

Human activity recognition using smartwatch gyroscope: A data mining approach

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A dynamic photograph of a woman with long blonde hair tied back, wearing a teal jacket and black leggings, jogging on a rocky mountain trail. She is captured mid-stride, moving towards the left. The background features a vast, green mountain range under a bright blue sky with scattered white clouds. The sun is positioned in the upper right corner, casting a warm glow and creating lens flare. The overall scene conveys a sense of energy, movement, and achievement.

Data Analytics and Visualisation

Dr Ah-Lian Kor

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Introduction

Aim & Objectives

02

Findings

Level 1-4

03

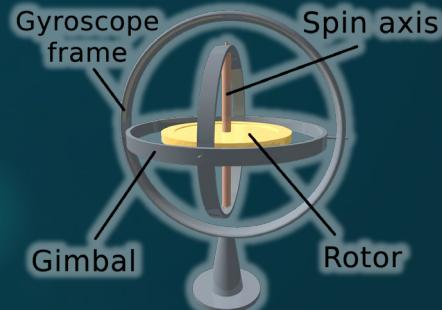
Methodology

Macro & Micro

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Future Works



WISDM Dataset

Jogging Typing and Folding Clothes

Introduction



AIM

The aim is to recognise human activities using the smartwatch's gyroscope, biometric data of daily routines, including jogging, typing and folding clothes, by taking advantage of data mining processes

Objectives

RO3 Level 3: Machine Learning techniques

RQ4: Can the subject activity be predicted based on the categorised biometric data captured by the gyroscope sensor?

RO4: Level 4: Deep Learning

RQ6: Can the subject activity be predicted by the raw biometric data captured by the sensors?

RO1 Level 1: Descriptive statistics analysis

RQ1: Are the biometric sensor data different in each task?

RQ2: How different are the biometric sensor data in various people?

RO2 Level 2: Inferential statistics analysis

RQ3: Is there any significant pattern for each activity compared to other activities?



Macro Methodology

Crossindustry standard
process for data mining



CRISP-DM

Sample, Explore, Modify,
Model, Assess



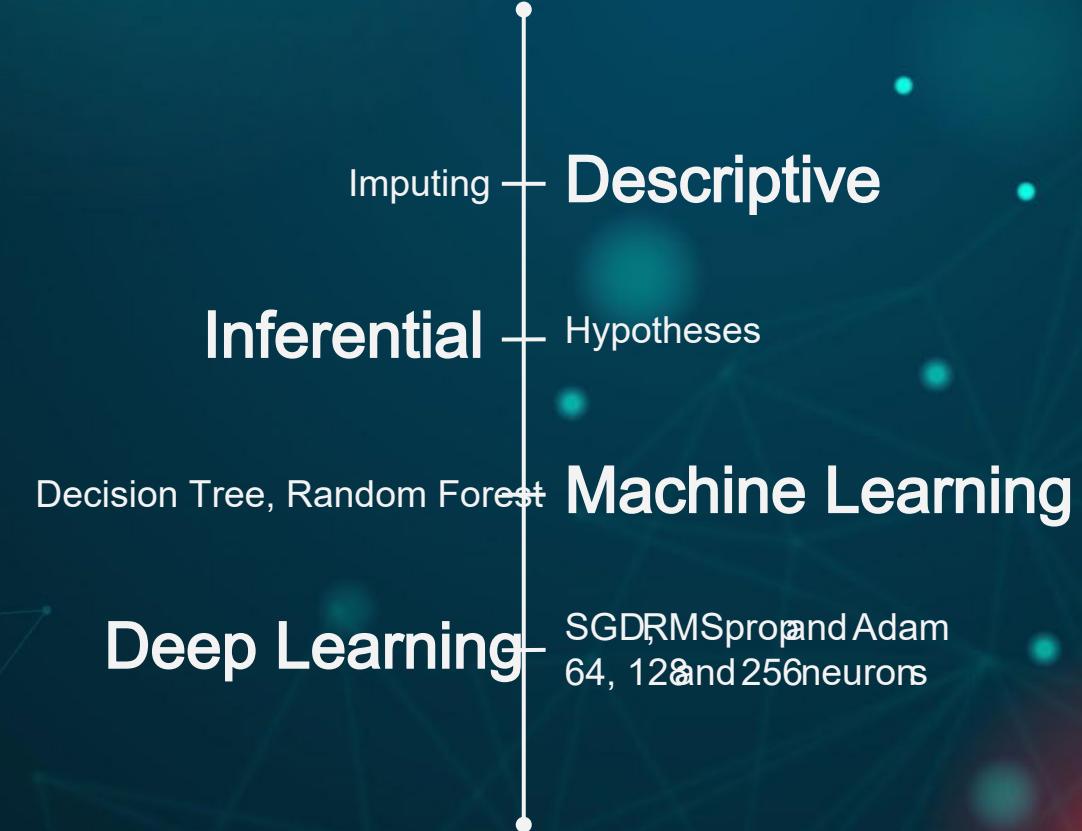
SEMMA

Knowledge Discovery in
Databases



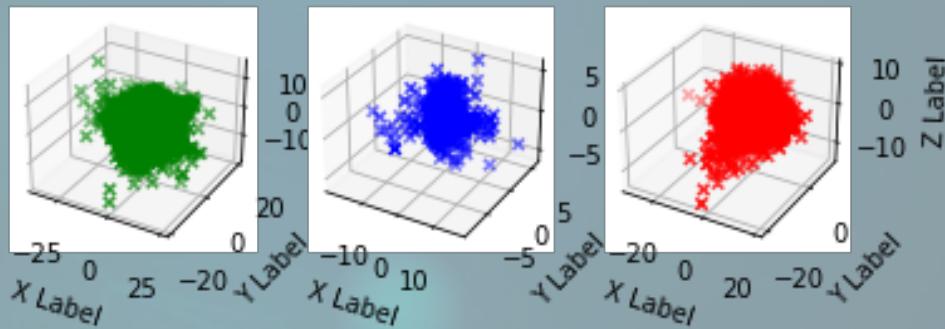
KDD

Micro Methodology



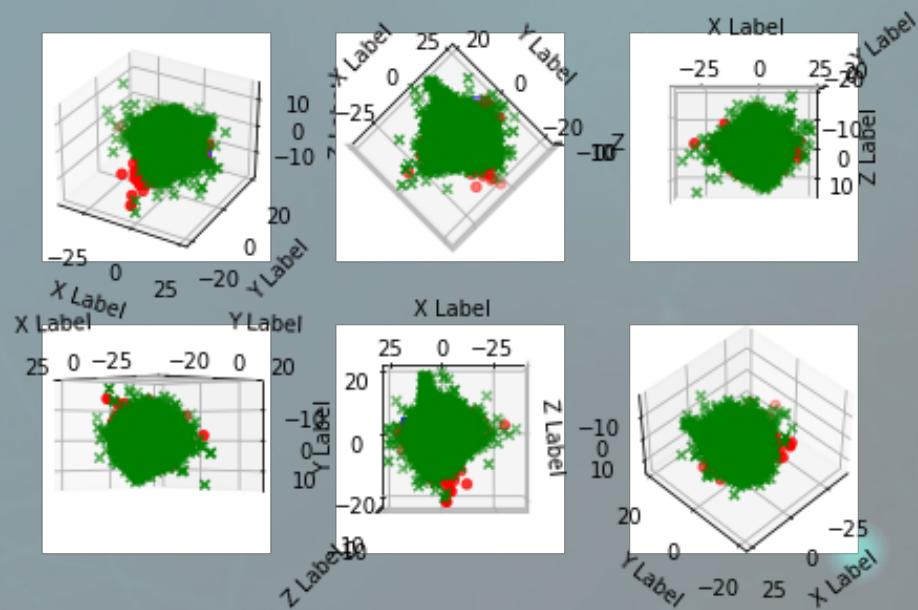
Type of Activity	Descriptive Analysis								
	count	mean	std	min	25%	50%	75%	max	
Jogging	0	187834.0	-0.251163	2.384040	-34.858818	-1.495725	-0.191051	1.033047	24.217474
	1	187834.0	-0.017893	2.758686	-18.896862	-1.853837	0.079589	1.886868	19.104145
	2	187834.0	0.025555	2.632422	-17.444334	-1.542882	0.015315	1.602832	14.072606
Typing	0	187175.0	0.000827	0.376592	-18.084496	-0.096836	0.000000	0.095923	15.814603
	1	187175.0	-0.000038	0.210979	-8.617611	-0.051872	0.000899	0.052285	5.622283
	2	187175.0	0.000090	0.212114	-5.717322	-0.042782	0.000583	0.047937	5.517232
Folding Clothes	0	193373.0	-0.017581	2.032569	-29.129051	-0.863939	-0.004474	0.815522	19.209053
	1	193373.0	-0.010080	1.161938	-20.301973	-0.534951	0.003196	0.522558	11.141437
	2	193373.0	0.001540	1.163480	-13.460214	-0.484236	0.013848	0.559211	9.442167

0: x-axis, 1: y-axis, 2: z-axis



3D scatter plot of the features (Green: Jogging, Blue: Typing and Red: Folding clothes)

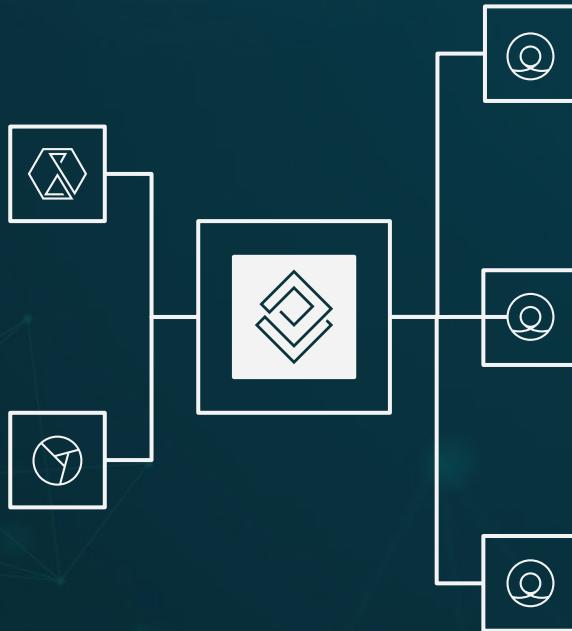
3D scatter plot of the features in one graph from six different angles (x: Jogging, star: Typing and dot: Folding clothes)



Oneway ANOVA

Null Hypotheses are as follows for each axis (H_0): mean of Jogging activity data = mean of Typing activity data = mean of Folding clothes activity data

Alternative Hypotheses for each axis are as follows (H_a): At least one means for the activities is not equal to the other



F Value (x) = 1116.34

P Value (x) = 0

The null hypothesis can be rejected

F Value (y) = 5.02549

P Value (y) = 0.00656867

The null hypothesis can be rejected

F Value (z) = 13.9398

P Value (z) = 8.83457e

The null hypothesis can be rejected

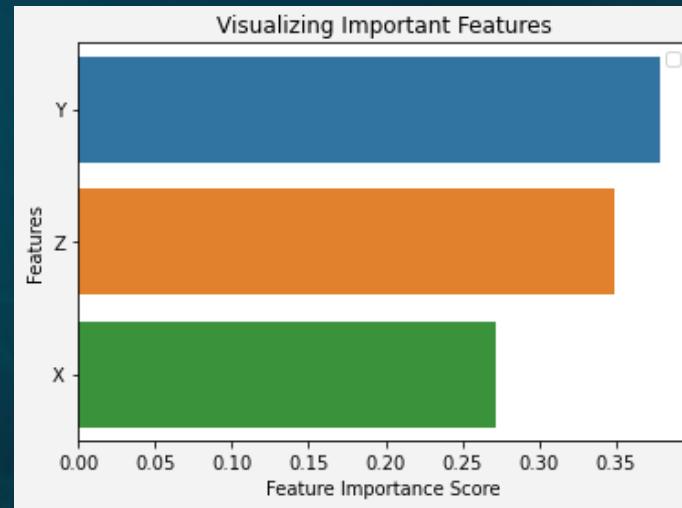
Max depth	Decision tree Accuracy				
	Attempt #1	Attempt #2	Attempt #3	Attempt #4	Attempt #5
1	46.479%	46.479%	46.479%	46.479%	46.479%
2	59.891%	59.891%	59.891%	59.891%	59.891%
3	67.20%	.29667	67.296%	67.296%	67.296%
4	71.72%	.729%71	71.729%	71.729%	71.729%
5	72.970%	72.970%	72.970%	72.970%	72.970%
6	73.801%	.801%73	73.801%	73.801%	73.801%
7	74.438%	74.438%	74.438%	74.438%	74.438%
8	74.632%	74.634%	74.632%	74.634%	74.633%
9	74.754%	74.754%	74.755%	74.755%	74.756%
10	74.858%	74.858%	74.862%	74.856%	74.860%

Decision Tree

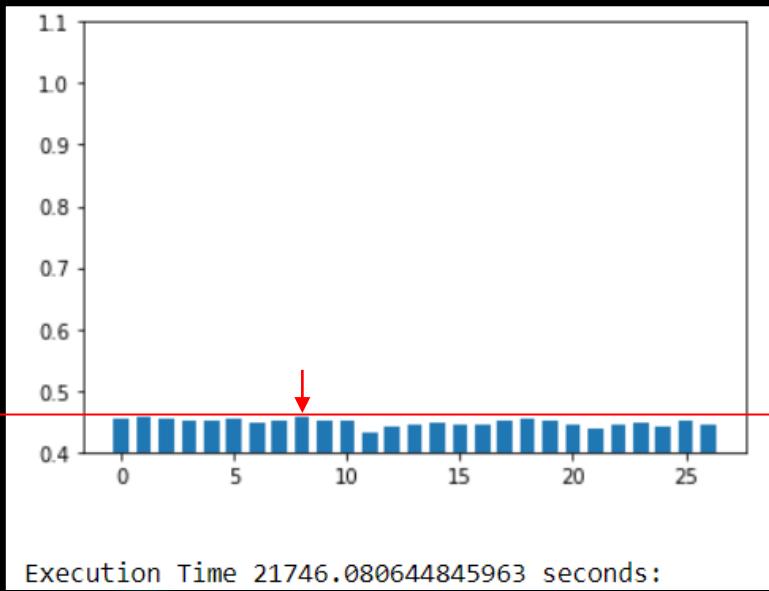
(Max depth = 4)



Random Forest Accuracy				
Attempt #1	Attempt #2	Attempt #3	Attempt #4	Attempt #5
74.489%	74.474%	74.520%	74.472%	74.509%
Attempt #6	Attempt #7	Attempt #8	Attempt #9	Attempt #10
74.545%	74.470%	74.491%	74.539%	74.475#



Deep Learning

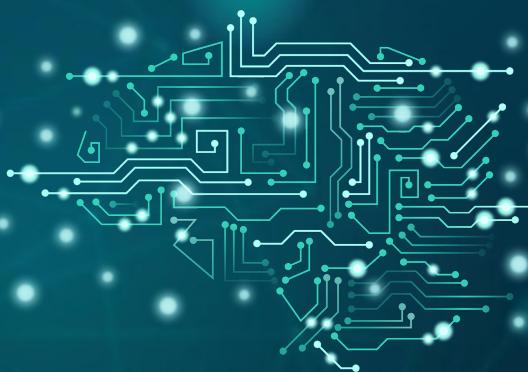


Model: "sequential_30"

Layer (type)	Output Shape	Param #
<hr/>		
dense_90 (Dense)	(None, 14)	56
activation_87 (Activation)	(None, 14)	0
dense_91 (Dense)	(None, 128)	1920
activation_88 (Activation)	(None, 128)	0
dense_92 (Dense)	(None, 3)	387
activation_89 (Activation)	(None, 3)	0
<hr/>		
Total params:	2,363	
Trainable params:	2,363	
Non-trainable params:	0	

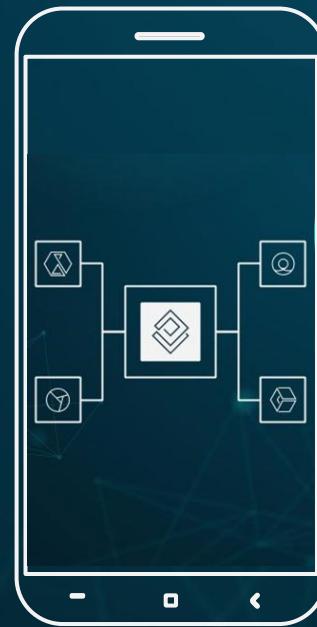


Conclusion



Future Work

- Accelerometer data
- Smartphone data
- Testing with realworld data



THANKS!

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