JADAVPUR UNIVERSITY

MASTER DEGREE THESIS

Intensive Human Activity Recognition using a combination of Accelerometer and HeartRate sensors

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Engineering

in

Computer Science and Engineering
Jadavpur University

By
Asmita Nandy
Class Roll No.: 001710502027
Examination Roll No.: M4CSE19029
University Registration No.: 140766 of 2017-18

Under the Guidance of
Dr. Chandreyee Chowdhury

Department of Computer Science and Engineering
Faculty of Engineering and Technology,
Jadavpur University, Kolkata

May 2019

To whom it may concern

This is to certify that the work in this thesis entitled ***"Intensive Human Activity Recognition using a combination of Smartphone Accelerometer and HeartRate sensors"*** has been satisfactorily completed by ***Asmita Nandy*** (Examination Roll No. M4CSE19029, University Registration No. 140766 of 2017-2018). It is a bonafide piece of work carried out under my supervision at *Jadavpur University, Kolkata*, for partial fulfillment of the requirements for awarding of the ***Master of Engineering*** in ***Computer Science and Engineering (MCSE)*** degree of the ***Department of Computer Science and Engineering, Faculty of Engineering and Technology, Jadavpur University*** during the academic session 2017-2019.

____

Dr. Chandreyee Chowdhury
Assistant Professor,
Department of Computer Science and Engineering,
Jadavpur University,
Kolkata.

Forwarded By:

____

Prof. Mahantapas Kundu
Head of the Department,
Department of Computer Science and Engineering,
Jadavpur University,
Kolkata.

____

Prof. Chiranjib Bhattacharjee
Dean, Faculty of Engineering and Technology,
Jadavpur University,
Kolkata.

Certificate of Approval

This is to certify that the thesis entitled ***"Intensive Human Activity Recognition using a combination of Smartphone Accelerometer and HeartRate sensors"*** is a bonafide record of work carried out by ***Asmita Nandy*** in partial fulfillment of the requirements for the award of the degree of ***Master of Engineering in Computer Science and Engineering (MCSE)*** in the ***Department of Computer Science and Engineering, Jadavpur University*** during the period August 2017 to May 2019. It is understood that by this approval the undersigned does not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein but approve the thesis only for the purpose for which it has been submitted.

Examiners:

____

(Signature of Examiner)
Date:

____

(Signature of Examiner)
Date:

Declaration of Originality and Compliance of Academic Ethics

I, Asmita Nandy, declare that this thesis titled, “Intensive Human Activity Recognition using a combination of Accelerometer and HeartRate sensors” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a Master degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

Abstract

Human Activity Recognition is playing a great role in many applications like health monitoring and fitness tracking, which focus on those who need help and on aged people. It has become a trend to use smartphone more often than any other gadgets, since it is equipped with many useful functionalities like that of multitasking and embedded accelerometer, gyroscope and also easy to carry, so it can be convenient for monitoring our activities for recognition. In order to identify activities which are intense in nature, like that of running carrying weight, body sensors will be needed which can capture more type of physiological signals for different activities. Using only accelerometer or gyroscope, it is difficult to focus on the details of recognition. Detailed Activity Recognition is important to help health monitoring more, since any kind of abnormalities in health can be found due to detailing. So to help in this case, we have also collected heartrate data from a heartrate sensor attached to the body during data collection. Very few paper have used hearrate to work with, but it is an important asset to include since health deterioration is related to heartrate, so proper attention is needed on heartrate. Hence we propose system where we consider the features of accelerometer and heartrate together to help identifying the intense activities. Also, an ensemble classifier is proposed which helps capturing the conditions that its base classifiers fail to recognize individually, hence voting can capture the activity classes if the correlation between two classifier predictions is low. We have collected a real-life dataset from four users keeping the smartphone in left pant pocket and attaching the heartrate sensor to the chest. In both the procedure, we used this dataset and we observe to have achieved above 90% accuracy in recognition.

Keywords: Human detailed activity, Machine Learning, classifier fusion, sensors, heart rate, intensity, ensemble classifier

Acknowledgements

I take this opportunity to express my deepest gratitude and appreciation to all those people whose guidance and encouragement have helped me towards the successful completion of this thesis.

I would like to express my sincere, heartfelt gratitude to my respected guide Dr. Chandreyee Chowdhury, Assistant Professor, Department of Computer Science and Engineering, Jadavpur University, for her unfailing guidance, prolific encouragement, constructive suggestions and continuous involvement during each and every phase of this research work. I feel deeply honored that I got the opportunity to work under her guidance.

I would like to express my sincere, heartfelt gratitude to Mrs. Jayita Saha, Research Fellow, Jadavpur University, Kolkata, for suggestions and guidance.

I would also wish to thank Prof. Nandini Mukherjee, Course Coordinator, Master of Engineering in Computer Science and Engineering, Jadavpur University, Prof. Mahantapas Kundu, Head of the Department of Computer Science and Engineering, Jadavpur University, and Prof. Chiranjib Bhattacharjee, Dean, Faculty of Engineering and Technology, Jadavpur University for providing me all the facilities and for their support to the activities of this research.

During the last one year I had the pleasure to work in our laboratories. I am grateful to all the members of DST-FIST laboratory, Jadavpur University for their kind co-operation and help, and kind attitude towards me.

I would like to express my gratitude and indebtedness to my parents and all my family members for their unbreakable belief, constant encouragement, moral support, and guidance.

Last, but not the least, I would like to thank all my classmates of Master of Engineering in Computer Technology batch of 2017-2019, for their co-operation and support. Their wealth of experience has been a source of strength for me throughout the duration of my work.

Signed:

Asmita Nandy

Examination Roll No.: M4CSE19029

University Registration No.: 140766 of 2017-2018

Department of Computer Science and Engineering

Jadavpur University

Contents

List of Figures

List of Tables

List of Abbreviations

HAR	**H**uman **A**ctivtiy **R**ecognition
HR	**H**eart **R**ate
KNN	**K**-**N**earest-**N**eighbour
ANN	**A**rtificial **N**eural **N**etworks
SVM	**S**upport **V**ector **M**achine
MLP	**M**ulti-**L**ayer **P**erceptron
DT	**D**ecision **T**ree
FFT	**F**ast **F**ourier **T**ransform
GNB	**G**aussian **N**aive **B**aye's
MAD	**M**ean **A**bsolute **D**eviation
SVMag	**S**ignal **V**ector **M**agnitude

List of Symbols

A_X, A_Y, A_Z	Acceleration of X,Y and Z axis
F_i	Feature set
PSD	Power Spectral Density
A_{SVM}	SVM acceleration

Chapter 1

Introduction

1.1 What is Human Activity Recognition

Activity recognition has been one of the largest fields of research and development, which currently uses advanced machine learning algorithms, innovations in the field of hardware architecture, and on decreasing the costs and energy consumption of monitoring while increasing safety. In this thesis, we will present how correctly we can recognize activities on the basis of different sensors and Smartphone sensors. Before doing so we need to know what Human Activity Recognition (HAR) is. HAR aims at recognizing activities of a human based on the measurements taken from variable sensors, where the sensors may be attached to body parts of humans or they can carry the sensors along with them, also measurements can be taken from Smartphones. Sensor-based activity recognition integrates the emerging area of body sensor with data mining and machine learning techniques to model a wide range of human activities [1] [2].

The main aspects of HAR are sensing, recognition and classification of human movements, intensity estimation of the activities, and observation of specific processes. This field has captured the attention of several researchers due to its ability for providing aid to many application domains and its connection with many other research fields. A lack of details in activity recognition is a huge problem in our society. In order to correctly examine health problems, fall detection or track fitness, we are trying to cope up with those drawbacks so that we will be able to deal with broader aspects of activity recognition, which we have termed here as detailed activity recognition. Detailed activity recognition deals with the specification of information regarding the state, position, and place of an activity. We will see later in this paper what it is and why it is required.

1.2 Applications of Human Activity Recognition

During the last few years, there was a significant growth in the number of applications in the field of Activity Recognition. Many researchers have explored application domains, to identify specific activity types or behaviors to reach specific goals in these domains.

1.2.1 Assisted Living Applications[3]

On the lap of modern era, technologies have provided innovative ways to enhance the quality of independent living of people. An active and assisted living system is one of the solutions for this. They take the help of AR techniques to monitor residents and assist them with their safety and well being. Recently, research has been conducted, aimed at using a combination of wearable sensors and that of sensors implanted into the environment, together with audio and video interactions. Assisted living can be categorized into the fields given below:

Smart Home

Around the whole world, people are getting older than that of their age. Projections show that by 2050, more than 20% of the population will be more aged than that of what he or she should be at 64. This will lead to an increase in aging-related illness, a decrease in informal support, and ultimately issues with providing care for these individuals. Assistive smart homes provide a promising solution to some of these issues[4]. According to Demiris et al. [5], Smart home is an environment equipped with sensors that enhance the safety of residents and monitor their health conditions. Hereby improving the level of in-dependency and quality of life, it helps people who require support for physical and cognitive functions [6]. Inside a smart home, behaviour of residents and their interactions with the environment are analyzed with the help of the data collected from sensors like audio/visual sensors, environment sensors, and wearable sensors. Smart homes are very useful in this developing society, since they detect the activities of elder people and can help during emergency purpose by informing medical personnel, also they are able to detect theft by the activity recognition and notify the owners of the house. Projects like GER'HOME [7], universAAL [8], SWEET-HOME [9], and MOBISERV [10] used multi-sensor for monitoring activities of the elderly people to improve their living conditions and reduce the cost of long hospitalization.

Healthcare Monitoring System

The development and combination of medical science and technology effectively increased the life quality of patients. Hence researchers try to enhance the healthcare monitoring systems that would handle urgent medical situations and reduce the hospital stay and regular visit hours of a patient. Basically, design, of healthcare monitoring approaches, is based on the combination of AR components like fall detection, human tracking, security alarm, and cognitive assistance components. Most of the system use body-worn and contextual sensors based on patients' bodies and their environments. Once help is needed, the system notifies the medical personnel about the situation and that they should assist the patient quickly. Then the external correspondents are also notified. Projects like SAIL [11] and CAALYX [12] aim at assisting elderly people by this process.

Fitness Tracking

Fitness tracking primarily refers to recognizing user activity/movements and records a person's fitness activity. Fitness tracker is a device or application for monitoring and tracking fitness-related metrics such as distance walked or run, calorie consumption, and in some cases heartbeat and quality of sleep. Activity trackers are available both with and without display. Early examples include wristwatch-sized bicycle computers that monitored speed, duration, distance, etc., available at least by the early 1990s. Wearable heart rate monitors for athletes were available in 1981. Wearable fitness tracking devices, including wireless heart rate monitoring that integrated with commercial-grade fitness equipment found in gyms, were available in consumer-grade electronics by at least the early 2000s. Fitbit[1], Apple Watch[2], and many other smartwatches and GPS trackers serve the purpose of fitness tracking.

Fall Detection

Falls represent a significant threat to the health and independence of elderly people. Fall detection is an active research area that strives to improve people's lives through the use of pervasive computing. It utilizes the sensors (accelerometer, gyroscope) to identify the location of the user's body (chest, pocket, holster, etc), and to find known patterns associated with falls. These systems feature detection sensors (multiple accelerometers and processors) that can detect between normal activity, and an actual fall. By continuously measuring the speed of movements in all directions, the fall detector can compare what it senses to what it considers an actual fall. Since fall alert detectors can sense what position they are in, how fast they are moving, and how they are moving (smoothly or abruptly) 80% of users experience no false fall detection per month while 90% of users experience one or fewer false detection per month.

1.2.2 Security And Surveillance Applications

Traditional surveillance systems were monitored by human operators but they should continuously monitor human activities that are observed via

[1] *https://www.fitbit.com/in/home*
[2] *https://www.apple.com/in/watch/*

the camera views. Security firms are seeking help from vision-based technologies to enhance the human operator processes and detect anomalies in camera views. The surveillance system introduced in [7], as used by them, is based on the Video Surveillance Interpretation Platform (VSIP) and is able to recognize human behaviors such as fighting and vandalism events occurring in a metro system using one or several camera views. The researchers used multiple camera views to detect situations such as loitering, distinct groups, and aggression scenarios in real time and in a crowded environment. The airport surveillance system proposed by Fusier et al. [13] is able to recognize 50 types of events which include complex activities such as baggage unloading, aircraft arrival preparation, and refueling operation through the use of video surveillance cameras.

1.2.3 Tele-Immersion Application [14]

Tele-immersion allows users to share their presence in a virtual environment and interact with each other in real time such as presence in the same physical but in different geographical environments. It requires a higher amount of computer processing power and generates a large amount of data that need to be transferred through a network in real time. The kinematic parameters of a human body in each frame can be extracted from cloud data using motion estimation, thus effectively minimizing the network transfer between the remote sites. The i3DPost project [15] used Tele-Immersion techniques to enhance the existing appearance of 2D layouts by converting 2D CAD planning into full colour motion-rendered pictures.

1.3 Role of Heart Rate in HAR

Accelerometer and Gyroscope data has been playing a great role in detecting activities, since from accelerometer data we are able to track the orientation of the body with the ground and from gyroscope data we are able to detect the angular speed of rotation during performing an activity. But this data is not enough to detect some kind of activities we need to track for health care monitoring, smart living or fitness tracking. By these systems, we want to detect strainful or intense activities which can exhaust a person. These kinds of activities can prove to be a result of anomalous health of a person or this kind of activities can reflect the fitness of a person. Hence we also need to know the heartrate occurring during an activity performed by a person. If heartrate is taken into account, then exhaustive or intense activities can be recognized upto an extent. For example, in case of walking and walking while carrying weight - accelerometer data or gyroscope data can have the same pattern for both activities, but the heartrate will not be same for both activities and the later one being intense will have more heartrate than the former one. Here lies the significance of heartrate.

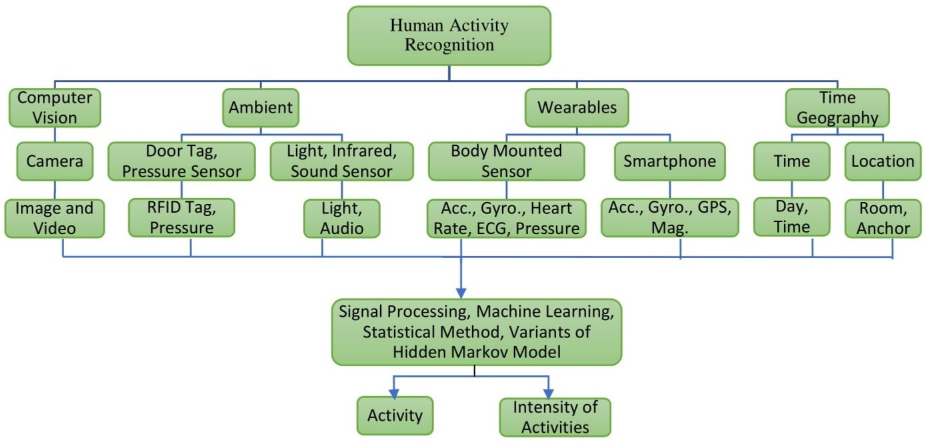

FIGURE 1.1: Taxonomy of activity Recognition

Fig. 1.1 shows the taxonomy of the Activity Recognition works done until now, where the Human Activity Recognition can be divided into 4 parts -

- *Computer Vision* : Camera is used for video and image collection, so as to use image processing for HAR.
- *Ambient* : Pressure sensor, Door tag collects RFID tags, feet pressure, etc. from a user. And Infrared , the sound sensor collects light and audio for HAR.
- *Wearable* : Wearable sensors are attached to the body, and carried by a user so as to collect data for HAR.
- *Time Geography* : Activities can be recognized on the basis of time and location of a user.

1.4 Overall Framework

We briefly describe the procedure of HAR through this diagram given below, so that it will help us to understand each step later in this context.

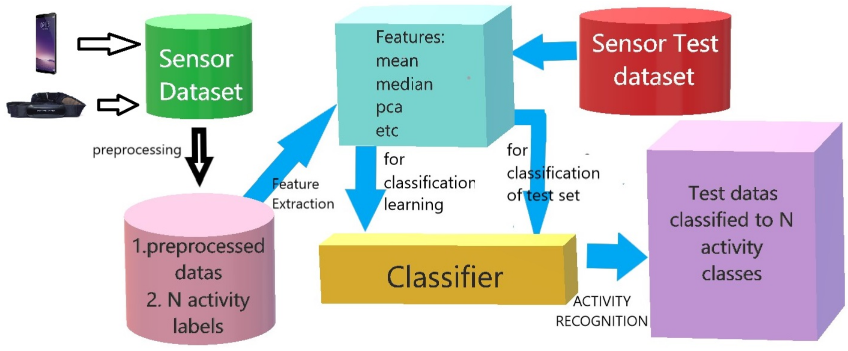

FIGURE 1.2: Overall Workflow of Activity Recognition

At the top left corner of this Fig. 1.2, we see two sensors are given – the upper one is a Smartphone-based sensor and the one below is the sensor which can be attached to a subject's body. While the subjects perform certain activities, we acquire certain values at each instance from those sensors, thus data set acquisition is the first step of HAR. The datasets are then preprocessed for feature extraction, the process of which we will see in detail after this. Features like mean, median, PCA, and many other features are collected from the pre-processed data and are sent for classification learning. The classifier model, after learning, is used for predicting activities on the basis of features extracted from the test datasets. Now we will focus on each phase of HAR, so that we can get a clear view of the whole procedure.

1.4.1 Data Collection

Data is being collected from different sensors. Sensors popularly known to have been used for HAR are as follows:

- *Accelerometer:* It measures acceleration in 'g's for x, y, and z axes, correspondingly. (Where $g = 9.8m/s^2$ for rest and zero for free falling)
- *Gyroscope:* It measures the angular speed of rotation in degree per second or revolution per second for x, y and z axes, correspondingly.
- *Heart Rate Monitor:* A heart rate monitor is a personal monitoring device that allows one to measure one's heart rate in real time or record the heart rate for later study. (Unit is beats per minute or bpm).
- *Magnetometer:* It measures Magnetic field strength in micro Teslas for x, y and z axes, correspondingly. The sensors may either be attached to the body (using a strap), may be carried with them (pocket or hand) or it can also be embedded in a Smartphone.

Sensors are connected to a remote station so that data can be exported there for remote processing. Any of the formats can be used to store them, like .dat, .txt, .csv and so on.

1.4.2 Pre-Processing of Data

In this phase, raw data signal is filtered and segmented in order to achieve ease for performing other operations. There lie some problems in raw data, viz. noise, outliers, and missing values. To make data more suitable for mining, certain things need to be managed in following ways.

Filtration Of Noise

Filtration is a process that removes some unwanted components or features from a signal. We can use linear continuous time filters to remove certain frequencies and allow others to pass, for example: a low-pass filter allows only low frequencies to be passed and high frequencies are attenuated, high filter does the reverse, Butterworth filter is a type of low pass filter whose cut-off frequency [3] was normalized to 1 radian per second and whose gain was $G(\omega) = \frac{1}{\sqrt{1+\omega^{(2n)}}}$. [4]

We should know why Butterworth filter is useful. This is because it not only completely rejects the unwanted frequencies but it also has uniform sensitivity for the wanted frequencies.

Handling Missing Values

We can eliminate objects with missing values only if the amount of missing values do not exceed more than 5% of the records. We can try estimating missing values by replacing them by most frequent value, average, last non-missing value before starting of a missing value or first non-missing value after end of a missing value. We can take the help of expert knowledge. We can use non-missing data to predict the missing values in the following manner:

- *Linear regression - By putting non-missing values in the equation to find the constant and later finding the missing value with the help of the constant and other known variables.*
- *Most correlated value*

[3] *Cut-off frequency is the frequency beyond which the filter will not pass signals. It is usually measured at a specific attenuation such as 3 dB.*

[4] *ω is the angular frequency in radians per second and n is the number of poles in the filter*

- *Trying to maintain the relationships between attributes*

Thus Different replacements can be generated for the same attribute

Sampling

First, we can split the data into several partitions and then draw samples from each partition with the help of windowing with overlap or non-overlap. When the length of a data set to be transformed is larger than necessary, to provide the desired frequency resolution, a common practice is to subdivide it into smaller sets and window them individually. Using overlap windowing is more useful since, to mitigate the "loss" at the edges of the window, the individual sets might overlap in time.

Example

Suppose we want to pre-process the data of accelerometer. Accelerometer has dataset $A = \{X, Y, Z\}$,

$X = [x_1, x_2, \ldots, x_n]^T$, $Y = [y_1, y_2, \ldots, y_n]^T$, $Z = [z_1, z_2, \ldots, z_n]^T$.

These are sets of values for X-axis, Y-axis, and Z-axis respectively. If they have noise (noise detection can be done by using Mean-Squared Error), filtration is applied on them. If they have missing values, then they can be removed or replaced (ways mentioned above). If the missing values are not handled then the next phases will incur certain errors. Now for sampling the dataset, A is split into 3 subsets like that shown above (X, Y and Z) and windowing is applied on each individual subsets. If suppose sampling rate of the accelerometer is 100Hz and window we want to take is 2.56 sec, then we can transform the subsets into a (m-by-256) matrix where m is the number of rows and 256 is the number of columns, constructed on the number of elements taken from the subsets.

Similarly, Y and Z will also be transformed. Now overlapping can help avoiding the loss due to a break between x_{256} and x_{257} and so on, so if we use 50% overlap then the second row will start from x_{128}. It is not always necessary that last element of this matrix will be x_n, it can also have last row with x_n somewhere in between that row. Similar is the approach of pre-processing for gyroscope and other sensor datasets.

1.4.3 Feature Extraction

Feature selection is the most important step since it is the features that determine the accuracy of activity recognition. From the datasets, different features are being collected like mean, variance, standard deviation, PCA, etc. so that it can help the classifier to categorize the activities on the basis of the features and labeled activities. Features are extracted from both training and test datasets. Various features are calculated in time domain or frequency domain or both like mean, variance, energy, gradient, etc. Feature is extracted from each window of each of Transformed-X, Transformed-Y and Transformed-Z subsets (of each sensor datasets). For example, let us consider the matrix Transformed-X. If we want to extract features from then we will have:

$F = \{f_1, f_2, \ldots, f_n\}$ is the set of features

$f_1 = \{f_{1_{A_X}}, f_{1_{A_Y}}, f_{1_{A_Z}}, f_{1_{Hr}}, \ldots\}$ is the specific feature set having feature f_1.

$f_{1_{A_X}} = \{f1_{A_X}(x_1, \ldots, x_{256}), f1_{A_X}(x_{128}, \ldots, x_{383}), \ldots\}$ is the extraction of f1 feature from each window of Transformed-X matrix of accelerometer.

Similarly are $f_{1_{A_Y}}, f_{1_{A_Z}}, f_{1_{gyrox}}, f_{1_{gyroy}}, f_{1_{gyroz}}, \ldots$ defined.

For example. Mean of each window $f(x_1, \ldots, x_N)$ is defined by : $\frac{\sum_{(i=1)}^{n} x_i}{N}$, where x_1 to x_N are the readings of one window.

1.4.4 Classification

Classifiers will learn from the categorization of the training data according to different activity classes and create a learning model, which will be useful in the next phase Activity recognition generally involves Supervised Machine Learning, which includes techniques commonly used like:

- *Support Vector Machines :* An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called kernel, implicitly mapping their inputs into high-dimensional feature spaces.
- *Decision trees :* A decision tree is a predictive machine-learning model that decides the target value (dependent variable) of a new sample based on various attribute values of the available data. The internal nodes of a decision tree denote different attributes; the branches between the nodes tell us the possible values that these attributes can have in the observed samples, while the terminal nodes tell us the final value (classification) of the dependent variable. The attribute that

is to be predicted is known as the dependent variable, since its value depends upon, or is decided by, the values of all the other attributes. The other attributes, which help in predicting the value of the dependent variable, are known as the independent variables in the dataset.

- *k- Nearest Neighbour algorithm :* the k-Nearest Neighbour is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression:

  – In k-NN classification, the output is a class membership. An object is classified by a majority consensus of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small).

    If k = 1, then the object is simply assigned to the class of that single nearest neighbour.

  – In k-NN regression, the output is the property value for the object. This value is the average of the values of its k-nearest neighbors.

- *Artificial Neural Networks :* The idea of ANNs is based on the belief that working of human brain can be imitated using silicon and wires as living neurons and dendrites, by making the right connections ANNs are composed of multiple nodes, which imitate biological neurons of human brain. The neurons are connected by links and they interact with each other. The nodes take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation or node value. Each link is associated with weight. ANNs are capable of learning, which takes place by altering weight values.

Some classifiers give best results for specific activities, e.g. K-NN for Laying. The trained model of classifier will then be given features of test dataset, from which predictions will be made to recognize the activities. N-fold cross-validation will give best results by shuffling among test datasets and training datasets.

1.5 Motivation

With this advancement, there is a demand for recognition of detailing in activities, so as to help serve the purposes better for health monitoring and fitness tracking. Also, the use of only accelerometer and gyroscope is not enough to identify the details, since accelerometer or gyroscope data for two activities can have the same pattern. It is necessary for healthcare monitoring, fitness tracking, smart home or any other system to recognize details of activities. For example, if a person is sitting on a chair with abnormal heartrate, then healthcare monitoring system will take a step towards informing a healthcare center immediately since it may be a health problem. So, in that case, the problem can be solved using heartrate data since activities having the same pattern of accelerometer or gyroscope can have different heartrate. Very few works are there which have used heartrate signals to recognize activities. The motivation behind our work is to propose a system using Smartphone embedded accelerometer and heartrate sensor for identifying intense activities for detailing, with high accuracy, so that along with static and dynamic activities, detailed activities can also be recognized - like *sitting on chair or floor, slow or brisk walk, running with weight* .

1.6 Contribution

Our contribution has been to propose a solution for the purpose of detailing in identification for both static and dynamic activities, as well as their intense activities with the help of wearable sensors like Heartrate sensor and Smartphone-embedded sensors, like Accelerometer. For identifying detailed activity, we have proposed a system with novel heartrate features, since we want to recognize certain activities which are intense in nature, but may not be recognized because of same accelerometer or gyroscope pattern with any other activity. Since heartrate will be different for an activity and for its intense one, we will highlight the small details like how fast the heartrate is changing, or by how much the heartrate, at that instant, is greater or less than the Resting HeartRate of a user. To validate our system, we have implemented a dataset collected from four users.

We have seen that classifiers individually are not able to capture all the conditions, so We implemented a system by designing an ensemble of classifiers since ensemble classifier is more generalized and better than its base classifiers. The ensemble is designed so as to apply weighted majority voting for classification of test instances. Ensemble classifier is used to differentiate efficiently between the detailed static activities (sitting, sitting with weight, standing, standing with weight, lying down, lying down with weight) and dynamic activities (walking, walking with weight, climbing stairs, climbing stairs with weight). We have also tested the system on our collected dataset.

1.7 Organization of the thesis

The rest of the thesis is organized as follows:

Chapter 2 Discusses the pros and cons of existing activity recognition systems using different techniques. A comparative study of different activity recognition strategies is presented in this chapter, followed by different Machine Learning approaches.

Chapter 3 Covers our proposed work based on novel heartrate features. It covers the architecture of the work, data collection procedure, and analysis of collected data in detail.

Chapter 4 Covers our proposed work based on Ensemble Classifier. Functions of different phases are elaborated in this chapter.

Chapter 5 Discusses experimental results. A comparative study is presented with respect to different scenarios, time and devices.

Chapter 6 Finally draws the conclusion of the thesis and discusses the limitations and scopes of future work.

Chapter 2

Related Works

2.1 Overview

This chapter focuses on the advantages and limitations of the existing works. Also, a hierarchy of the existing works is presented.

2.2 Existing works on Activity Recognition

Since the early years of 1980's computer science community trying to solve the challenges in the field of Human activity Recognition. The current work in this area has reached a new high which helps us to improve and get more accurate HAR system. Human activity recognition is often carried out using gyroscopes, and tri-axial accelerometers. The sensors are involved with many different aspects, such as classification methods, attachment locations, number of sensor axes, etc. For this reason, the existing works have been gradually trying to improve HAR system in order to meet the needs in this modern era.

There are two broad categories of the related works: One belongs to the category of the existing works having solutions for activity recognition, and the other one belongs to that of the existing datasets, which are provided so that the researchers can validate their work by testing on those datasets. Girija Chetty et. Al. [16] reported the application of body sensors in case of automatic activity recognition, for elderly people, with the help of wireless body sensors and Smartphone sensors. For validation and comparison of baseline, they compared with publicly available datasets – UCI HAR [17], which is a smartphone based dataset and OPPORTUNITY [18] [19], which is not Smartphone-based.

Automatic activity Recognition has proved to be a popular field of attraction for the researchers, and also because of being very useful in real-time recognition of physical activities in real life. Same Activity can be performed by different people, or can be performed by the same person with different intensities. For Fitness tracking and Health Monitoring, it is very important to recognize it as the same activity. Hence the intensity of activities should be given focus on. An attempt was made by E.M. Tapia et. Al.[20] to solve such problem, by trying to make an algorithm for real time automatic recognition of physical activities, and their intense activities in some cases. They used five tri-axial accelerometers along with a wireless heartrate monitor. They segmented the data with the help of windowing of each axis (for 5 accelerometers). They extracted time domain and frequency domain features from each window. They included features like :

- *Area Under Curve (AUC)*

- *Variance for capturing variability of signals*
- *Mean distances between axes*
- *Mean to reflect sensor inclination with ground for postures*
- *Entropy to differentiate activity type*
- *Correlation Coefficients to capture simultaneous motion of limbs*
- *Fast Fourier Transform(FFT) peaks and energy for intensity detection*
- *Number of heartbeats above the resting heartrate (HR) value*

Classifiers C4.5 decision tree and naïve bayes were used to evaluate the performance of the recognition algorithm they used. They computed True Positive and False Positive rates along with Precision, Recall and F-measure over the segmented activity classes using subject-dependent and subject-independent training. HR feature is added to test the recognition of different intensity levels and got the results to be exceeded by 1.2% (subject-dependent) and by 2.1% (subject-independent). Most of the confusion was taking place while identification of different intensity levels of activity. When no intensity levels are present, they found the C4.5 Decision Tree(Subject Independent) to perform well while training. But their algorithm did not determine activities with different intensities successfully in real-time, so the algorithm was needed to be improved.

A system is proposed for real-time recognition by D. Curone et. Al.[21], using small integrated sensors, which combines accelerometer and an ECG lead. Microprocessors are integrated into Rescuers' garments, and they developed algorithm which detects inertial acceleration, step frequency, trunk inclination, Heartrate(HR) and HR trend in real time. Specific activities, which seems dangerous to a rescuer during operation such as "subject lying down motionless" or "subject resting but with abnormal HR", are needed to be recognized. They considered nine classes of activities involving certain physical activities (walking, running, moving on site), with intensities (intense, mild, or at rest) and postures (lying down, standing up). The algorithm they used identifies each "standard activity" with the help of arrays with five ordered values - SMA, inclination, step frequency, HR, and HR trend. Each array represents a point "centroid," whose coordinates are set for activity recognition. Each time the setup produces a new data, the classifier assigns it to the class of the nearest centroid, based on Euclidean metrics. Their work was successful in recognizing the conditions we were indicating as dangerous, and also the activities with different intensity levels. Still there lies some drawback, as observed – activities having same accelerometric centroid coordinates but characterized by different intensity levels are confused, like "stationary intense movement classes" are confused with "moving trunk and arms classes".

A similar system is proposed by Eka Adi et. Al. [22]. But they involved wearable sensors, a Smartphone and a remote server. The proposed system is lightweight, compact and easy to use with comfort. The Smartphone provided an Application, which displayed data related to HR and waveforms of ECG, Step Count(SC), exercise intensity, distance, speed, calories burned and Step cycle in real time. They aimed at limiting the likelihood of over-exertion and/or under-exertion in order to maximize the efficiency of training. The detection accuracy of ECG peaks and HR and the number of steps were verified. MIT-BIH ST Change Dataset [23] was used for validation of their work, also they did treadmill experiment involving 5 subjects. For ECG peak detection, the accuracy result is 99.7% and that for HR detection remained consistent across all speed to 98.89%. Because of instabilities in the ECG data, there are certain detection failures. Accuracy during the treadmill test was high, hence this project is enhancing the usability and malleability of the device for monitoring health.

Gradually, more systems got proposed in this field, where researchers came up with new thoughts useful for this field. They came up with the term Energy-Expenditure (*EE*). Both activity Recognition and EE being investigated for a long time, still they face certain challenges that remain unsolved, for example, confusion between energy consuming activities involving less or no movement. An attempt is made to solve the problem by Sun-Yeon Dong et. Al. [24]. They used Accelerometer and ECG to collect data from 13 voluntary participants for 6 activities. They proposed a system with the Heart-Rate Variability(*HRV*) parameters, and compared the HAR performances, with respect to input data, of three models –

- No HRV parameters
- All of them
- Some selected HRV parameters

Recognition performance was found to be best with the last option. EE was also measured for input types - with and without HRV parameters; and for model type - single and activity specific. The activity-specific model with HRV parameters found to be the best. The results signify that human physiological data is effective on HAR and EE, which are crucial for assisted living as it helps Healthcare systems in a productive way.

Most of the existing works involve single classifier of Machine Learning. In [25], Decision Tree is used for good accuracy. Classifiers like Naïve Bayes', Decision Trees (*J48*), and Sequential Minimal Optimization (*SMO*) can be used along with Cross-Validation for Activity Recognition, as mentioned in [26]. Decision Tree succeeded to achieve accuracy of 89.6%. Another paper [27] where authors used classifiers for recognition like Decision Tree, Random Forest(RF), Support Vector Machine (SVM), Naïve Bayes', K-Nearest Neighbor(K-NN) and Discriminant Analysis, with 4- fold Cross Validation and SVM successfully achieved 91% accuracy. In the paper [28], the authors achieved good overall accuracy for many offline activities using K-NN and KStar.

Very few works considered ensemble learning, that is the fusion of classifiers, to recognize daily life activities [29] [30]. An ensemble classifier, Random Forest(*RF*), is used by the authors in [31], to identify the smartphone position, while detecting basic activities with an accuracy of 85%. Several Base classifiers can be clubbed together to form an ensemble classifier. An ensemble classifier, based on Majority Voting, is designed in [32] with the combination of base classifiers like Logistic Regression, Decision Tree and Multi-layer Perceptron. Boosting and Bagging algorithms [33] are ensemble classifiers, which reduce the bias and variance of the datasets and calculate classification accuracy.

Sensor readings can vary for same activity but carried out with different behavior and intensity level. Thus intensity level of activities is also taken into account for Detailed HAR. It can be done with the help of heartrate of individual users. In [34], several detailed activities are considered, but individual intensity level is not considered. Whereas Eka Adi et. Al. [22] considered intensity of activities as we have seen earlier. Hence, a Detailed HAR framework is proposed in this work that takes into account smartphone-embedded accelerometer and wearable heart rate sensor to identify detailed daily activities including intense activities. Table. 2.1 shows a summary of the features used, sensors used with position, performance metric and Table. 2.2 shows a summary of Reference, ML technique and drawbacks of the existing papers which have taken into account sensors for accelerometer and heartrate .

TABLE 2.1: Summary of Features used, Sensors used and their positions, and Performance Metric of the related papers

Features Used	Sensor, position	Performance Metric
IMU, ECG, Heart-Rate, Variability(HRV) parameters [24]	IMU sensor, Wrist ECG sensor, Chest	Energy Expenditure(EE), Root Mean Square Error (RMSE), Accuracy
Area Under Curve (AUC)}, Variance for capturing variability of signals, Mean distances between axes, Mean to reflect sensor inclination with ground for postures, Entropy to differentiate activity type, Correlation Coefficients to capture simultaneous motion of limbs, Fast Fourier Transform(FFT) peaks and energy for intensity detection, Number of heartbeats above the RHR value [20]	Five triaxial wireless wearable accelerometers with positions : 1.top of the dominant wrist just behind the wrist joint 2.side of the dominant ankle just above the ankle joint 3.outside part of the dominant upper arm just below the shoulder joint 4.on the upper part of the dominant thigh 5.on the dominant hip A wireless HR monitor based on the Polar chest strap, chest	False positives (FP), precision (P), recall (R) F-measure (F)
Exercise Intensity, Step counter [22]	3-axis accelerometer and an ECG captive sensor integrated in a single device, chest	Accuracy
Inertial acceleration, Step frequency, Trunk inclination, Heartrate(HR), HR trend [21]	Garment integrated with accelerometer and an ECG lead	Accuracy

TABLE 2.2: Summary of Machine Learning Techniques used, and Drawbacks of the related papers

Reference	ML Techniques	Drawbacks
[24]	For HAR: SVM kNN EE: Linear Regression	The activity-specific model with HRV parameters found to be better than that having no or some HRV parameters and also better than that of the single model.
[20]	For HAR: C4.5 DECISION TREE NAÏVE BAYES	Most of the confusion was taking place while identification of different intensity levels of an activity. Their algorithm did not determine activities with different intensities successfully in real-time.
[22]	Detection of accuracy of ECG peaks, HR and number of steps – verified using MIT-BIH ST Change database and treadmill test	Because of instabilities in the ECG data, there are certain detection failures.
[21]	Nearest Neighbour of centroid	Activities having same accelerometric centroid coordinates but characterized by different intensity levels are confused (for eg. “stationary intense movement classes” are confused with “moving trunk and arms classes”)

2.3 Summary

This chapter gives a brief overview of the previous works of activity recognition and also that of ensemble classifier.

Chapter 3

Novel Features for Heartrate Based Human Activity Recognition

3.1 Overview

In this chapter, a framework for detailed HAR based on novel features on Heart Rate is presented. We collected data from four users with the help of Smartphone-embedded Accelerometer and Heartrate Sensor. The experimental setup, along with the results of the work is also explained in this chapter.

3.2 Features of Accelerometer

Acceleration is the measurement of the change in velocity, or speed divided by time, i.e. measurement of accelerometer forces. Such forces may be static, like the gravity; or dynamic, to sense movement or vibrations. Nowadays, smartphone embedded accelerometer is more convenient and flexible for collecting data while a subject performs certain activities, hence collecting accelerometer data is an important part of Human activity Recognition. Fig. 3.1 shows the raw plot of accelerometer data for the X, Y and Z axes (A_X, A_Y, A_Z), collected from a Smartphone by us. We first filtered the raw data and considered another dimension along with the three axes, namely Signal Vector Magnitude (*SVMag*), since SVMag is position independent and does not depend on usage behavior of the smartphone. SVMag is defined as :

SVMag=$\sqrt{(A_X^2 + A_Y^2 + A_Z^2)}$

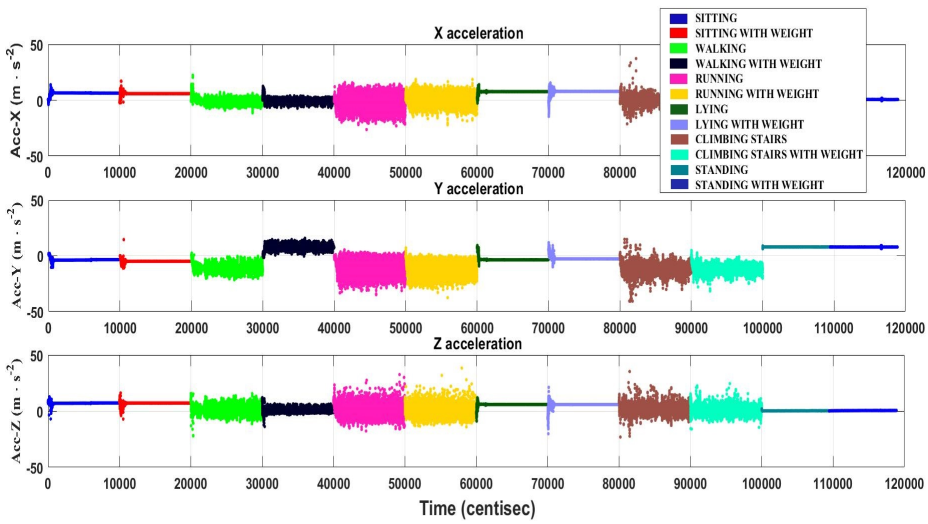

FIGURE 3.1: Raw accelerometer readings, collected by us, of different activities collected for 1200 Seconds from a smartphone kept at Left pant pockeT (LPT)

After that, Accelerometer signals and SVMag are being segmented with the help of windowing with a percentage of overlap. We converted them to a smaller dataset, where each window consisted of 256 readings (since the sampling rate of the accelerometer signal is 99.5Hz, i.e. approximately 100Hz and we wanted a window of 2.56 sec). From each window, we extract features, which is used by the classifiers for activity recognition. Accelerometer features may be of two types: *Time Domain Features* and *Frequency Domain Features*.

3.2.1 Time Domain Features

Time domain refers to the variation of the amplitude of signal with respect to time. Hence time domain features are those extracted from the signal data corresponding to a time series. Time domain features used for this work are as follows:

- Variance = $\frac{1}{N-1} \times \sum_{(i=1)}^{n} |F_i - \mu|$
- Mean Absolute Deviation(MAD) = $\frac{\sum_{(i=1)}^{n} |F_i - \mu|}{N}$

  F_i belongs to window(filter($A_X, A_Y, A_Z, SVMag$))
- Square of Variance values
- Square of MAD values

We have applied Variance and MAD on all the four dimensions, i.e. A_X, A_Y, A_Z and $SVMag$. In order to consider only the magnitude and discard the sign of the dimensions, we used the square of the variance values and MAD values extracted from A_X, A_Y, A_Z, as mentioned in the previous line.

3.2.2 Frequency Domain Features

On applying the classifiers to these time domain features, static activities without weight activities(*sit, stand, lie down*) are more or less recognized, those which are dynamic activities and their corresponding intense activities (executed by carrying weight)like run and run with weight, etc. fails to be recognized; since there are relatively fewer fluctuations in acceleration data for static ones, but not for dynamic detailed activities. So frequency domain features are considered additionally with the time domain features. Frequency domain refers to the analysis of signals with respect to frequency. A given signal can be converted from time domain to frequency domain with the help of Fourier Transformation. Hence we first used Fast Fourier Transform on A_X, A_Y, A_Z in python, which converts a time domain function into integral of sinusoidal waves of different frequencies, each of which indicates frequency component. The frequency domain representation of a signal data refers to the spectrum of a frequency component. After transformations, We extracted Frequency domain features, namely Power Spectral Density PSD, which represents the power present in the accelerometer signal as a function of frequency. It is defined as:

$$PSD = \frac{\sum_{(i=1)}^{n} freq_i \times P_i}{\sum_{(i=1)}^{n} P_i}$$

3.3 Features of Heartrate Sensor

Still, there are certain confusions between the activities and their intense counterparts, since the acceleration data will be almost same for the activity and its corresponding intense activity. For example, sit and sit carrying weight will have the same acceleration data, hence having the same mean, variance, etc., patterns. So we have introduced heartrate features along with the accelerometer features. Fig. 3.2 shows the raw plot of heartrate data, taken when activities are performed while Zephyr HXM sensor is attached to the chest with a strap.

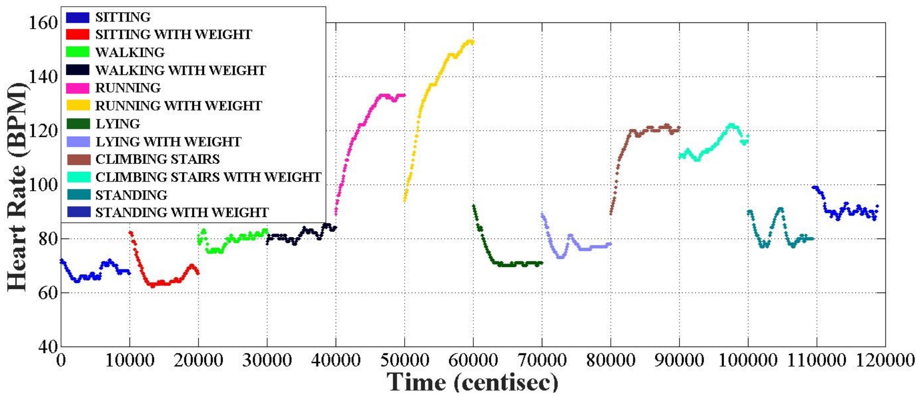

FIGURE 3.2: Raw Heartrate readings, collected by us, of different activities collected for 1200 Seconds from a smartphone kept at Left pant pockeT (LPT)

On adding the heartrate features we got the best accuracy results given by the classifiers, since heartrate patterns may be different for different activities. To find out the new features, we first needed to calculate the Resting Heart Rate(RHR) of the user, whose data is taken. RHR is calculated by considering three times the heart rate having more number of occurrences when the person is sitting(i.e. in resting phase), and then taking the average of those heart rates while dividing by 3. After that, we partition each window into subdivisions, and extract heartrate features from them. We divided each window into 3 subdivisions, since considering the whole window can give less speed as output sometimes because of the constant heartrate throughout the window, or at times if there are only one changes in the window then also many columns remain constant,hence 3 gives more accurate results rather than considering less number of subdivisions. The new features introduced are :

- *RelativeMinMaxHr*

  We took the maximum heartrate from each subdivision[15] of a window. Among the maximum heartrate, we get from the subdivisions, we chose the minimum heartrate to find out by how much it is different from the RHR of the user. We do this for each window

- *RelativeMaxMinHr*

  For extracting this feature, the process is the opposite of the previous one. From each subdivisions, we took the minimum heartrate. Among them, we chose the maximum heartrate. Again here also, we do this for each window reading. Both the features RelativeMinMaxHr and RelativeMaxMinHr are computed since there can be a haphazard increase or decrease in heartrate.

- *TransientMaxHr*

  We find out maximum heart rate from each subdivision of a window. This is done to find out the rate of change of heartrate. We are then finding out the average speed accordingly.

3.4 Experimental Setup

At first, data is collected from four healthy subjects, three of them are male subjects and the remaining one is a female subject. They are having an average age of 22 years, with average weight of 64.75±4.75 Kg. The set of 12 activities performed by each subject is shown in Table 3.1.

TABLE 3.1: List Of Activities

Activity ID	**Detailed Activity Class**
1	Sitting
2	Sitting with weight
3	Walking
4	Walking with weight
5	Running
6	Running with weight
7	Lying
8	Lying with weight
9	Climbing Stairs
10	Climbing stairs with weight
11	Standing
12	Standing with weight

The sequence of activities are taken in such a way that one can be able to feel relaxed, executing each activity since heartrate will come down to normal at the beginning of each activity. But one thing we are keeping the same for all activities, i.e. alternation of an activity and its corresponding intense one (*walking and walking with weight*). Accelerometer data is collected while the user carries the smartphone in the left pant pocket in upright and front-facing manner. Heartrate is collected while the user is wearing a chest strap, where the heartrate sensor Zephyr HXM is attached. For accelerometer data collection, the smartphone is having embedded accelerometer, which is used via an Android Application, G-Sensor Logger, and that for monitoring the heartrate, another smartphone is connected to the sensor via bluetooth, where Zephyr HxM Heart Monitor Application is installed. That application captures the heartrate signals and saves them as .csv files, which contains two columns - one for timestamp and other for the corresponding heartrate. The G-Sensor Logger also saves the accelerometer signals as .csv files, which contains the timestamp, and the corresponding A_X, A_Y and A_Z values. Fig.3.3 (a) and Fig. 3.3 (b) shows a sample of accelerometer data and heartrate data respectively. During the whole session of data collection, each activity lasted for a period between 1 to 2 minutes, which resulted in 11640 seconds of total recording. After data collection was over, we first removed the beginning of each activity data set (that of accelerometer and heartrate data) manually, since, at the beginning of each activity data collection, the user takes the Smartphone and keeps in the left pant pocket, so, that data would not be needed. Accelerometer data of three axes, A_X, A_Y, A_Z, are then filtered first by using Butterworth filter to remove noise and low-frequency acceleration. Then the filtered data was passed to Median filter to remove any other remaining traces of spikes. These were done using python programming.

Time (s)	X	Y	Z
0	0.459	1.34	8.102
0.009	0.689	1.187	7.489
0.021	0.842	1.034	6.876
0.03	0.766	1.187	6.799
0.039	0.612	1.34	7.106
0.057	0.536	1.8	8.561
0.063	0.536	1.8	8.715

(a)

Time	Heart rate
00:00	71
00:01	72
00:02	72
00:03	71
00:04	71
00:04	71
00:06	71

(b)

FIGURE 3.3: (a)Acceleration data collected from G-Sensor Logger Application embedded in Smartphone (b)Heartrate data collected, from Zephyr HXM attached to chest, in another Smartphone using the application Zephyr HXM Heart Monitor

The sampling rate of G-Sensor Logger Accelerometer is almost 100Hz and that of Zephyr HXM Heartrate Sensor is 250 Hz, hence the number of rows in the former one does not match with the later one. Next phase is to interpolate the heartrate data so as to fill the missing values and match the number of rows of heartrate data. So, being done with the processing of data, the accelerometer features as mentioned in section 3.2 and the heartrate features in section 3.3 are applied on the processed dataset.

3.5 Experimental Results

For validation of our work we used the classifiers: i. Linear Regression (LR) ii. Decision Tree (DT) iii. Bagged Trees iv. K-Nearest Neighbors ($K-NN$) v. Multilayer Perceptron (MLP) vi. Gaussian Naıve Bayes' (GNB) vii. Support Vector Machine (SVM). Initially, we considered the features Variance, MAD, Squares of Variance and Squares of MAD of each dimension A_X, A_Y, A_Z and $SVMag$ in Subpart 1, and applied them over the processed data. It performs well, with less error, for static activities and gives the best overall accuracy as 67.13%, since already mentioned earlier, static activities have little fluctuations. For dynamic activities, the accelerometer values are almost overlapping and sparse, hence failing to distinguish properly. So we introduced Subpart 2, consisting of the features in subpart 1 and an additional feature PSD, which resulted in an overall accuracy of 92.87%. It improved the recognition of dynamic activities like run, walk, climb and their corresponding intense counterparts. But still, it has confusions for some activities and their intense ones. So we have introduced new heartrate features along with Subpart 2 features, in Subpart 3. We observed that accuracy improved for each activity since heart rates are different for different activities, viz. standing and standing with weight. Table. 3.2 shows the comparison between the accelerometer features and the overall features which include accelerometer as well has heartrate features. All the accelerometer features consist of the features in Subpart 2 and the overall features consist of the features in Subpart 3.

TABLE 3.2: Summary of classification results (%) comparison between the accelerometer features and all the features together

Accuracy : A1, Precision : P1, Recall : R1, F-measure : F1					
CLASSIFIER	**PERFORMANCE EVALUATION**	**ACCELEROMETER FEATURES (SUBPART 2)**		**OVERALL FEATURES (SUBPART 3)**	
		CV	**TRAIN TEST**	**CV**	**TRAIN TEST**
MLP	A1	79.92 ± 0.28	88.80516684	81.55 ± 0.21	74.16576964
	P1	80.26 ± 0.34	89.62803618	84.00 ± 0.19	73.15281550
	R1	79.92 ± 0.28	88.80516684	81.55 ± 0.21	74.16576964
	F1	77.44 ± 0.33	88.80942487	79.60 ± 0.25	70.57143680
KNN	A1	83.92 ± 0.31	92.57265877	86.20 ± 0.19	83.63832078
	P1	85.40 ± 0.32	92.97406897	88.13 ± 0.20	87.00167107
	R1	83.92 ± 0.31	92.57265877	86.20 ± 0.19	83.63832078
	F1	82.94 ± 0.33	92.51544013	85.19 ± 0.21	82.58387049
BAGGING TREE	A1	93.70 ± 0.19	93.75672766	94.37 ± 0.17	93.64908504
	P1	94.73 ± 0.13	94.0342628	94.81 ± 0.15	93.90471769
	R1	94.29 ± 0.17	93.75672766	93.74 ± 0.19	93.64908504
	F1	93.34 ± 0.21	93.78986116	93.64 ± 0.19	93.69442801
DT	A1	92.82 ± 0.20	92.35737352	93.24 ± 0.19	93.54144241
	P1	93.00 ± 0.20	92.7555038	93.27 ± 0.20	93.7562777
	R1	92.82 ± 0.20	92.35737352	93.24 ± 0.19	93.54144241
	F1	92.47 ± 0.21	92.3725854	92.91 ± 0.21	93.55784115

3.6 Summary

This chapter gives a overview of our framework with novel features of Heartrate and the results of our proposed work. The next chapter describes our proposed framework of ensemble classifier .

Chapter 4

Ensemble Classifier For Heart Rate Based HAR

4.1 Overview

In this chapter, a framework for detailed HAR based on Ensemble of Classifiers is presented. We have used the data collected by us, as mentioned in the previous chapter. The experimental setup, along with the results of the work is also explained in this chapter.

4.2 Definition of Ensemble Classifier

Ensemble method is a learning algorithm that takes feedback from other individual base classifiers and then classifies new data set by taking into account the predictions of those base classifiers and applying weights on them so as to use the vote of their predictions. Hence, Ensemble model[30], being derived from the other classifiers, can prove to be stronger than the base classifiers.

4.3 Proposed Ensemble Classifier

In this work, twelve detailed daily activities are recognized following the phases as shown in Figure 4.1. Phases of this technique is discussed below:

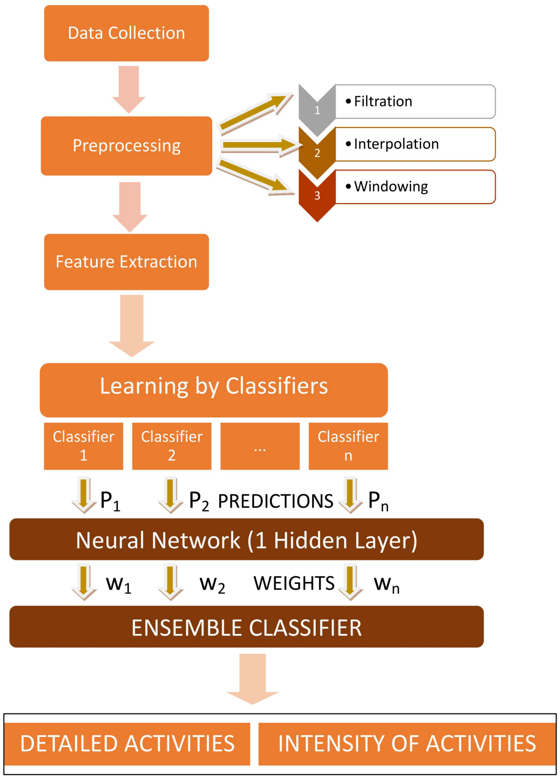

FIGURE 4.1: Workflow of Recognition of activities using Ensemble Classifier

4.3.1 Data Collection

We have considered 12 activities for this work, six of them being static activities (*sitting*, *sitting with weight*, *standing*, *standing with weight*, *lying down*, *lying down with weight*) and other six being dynamic activities (*walking*, *walking with weight*, *running*, *running with weight*, *climbing stairs*, *climbing stairs with weight*). At first, data is collected in the form of accelerometer signals and heart rate signals. To do so, users carried the smartphone embedded accelerometer in their front left pant pocket, while the heart rate sensor is attached to their chest, by using a strap.

4.3.2 Pre-Processing

The collected data may contain unwanted spikes because of the changes caused by the movement of the subjects, since accelerometer readings are taken with respect to the inclination towards the ground. Hence that data is sent to a server machine where it is filtered in order to remove the noise from the data. To filter the accelerometer data we have used Butterworth filter and Median filter, hereby removing the low-frequency signals also. The sampling rate of the smartphone embedded accelerometer is 99.5Hz and that of the heart rate sensor is 250 Hz. Hence we have to interpolate the heartrate data to match the number of rows with the accelerometer data. The filtered data (including the filtered accelerometer data and the interpolated heartrate data) is then segmented by windowing with 50% overlap, so that it does lose the edge data, enabling easy extraction of features. Another dimension is added to the other three accelerometer dimensions (A_X, A_Y, A_Z), namely Signal Vector Magnitude ($SVMag$), defined as :

$SVMag = \sqrt{(A_X^2 + A_Y^2 + A_Z^2)}$

It is considered since it is independent of device orientation, helping features to be extracted irrespective of usage behavior.

4.3.3 Feature Extraction

After the processing of data is over, the next step is the extraction of features from the processed data. At first, we extract time-domain features on the four dimensions, including accelerometer axes and the $SVMag$ dimension. The features included variance and Mean Absolute Deviation (MAD) of the four dimensions on the processed windowed data. Also, the other features included squares of the original dimensions, which will neutralize the effect of sign and reflect the magnitude. Frequency-domain features were added to the time-domain features which included Power Spectral Density (PSD) [35].

These were the features of accelerometer. Now comes the introduction of heart rate features since accelerometer features alone cannot identify those activities having same accelerometer values, so only features having different pattern can help identify and for each activity heart rate is different. Also, there is confusion between dynamic activities and their corresponding intense one (*For example, running and running with weight*), since accelerometer data have fewer fluctuations for static ones rather than for intense ones. Heartrate features included variance and MAD of the windowed heartrate. Also, the other heart rate features were there like, the ratio of the variance found to the Resting Heart Rate (RHR) of the user and ratio of the MAD found to the RHR of the user, for each window. RHR is calculated by considering three times the heart rate having more number of occurrences when the person is sitting(i.e. in resting phase), and then taking the average of those heart rates while dividing by 3. Additional heartrate features like *Exercise Intensity* is also considered, which is calculated by two methods :

- ratio of that variance to the maximum heart rate of the user, multiplied by 100
- ratio of that MAD to the maximum heart rate of the user, multiplied by 100,

where Maximum Heartrate = 220 - Age of the user

4.3.4 Classification

As we can see in Fig. 4.1, the next step of feature extraction is Learning of classifiers. The features of the training set are fetched to the classifiers so that they learn and predict the activities. For validation of our work we used the classifiers: i. Linear Regression (LR) ii. Decision Tree (DT) iii. Bagged Trees iv. K-Nearest Neighbors ($K - NN$) v. Multilayer Perceptron (MLP) vi. Gaussian Naıve Bayes' (GNB) vii. Support Vector Machine (SVM).

4.3.5 Ensemble Classifier

The classifiers can recognize the activities from the test instances with acceptable accuracy up to a certain extent, since certain conditions of the activities cannot be recognized by base classifiers. It becomes challenging to find out that one classifier which can be tuned for every system, for identifying detail activities. An Ensemble model is derived from the other base classifiers, thus making it stronger than the individual base classifiers, also because the conditions which the individual classifiers fail to identify, can be highlighted by an ensemble model. We have used an amalgamation of artificial neural network and ensemble classifier for the proposed framework to detect detailed activities from the samples.

The predicted outputs of the base classifiers we got, by fetching the training samples, are fed as input to a neural network having one hidden layer. The Neural Network (NN) or Multilayer Perceptron (MLP) give certain weights as output on the basis of the predictions made by it on the sample constituting of the base classifier predictions, made on the training samples. Those weights are assigned to the predictions, made by the base classifiers. On the next step we feed the sample constituting of the base classifier predictions, made on the test set, along with the weights assigned, and the probability set (that is prediction probability of the labels made by the classifiers). We propose the Ensemble classifier, so that for making effective decisions on recognizing activities, it can apply the product of weights and probabilities. The proposed work for our work, explained in this chapter, is summarized as Algorithm 1. The proposed framework is implemented to carry out real life experiments. The experimental setup and results are illustrated in the next section.

Algorithm 1: RecogniseDetailedActivity()

input : train and test feature set $(A_X, A_Y, A_Z, A_{svm}, Hr)$
output: $labelledtestset$
Extract D_A = $A_X;\ A_Y;\ A_Z$
Extract D_H = Hr
D_p= window(filter(D_I), D_H)
SVMag=$\sqrt{(A_X^2 + A_Y^2 + A_Z^2)} : (A_X; A_Y; A_Z) \in D_p$
for *each* $F_i \in D_p$ **do**
    Variance = $\frac{1}{N-1} \times \sum_{(i=1)}^{n} |F_i - \mu|$
    MAD = $\frac{\sum_{(i=1)}^{n} |F_i - \mu|}{N}$
    $PSD = \frac{\sum_{(i=1)}^{n} freq_i \times P_i}{\sum_{(i=1)}^{n} P_i}$
    $HR_{bmi} = \frac{Variance(D_H)}{RestingHR}$ and $\frac{MAD(D_H)}{Resting\ HR}$
    $Intensity_{Exercise} = \frac{Variance(D_H)}{HR_{Max}} \times 100$ and $\frac{MAD(D_H)}{HR_{Max}} \times 100$ where $HR_{Max} = 220 - Age$
    $F' \leftarrow variance; MAD; PSD; HR_{bmi}; Intensity_{Exercise}$
end
clf=Classify(F': labels)
pred=clf.predict(F_{test})
prob=clf.probability(F_{test})
result=accuracy ($labels_{test}$: pred)
return result

4.4 Performance Evaluation

4.4.1 Experimental Setup

We have used the processed data from the dataset made by us, which is already mentioned in section 3.4. Fig.4.2 (a) and Fig. 4.2 (b) shows a sample of accelerometer data and the heartrate data which is being interpolated to keep the number of rows the same as the accelerometer signals respectively. Fig. 4.3 shows the set of features as shown in Algorithm 1.

Time (s)	X	Y	Z
0	0.459	1.34	8.102
0.009	0.689	1.187	7.489
0.021	0.842	1.034	6.876
0.03	0.766	1.187	6.799
0.039	0.612	1.34	7.106
0.057	0.536	1.8	8.561
0.063	0.536	1.8	8.715

(a)

Time	Heart rate
0	71
1	72
2	72
3	71
4	71
5	71
6	71

(b)

FIGURE 4.2: (a)Acceleration data collected from G-Sensor Logger Application embedded in Smartphone (b)Interpolated Heartrate data matched with acceleration signals

Var_X	Var_Y	....	MAD_X	MAD_Y	....	PSD_X	....	Var_hrbmi	....	Var_exercise_intensity	....
0.218845	0.04108		0.597993	0.116997		0.003547		0.00267		0.086312	
0.276583	0.168014		0.274855	0.484027		0.213621		0.003898		0.125985	
						⋮					
0.149815	0.140114		0.120669	0.194608		0.606682		0.006202		0.20046	
0.218845	0.04108		0.597993	0.116997		0.003547		0.00267		0.086312	

FIGURE 4.3: Features used by our work

Based on the classification of the training dataset, the test dataset is classified and accuracy comparison is done between predicted activities and the actual activities of the test dataset.

4.4.2 Experimental Results

The results are being examined for a combination of accelerometer and heart rate features mentioned in subsection 4.3.3. Amalgamation of time domain and frequency domain features work well with less error if static activities are considered. But it fails to differentiate between some dynamic activities and their corresponding intense activities, for example, walk is confused with its intense one i.e. walk with weight; climbing and climbing with weight are confused. So, Ensemble of classifiers is applied since the introduced features are found to be unsuccessful in distinguishing the detailed or intense activities using the individual base classifiers. It is observed that activities and their intense ones like, walk and walk with weight, climbing stairs and that with weight can be better distinguished. However, running is confused very less with running with weight and walk with weight. Our Ensemble Classifier is able to identify the test data set with little misclassification error than the other classifiers. Experimental results, including classifier accuracies including Ensemble Classifier (with the base classifiers), are illustrated in Table. 4.1.

TABLE 4.1: Summary of classification accuracy (in %)

Dataset	Classifier	Accuracy(%)	Error(%)
TEST DATA	LR	53.92	24.32
D1-LPT	DT	93.54	4.62
	BAGGING	93.54	4.57
	KNN	91.28	5.43
	MLP	77.07	12.48
	GNB	73.73	14.80
	SVM	82.13	9.63
	Ensemble(LR,DT,GNB, kNN,SVC,MLP)	94.61	3.65

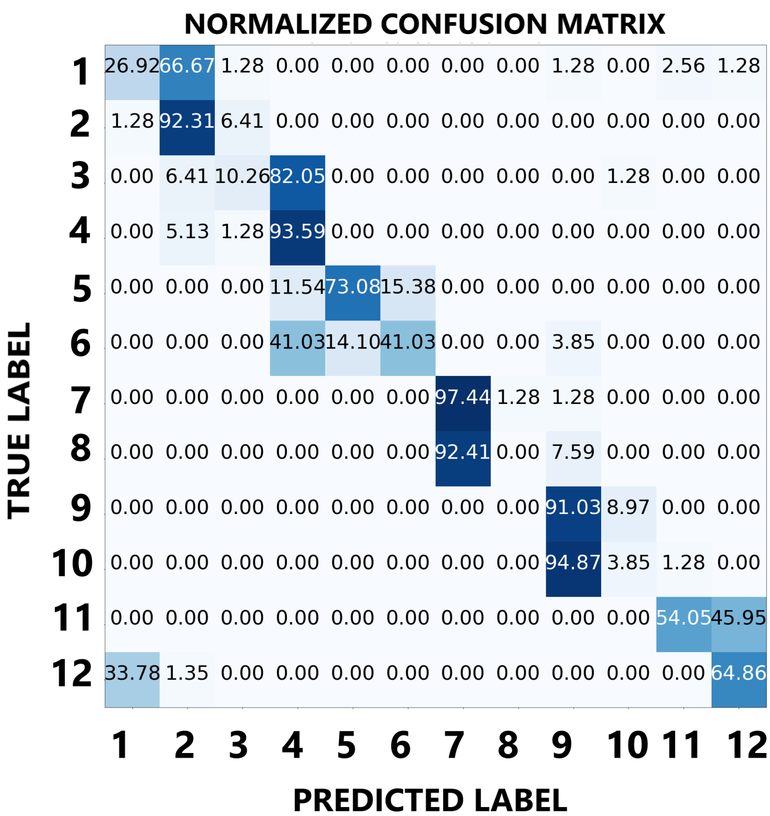

FIGURE 4.4: Confusion matrices for activity recognition using Linear Regression, for both accelerometer and heart rate sensor readings

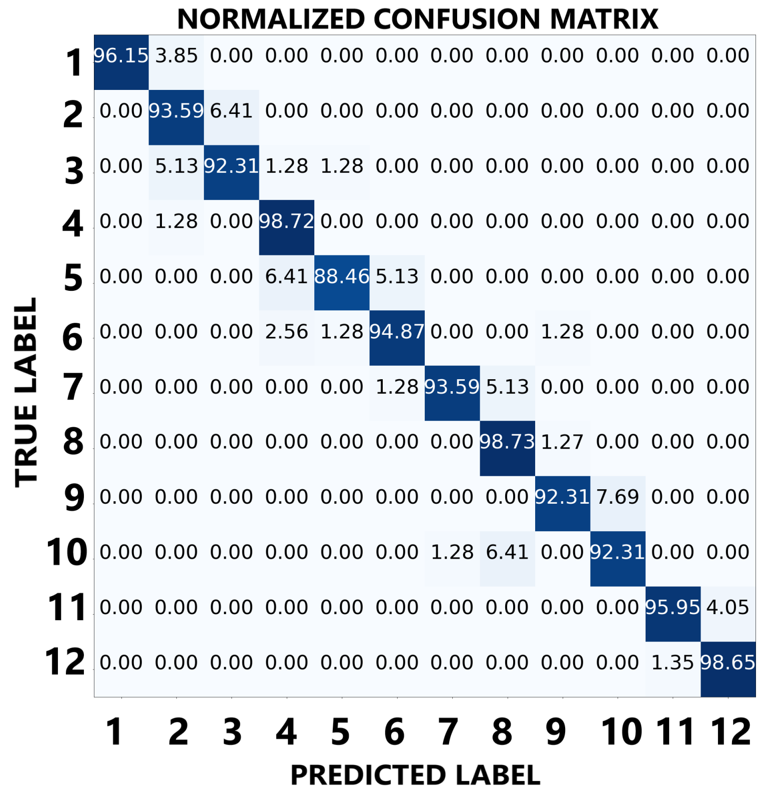

FIGURE 4.5: Confusion matrices for activity recognition using the ensemble classifier, for both accelerometer and heart rate sensor readings

Confusion matrix for the classifier Linear Regression is shown in Fig. 4.4 to put some light on the performance of individual classifiers. But it fails to distinguish between some dynamic activities and their corresponding intense ones like we can see in Fig 4.4, *walk* is confused with its intense activity i.e. *walk with weight*; *climbing* is confused with *climbing with weight*. The features included proves to be unsuccessful in recognizing the intense activities using the classifiers, hence Ensemble Classifier is applied, as we can see in Fig 4.5, the confusion matrix of the proposed ensemble is shown. Activities and their corresponding intense ones like, *walk* and *walk with weight*, *climbing stairs* and *climbing stairs with weight* can be differentiated properly.

4.5 Summary

This chapter gives a brief overview of our framework with ensemble classifier, along with features of accelerometer and heartrate. The next chapter depicts the result of different circumstances and analysis of the results.

Chapter 5

Result and Discussion

Result Analysis and Discussion

The results are being examined for both our proposed systems. One for the System based on Novel Features, where new heartrate features are being proposed to highlight the details of activities so that we can recognize even the intense activities. We observed from Chapter 3 that we can achieve more than 93% above on Subpart 3, where all the features of accelerometer and heartrate are involved. We compared the classifier accuracies for 10-fold-cross-validation and that of a test set, between all the accelerometer features and all the overall features. We come up with the result that the overall features give better than the accelerometer features. It happened so because, on involving the heartrate features proposed, the intense activity got highlighted more due to the fact that heartrate pattern is not the same for different activities. It can be observed that the Decision Tree gave the best result with above 93%.

Another system we have proposed, which involves an Ensemble classifier proposed by us. Combining the accelerometer data with heart rate data has clearly proven to be beneficial. Ensemble of classifiers based on weighted majority voting is proposed in order to improve the recognition accuracy of detailed intense activities. The ensemble is found to predict the intensive activities efficiently better than the individual base classifiers. Our Ensemble Classifier is able to identify the test data set activities with less error than the other classifiers as we have seen in Chapter 4. More than 94% accuracy can be achieved by using the ensemble classifier designed.

Summary

This chapter gives a brief discussion of results produced by some machine learning algorithms with different parameter settings. Analyzing all the results it can be concluded that DT gives better accuracy.

Chapter 6

Conclusion and Future Work

Conclusion

In this thesis, activity frameworks based on -

- *new heartrate features along with accelerometer features*, and
- *ensemble classifier with heartrate and accelerometer features*

are explained with the illustration of effect of different features on classification performance. Activities with different intensities are challenging to distinguish with good accuracy because of the factors like body movements and position of sensors. Features extracted on data collected from heartrate sensor is found to be helpful. An amalgamation of accelerometer and heartrate features proved to be advantageous as well. At several times, it is difficult to get good accuracy by the individual classifiers, in that case, an ensemble of classifier can prove to be strong to get a better result than all the base classifiers. A weighted majority voting based ensemble is proposed in our work in order to give a better result than that of its base classifiers. Both the experiments were carried on our collected data from four users. In both the cases, we observed to have achieved more than 93%
.

Future Work

For Detailed HAR, we sometimes need to identify static activities as well as intense. But exact labeling of activities in training becomes difficult, since, real life activities are complex in nature, where they could be a part of any complex routine. It becomes challenging when we have to label a certain set of activities that frequently occur together like a logical sequence. A person performs certain activities concurrently for an unequal interval of time. Sometimes, it is challenging to collect training data with accurate activity labels if the transition between the activities is too fast, thereby ambiguous information in labels leading to difficulty for traditional supervised classification. So, if an instance is recognized as a group of activities then the training becomes flexible where the system needs to identify a sequence of activities. In that case, the ambiguity of labels leads to the idea of multiple instances being assigned the same relevant label or a combination of labels for classification. Also if data is grouped and classified for a longer duration, then it may be found that two users are performing the same set of activities(same composite activity) Hence, We will look forward to proposing Multi-Instance Multi-Learning (*MIML*) frameworks to make Activity Recognition more efficient, covering a wide area of combinations of activities.

Bibliography

[1] T. Choudhury et al. “The Mobile Sensing Platform: An Embedded Activity Recognition System”. In: *IEEE Pervasive Computing* 7.2 (2008), pp. 32–41.

[2] N. Ravi et al. “Activity Recognition from Accelerometer Data”. In: *Proceedings of the Seventeenth Conference on Innovative Applications of Artificial Intelligence,Pittsburgh, Pennsylvania*. Vol. 3. 2005, pp. 1541–1546.

[3] Qin N., A.B.G. Hernando, and I.P. de la Cruz. “The elderly’s independent living in smart homes: A characterization of activities and sensing infrastructure survey to facilitate services development”. In: *Sensors2015* (2015), pp. 11312–11362.

[4] J. Rafferty et al. “From Activity Recognition to Intention Recognition for Assisted Living Within Smart Homes”. In: 47.3 (2017), pp. 368–379.

[5] Demiris G et al. “Senior residents perceived need of and preferences for smart home sensor technologies”. In: *Int J Technol Assess Health Care 2008 Winter* (2008), pp. 120–124.

[6] Suneth Ranasinghe et al. “A Review on Applications of Activity Recognition Systems with Regard to Performance and Evaluation”. In: *International Journal of Distributed Sensor Networks* 12.8 (2016).

[7] N. Zouba, F. Bremond, and M. Thonnat. “Monitoring Activities of Daily Living (ADLs) of Elderly Based on 3D Key Human Postures”. In: *In the 4th International Cognitive Vision Workshop, ICVW 2008 - Santorini, Greece* (2008).

[8] Roni Ram et al. “universAAL: Provisioning Platform for AAL Services”. In: *Ambient Intelligence - Software and Applications*. Ed. by Ad van Berlo et al. Heidelberg: Springer International Publishing, 2013, pp. 105–112.

[9] Vacher M1 et al. “The SWEETHOME Project: Audio Technology in Smart Homes to improve Well-being and Reliance”. In: *33rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2011)* (2011), pp. 5291–5294.

[10] H Heuvel et al. "Mobiserv: a service robot and intelligent home environment for the Provision of health, nutrition and safety services to older adults". In: *Gerontechnology 2012* 11.2 (2012), p. 373.

[11] Zhu C and Sheng W. "Wearable sensor-based hand gesture and daily activity recognition for robot-assisted living". In: *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 41.3 (2011), pp. 569–573.

[12] Kamel Boulos MN et al. "CAALYX: a new generation of location-based services in healthcare". In: *International Journal of Health Geographics* (2007).

[13] F Fusier et al. "Video understanding for complex activity recognition". In: *Machine Vision and Applications* 18.3-4 (2007), pp. 167–188.

[14] J.M. Lien, G. Kurillo, and R. Bajcsy. "Multi-camera teleimmersion system with real-time model driven data compression". In: *The Visual Computer* (2010), pp. 3–15.

[15] N. Gkalelis et al. "The i3DPost multiview and 3D human action/interaction". In: *conference for visual media production,London,New York* (2009), pp. 159–168.

[16] G. Chetty and M. White. "Body sensor networks for human activity recognition". In: *2016 3rd International Conference on Signal Processing and Integrated Networks (SPIN), Noida* (2016), pp. 660–665.

[17] D. Anguita et al. "A Public Domain Dataset for Human Activity Recognition Using Smartphones". In: *European Symposium on Artificial Neural Networks, Computational Intelligenceand Machine Learning. Bruges, Belgium* (2013).

[18] D. Roggen et al. "Collecting complex activity data sets in highly rich networked sensor environments". In: *Seventh International Conference on Networked Sensing Systems* (2010).

[19] R. Chavarriaga et al. "The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition". In: *Pattern Recognition Letters* (2013), pp. 2033–2042.

[20] E. M. Tapia et al. "Real-Time Recognition of Physical Activities and Their Intensities Using Wireless Accelerometers and a Heart Rate Monitor". In: *11th IEEE International Symposium on Wearable Computers, Boston, MA,* (2007), pp. 37–40.

[21] D Curone et al. "Heart rate and accelerometer data fusion for activity assessment of rescuers during emergency interventions". In: *IEEE Transactions on Information Technology in Biomedicine* 14.3 (2010), pp. 702–710.

[22] E. A. P. J. Prawiro et al. "Integrated Wearable System for Monitoring Heart Rate and Step during Physical Activity". In: *Mobile Information Systems* 2017 (2017), pp. 1–2.

[23] Goldberger AL et al. “Components of a New Research Resource for Complex Physiologic Signals”. In: *Circulation, 2000.* 101.23 (2000), e215–e220.

[24] P. Heesu et al. “The Role of Heart-Rate Variability Parameters in Activity Recognition and Energy-Expenditure Estimation Using Wearable Sensors”. In: *Sensors (Basel) 2017* 1698.7 (2017).

[25] T. Kao, C. Lin, and J. Wang. “Development of a portable activity detector for daily activity recognition”. In: *2009 IEEE International Symposium on Industrial Electronics, Seoul* (2009), pp. 115–120.

[26] F Miao et al. “Identifying typical physical activity on smartphone with varying positions and orientations”. In: *Bio Med Eng* 14:32 (2015).

[27] R.Yang and B.Wang. “PACP: a position-independent activity recognition method using smartphone sensors”. In: *Information* 7.4 (2016).

[28] J. Wannenburg and R. Malekian. “Physical Activity Recognition From Smartphone Accelerometer Data for User Context Awareness Sensing”. In: *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 47.12 (2017), pp. 3142–3149.

[29] ZH.Zhou. “Ensemble learning”. In: *Encyclopedia of biometrics,Springer* (2009), pp. 270–273.

[30] J. Saha, C. Chowdhury, and S. Biswas. “Two phase ensemble classifier for smartphone based human activity recognition independent of hardware configuration and usage behaviour”. In: *Microsystem Technologies* 24 (2018), pp. 2737–2752.

[31] D.Coskun, OD.Incel, and A.Ozgovde. “Phone position/placement detection using accelerometer: impact on activity recognition”. In: *IEEE tenth international conference on intelligent sensors,sensor networks and information processing (ISSNIP)* (2015), pp. 1–6.

[32] Y. Yuan et al. “An Ensemble Approach for Activity Recognition with Accelerometer in Mobile-Phone”. In: *IEEE 17th International Conference on Computational Science and Engineering,Chengdu* (2014), pp. 1469–1474.

[33] SL.Lau, I.Konig, and K.David. “Supporting patient monitoring using activity recognition with a smartphone”. In: *The 7th international symposium on wireless communication systems York* (2010), pp. 810–814.

[34] A.Bayat, M.Pomplun, and D.A. Tran. “A Study on Human Activity Recognition Using Accelerometer Data from Smartphones”. In: *Procedia Comput. Sci.* 34 (2014), pp. 450–457.

[35] C. Altın and O. Er. “Comparison of different time and frequency domain feature extraction methods on elbow gesture’s EMG”. In: *Eur. J. Interdiscip. Stud,* 2.3 (2016), pp. 35–44.