Daily Tracker

Smartphone Computing Term Project (Autumn, 2017)

Group

Abhisek Chowdhury (16CS71P07)
Aditi Chandra (16CS71P02)

Mentor

Snigdha Das

1. Problem Statement

Monitoring daily activity routine to know your health status and

RECOMMEND HEALTH TIPS

2. Motivation

Analysis of human daily activities is an important method for **physical as well as mental health status monitoring and disease prevention**

3. Road Map

Data Acquisition

- Gathering of Accelerator sensor data
- Integration of Google Activity Recognition API

Data Pre-processing

- Filtration of the dataset
- Smoothening
- Displacement Measurement

Detection of Health Status

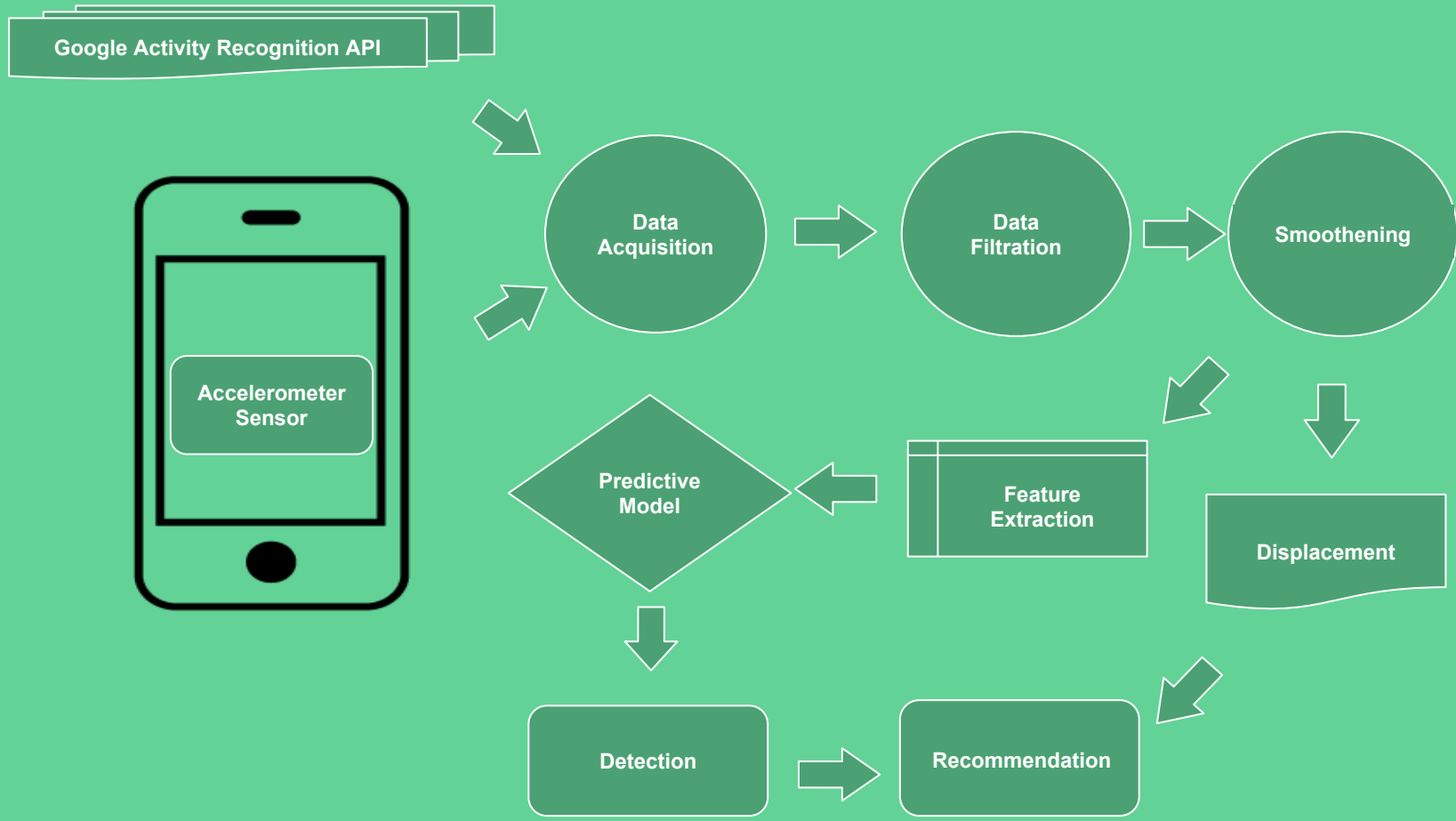
- Feature Extraction
- Classification using SVM , kNN, Random Forest etc
- Activity Detection, Suggestion

Recommendation

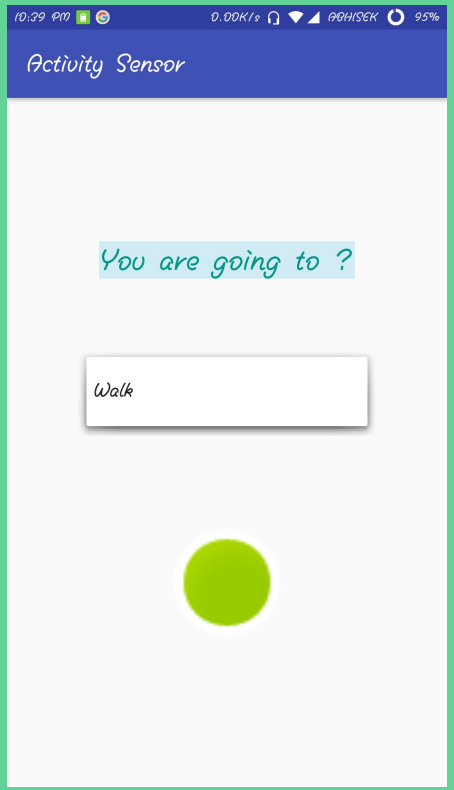
- Suggesting Tips

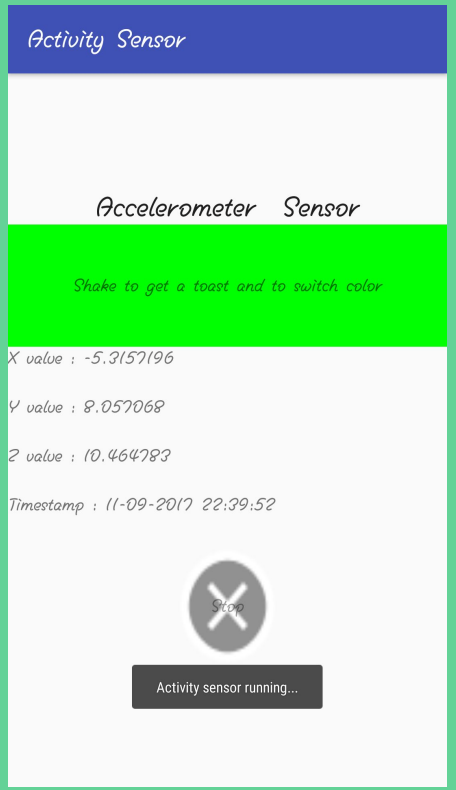
eg. You've not run much today !

4. Framework


Google Activity Recognition API
Accelerometer Sensor
Data Acquisition
Data Filtration
Smoothening
Displacement
Feature Extraction
Predictive Model
Detection
Recommendation

Data Acquisition





Data Filtration and Smoothening

ALGORITHM FILTRATION

for each tuple $tp(x_i, y_i, z_i, t_i, l_i)$

threshold$_{acc} \leftarrow 2$

acceleration $\leftarrow \sqrt{ (x_i^2 + y_i^2 + z_i^2)}$

if (acceleration > threshold$_{acc}$)

$filter\_tp(x_i, y_i, z_i, t_i, l_i) \leftarrow tp(x_i, y_i, z_i, t_i, l_i)$

ALGORITHM SMOOTHENING

for every $min(t_i)$ in each tuple $filter\_tp(x_i, y_i, z_i, t_i, l_i)$

calculate mean(x), mean(y), mean(z)

for every min in t_i

$smooth\_tp(x_i, y_i, z_i, min(t_i), l_i) \leftarrow filter\_tp(mean(x), mean(y), mean(z), t_i, l_i)$

	A	B	C	D	E
1	x-value	y-value	z-value	timestamp	travel_mc
2	5.568634	29.42409	-0.97112	7/9/2017 10:01	Biking
3	-1.76418	13.06555	4.343353	7/9/2017 10:01	Biking
4	1.101227	20.59097	-0.4758	7/9/2017 10:01	Biking
5	-0.70773	14.25478	3.088318	7/9/2017 10:02	Biking
	0.465942	15.17841	0.872559	7/9/2017 10:02	Biking
	0.465942	15.17841	-0.04628	7/9/2017 10:02	Biking
	1.383591	18.30225	0.081726	7/9/2017 10:02	Biking
	0.6801	13.8468	0.958694	7/9/2017 10:02	Biking
10	-0.59767	15.0827	3.545334	7/9/2017 10:02	Biking
11	1.004318	13.90782	0.123611	7/9/2017 10:02	Biking
12	0.053177	16.12238	0.896484	7/9/2017 10:02	Biking
13	-0.89796	13.82646	1.439652	7/9/2017 10:02	Biking
14	1.632446	16.78639	-0.54997	7/9/2017 10:02	Biking
15	1.766434	14.19377	-0.07858	7/9/2017 10:02	Biking
16	-3.90910	-15.8455	-0.89334	7/9/2017 10:03	Biking
17	-2.41142	-15.6304	-2.96793	7/9/2017 10:03	Biking
18	-1.30116	-13.6934	-4.13802	7/9/2017 10:03	Biking
19	1.393158	-15.9414	-2.99304	7/9/2017 10:03	Biking

Data Acquisition

	A	B	C	D	E
1	x-value	y-value	z-value	timestamp	travel_mode
2	7.090394	-5.9873	13.54592	7/9/2017 9:57	Biking
3	10.4464	8.637634	13.58801	7/9/2017 9:58	Biking
4	3.419159	10.77203	9.686996	7/9/2017 9:59	Biking
	0.875107	14.69507	0.36528	7/9/2017 10:02	Biking
8	0.951088	16.02367	1.382828	7/9/2017 10:04	Biking
9	-0.41791	15.21311	2.11832	7/9/2017 10:05	Biking
10	1.869092	21.68641	1.739478	7/9/2017 10:06	Biking
11	-0.33147	16.82826	1.933777	7/9/2017 10:07	Biking
12	0.384927	15.10731	1.231995	7/9/2017 10:08	Biking
13	0.053177	16.12238	0.896484	7/9/2017 10:09	Biking
14	0.833639	14.93554	0.270365	7/9/2017 10:10	Biking
15	-0.92378	-15.0781	-0.88617	7/9/2017 10:11	Walk
16	-3.93853	-13.759	-0.01303	7/9/2017 10:12	Walk
17	-2.69458	-13.9913	0.371262	7/9/2017 10:13	Walk
18	-4.55779	-14.5875	0.776047	7/9/2017 10:14	Walk
19	-2.45689	-20.7076	0.930671	7/9/2017 10:15	Walk

Filtration and Smoothening

Displacement Measurement

$$\text{displacement} = \iint_0^T \text{acceleration}$$

ALGO DISPLACEMENT

for each tuple smooth_tp(x_i, y_i, z_i, min(t_i), l_i)

init t ← 60

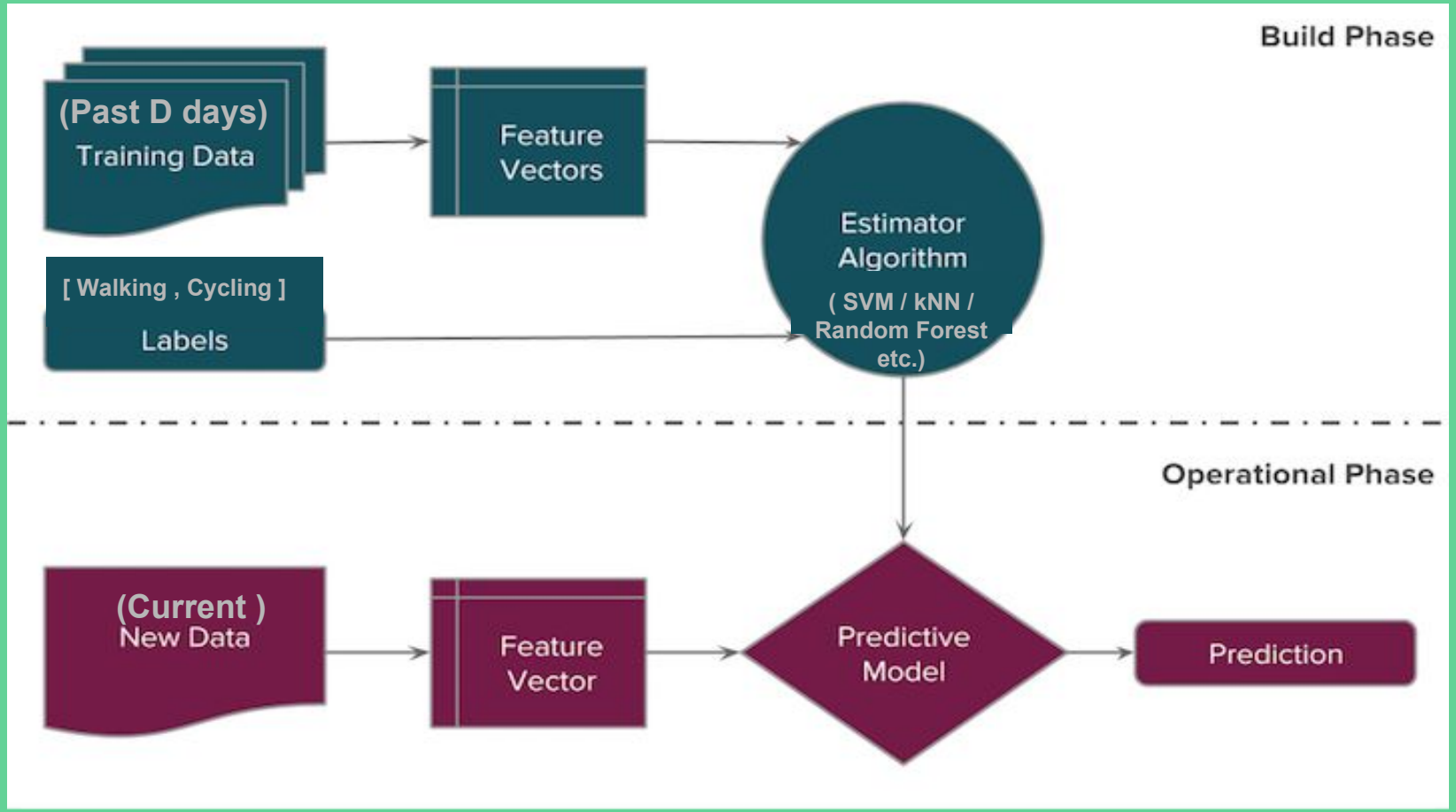
$\text{acceleration}_i \leftarrow \sqrt{(x_i^2 + y_i^2 + z_i^2)}$

$\text{displacement}_i \leftarrow \iint_0^t \text{acceleration}_i$

	A	B	C	D	E	F
1	x-value	y-value	z-value	timestamp	travel_mc	disp(m)
2	7.090394	-5.9873	13.54592	7/9/2017 9:57	Biking	280.21
3	10.4464	8.637634	13.58801	7/9/2017 9:58	Biking	291.5965
4	3.419159	10.77203	9.686996	7/9/2017 9:59	Biking	310.4425
5	0.613098	15.05638	-0.32445	7/9/2017 10:01	Biking	322.5362
6	0.875107	14.69507	0.36528	7/9/2017 10:02	Biking	313.3628
7	0.856689	17.07473	1.52843	7/9/2017 10:03	Biking	355.5822
8	0.951088	16.02367	1.382828	7/9/2017 10:04	Biking	341.0557
9	-0.41791	15.21311	2.11832	7/9/2017 10:05	Biking	352.6828
10	1.869092	21.68641	1.739478	7/9/2017 10:06	Biking	332.9181
11	-0.33147	16.82826	1.933777	7/9/2017 10:07	Biking	327.4711
12	0.384927	15.10731	1.231995	7/9/2017 10:08	Biking	319.5812
13	0.053177	16.12238	0.896484	7/9/2017 10:09	Biking	288.0737
14	0.833639	14.93554	0.270365	7/9/2017 10:10	Biking	210.4806
15	-0.92378	-15.0781	-0.88617	7/9/2017 10:11	Walk	30.56619
16	-3.93853	-13.759	-0.01303	7/9/2017 10:12	Walk	31.15578
17	-2.69458	-13.9913	0.371262	7/9/2017 10:13	Walk	27.12662
18	-4.55779	-14.5875	0.776047	7/9/2017 10:14	Walk	25.65132
19	-2.45689	-20.7076	0.930671	7/9/2017 10:15	Walk	29.4368

Displacement

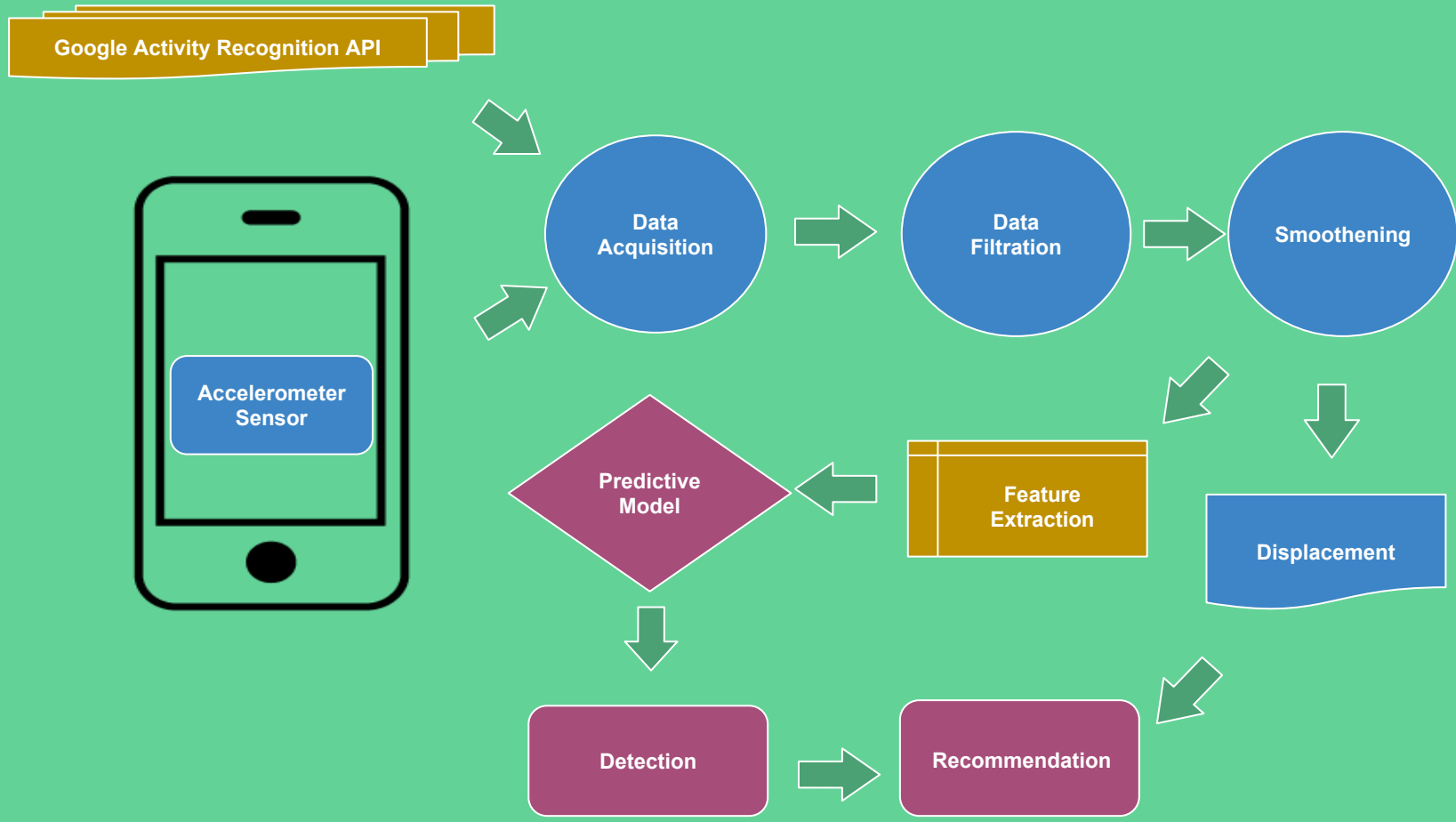
Use of Artificial Intelligence in Ambient Intelligence



1995	Aminian et al,	Walking speed estimation using neural network	
1997	Yang et al	Human action learning via Hidden Markov Model	HMM
2004	Mathie et al, Lukowicz et al,(w) **Bao et al,**	Classification of daily movement by triaxial accelerometer Recognizing activity using body worn accelerometer **Activity recognition from user annotated acceleration data**	Binary decision tree (FU) LDA & HMM (FU) Nearest neighbor, C4.5 Decision Tree, Naïve Bayes classifier
2003	Sundaresan et al	A Hidden Markov Model based framework for recognition of humans from gait sequences	HMM
2005	Ravi et al, Zhang et al Begg & Kamruzzaman	**Activity recognition from accelerometer data** Assessment of human locomotion by using an insole measurement system and artificial neural networks. A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data	: activity recognition and classification – decision trees, decision tables, naïve Bayes classifier, nearest neighbour SVM
2006	Karantonis et al, Ward et al, (w) Allen et al,	Real time human movement classifier using accelerometer : Activity recognition using body worn accelerometer : Classification of a known sequence of accelerometry data using Gaussian mixture model	SVM HMM :Rule-based Heuristic system and Gaussian mixture model
2007	Rothney et al	An artificial neural network model of energy expenditure using nonintegrated acceleration signals.	

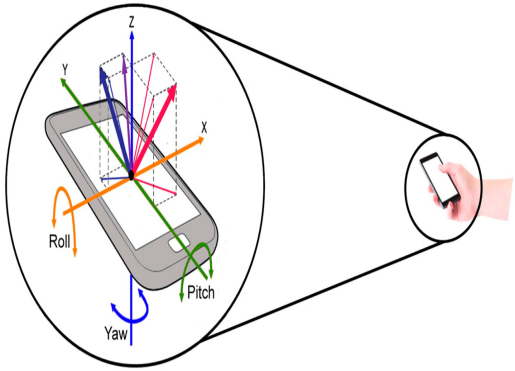
2008	Yang et al, Preece et al, Stikie et al	Acceleration measurements Feature extraction methods for classification of dynamic activities ADL recognition based on RFID and accelerometer sensing	: learning algorithms for neural classifier K-NN Naive Bayes, Hidden Markov Models (HMMs) and Joint Boosting.
2009	Bonomi et al, Amstutz et al,	Type of physical activity using accelerometer HMM based gesture recognition using wristwatch device	Decision trees and multiple regression HMM
2010	Mannini et al, (w) Kwapisz et al	Machine learning methods for classifying activity from on-body accelerometer Activity recognition using cell phone accelerometer	HMM Decision trees, k-Nearest Neighbor, Naïve Bayes, and Bayes Net classifiers with five-fold cross validation were used for learning
2012	Anguita et al	Human activity recognition on smartphones using a multiclass hardware-friendly SVM	SVM
2013	Cleland et al (w)	Optimal placement of accelerometer ..	SVM
2014	Gao, et al Bayat et al, Gupta et al, Gracia-Ceja et al, Ronao et al	Accelerometer based multi-sensor vs single sensor activity recognition Accelerometer data from smart phone Activity recognition using triaxial accelerometer Long term activity recognition from wristwatch accelerometer Human activity recognition using smartphone sensor...	ANN , Decision Tree , KNN Naïve Bayes & SVM classifier SVM RF Na¨ıve Bayes and kNN HMM CRF HMM
2015	Nef	Evaluation of 3 state of the Art Classifiers for recognition of ADL...	naive Bayesian (NB), support vector machine (SVM) and random forest (RF).
2016	Cufoglu & Coskun Sonderen Mo & Feng Debes et al,	Testing & analysis of ADL data with Machine Learning Algorithm Detection of transportation mode solely using smartphones Human daily activity recognition with wearable sensors, incremental learning Monitoring activities of daily living in smart homes	Decision Trees, Random Forest and k-Nearest Neighbors. Learning algorithm Hybrid models relying on kernel metric distances

5. Progress Made


Google Activity Recognition API
Accelerometer Sensor
Data Acquisition
Data Filtration
Smoothening
Displacement
Feature Extraction
Predictive Model
Detection
Recommendation

6. Remaining Task

A recommendation system for monitoring and detection of physical and mental health status



Thank You !