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Smart Home Automation using IoT and Deep Learning

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Abstract – *Human Activity Recognition and Home Automation have been important topics of interest to many researchers in recent years. Due to its numerous benefits, home automation is becoming popular. Home automation refers to control of home appliances and domestic features through local networking or remote control. Artificial Intelligence provides us with the real-time decision-making and automation framework for Internet of Things (IoT). The work focuses on the concept of home automation by using their smartphone data to recognize the residents ' human activities. In this paper, we propose a smart home system that recognizes human activities through a Long Short Term Memory (LSTM) Deep Learning algorithm and then performs pre-determined tasks based on the recognized activity.*

Key Words: Smart Home, Home Automation, Deep Learning, Long Short Term Memory, LSTM, Smartphone, accelerometer, sensors, Human Activity Recognition, Raspberry Pi.

1. INTRODUCTION

For many researchers, there has been a topic of interest in recognition of human activities in recent years. In this project, we are proposing a smart home system that by deep learning algorithm recognizes human activities. We use the WISDM (Wireless Sensor Data Mining) dataset [1], where data is collected in a controlled laboratory setting using the smartphone's accelerometer. With these data, we will train our deep learning model to predict human activities performed inside the home and use these predictions to react to various human activities inside the smart home.

A convergence of technologies in machine learning and omnipresent computing as well as the development of robust sensors and actuators has brought interest in the development of smart environments to emerge and support valuable functions in Daily Living Activities (ADLs). The need for such technologies to be developed is underlined by population aging, the cost of formal health care, and the importance individuals place on remaining independent in their own homes. Individuals need to be able to complete daily living activities such as eating, dressing, cooking, drinking, reading, taking medicine, sleeping, to function independently at home. Automating activity recognition is a crucial step towards monitoring a smart home resident's functional health and helping them perform these activities effectively.

Before smart home technologies can be deployed for these older people, several challenges should be resolved, including data collection, algorithms for activity recognition, etc. This technology can be used wildly in the future if the accuracy is sufficiently higher. There is a research project called the Advanced Studies Center in Adaptive Systems (CASAS) where only passive, non-intrusive sensors [2] are deployed at Washington State University to create an intelligent home environment.

First, we should design a suitable algorithm. And then the actual data is used to test the algorithm that we choose. We will use data collected from accelerometer sensors. Virtually every modern smartphone has a tri-axial accelerometer that measures acceleration in all three spatial dimensions. Additionally, accelerometers can detect device orientation. We will train an LSTM Neural Network for Human Activity Recognition (HAR) from accelerometer data. The trained model will be used to predict different activities by the resident of the home. After that we will Implement different IoT based applications using the result of the different recognized activities.

We are not just limiting the control with the trained model, but the smart home will also be designed in such a way that the users can control and get all the details of the smart homes in their smartphones in case of emergency or the failure of the above system.

2. LITERATURE SURVEY

Deep learning algorithm is an effective way for recognizing human activities in smart homes [3]. They used a network having 4 hidden layers and this was pre-trained layer by layer using the algorithm called Restricted Boltzmann Machine (RBM). Then the fine-tuning work started using CG algorithm. Their deep learning model is used to solving the problem about recognizing human activities, the results was compared with hidden Markov model and naïve Bayes classifier. But there are still some challenges we must resolve, such as the number of the units in each layer, and the value of the epoch. Ultimately, they found deep learning to be more effective in terms of activity recognition. The performance evaluated with the real data that were collected from smart homes showed great significance in this aspect. The results of their deep learning model are better than those traditional approaches, such as HMM and NBC.

S. Szewcyzk, Dwan, Minor, Swedlove, and Swedlove, and D. Cook[4] investigated four alternative mechanisms with a corresponding activity label to annotate sensor data. They used sensor data collected in a real smart apartment to evaluate alternative methods along the dimensions of annotation time, resident burden, and accuracy. Motion sensors, Burner sensors, hot water sensor in the kitchen, and cold water sensor in the kitchen are the sensors used for data collection. The labeling activities include sleeping, eating, personal hygiene, preparing a meal, working on a computer, watching television, and others.

The home automation system that uses Wi-Fi technology system consists of three main components; a web server that presents system core that controls and monitors the home and hardware interface module of users, providing the appropriate interface for home automation system sensors and actuators. The system is better than the commercially available home automation systems from the point of view of scalability and flexibility. The user can use the same technology to connect to the web-based application on the server. If server is connected to the internet, so remote users can access server web-based application through the internet using compatible web browser.

Many home automation systems are now using the protocol Message Queuing Telemetry Transport (MQTT) to communicate with the devices. MQTT's popularity can be attributed to the fact that it is an easy to implement lightweight protocol. Although MQTT messaging uses an unsecured Transmission Control Protocol (TCP), when implementing mission-critical business, we can encrypt data with TLS / SSL Internet security to make it robust. A client can subscribe on the basis of a pattern to all published topics. MQTT defines three QoS which, based on the importance of each message and the repetitiveness of the messages in the environment, can cater to the client.

Arun Cyril Jose and Reza Malekian [5] show how modern homes have changed the concept of security and the meaning of the word "intruder." The paper highlights the weaknesses in identifying and preventing sophisticated intruders in a home environment from existing home automation systems. For future work in the field of home automation security, the researchers are encouraged to consider a home automation system and develop behavior prediction and advanced sensing parameters that can help to identify and prevent skilled and sophisticated intruders. Security is vital for the proper implementation and development of the home automation systems.

The methods which utilized inhabitant feedback not only increased the accuracy of the models but also decreased the annotation time, since the annotators had a much smaller set of possible activities to associate with each half hour of sensor data. In addition, the visualizer provided better results than the raw data because the annotator got a better sense of what was happening in the smart apartment.

3. METHODOLOGY

This section describes the activity recognition task and the process for performing this task. We trained a Deep Neural Network (DNN) to recognize the type of movement (Walking, Running, Jogging, etc.) based on a given set of accelerometer data from a mobile device carried around a person's waist. The recognized activity was then used to carry out various control operations inside the smart home using Raspberry Pi.

3.1 Proposed Algorithm

The block scheme of the proposed algorithm for LSTM Human Activity Recognition is shown in figure.

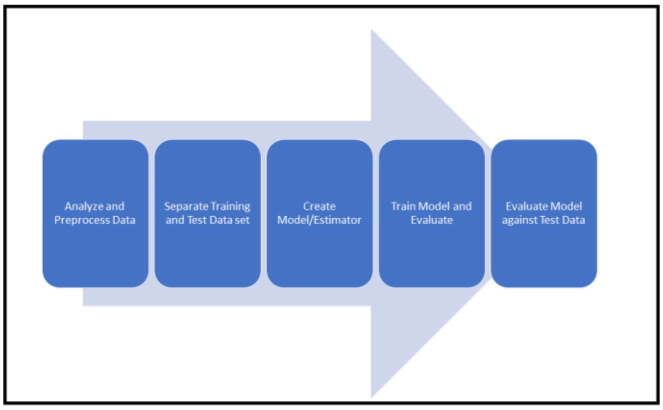

Fig-1: Steps in the proposed algorithm

The algorithm is performed predominantly in the following steps:

a) Pre-processing the data and changing its dimension to 54901x200x3.
b) Building a model which contains 2 fully-connected and 2 LSTM layers (stacked on each other) with 64 units each.

c) Training the Model for 50 epochs.

d) Evaluating the model and predicting the human activity by taking input from the mobile phone's accelerometer.

e) Performing the pre-determined actions through Raspberry Pi inside the smart home based on the recognized activity.

3.2 The Data

We used data provided by the Wireless Sensor Data Mining (WISDM) Lab. The dataset was collected in a controlled, laboratory setting. The dataset contains 1,098,207 rows and 6 columns. There are no missing values. This dataset is a collection of accelerometer data taken from a smartphone that various people carried with them while conducting six different activities i.e., Jogging, Sitting, Standing, Walking, Upstairs, and Downstairs.

For each activity, the acceleration for the x, y, and z axis was measured and captured with a timestamp and person ID.

	user	activity	timestamp	x-axis	y-axis	z-axis
0	33	Jogging	49105962326000	-0.694638	12.680544	0.503953
1	33	Jogging	49106062271000	5.012288	11.264028	0.953424
2	33	Jogging	49106112167000	4.903325	10.882658	-0.081722
3	33	Jogging	49106222305000	-0.612916	18.496431	3.023717
4	33	Jogging	49106332290000	-1.184970	12.108489	7.205164

Fig-2: Accelerometer Data (WISDM Lab Dataset)

The columns we were more interested in were activity, x-axis, y-axis, and z-axis. The number of training examples by activity type and by user are shown.

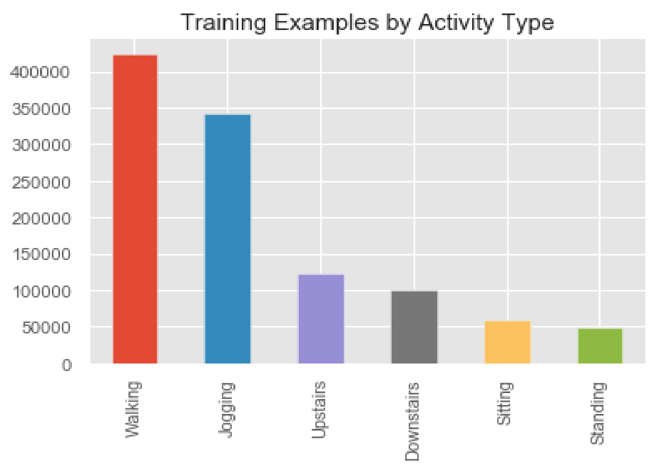

Chart-1: Training Examples by Activity Type

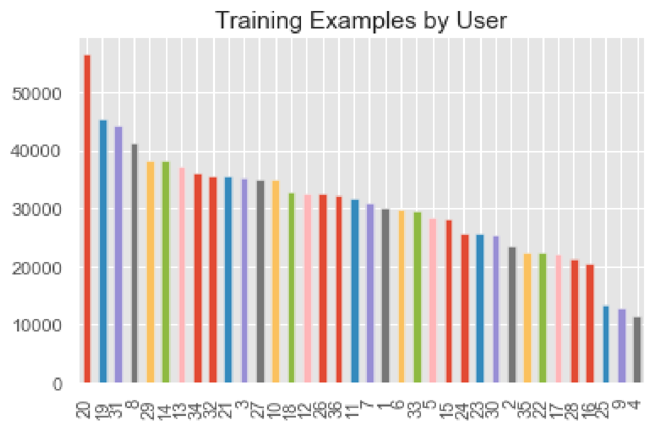

Chart-2: Training Examples by User

As we can see, the dataset contains more data for walking and jogging activities than the others. Also, it is visible from the above chart that 36 persons have participated in the experiment. The accelerometer data for each of the three axes for all six possible activities is recorded at a sampling rate of 20 Hz (20 values per second). Since we show the first 180 records, each chart shows a 9 second interval for each of the six activities (calculation: 0.05 * 180 = 9 seconds).

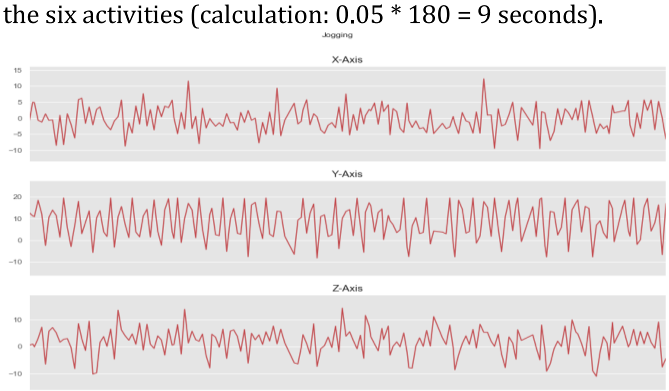

Fig-3: Jogging Accelerometer Data

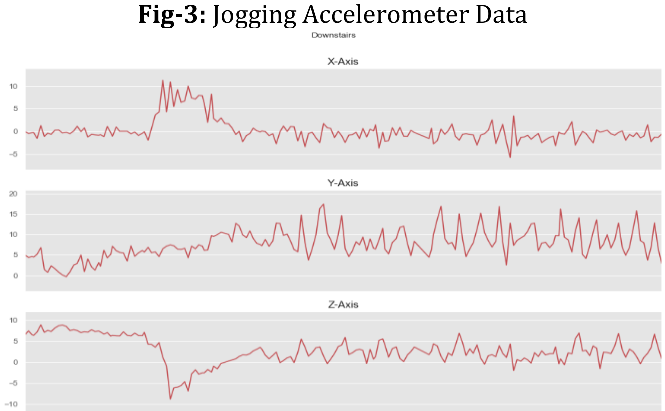

Fig-4: Downstairs Accelerometer Data

3.3 Data Preprocessing

Since our LSTM model expected fixed length sequences as training data, so we generated sequences each containing 200 training examples. After this step, the training data size was drastically reduced. We took the most common activity and assigned it as a label for the sequence. The data was then transformed into sequences of 200 rows, each containing x, y, and z. A one-hot encoding was also applied to the labels. Finally, the data was split into training (80%) and test (20%) set.

3.4 Building Model and Training

The model contains 2 full-connected and 2 LSTM layers (stacked on each other) with 64 units each. We used an optimizer with a learning rate of 0.0025 and trained the model for 50 epochs keeping track of accuracy and error.

4. RESULTS

Our model seems to learn well with accuracy reaching above 97% and loss hovering around 0.2.

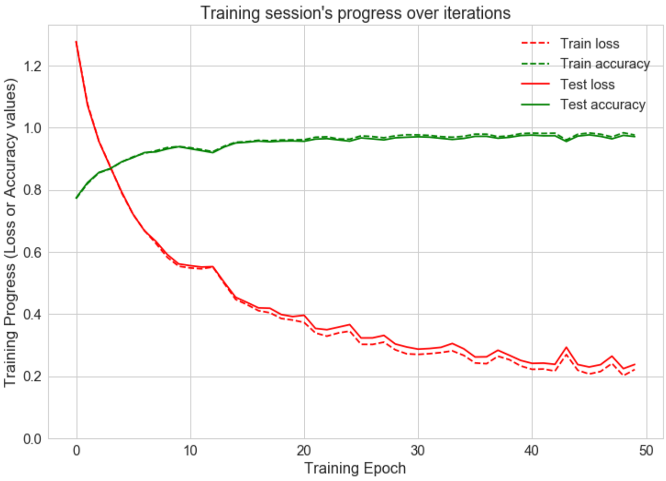

Fig-5: Training Session's progress over iteration

The confusion matrix for model's prediction is shown in figure:

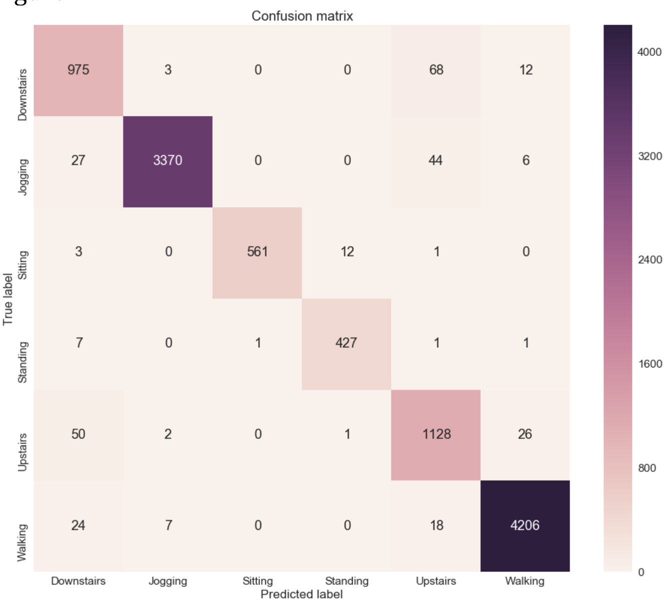

Fig-6: Confusion Matrix for Model's Prediction

Again, it looks like our model performed good. Some notable exceptions include the misclassification of Upstairs for downstairs and vice versa.

5. CONCLUSIONS

We have built an LSTM model that can predict human activity from 200 time-step sequence with over 97% accuracy on the test set. The identified smart home project utilizes a wide range of technologies serving different goals. The integration of Bluetooth and Wi-Fi technology in the control of home appliances can help and improve the lifestyle of all user groups in terms of safety and comfort, especially for the disabled and the elderly. In terms of recognition of activity, deep learning is quite effective. In this aspect, the performance assessed with the actual data collected from smart homes shows great significance.

REFERENCES

[1] Jennifer R. Kwapisz, Gary M. Weiss and Samuel A. Moore (2010). Activity Recognition using Cell Phone Accelerometers, Proceedings of the Fourth International Workshop on Knowledge Discovery from Sensor Data (at KDD-10), Washington DC.

[2] Rashidi, P., & Cook, D. J. (2008). Adapting to resident preferences in smart environments.In AAAI Workshop on Preference Handling (pp. 78-84).

[3] Fang, Hongqing, and Chen Hu. "Recognizing human activity in smart home using deep learning algorithm." In Control Conference (CCC), 2014 33rd Chinese, pp. 4716-4720. IEEE, 2014.

[4] S. Szewcyzk, K. Dwan, B. Minor, B. Swedlove, and D. Cook, Annotating smart environment sensor data for activity learning. Technology and Health Care, special issue on Smart Environments: Technology to support health care, 2009.

[5] Arun Cyril Jose and Reza Malekian, "Smart Home Automation Security: A Literature Review", Smart Computing Review, vol. 5, no. 4, August 2015