

**ACTIVITY RECOGNITION BASED  
RECOMMENDATION SYSTEM**

Project report submitted in partial fulfillment of the requirement for  
the degree of Bachelor of Technology

in

**Computer Science and Engineering**

by

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under the supervision of

***Dr. Rajinder Sandhu***

to



Department of Computer Science & Engineering and Information  
Technology


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## Candidate's Declaration

I hereby declare that the work shown in this report entitled "Activity Recognition based Recommendation System" in partial fulfillment of the requirements for the degree of Bachelor of Technology in Computer Science and Engineering submitted in the Department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology, Wagnaghat is a valid and authentic record of our own work carried out over a duration from August 2019 to December 2019 under the supervision Dr. Rajinder Sandhu, Assistant Professor.

The matter written in the report has not been submitted for the award of any other degree or diploma.

Shivam Shama, 161242 

This is to certify that the above statement made by the candidate is true to the best of my knowledge.

  
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Dated:

## **Acknowledgement**

We would like to express our greatest regard to the people who have helped & supported us throughout our project. We are grateful to our mentor **Dr. Rajinder Sandhu** for his continuous support for the project, for initial advice & teachings in the early stages of conceptual inception & through ongoing advice & encouragement to this day.

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## List of Abbreviations

<b>Abbreviation</b>	<b>Explanation</b>
CSV	Comma-Separated Values
RBM	Restricted Boltzmann Machine
SAE	Stacked Auto Encoder
HAR	Human Activity Recognition
NA	Not Applicable
EDA	Exploratory Data Analysis
SVM	Support Vector Machine
DL	Deep Learning
kNN	k Nearest Neighbour
WRT	With Respect To
ML	Machine Learning
ANN	Artificial Neural Networks
AI	Artificial Intelligence

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## **Abstract**

In this project, our system will recognize activities in the home setting and then this system further learns the daily routine of the person and raising an alarm that recommends the person if an activity is missed by that person. This system uses a set of small and simple binary sensors, ML algorithms, DL algorithms and electronic experience sampling is introduced. The sensors are designed to be “tape on and for-get” devices that can be quickly and installed anywhere in home environments. The proposed sensing system presents an alternative to sensors that are sometimes perceived as intrusive, such as cameras and microphones. Unlike previous systems, this system was deployed in multiple residential environments with non-researcher occupants. Preliminary results show that it is possible to recognize activities of interest to medical professionals such as toileting, bathing, and grooming with detection accuracies ranging from 25% to 89% depending on the evaluation criteria used. Although these preliminary results were based on small datasets collected over a two-week period of time, techniques have been developed that could be applied in future studies and at special facilities to study human behavior such as the MIT Placelab. The system can be easily modified in existing home environments with no major modifications and can be used to enable IT and health researchers to study the behavior in the home. Activity recognition is increasingly applied not only in home-based proactive and preventive healthcare applications, but also in learning environments, security systems, and a variety of human-computer interfaces.

## Chapter 1 Introduction

The study and research in (HAR)Human Activity Recognition is in big demand due to its emerging and important applications in Health care domain, Computer Vision domain, Household safety domain and Robot Learning domain. A very big amount of resources and money can be saved if sensors collect and monitor data of patients. System can itself automatically send those reports to medical personnel or doctor in case of any offroad or unnatural behavior of patients.

So to achieve this we have used low cost binary sensors to collect the data and identify human activities. Today, we can see a strong interest in the market of smart homes in future plans of large tech giants like Google, Samsung, Amazon, and many more. It is being expected by computer scientists that the market for smart homes will exceed \$ 45 billion by 2021. But however, despite the exponential growth of market, smart homes still have a number of drawbacks and limitations, including they cannot analyze the correct behavior of people. At this time there is not a single solution and approaches that can be used to completely solve this thing.

Main aim of HAR is to find the activities done by someone given some set of observations of him/her and their native environment. This task can be done by using the information which can be retrieved from different sources like resident's environment or body-worn sensors. Our primary aim is to classify some human activities in form of a dataset which will have 11 no of labels. These activities which will become our labels are, Meal\_Preparation (1606), Relax (2910), Eating (257), Work (171), Sleeping (401), Wash\_Dishes (65), Bed\_to\_Toilet (157), Enter\_Home (431), Leave\_Home (431), Housekeeping (33), Resperate (6). The no. in ()parentheses tells the no. of times an activity appeared in our dataset.

Then after successfully recognizing the activities our system tends to learn the daily routine of the person with the help of dataset that contains the records of past 30 days.

## **1.1 Problem Statement**

Recognizing the activities from home setting binary sensors dataset was a difficult work because of disordered dataset and ambiguous activities . Different ML approaches have been used in the past to recognize activities of human. So,we used a system which initially preprocesses our dataset and uses ML algos in optimized manner to produce perfect outcomes and learn the daily routine of user using some DL algorithms and when once learned the daily routine of the user, it can be used to raise alarms and recommend the missed activities from daily routine.

## **1.2 Objectives**

- i. Go clean the ambiguous dataset.
- ii. Thoroughly study that dataset .
- iii. To identify suitable ML algos to analyze that dataset.
- iv. Applying ML algos to the cleaned datasets and generate the confusion matrix(cm).
- v. Get error rates from cm.
- vi. Calculates time taken in training the ML models.
- vii. Compares time taken and error by different ML algorithms.
- viii. To monitor the recognised activity of the user and make an activity log by learning users day to day activity .
- ix. Activity log will be learned by applying various deep learning models like RBMs and SAEs.

- x. g. Raise an alarm/Recommend an activity to user if user goes off the schedule of his daily activities.

### **1.3 Methodology**

Right now so many research project are focussing on collecting data in home setting. In this report dataset from [CASAS Smart Home Project](#) (Center for Advanced Studies in Adaptive Systems at Washington State University) is used. We are using the datasets naming *Aruba*. Data is collected in the house of volunteered old woman for 1 month. Then thatData was impoted, cleared and normalised. This dataset is procesed through different supervised ML algos like RandomForest, SVM, ANN and KNN to classify data into 11 catagories. Accuracy of the model is calculated by making confusion matrix and by random simulation.

### **1.4 Organisation**

Chapter2 describe some works which have association with our works. Method and SystemDesign is described in the Chapter3. Working and the results of various ML algos have been compare in Chapter4. Testing in performed in Chapter 5. Chapter 6 and Chapter7 has conclusions from the analysed work that we did.

## Chapter 2 Literature Survey

### 2.1 Human Activity Recognition

It is found that there are minimum 4 ways for a machine to gather the data about people's activity by sensors system:

- (1) ask from the man, as in experience samplings
- (2) remote observation the scenes using audios, visuals, em fields or other sensors and interpreting the signals reading
- (3) attaching sensor to the body-parts and interpreting the signals reading
- (4) attaching sensor to things and devices in the environments and interpreting the sensors reading.

Ask question directly is a good and effective way but 1 that is used provided. Frequent interruptions may annoy people. Although progresses are being done on algos which monitors scenes and interpret the sensor signal, the acquired sensor data is mostly highly corrupted. The various sound found in a house are however, considerable, and could be particularly hard to differentiate sound generated by different people.

Extra complex sensor like camera in (CV) computer visions also being used for recognising activities. Computer vision sensors for monitoring and action identification often work in the labs but fail in real life home settings due to clutter, variable lightings, and highly varied activities which takes place in real scenarios. Small of this type of works have been broadly tested in fields because of difficulty in handling change in the scenes, like lights, different

persons, clutter, etc. In the end due to sensor like microphone and camera are so normal and mostly common used as recording device, they could also be seen as interfering by many persons.

Attach sensor to the body parts is an encouraging and relatively less costly method of acquiring data of some type of human movements. Also, they are effortlessly used in real environment.

The following methods are being used to classify different activities. A wearable sensory jacket uses stretched sensor for detecting activities like walk and run; an audio processing wearable computers for recognising social interactions in the workplaces, video processing wearable computers for finding patterns of activities of everyday life, biometrics wearable sensor to visualise exercises in day-to-day activity, and a context aware PDA and GPS to find activities like "grocery shopping", "go for working", and "do laundry" and many more.

Various activities, include physically complexed motions and some interactions with an environment. Signal from very much varying arms and legs movement in time of cooking and cleansing may not allow the activity to be differentiated from others. Movements are no dependent on things in our environments. Also, if sensor is embedded in our environments, activity like cooking may be shown by different set of sensor activations (e.g. the stove, cabinetry) with only minor day to day variations. Simple sensors can often provide powerful idea about activity. For example, a switch sensor in the bed can strongly suggest sleeping, and pressure mat sensors can be used for tracking the movement and position of people.

Last works where sensor were kept on things in the environments include an adaptive controlling of house environment like (ACHE) systems made for controlling the basic resident system like (airing, heat, light, ventilator and water heating) for monitoring the lifestyles and dramas of the residents. Less complexed sensor in kitchens (temp on stove, mat's sensor, or cabinet door's sensor) were used for finding activities like food preparing in a special wire deployed house kitchens.

Taking care and using the intelligent versatile house (MavHome) are systems which tend to increase resident's comfortness and decrease cost by prediction mobility pattern and digital use. The main difference in the previous works and the current works are those systems are not used in these residents' environments with real inhabitants. They were usually used in labs or houses of the research workers and their assistants. Again, each of those systems would use very careful installation and maintenance by research staff and students.

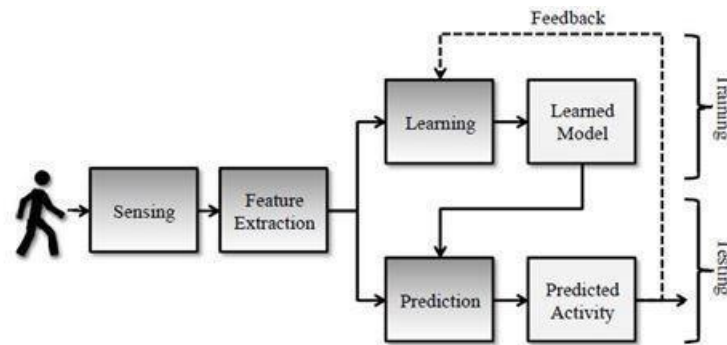


Figure 2.1: HAR development Process

## 2.2 Sensors used

### 2.2.1 Binary Sensors

Binary sensors collect data or info of devices; its state info that gives digitalized values like 0 or 1. They could be switch, contact pin, etc. They have only 2 state: **0/off/low/closed/false** and **1/on/high/open/true**. As we know that there are only 2 states allowed in House Assist to present the sensor in a more efficient way in the leading end according to the works or the functions.

We use 3 types of sensors in this research: that are: motion sensors (their IDs start with "M"), door closing sensors (their IDs start with "D"), and temp sensor (their IDs start with "T").

## Motion Sensor

Motion on shows that sensor is detecting a motiuonal activity and Motion Off means there is no motion being detected by that sensor.



Figure 2.2: Motion sensor denotations

## Door closure sensors

ON means door open and OFF means door closed.



Figure 2.3: Door closure sensor denotations

## Temperature sensors

On means HOT and OFF means normal.



Figure 2.4: Temperature sensor denotations

In this project we collected, sensory activities were gathered with the time. An eg of the data you canbe seen in the following figure:



2010-11-04	05:40:51.303739	M004	ON	Bed_to_Toilet	begin
2010-11-04	05:40:52.342105	M005	OFF		
2010-11-04	05:40:57.176409	M007	OFF		
2010-11-04	05:40:57.941486	M004	OFF		
2010-11-04	05:43:24.021475	M004	ON		
2010-11-04	05:43:26.273181	M004	OFF		
2010-11-04	05:43:26.345503	M007	ON		
2010-11-04	05:43:26.793102	M004	ON		
2010-11-04	05:43:27.195347	M007	OFF		
2010-11-04	05:43:27.787437	M007	ON		
2010-11-04	05:43:29.711796	M005	ON		
2010-11-04	05:43:30.279021	M004	OFF	Bed_to_Toilet	end
2010-11-04	05:43:45.7324	M003	ON	sleeping	begin
2010-11-04	05:43:52.044085	M003	OFF		
2010-11-04	05:43:53.185335	M002	ON		
2010-11-04	05:43:53.253809	M003	ON		
2010-11-04	05:43:59.493281	M002	OFF		
2010-11-04	05:44:04.048766	M003	OFF		
2010-11-04	05:44:06.14204	M003	ON		
2010-11-04	05:44:11.229146	M003	OFF		

Figure 2.5 : Dataset example

## Chapter 3 System Development

### 3.1 Introduction

Here, we will elaborate every-step procedure deployed to designing the model;. The AI application we are solving comes in the class of classification problems. We are using Spyder(Anaconda3) App Studio version 3.3.6 on windows 10 Operating ZSystem and GoogleColaboratory to do our whole experimentss.

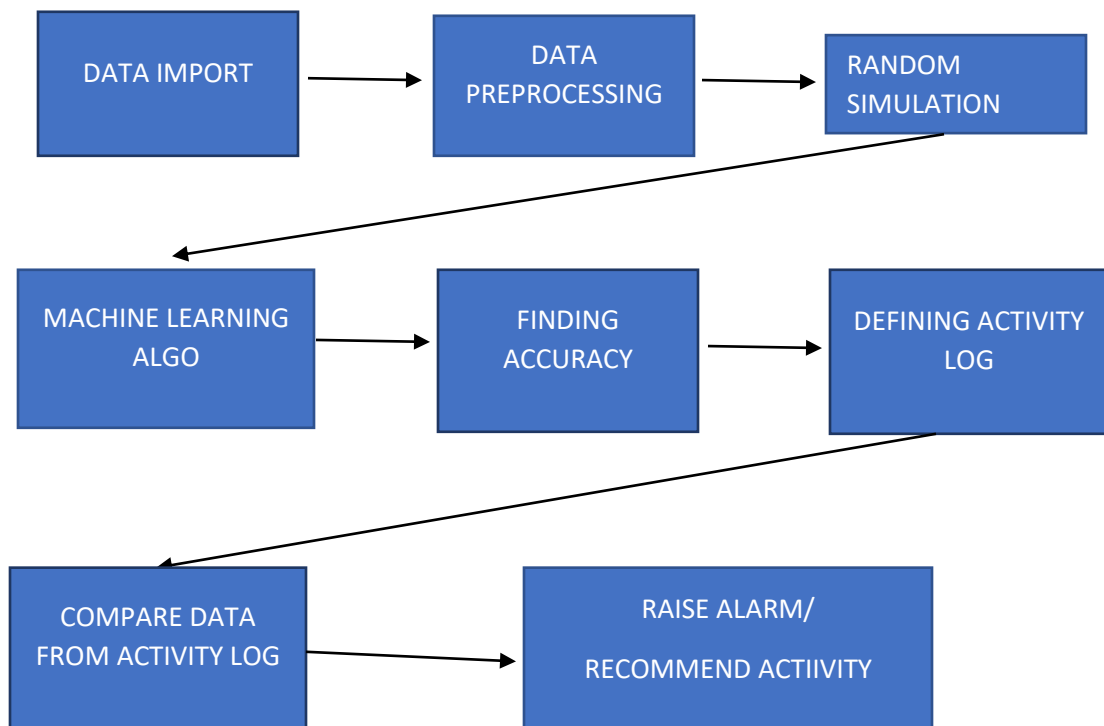


Figure 3.1: Flow diagram of Activity Recognition base recommendation System

### **3.2 Importing and Preprocessing Data**

Pre-processing of data is very important part of datamining. The main aim of pe-processing is to filtering the datas and to take away the corrupted valued toget or selection offeatures. In the approach that we foloow rthgat is windows method the sensory signal are breaked into little time segmentations. They are used in extraction of features. After that, on every unique windowsegment, segmentalization and classification algos are used. We use three types of window technique that are (a) slidingwindow (b) definedevent (c) defined activity-. The mostly affective techniques is slidingwindow for real-time apps

The aim of pe-pocessing is to filtering datas, to exchange the corrupt nos and find selected featuresss.

### **3.3 RandomSimulation**

RandomSimulisationonn are done to find accuracy\_yscore of predicting systems and preventing of overfit or underfit of dataset. Theis technssque includes random division of datas into train and test sets in the proportion of 7by3. This complete process is done 60 times for better acuracy of system according to statistics (CLT) Centrallimit theorem. Test data gives approximateof realtime dataset and gives a method for testing stableness of the system in reality examples.

### **3.4 Machine learning models**

Various ML classification algos such as Randomized Forestts, SVMs, kNNs were tried and tested on our dataset and depending upon their performance one of the algorithm was selected for our model. More information on ML models is given in next chapters.

# Chapter 4 Algorithms

## 4.1 ML algorithms

### 4.1.1 Random\_Forest

The random\_forest is an ensemble method which could be considered like nearest\_neighbor prediction model. Ensemble learning approaches are like divide and conquering ways for improving the performance and accuracy. The idea of ensemble method is that many of “weak learners” could come and may work in groups to create a “strong learner.” Individually, every learner is a “weak learner,” but with all together they make “strong learner.”

The random\_forest leads with a standard ML method which is named as “decision\_tree.” In ensemble language it belongs to learner that is weak. Here, an i/p is provided at the upper end that goes down the tree, the data gets collected into increasingly little subsets. Whenever a new i/p is given to the systems, it runs down to all of the trees. The o/p may be an average—or weight averaged—to every end or leaf nodes those were reached, or a voting majority in scenario of category full datasets.

Random forest predictors lead to a dissimilarity between observations. A random forest can also be attractive because it handles missing values well. It also reacts well to outside observations.

The concept of “extremely randomized trees” or “Extra Trees” adds yet another layer of randomization. Each Extra Tree is trained using bagging and the random subspace method, but randomizes the top-down splitting in the tree, too. In this case, the system chooses a randomized value to split, rather than computing and assigning a local level best feature and split combos. The random value is selected from the empirical range of the feature.

Random\_Forest were ensemble learning techniques for classifying, regression and many different works. It constructs so many decision\_trees at time of training and o/p is the category which is the avg result of all the decision trees. Random\_forest exempts over fitting the datasets. In our report and project we used Random Forest provided in Scikit-Learn library. There are very large no. of entities in this dataset which is why we used the

first three weeks of data to train data and last some weeks to testing data. This dataset is very im-balanced so we did 'balanced' values in 'classweight' parameter. The "balanced" data used the value of ys to auto adjusting weighsss inversed to frequency of each label of the i/p dataset.

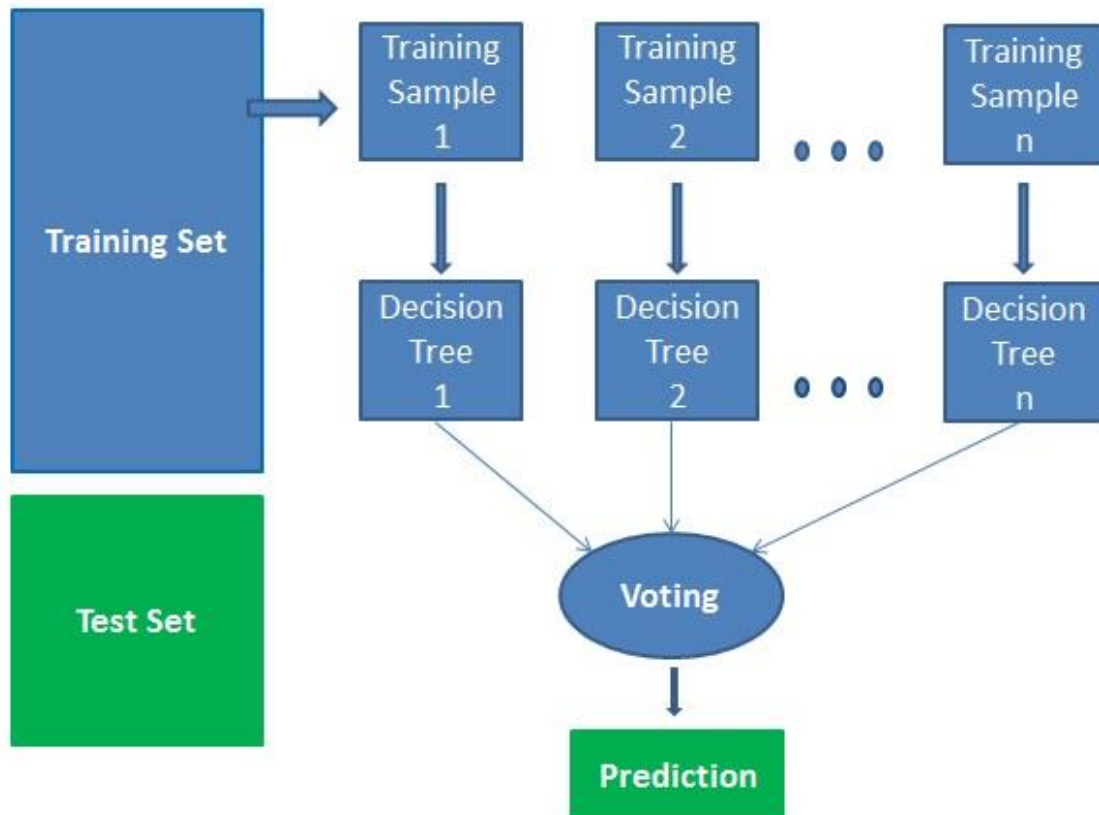


Figure 4.1: Flow diagram depicting the working of Random forest

## 4.2 Deep learning algorithms

### 4.2.1 Restricted Boltzmann Machine

RBMs (Restricted Boltzmann Machine) is a special type of Markov Random Fields (MRF) that are log-linear which means the function of energy is linear in the parameters that are free. For making them bold and effective in depicting complicated distributions like, going from limit no of parametrized settings to a nonparameterized 1 we think that some of the variables are not even observable and are known as hidden. If we have more of these variables (also known as hidden units) we could maximize the model capacity of Boltzmann Machines (BM). Restricted Boltzmann Machine RBMs to these w/o visible-invisible and hidden-unhidden connecting lines. A graph depicting of RBM is:

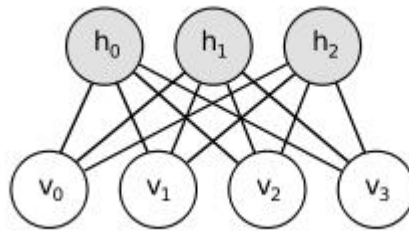


Figure 4.2: Structure of RBM

Function which gives the energy  $E(v, h)$  of an RBM is given as:

$$E(v, h) = -b'v - c'h - h'Wv$$

;here  $W$  shows the weights lines which connects hidden to visible nodes and  $b$  and  $c$  are the offsets of their model layers.

So the new formula of free energy is:

$$\mathcal{F}(v) = -b'v - \sum_i \log \sum_{h_i} e^{h_i(c_i + W_i v)}.$$

## 4.2.2 Stacked AutoEncoders

Auto-encoders are a type of learning that is unsupervised. Its architecture has 3 layers: i/p layers, hidden layers, and o/p layers as depicted in the diagram. The training of an auto-encoder has two sections which are 1) encoding and 2) decoding. Encoding is done by encoders to map the i/p data values to hidden nodes, and decoding is referred to as again making i/p data values from the hidden presentation. The encoding is shown below:

$$h_n = f(W_1 x_n + b_1)$$

Here above is an encoder's function,  $W_1$  is the weight matrices of the encoding unit, and  $b_1$  is a vector which contains bias.

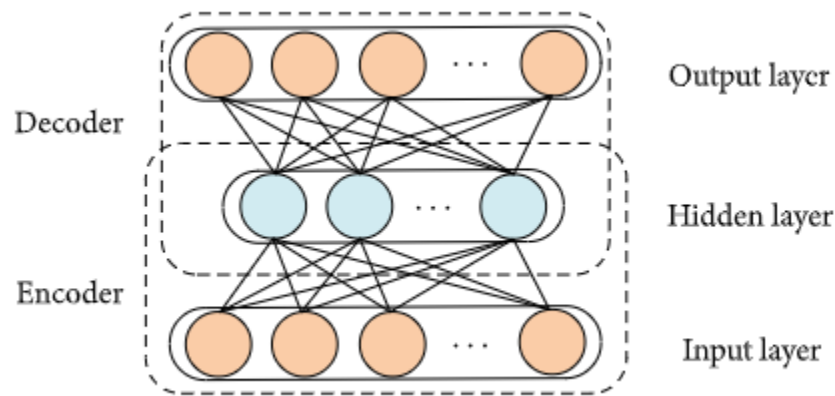


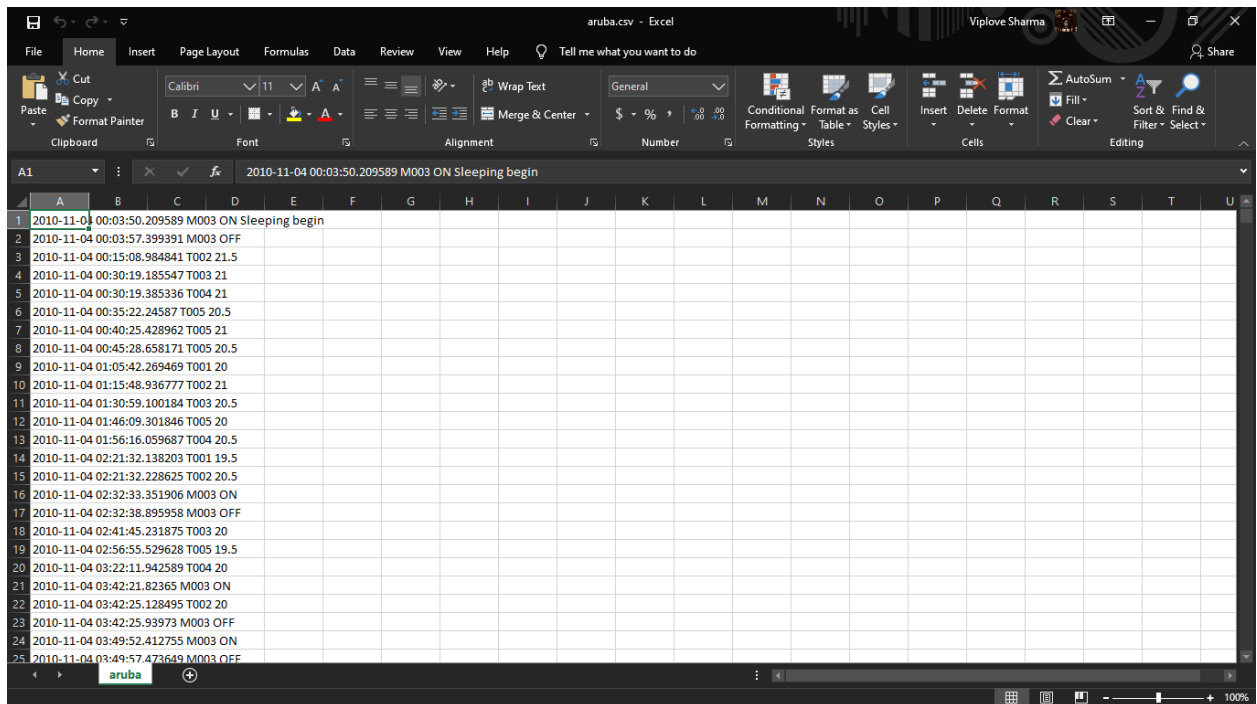
Figure 4.3: Structure of SAE



## Chapter 5 Implementation

### 5.1 Dataset:

Our dataset is a .csv(comma separated values) file named ARUBAs.csv that has 1719557 continuesactivities written after record in 218 days of years2010-2011. This data has 6462 annotats of 11 several activities.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	2010-11-04	00:03:50.209589	M003 ON	Sleeping begin																	
2	2010-11-04	00:03:57.399391	M003 OFF																		
3	2010-11-04	00:15:08.984841	T002	21.5																	
4	2010-11-04	00:30:19.185547	T003	21																	
5	2010-11-04	00:30:19.385336	T004	21																	
6	2010-11-04	00:35:22.24587	T005	20.5																	
7	2010-11-04	00:40:25.428962	T005	21																	
8	2010-11-04	00:45:28.658171	T005	20.5																	
9	2010-11-04	01:05:42.269469	T001	20																	
10	2010-11-04	01:15:48.936777	T002	21																	
11	2010-11-04	01:30:59.100184	T003	20.5																	
12	2010-11-04	01:46:09.301846	T005	20																	
13	2010-11-04	01:56:16.059687	T004	20.5																	
14	2010-11-04	02:21:32.138203	T001	19.5																	
15	2010-11-04	02:21:32.228625	T002	20.5																	
16	2010-11-04	02:32:33.351906	M003 ON																		
17	2010-11-04	02:32:38.895958	M003 OFF																		
18	2010-11-04	02:41:45.231875	T003	20																	
19	2010-11-04	02:56:55.529628	T005	19.5																	
20	2010-11-04	03:22:11.942589	T004	20																	
21	2010-11-04	03:42:21.82365	M003 ON																		
22	2010-11-04	03:42:25.128495	T002	20																	
23	2010-11-04	03:42:25.93973	M003 OFF																		
24	2010-11-04	03:49:52.412755	M003 ON																		
25	2010-11-04	03:49:57.473649	M003 OFF																		

Figure 5.1: ARUBA.csv

CSVfile is a straight and forward excel sheet layout of the form of tables which contains infor, like, a spread sheet or databaseMS. Documents in this organization couldbe foreign

made or traded of models which stores info in tabular form, like, MicrosoftExcel or Open CV OfficeCalculator. CSV stands for "coomma-separated values".Rows indicatess detection of motion or not any emotion by motional sensorsss and detecting close or open of the doorss by those door's sensor.

## 5.2 Pre-processing the dataset

In reality, we would had to categorize every sensor's activate as single task, so thatwe couls state this project a multi-class classificationproblem. To make the data used to train we have to break thios unstructureddata with sliding window techniques. We have shown 3 different ways:

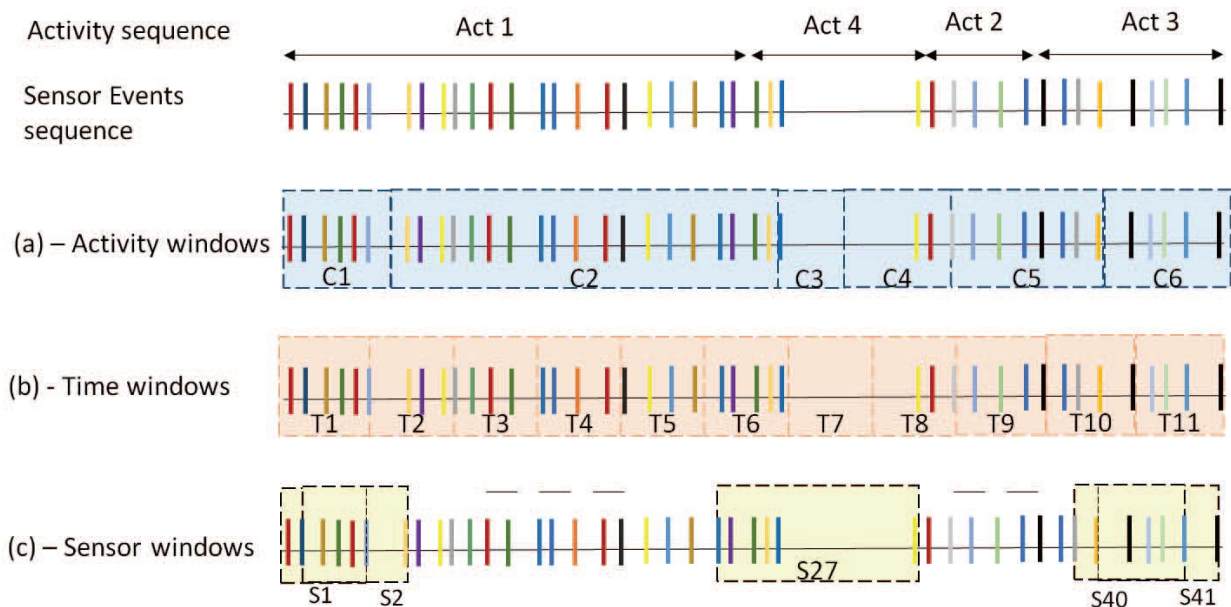


Figure 5.2: Types of segmentation

i. In a) type of segmentation, we would break the data on different window in the case of detecting of change in the activities, so that every window segment may have 1 activity each.

As most of the times, these are not properly differentiable so window-boundary were not accurate. Also it's unsuitable for the recognition that is online due to time bondness constraints to take further results.

ii. Second way of segmening is time-based segmenting windows. We break the dataset to windows having fixed time duration. Small size of window will not have enough info for taking any decision. And for big window size which have sovarious activities, the 1 that is dominating would be depicted more as comparison with others, which can affect the result in a bad way.

iii. Third way is making windows which are sensor-based, using sliding window techniques we can break the data on different windows with each window having same no ofactivation of sensors. This technique also have disadvantages. Like 1 windowsegment may have sensors being activarted for different activities. So to deal with that we classifies only the last sensor's activation, not any other.

**For our project last method will be used**

### 5.2.1 Feature Extraction

Firstly we started with creating dataset which can be used by ML or DL models. Using the approach that we discussed earlier that is sensors\_based windows approach we extracted features like starting time, ending time,their time difference, and the no of times each sensor is activated from each window, these are weighted by mutual info procedure. We, also added ids of sensors that activarted in last two spots in every window. So the no. feature becomes 5 + no of sensors in our whole data. For disadvantage of the method, we calculated the mutual info matrices,:

$$MI(i, j) = \frac{1}{|Q|} \sum_{k=1}^{|Q|} \partial(i, j)$$

Aim here is to minimize the influences of activation of sensors that occurs sometime and are not frequent. The formula that we used that is:  $\delta(i, j)$  gives 1 if sensor  $i$  and  $j$  are used while an activity is being done. No  $Q$  here is the no of windows are in total. so we'll get a matrices of  $N \times N$  size, where  $N$  is a no of sensor in dataset and each cell have values in range of (0 to 1) which will get multiplied to the correspond values in the feature vector. That feature vector has activations of last 2 sensors.

### 5.3 Code

We divided the code into two .py files.

- i. Data\_processor.py – This .py file does the pre-processing work and preprocesses the unorganised data.
- ii. Activity\_recognition.py – This .py file does the main work of applying the random forest classifier and predicting the accuracy.

```

7
8 import numpy as np
9 import pandas as pd
10 import itertools
11 import os.path
12 import matplotlib.pyplot as plt
13 from datetime import datetime
14 from sklearn.preprocessing import LabelEncoder
15 from sklearn.ensemble import RandomForestClassifier
16 from sklearn.metrics import accuracy_score, confusion_matrix
17
18 class Processor:
19     def __init__(self, sliding_window_length=6,
20                 columns_names=('date', 'time', 'sensor_id', 'value', 'activity1',
21                               | 'activity2', 'activity3', 'activity4',
22                               'activity5'),
23                 data_path=None, date='2011-01-21', date_sign='less',
24                 sensor_encoder=None, activity_encoder=None,
25                 mutual_matrix=None, sens_num=None, acts_num=None):
26         self.columns_names = columns_names
27         self.sliding_window_length = sliding_window_length
28         self.data_path = data_path
29         self.date = date
30         self.date_sign = date_sign
31         self.sensor_encoder = sensor_encoder
32         self.activity_encoder = activity_encoder
33         self.mutual_matrix = mutual_matrix
34         self.sens_num = sens_num
35         self.acts_num = acts_num
36         self.data = None
37         self.processed = None
38         self.data = pd.read_csv(data_path, header=None, sep='\s+', names=self.columns_names)
39

```

Figure 5.3: Data\_processor.py(i)

```
40 def markdown_activities(self):
41     activity_pool = []
42
43     for index, row in self.data.iterrows():
44         if row.activity2 == 'begin':
45             break
46         else:
47             self.data.drop(index, inplace=True)
48
49     for index, row in self.data.iterrows():
50         if row.activity2 == 'begin':
51             activity_pool.append(row.activity1)
52         elif row.activity2 == 'end':
53             activity_pool.remove(row.activity1)
54         elif activity_pool:
55             if len(activity_pool) > 1:
56                 self.data.drop(index, inplace=True)
57             else:
58                 self.data.at[index, 'activity1'] = activity_pool[-1]
59
60 def calculate_mutual_info_matrix(self, mutual_matrix, sensnum):
61     current_activity = self.data.iloc[0].activity1
62     wind = []
63     winds=[]
64     winnum = 0
65
66     for idx, row in self.data.iterrows():
67         if current_activity == row.activity1:
68             wind.append(row.sensor_id)
69         else:
70             sensors = np.unique(wind)
71             for sensor in range(0, sensnum):
72                 for sensor2 in range(0, sensnum):
73                     if sensor in sensors and sensor2 in sensors:
74                         mutual_matrix[sensor][sensor2] += 1
75                         winds.append(wind)
76             winnum += 1
77             current_activity = row.activity1
78             wind = [row.sensor_id]
79
```

Figure 5.4: Data\_processor.py (ii)

```

79
80     return mutual_matrix/winnunm
81
82 def process(self):
83     self.data['datetime'] = pd.to_datetime(self.data['date'] + " " + self.data['time'])
84
85     if self.date_sign == 'more':
86         self.data = self.data[(self.data['datetime'] > self.date)]
87     else:
88         self.data = self.data[self.data['datetime'] < self.date]
89
90     vls = ['begin', 'end']
91
92     #There are datasets that have activity name in
93     for index, row in self.data.iterrows():
94         if not row.activity2 in vls and not row.activity2 is np.nan:
95             if not row.activity3 in vls:
96                 if not row.activity4 in vls:
97                     self.data.loc[index, 'activity1'] = row.activity1 + "_" + row.activity2 + "_" + row.activity3 + "_" + row.activity4
98                     self.data.loc[index, 'activity2'] = row.activity5
99                 else:
100                     self.data.loc[index, 'activity1'] = row.activity1 + "_" + row.activity2 + "_" + row.activity3
101                     self.data.loc[index, 'activity2'] = row.activity4
102             else:
103                 self.data.loc[index, 'activity1'] = row.activity1 + "_" + row.activity2
104                 self.data.loc[index, 'activity2'] = row.activity3
105
106     #There are some typos in dataset in status column
107     one_vals = ['ON', 'OPEN', 'ONc', 'ON5', 'ON55', 'ON5c', 'ONcc', 'ONc5c', 'ONc5', 'OPENc', 'O', 'ONM026',
108               'ONM009', 'ONM024']
109     zero_vals = ['OFF', 'CLOSE', 'OFF5', 'OFFc', 'OFFc', 'OFFcc', 'OFF5cc', 'OFF5c', 'OFFc5', 'OFF', 'OFFccc5',
110               'OF', 'CLOSED']
111
112     self.data.loc[self.data['value'].isin(one_vals), 'value'] = 1
113     self.data.loc[self.data['value'].isin(zero_vals), 'value'] = 0
114     self.markdown_activities()
115     #we need no data from temperature data
116     self.data = self.data[~self.data.sensor_id.str.contains('c')]
117     self.data = self.data[~self.data.sensor_id.str.startswith('T')]
118

```

Figure 5.5: Data\_processor.py (iii)

```

110
119 self.data.loc[self.data['activity1'].isnull(), 'activity1'] = 'other'
120 self.data.drop(columns=['date', 'time'], inplace=True)
121
122 if self.sensor_encoder is None:
123     self.sensor_encoder = LabelEncoder()
124     self.sensor_encoder.fit(self.data.sensor_id)
125
126 if self.activity_encoder is None:
127     self.activity_encoder = LabelEncoder()
128     self.activity_encoder.fit(self.data.activity1.astype(str))
129
130 # We are not dealing with other activity here
131 self.data = self.data[self.data.activity1 != 'other']
132
133 self.data.sensor_id = self.sensor_encoder.transform(self.data.sensor_id)
134 self.data.activity1 = self.activity_encoder.transform(self.data.activity1.astype(str))
135
136 if self.sens_num is None:
137     self.sens_num = len(self.data.sensor_id.unique())
138
139 if self.acts_num is None:
140     self.acts_num = len(self.data.activity1.unique())
141
142 self.data = self.data.reset_index()
143
144 if self.mutual_matrix is None:
145     self.mutual_matrix = self.calculate_mutual_info_matrix(np.zeros((self.sens_num, self.sens_num)),
146                                                         self.sens_num)
147

```

Figure 5.6: Data\_processor.py (iv)

```

147
148 def get_segments(self):
149     windows_vectors, activities_vectors = [], []
150
151     for idx in range(0, self.data.shape[0], 1):
152         current_sens = []
153         if self.data.shape[0] <= idx + self.sliding_window_length:
154             break
155
156         freq = np.zeros(self.sens_num)
157         windows = self.data.iloc[idx:idx + self.sliding_window_length]
158         last_activity = windows.iloc[self.sliding_window_length - 1].activity1
159
160         start_time = windows.iloc[0].datetime
161         last_time = windows.iloc[self.sliding_window_length - 1].datetime
162         last_time = datetime(last_time.year, last_time.month, last_time.day, last_time.hour, last_time.minute,
163                             last_time.second)
164         start_time = datetime(start_time.year, start_time.month, start_time.day, start_time.hour, start_time.minute,
165                              start_time.second)
166         last_time = last_time.hour / 24 + last_time.minute / 60. + last_time.second / 3600.
167         start_time = start_time.hour / 24 + start_time.minute / 60. + start_time.second / 3600.
168         last_sensor_id = windows.iloc[self.sliding_window_length - 1].sensor_id
169         second_last_id = windows.iloc[self.sliding_window_length - 2].sensor_id
170
171         for ind, act in windows.iterrows():
172             freq[int(act.sensor_id)] += 1
173
174         #weighting frequencies using mutual matrix table
175         for ind, val in enumerate(freq):
176             freq[ind] = freq[ind] * self.mutual_matrix[last_sensor_id][ind]
177
178         timespan = last_time - start_time
179         freq = np.append(freq, (last_time, timespan, second_last_id, last_sensor_id))
180
181         windows_vectors.append(freq)
182         activities_vectors.append(last_activity)
183
184     return np.array(windows_vectors), np.array(activities_vectors)

```

Figure 5.7: Data\_processor.py (v)

```

187 def get_train_test_data(path, date1, date2):
188     train_processor = Processor(date_sign='less', data_path=path, date=date1)
189     train_processor.process()
190     test_processor = Processor(date_sign='more', data_path=path, date=date2,
191                               activity_encoder=train_processor.activity_encoder,
192                               sensor_encoder=train_processor.sensor_encoder,
193                               mutual_matrix=train_processor.mutual_matrix, sens_num=train_processor.sens_num,
194                               acts_num=train_processor.acts_num)
195     test_processor.process()
196     train_x, train_y = train_processor.get_segments()
197     test_x, test_y = test_processor.get_segments()
198     return train_x, train_y, test_x, test_y, train_processor.activity_encoder.classes_
199

```

Figure 5.8: Data\_processor.py (vi)

```

201 def plot_confusion_matrix(cm, classes,
202                           normalize=False,
203                           title='Confusion matrix',
204                           cmap=plt.cm.Blues):
205     """
206     This function prints and plots the confusion matrix.
207     Normalization can be applied by setting `normalize=True`.
208     """
209     if normalize:
210         cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
211         print("Normalized confusion matrix")
212     else:
213         print('Confusion matrix, without normalization')
214
215     plt.imshow(cm, interpolation='nearest', cmap=cmap)
216     plt.title(title)
217     plt.colorbar()
218     tick_marks = np.arange(len(classes))
219     plt.xticks(tick_marks, classes, rotation=45)
220     plt.yticks(tick_marks, classes)
221
222     fmt = '.2f' if normalize else 'd'
223     thresh = cm.max() / 2.
224     for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
225         plt.text(j, i, format(cm[i, j], fmt),
226                 horizontalalignment="center",
227                 color="white" if cm[i, j] > thresh else "black")
228
229     plt.ylabel('True label')
230     plt.xlabel('Predicted label')
231     plt.tight_layout()

```

Figure 5.9: Data\_processor.py(vii)



```

7
8 from sklearn.ensemble import RandomForestClassifier
9 from sklearn.metrics import accuracy_score, confusion_matrix, balanced_accuracy_score
10 from data_processor import get_train_test_data, plot_confusion_matrix, confusion_matrix
11 import matplotlib.pyplot as plt
12 import numpy as np
13 import sys
14
15 DATA_PATH = 'aruba.csv'
16 DATA_1 = '2011-01-21'
17 DATA_2 = '2011-05-23'
18
19 np.set_printoptions(threshold=sys.maxsize)
20 np.set_printoptions(precision=2)
21
22 train_x, train_y, test_x, test_y, classes = get_train_test_data(DATA_PATH, DATA_1, DATA_2)
23
24 clf = RandomForestClassifier(n_jobs=-1, random_state=42, n_estimators=40,
25                             max_depth=None, min_samples_split=2, verbose=False,
26                             class_weight='balanced')
27
28 clf.fit(train_x, train_y)
29 predictions = clf.predict(test_x)
30
31 accuracy_score(predictions, test_y)
32
33 balanced_accuracy_score(predictions, test_y)
34
35 cnf_matrix = confusion_matrix(predictions, test_y)
36 plt.figure(figsize=(18, 16))
37 plot_confusion_matrix(cnf_matrix, classes=classes, normalize=True,
38                       title='Normalized confusion matrix')
39 plt.show()
40
41 plt.figure(figsize=(18, 16))
42 plot_confusion_matrix(cnf_matrix, classes=classes, normalize=False,
43                       title='Normalized confusion matrix')
44 plt.show()

```

Figure 5.10: Activity\_recognition.py

## 5.4 Output

```

In [15]: accuracy_score(predictions, test_y)
Out[15]: 0.93493853273748

In [16]: balanced_accuracy_score(predictions, test_y)
Out[16]: 0.6177441787814696

```



Figure 6.1: Confusion Matrix(i)

Acc to this matrices we have some activities for eg ‘Respirate’, which do not get any predictions all. Let’s see the notnormalized cm:confusion matrix.

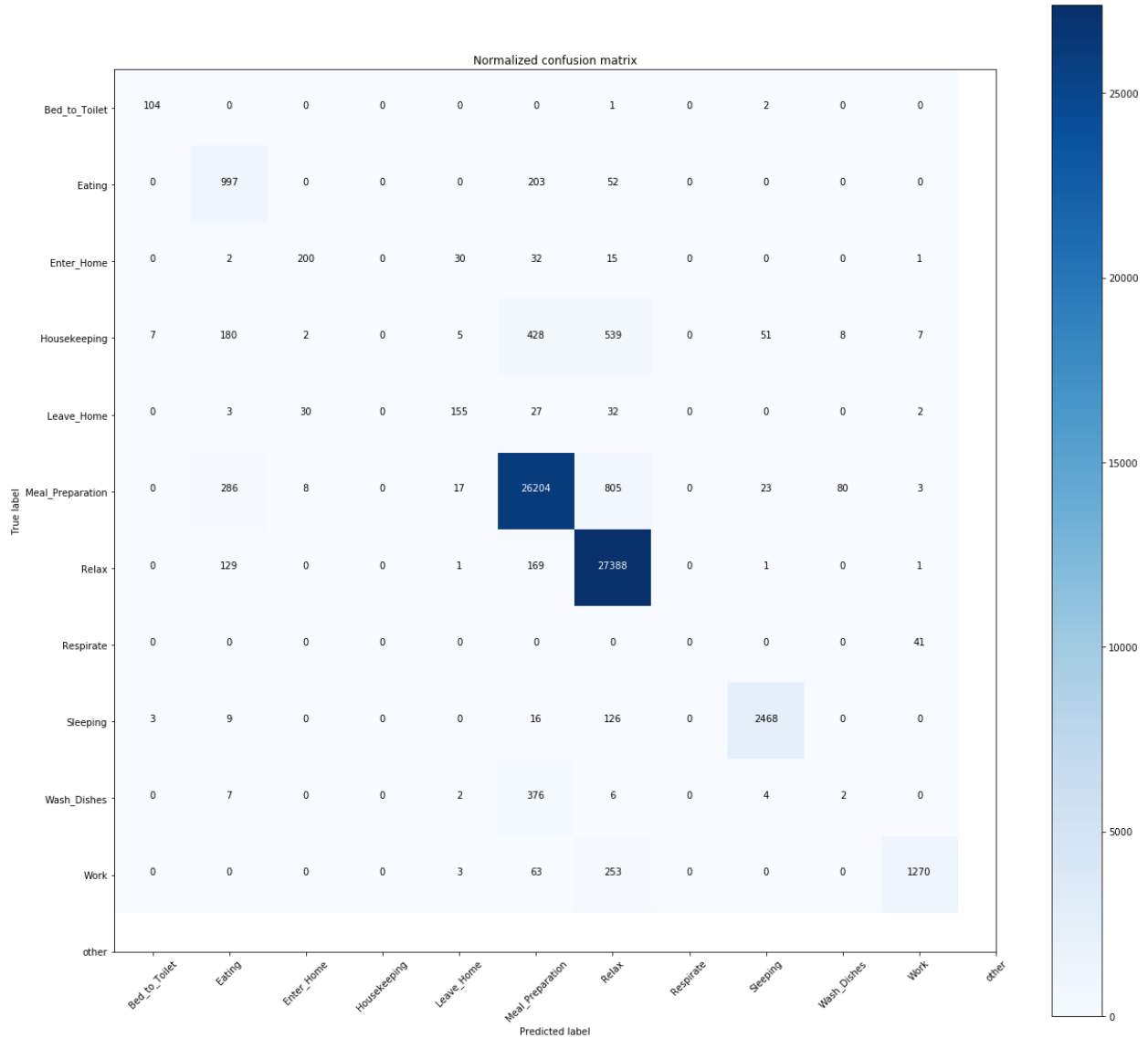


Figure 5.2: Confusion Matrix(ii)

According to thios cm some activities are very rare to be predicted or as happen..So to increase the accuracy of our model we can delete such activities.Activities

like 'Housekeeping' or 'Wash\_Dishes' were also get predicted wrong. This happens because of limitations of binary sensors, as our windowing technique may did overlapped the activities making it difficult to differentiate.

## **Chapter 7 Conclusion**

To conclude, we identified human activities from home setting binary sensors dataset by applying Random Forest Classifier and got accuracy up to 93%.

### **7.1 Future works**

Recognising activities in a smart house is very difficult and this problem is still open to all. There are somany various methods to sove this problem. Like, there is a researchpaper which uses kNNs and modified versions to that. There is an technique which uses the Latent DirichletAllocation method. Another paper proposed a fmwork, having 2 steps: off-line model making and online activity recognition.

And to further expands the applications and implementations of thi project a Reccomendation system can be develoved or modeled to blow an alarm or recommend an activity or send signal to distant places in case of the activities goes off track to the usual routine or any activity which looks suspicious. This will complete the purpose of recognizing the activity.

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