -	sitting_legfold -	standing -	transition_lyeSitStandWalk -	transition_sit_stand -	walking -	- 0	

Figure 8: Confusion Matrix (Proposed Model)

VIII. CONCLUSION

In this research, we assessed different human activities using an artificial neural network for that raw data which is collected preprocessed and analyzed then added into the model. Data is collected from an accelerometer that is transferred through a Bluetooth device and then the neural network is formed which consists of input, hidden (for mathematical computation), and output layer. Then, we analyzed and the performance of our model along with some training data to find the accuracy of the model training

As we know deeper the neural network better the performance but learning with more layers will be easier but this also leads to greater training time. Sometimes more training leads to overfitting and to balance them we have to add more data and we have to reduce architecture complexity.

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