Multimodal Human Activity Recognition From Wearable Sensors Using Machine Learning and A Feature Selection Approach

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OUTLINE

- **Introduction:**
  - Motivation
  - Problem and Thesis Statement
  - Related Work
- **Methodology:**
  - Data Preprocessing
  - Machine Learning Algorithms
  - Feature Extraction and Selection
- **Design and Implementation:**
  - Dataset Description
  - The Architecture of the System

OUTLINE

Thesis contributions:

- Optimal Selection of Sensor Placement from the lower limb.
- Optimal Machine Learning Algorithm for Activity Recognition.
- Optimal Number of Features and Single Axis vs Triple Axis
- Fusion of Accelerometer, Gyroscope, and Electromyography Sensors for Activity Recognition

Conclusion:

- Publications
- Future Work

INTRODUCTION

- Human activity recognition aims to identify and recognize the activities of a person over an observed period of time and via a series of actions.

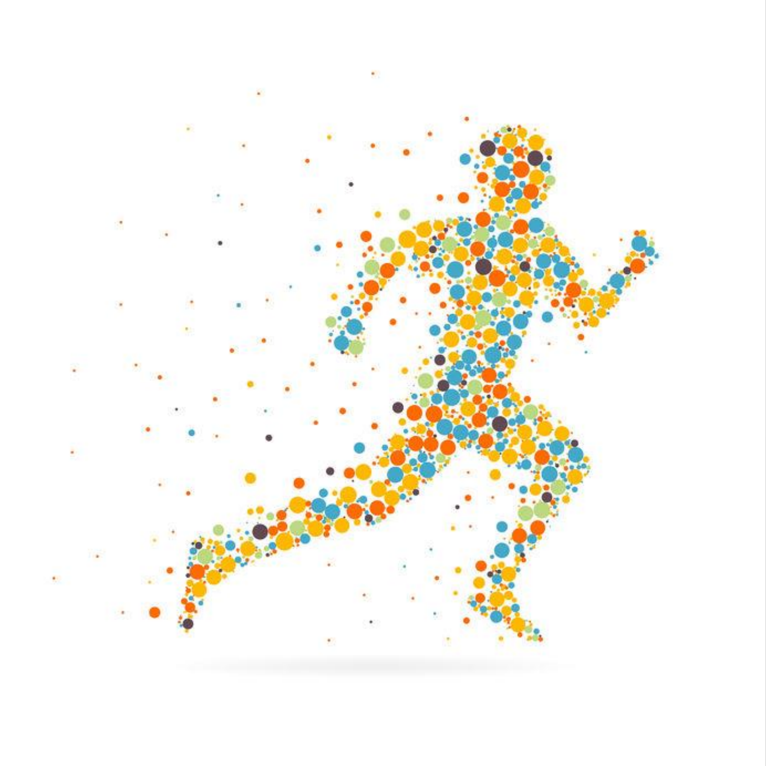
- The first step in developing an activity recognition system is the sensing of the activities.

- The classification of human actions from wearable sensors has become an integral part of remote health monitoring Systems.

INTRODUCTION

- On the other hand, machine learning (ML) has proven to be an important tool for data analysis.

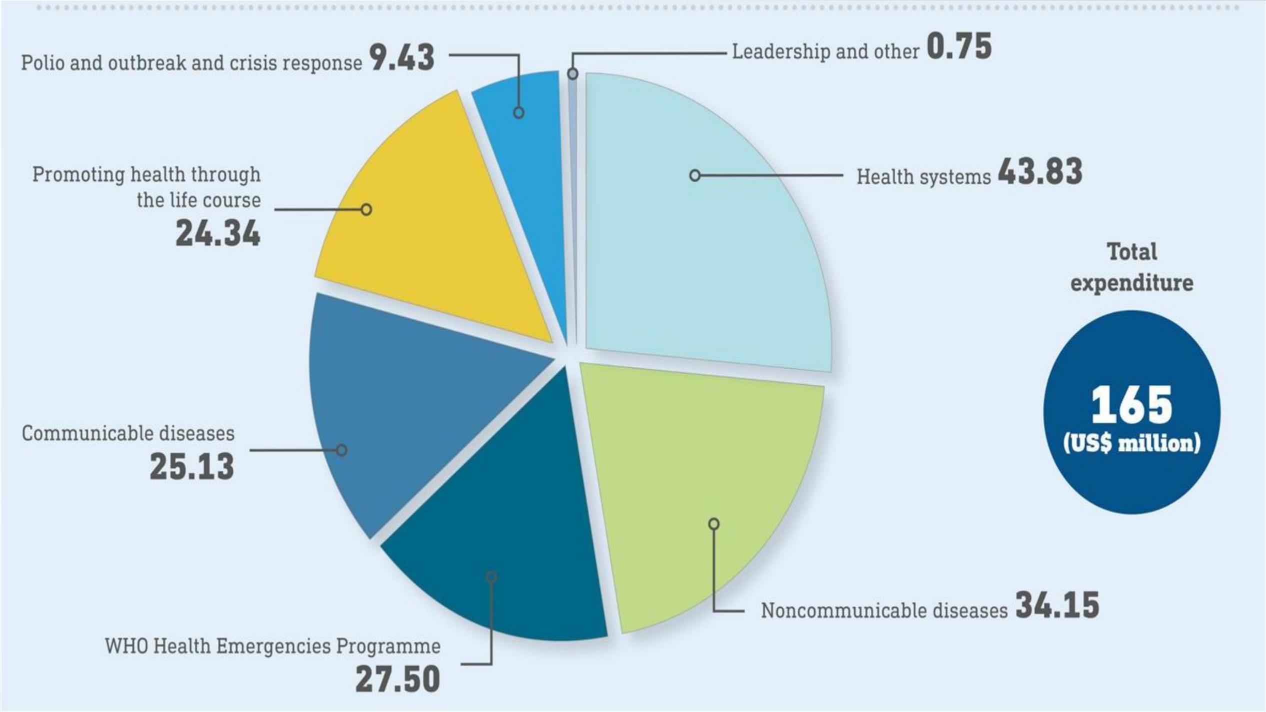
- Throughout the past few decades, machine learning techniques have been at the heart of bio-signal recognition, thanks to their ability to discover patterns and learn mappings effectively



INTRODUCTION : MOTIVATION

- According to the World Health Organization (WHO), the development of human actions from wearable sensors in the healthcare systems sector, has been the focus of many research during the past decade.

- 43.83 US$ million in 2017-2018 were allocated for the healthcare systems sector.



INTRODUCTION : MOTIVATION

- A big part of the smart Watches is health and fitness. It has two apps dedicated to keeping you active: “Activity” for tracking your daily health and “Workout”.

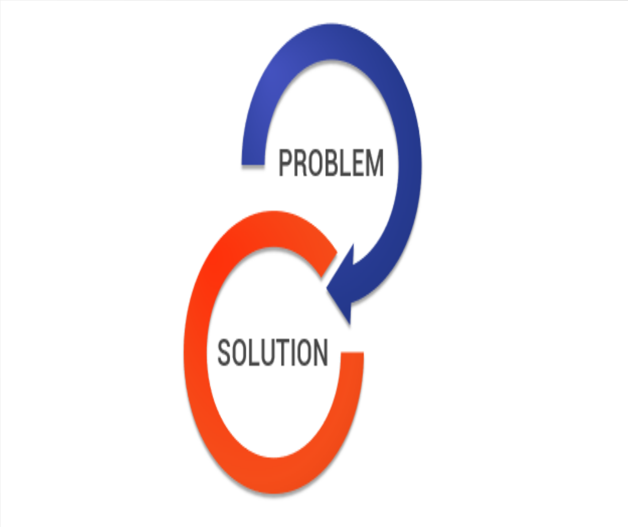
- Accelerometer and gyroscope data can be used for fitness and health-related activities or for games.

INTRODUCTION : PROBLEM AND THESIS STATEMENT

- With the rapid development of information technology, traditional health care systems are entering a more digital and electronic stage.

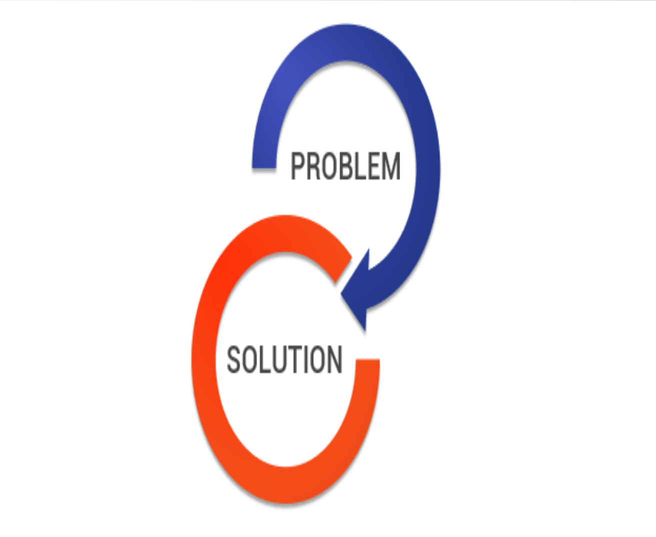
- In the current study stage, a variety of data mining techniques can be applied to the study of activities recognition based on the sensor data.

- However, due to the diversity and complexity of the sensor data, not every kind of data mining techniques can be perfectly applied to the sensor data.



INTRODUCTION : PROBLEM AND THESIS STATEMENT

- This requires the researchers to have a good understanding of a variety of data mining techniques, to be able to analyze them to obtain satisfactory results.



- This thesis aims to analyze several data mining techniques to data from accelerometer, gyroscope, and Electromyography sensors on the lower body to achieve the goal of daily living activities recognition.

- The ultimate goal is to build a machine learning model that can automatically categorize and log an movement on perspective of the number, the type, the position, and the sensor placement (*x*, *y*, and *z*) of the sensors used to gather the bio-signals.

INTRODUCTION : RELATED WORK

Study	# of Subjects	# of Activities	# of Features	# of positions	Sensor position	Sensor type	Classification algorithms
M. Lustrek et.al	5	8	8	4	Chest, ankle, thigh, and wrist	accelerometer	Naive Bayes, Decision tree, Random forest, SVM
W. Xu et al.	3	14	12	7	Waist, Arm, Thigh, Right and Left Wrist and Ankle	accelerometer and gyroscope	Naive Bayes Algorithms
Chuang et al.	10	7	11	2	Wrist and ankle	accelerometer	k-NN and PNN
N. C. Krishnan et al.	10	7	5	3	hip, ankle, and thigh	accelerometer	SVM, regularized linear regression, and Adaboost
Y. J. Hong et al.	15	18	4	3	wrist, waist, and thigh	accelerometer	Decision tree
L. Cheng et al.	4	5	12	4	thigh, arm, ankle and abdomen	accelerometer	SVM, HMM, ANN

INTRODUCTION : RELATED WORK

Study	# of Subjects	# of Activities	# of Features	# of positions	Sensor position	Sensor type	Classification algorithms
C. Tang et al	30	6	24	1	Waist	accelerometer and gyroscope	RF, SVM, NB, J48 NN, K-NN, Rpart, JRip, Bagging, and AdaBoost
Roy. SH	10	11	8	8	Arms, thigh, waist, and chest	Accelerometer and electromyography	ANN
Koskimäki	10	30	12	1	Arm	Accelerometer , gyroscope, magnetometer and EMG	LDA & QDA
Our work	18	12	14	6	Right and left thighs, shins, and feet	Accelerometer, gyroscope, and Electromyography	NN, Naive Bayes, Random Forest, (k-NN), SVM, and Decision Trees

METHODOLOGY

- The activity recognition process includes several stages, which include:

Pre-Processing

- Data Normalization
- Data Segmentation

Feature extraction

- Time Domain Features
- Others

Feature Selection

- Sequential Forward Selection
- Sequential Backward Selection
- Sequential Backward Floating Selection
- Sequential Forward Floating Selection

Machine Learning

- Multi-layer Perceptron
- Naive Bayes
- Random Forest
- Support Vector Machine
- Decision tree
- k-Nearest Neighbors

METHODOLOGY: DATA PREPROCESSING

- **Data Normalization:**

due to difference in units of the collected data, we needed to undergo a pre-processing step known as Data Normalization, through the commonly used method zero-mean and unit variance.

$$f_{norm} = \frac{f_{raw} - \mu}{\sigma}$$

- **Data Segmentation :**

fixed-width sliding window were used with 100 samples and 50% overlap from each sliding window

METHODOLOGY: FEATURE EXTRACTION

Feature	Description
Standard Deviation	Measure of the signal after spreading.
Standard Deviation auto- cor.	Deviation of the resemblance between a given time series and its lagged version.
standard deviation auto- cov.	Deviation of a measure of how much two random variables vary from each other.
Variance	The square root of standard deviation.
Mean	value of the signs / no. of signals.
Mean auto- covariance	Mean value of how two random variables vary from each other.
Mean auto- correlation	The mean value of the resemblance between a given time series and it’s lagged version.
Minimum	Lowest signal value over the window.
Maximum	Highest signal value over the window.
Skewness	Degree of asymmetry of each signal.
Kurtosis	degree of sharpness of each signal.
Root Mean Square	Square root of the mean squared value.
Mean Crossing Rate	The sum of signal changes from the above average to the below average.
Jitter	Different between previous and next reading.

METHODOLOGY: FEATURE SELECTION

Sequential feature algorithms (SFAs)

- SFS : Starting from the empty set, sequentially add the feature that least reduces the value
- SBS: Starting from the full set, sequentially remove the feature that least reduces the value
- SFFS: After each forward step, it performs backward step as long as the objective function increases
- SBFS: After each backward step, it performs forward step as long as the objective function increases

DESIGN AND IMPLEMENTATION: DATASET DESCRIPTION

The Human Gait Database (HuGaDB) is one of the most recent datasets in the literature:

- The dataset has covered the largest number of actions in the literatures. These actions are diverse in the sense that they include both static and dynamic activities.
- Three sensors from three different places from both legs, this results in the acquisition of a total of fifty-four signals
- HuGaDB features have a unique amount of details in the human gait including segmented annotations which help study the transition between different activities

DESIGN AND IMPLEMENTATION: DATASET DESCRIPTION

In this study, HuGaDB (Human Gait Database dataset) by Roman Chereshnev were used:

The data is comprised of twelve different activities, (walking, running, going up , going down, sitting, sitting down, standing up, standing , cycling, up by elevator , down by elevator , sitting in the car).

Data was collected from : accelerometer, gyroscope, and EMG

placed on the right and left thighs, shins, and feet.

The data was acquired from 18 healthy, young adults. The gender profile of test subjects is four females and fourteen males.

DESIGN AND IMPLEMENTATION

Thigh

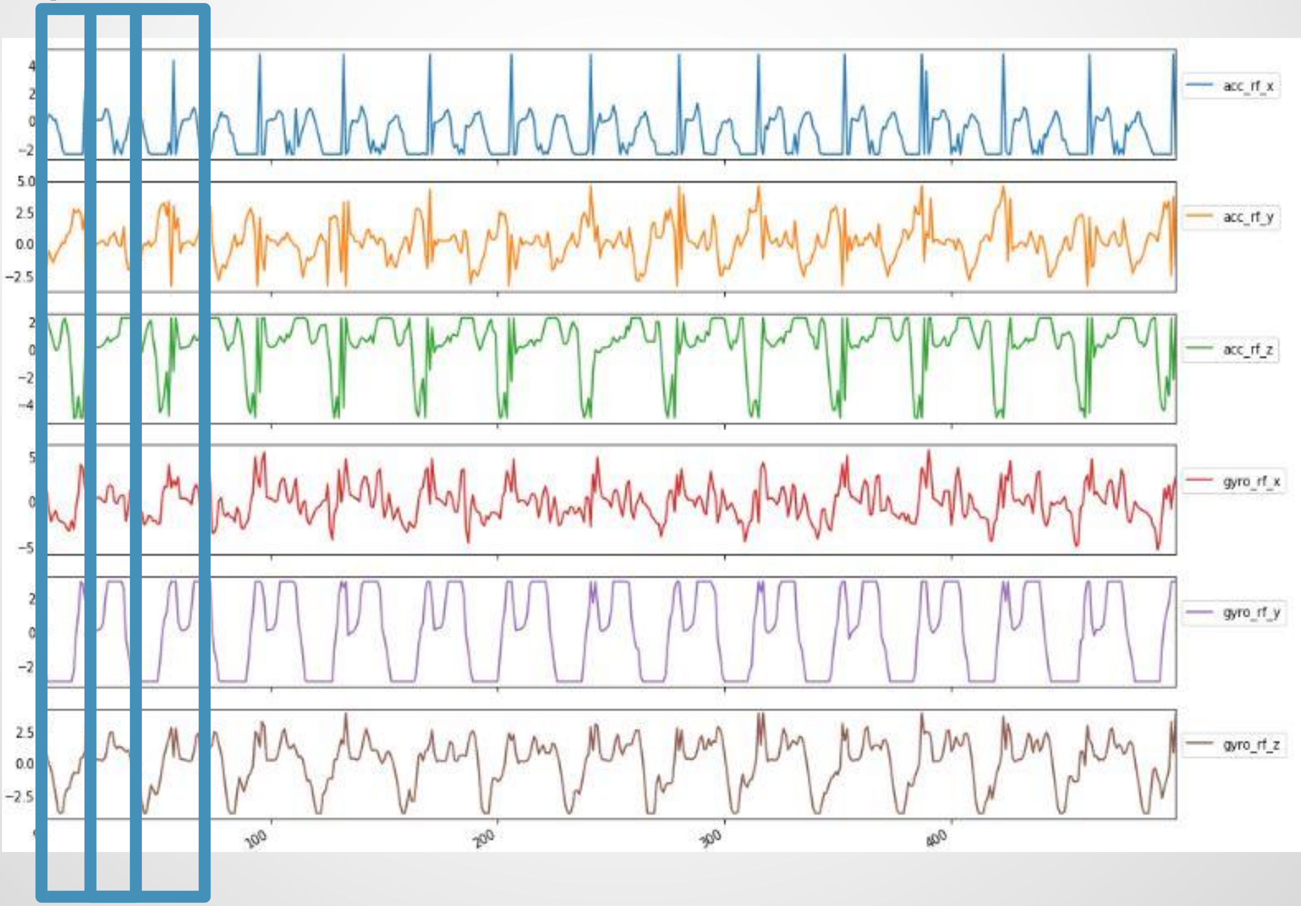
Shin

Foot

Accelerometer & Gyroscope :
x, y, z, and magnitude from left and right legs

Electromyography:
From right and left legs

100 samples

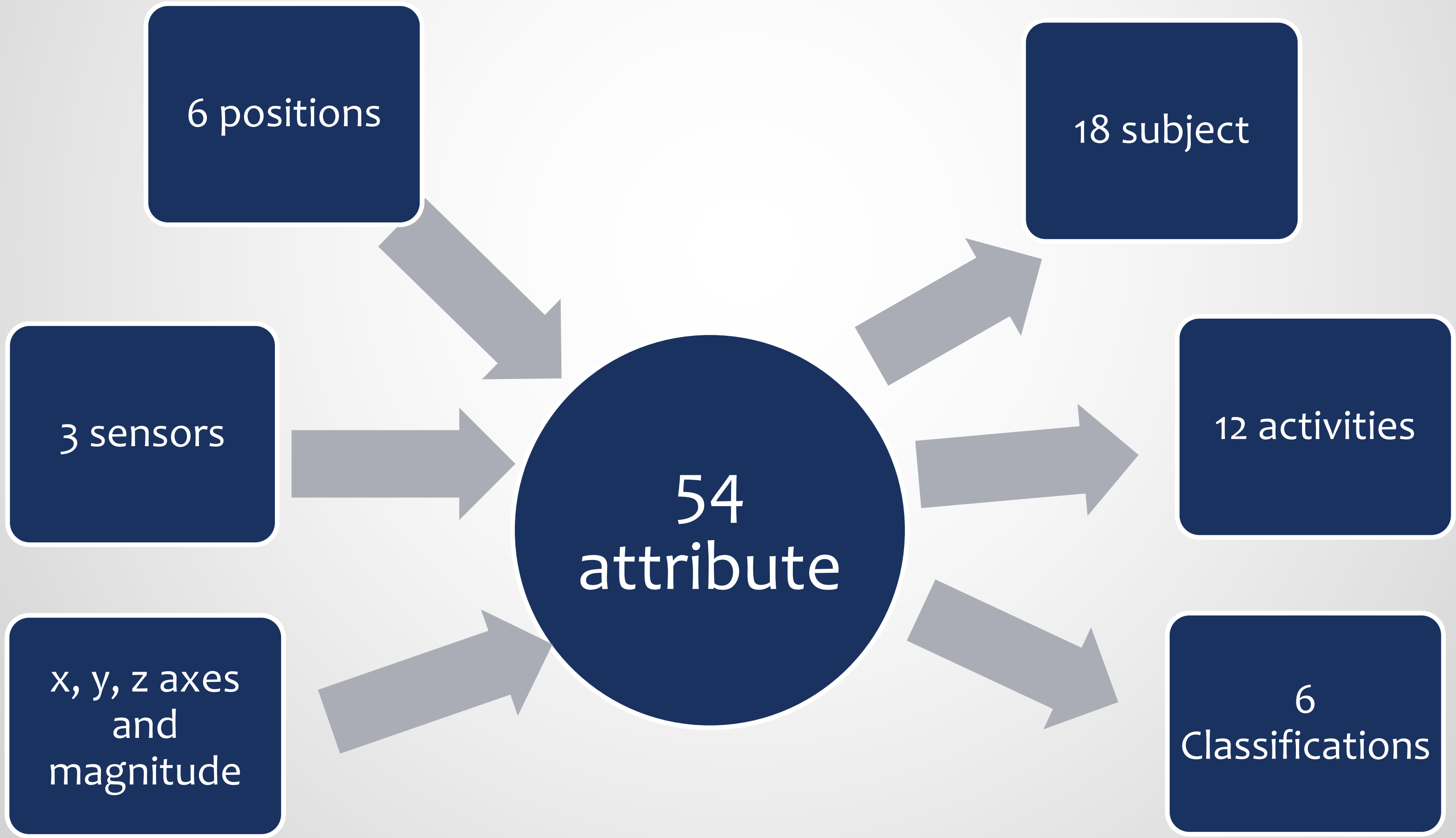


50% overlap

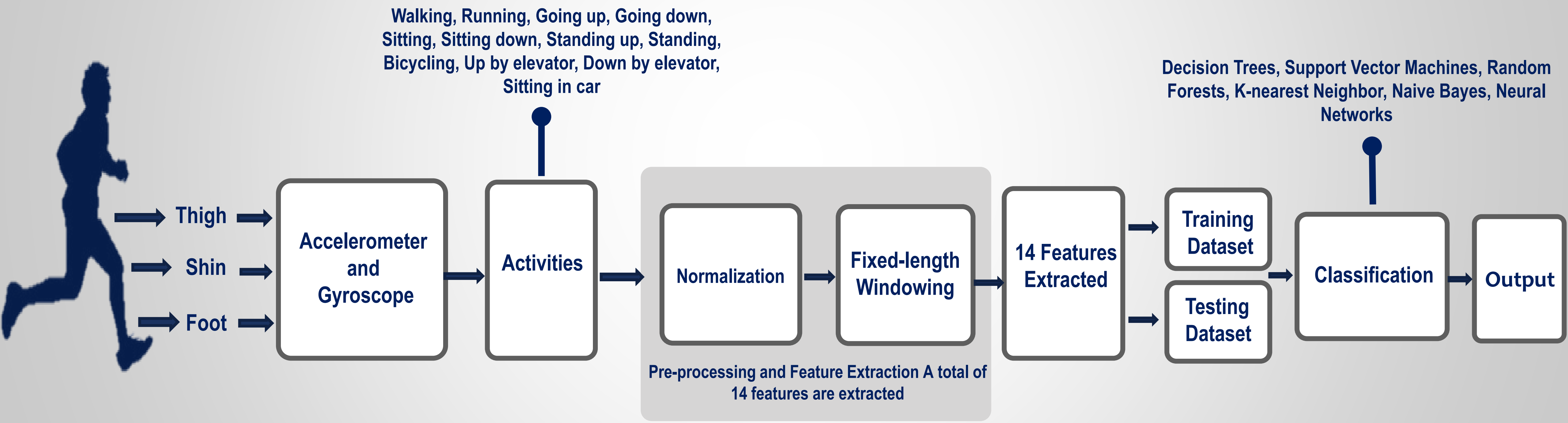
14 features extracted from each window

Standard Deviation
Standard Deviation auto- cor.
standard deviation auto-cov.
Variance
Mean
Mean auto- covariance
Mean auto- correlation
Minimum
Maximum
Skewness
Kurtosis
Root Mean Square
Mean Crossing Rate
Jitter

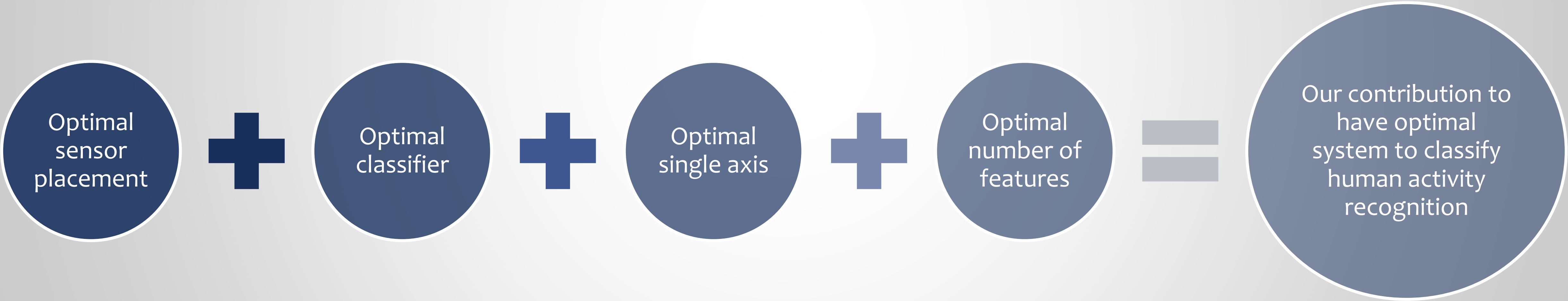
DESIGN AND IMPLEMENTATION



DESIGN AND IMPLEMENTATION: THE ARCHITECTURE OF THE SYSTEM



THESIS CONTRIBUTION



THESIS CONTRIBUTION: EXPERIMENT

- **Programming language is Python, and SQL were used for database .**
- **Each output is repeated 10 times and the average is calculated.**
- **Some definitions:**

1. **Acc_lf_x: Accelerometer left foot *x*-aixs**
2. **Acc_ls_y: Accelerometer left shin *y*-aixs**
3. **Acc_lt_z : Accelerometer left thigh *z*-aixs**
4. **Magnitude_acc_lf: Accelerometer left foot magnitude**

THESIS CONTRIBUTION: OPTIMAL SENSOR PLACEMENT

sensor/algorithm	DT	SVM	RF	kNN	NB	NN
acc_lf_x	86.40%	86.70%	88.70%	70.70%	76.70%	84.40%
acc_lf_y	82.10%	81.70%	86.80%	66.70%	77.10%	82.00%
acc_lf_z	81.30%	80.40%	84.10%	67.80%	76.30%	78.60%
magnitude_acc_lf	80.50%	84.00%	86.10%	66.70%	76.40%	79.20%
acc_ls_x	87.60%	87.10%	89.90%	74.60%	82.00%	88.10%
acc_ls_y	86.20%	86.90%	87.50%	77.20%	83.10%	85.60%
acc_ls_z	87.40%	84.60%	89.10%	77.30%	80.60%	85.60%
magnitude_acc_ls	87.70%	83.90%	89.00%	76.50%	80.00%	84.80%
acc_lt_x	**88.10%**	**89.40%**	**90.70%**	79.10%	81.80%	83.60%
acc_lt_y	86.20%	87.30%	88.40%	75.40%	81.20%	84.30%
acc_lt_z	88.00%	88.60%	88.90%	79.20%	82.80%	85.00%
magnitude_acc_lt	84.10%	85.60%	86.90%	77.60%	80.60%	83.90%

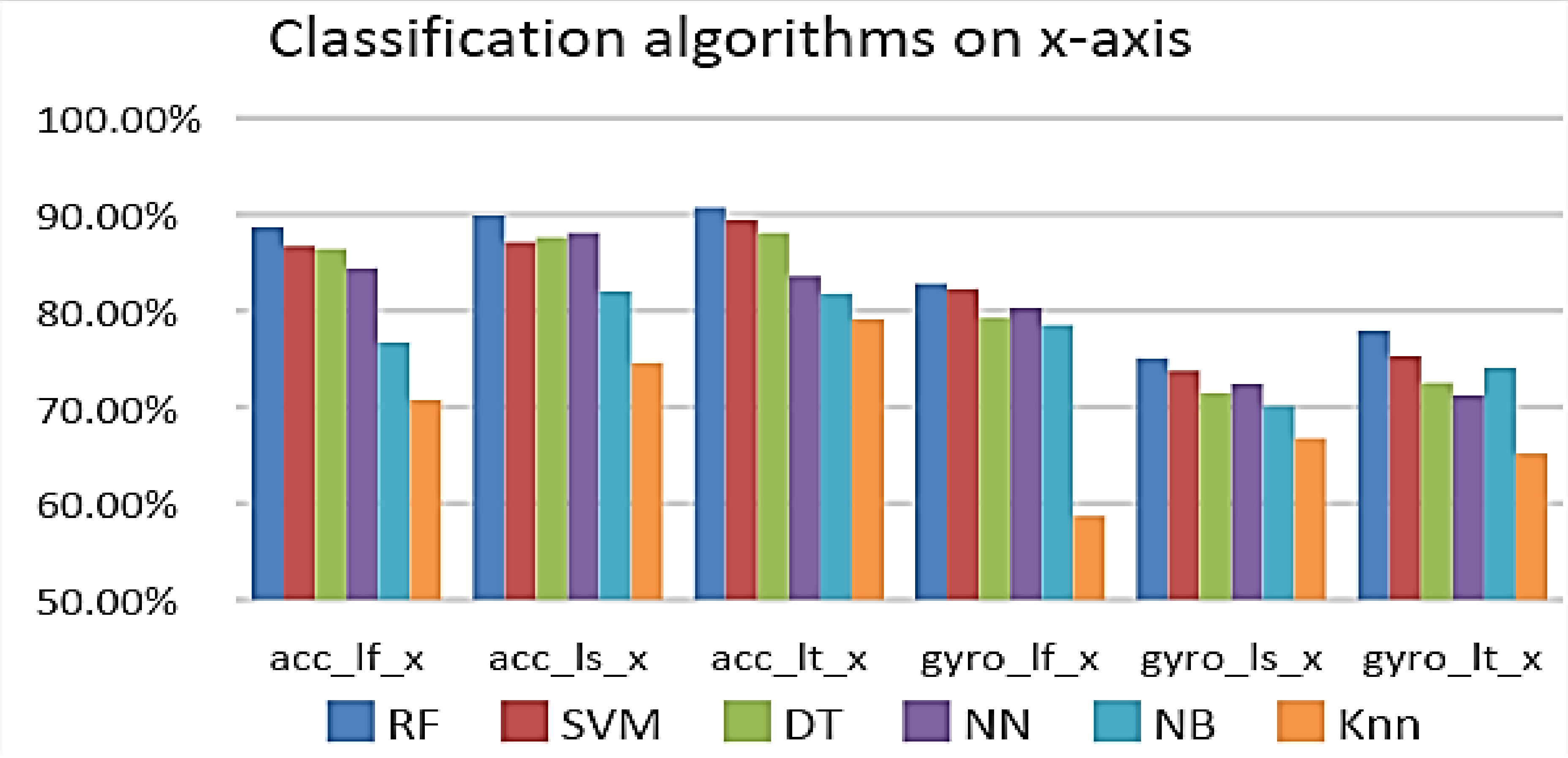
THESIS CONTRIBUTION: OPTIMAL SENSOR PLACEMENT

sensor/algorithm	DT	SVM	RF	kNN	NB	NN
gyro_lf_x	79.30%	82.30%	82.80%	59%	79%	80%
gyro_lf_y	83.00%	82.10%	84.60%	61.20%	85.00%	76.50%
gyro_lf_z	82.10%	79.20%	82.80%	56.80%	77.70%	74.90%
magnitude_gyro_lf	83.20%	82.40%	84.10%	66.50%	84.60%	80.60%
gyro_ls_x	71.50%	73.80%	75.10%	66.80%	70.10%	72.40%
gyro_ls_y	79.10%	78.60%	83.30%	66.10%	75.70%	73.30%
gyro_ls_z	80.40%	76.20%	83.10%	60.90%	67.80%	70.10%
magnitude_gyro_ls	81.70%	77.50%	85.10%	65.80%	69.20%	71.30%
gyro_lt_x	72.50%	75.30%	77.90%	65.20%	74.10%	71.20%
gyro_lt_y	**85.80%**	**83.90%**	**86.80%**	66.90%	85.80%	85.00%
gyro_lt_z	79.40%	80.00%	82.10%	64.50%	76.60%	76.00%
magnitude_gyro_lt	82.10%	83.10%	84.00%	65.00%	79.40%	80.60%

THESIS CONTRIBUTION: OPTIMAL SENSOR PLACEMENT

x, y, z, and mag / Algorithm	LEFT THIGH ACCELOMETER	RIGHT THIGH ACCELOMETER	LEFT THIGH GYROSCOPE	RIGHT THIGH GYROSCOPE	LEFT THIGH ACC+GYRO
Decision Tree	92.03%	91.10%	87.90%	88.20%	95.10%
SVM	93.30%	93.50%	88.60%	88.75%	95.40%
Random Forest	94.50%	94.40%	92.50%	91.70%	96.80%
Kneighbors	83.90%	84.4	81.20%	80.10%	84.80%
Neural network	88.10%	87.50%	85.80%	84.20%	88.70%
Naïve Bayes	88.90%	88.20%	88.10%	85.90%	92.70%

THESIS CONTRIBUTION: OPTIMAL CLASSIFIER



- **The classification accuracy of the six classifiers applied on the x-axis sensors placed on the foot, the thigh, and the shin of the left leg.**

THESIS CONTRIBUTION: OPTIMAL CLASSIFIER PARAMETERS

I. One of the main parameters that have high influence on RF classifier values is the number of trees in the forest used.

II. By default, the number of trees is 10. By increasing that number it was proven to get better results, reaching 98.6% for 256 trees.

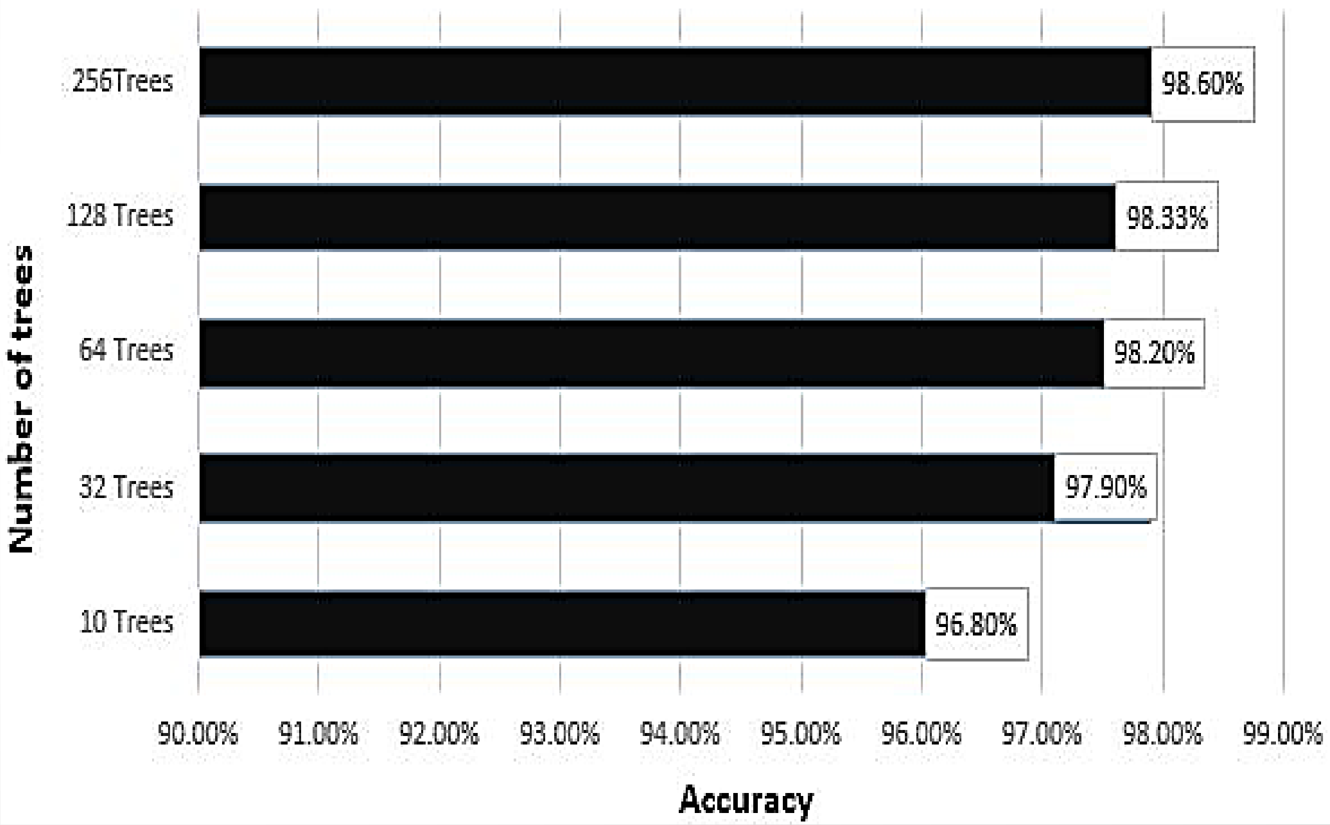


Fig.: The impact of the number of trees on the accuracy of the RF algorithm.

THESIS CONTRIBUTION: OPTIMAL CLASSIFIER

- **Figure depicts the confusion matrix of the RF classifier attaining a recognition accuracy of 98.6%.**

- **The figure shows only three false detections. These are:**

1) For activity ID 11 (sitting in the car), it was predicted as activity ID 6 (sitting down).
2) For activity ID 7 (standing), it was predicted as activity ID 8 (cycling).
3) For activity ID 6 (sitting down) and activity ID 11 (sitting in the car) twice.

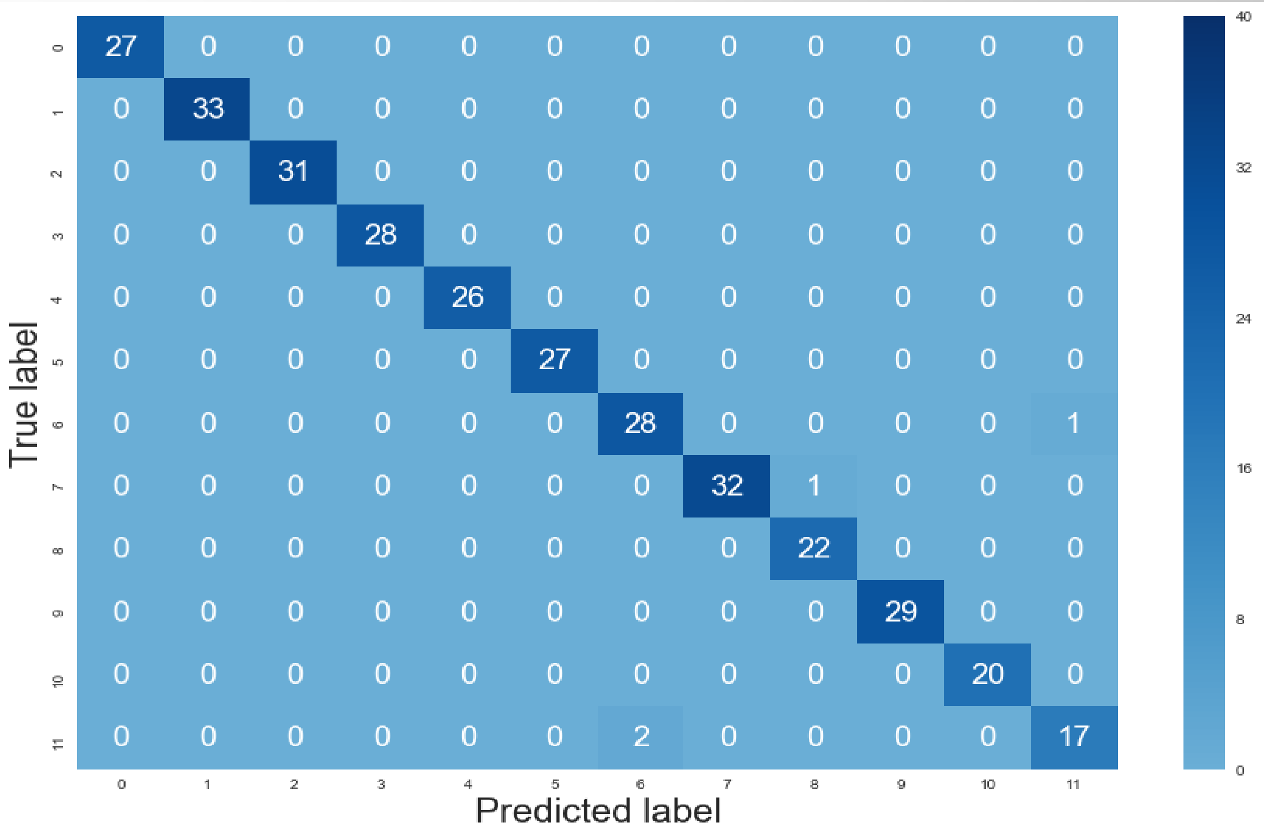
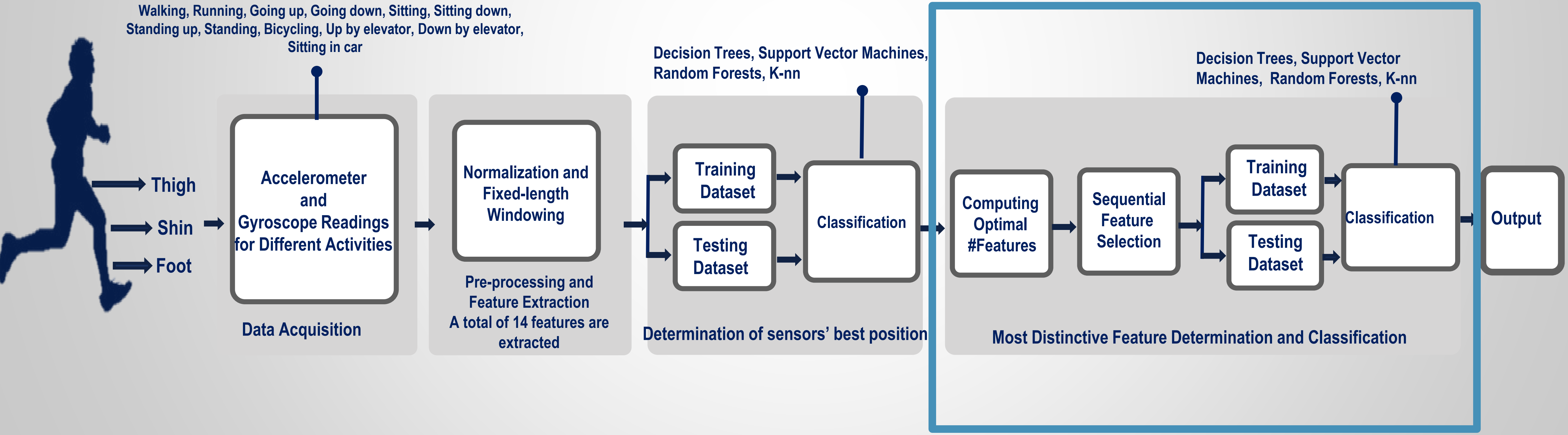


Fig. The confusion matrix corresponding to the RF classifier applied on the left thigh after merging the data of the accelerometer and the gyroscope.

DESIGN AND IMPLEMENTATION: THE ARCHITECTURE OF THE SYSTEM



THESIS CONTRIBUTION: OPTIMAL NUMBER OF FEATURES

1. The curve reaches the optimum accuracy when the optimal number of features are captured. This takes place when N = 8.

2. A gradual decline in the accuracy due to adding the non-informative features to the model learning process.

3. The sky-blue shaded area shows the variability of cross-validation.

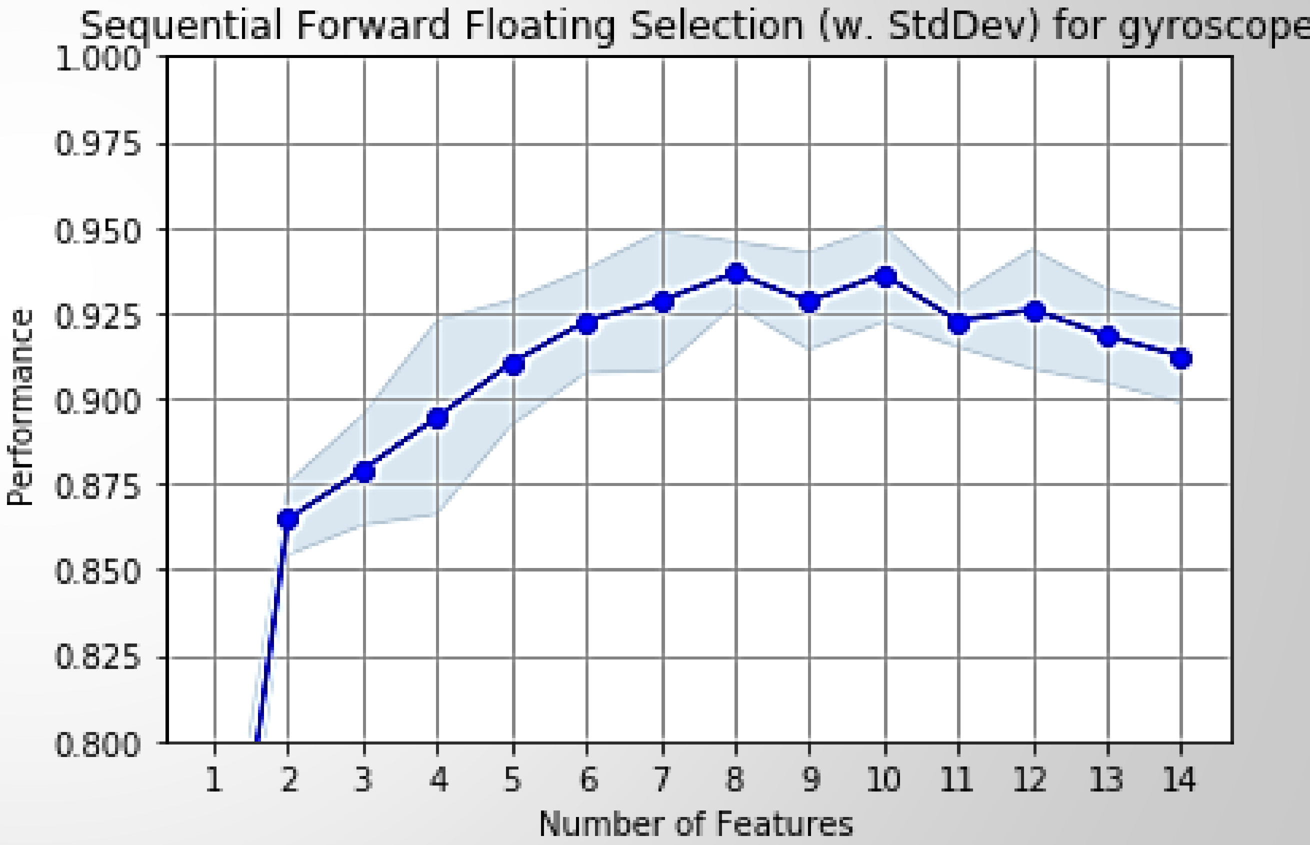


Fig. : The relation between performance and number of features for the gyroscope y-axis .

THESIS CONTRIBUTION: OPTIMAL NUMBER OF FEATURES AND SINGLE AXIS

❖ Comparison Between All and Selected Features:

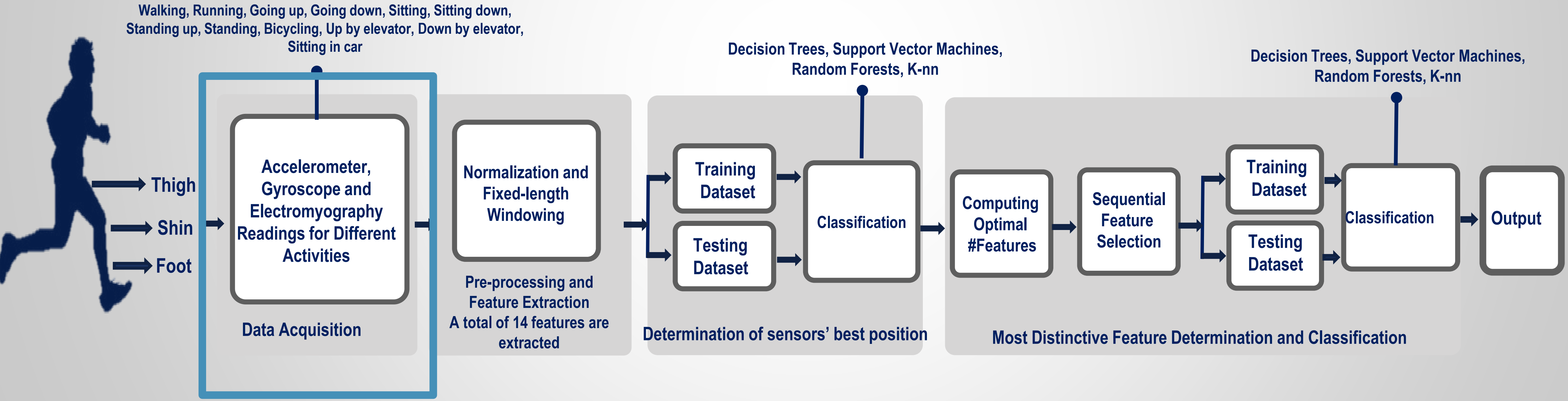
sensor/algorithm	DT	SVM	RF	kNN	No. of features
Acc_lt_x	88.10%	89.40%	90.70%	79.10%	N=14
Gyro_lt_y	85.80%	83.90%	86.80%	66.90%	N=14
Acc_lt_x , gyro_lt_y	90.00%	89.40%	**94.70%**	71.50%	**N= 28**
Acc_lt _x,y,z,mag	92.03%	93.60%	95.00%	83.90%	N=56
Gyro_lt _x,y,z,mag	87.90%	88.60%	92.50%	81.20%	N=56
Acc,Gyro_lt_x,y,z, mag	95.10%	95.40%	**96.80%**	84.80%	**N=112**

Table I Comparison between single axis vs triple axis before using feature selection.

sensor/algorithm	DT	SVM	RF	kNN	No. of features
Acc_lt_x	89.80%	91.50%	91.67%	82%	N=7
Gyro_lt_y	88.10%	85.20%	88.70%	87.80%	N=8
Acc_lt_x , gyro_lt_y	91.60%	91.20%	**96.90%**	75.00%	**N= 15**
Acc_lt _x,y,z,mag	94.20%	95.10%	96.20%	85.10%	N=23
Gyro_lt _x,y,z,mag	89%	90.10%	94.40%	82.90%	N=26
Acc,Gyro_lt_x,y,z, mag	96.40%	97%	**98.40%**	86.30%	**N=37**

Table II Comparison between single axis vs triple axis after using sequential floating forward feature selection.

DESIGN AND IMPLEMENTATION: THE ARCHITECTURE OF THE SYSTEM



FUSION OF THE THREE SENSORS

- **Accelerometer:**

Measures linear motion & acceleration of a moving

- **Gyroscope:**

Measures rotational motion -- human motion is rotational about joints.

- **Electromyography:**

Measures electrical current associated with muscular action. Does not measure movement directly

FUSION OF THE THREE SENSORS

1- Accelerometer and Electromyography:

sensor/algorithm	DT	SVM	RF	kNN	No. of features
acc_lt_x	88.10%	89.40%	90.70%	79.10%	N=14
EMG	76.90%	78.90%	79.20%	66.20%	N=14
acc_lt_x + EMG	87.45%	85.19%	**92.31%**	67.17%	**N=28**
Left thigh acc. ALL	92.03%	93.60%	95.00%	83.90%	N=56
left thigh acc All + EMG	93.65%	92.87%	**97.13%**	84%	**N=70**

Table I Comparison between single axis vs triple axis for accelerometer and electromyography signals before using feature selection.

sensor/algorithm	DT	SVM	RF	kNN	No. of features
acc_lt_x	89.80%	91.50%	91.67%	82%	N=7
EMG	78.00%	80.30%	84.30%	70.10%	N= 11
acc_lt_x + EMG	88.91%	87.65%	**94.52%**	70.22%	**N=16**
Left thigh acc. ALL	94.20%	95.10%	96.20%	85.10%	N=23
left thigh acc All + EMG	95.65%	95.01%	**98.22%**	85.83%	**N=30**

Table II Comparison between single axis vs triple axis for accelerometer and electromyography signals after using sequential forward floating feature selection.

FUSION OF THE THREE SENSORS

2- Gyroscope and Electromyography:

sensor/algorithm	DT	SVM	RF	kNN	No. of features
gyro_lt_y	85.80%	83.90%	86.80%	66.90%	N=14
EMG	76.90%	78.90%	79.20%	66.20%	N=14
gyro_lt_y + EMG	88.60%	90.41%	**93.11%**	72.96%	**N=28**
Left thigh gyro. ALL	87.90%	88.60%	92.50%	81.20%	N=56
left thigh gyro All + EMG	90.27%	90.83%	**95.41%**	73.10%	**N=70**

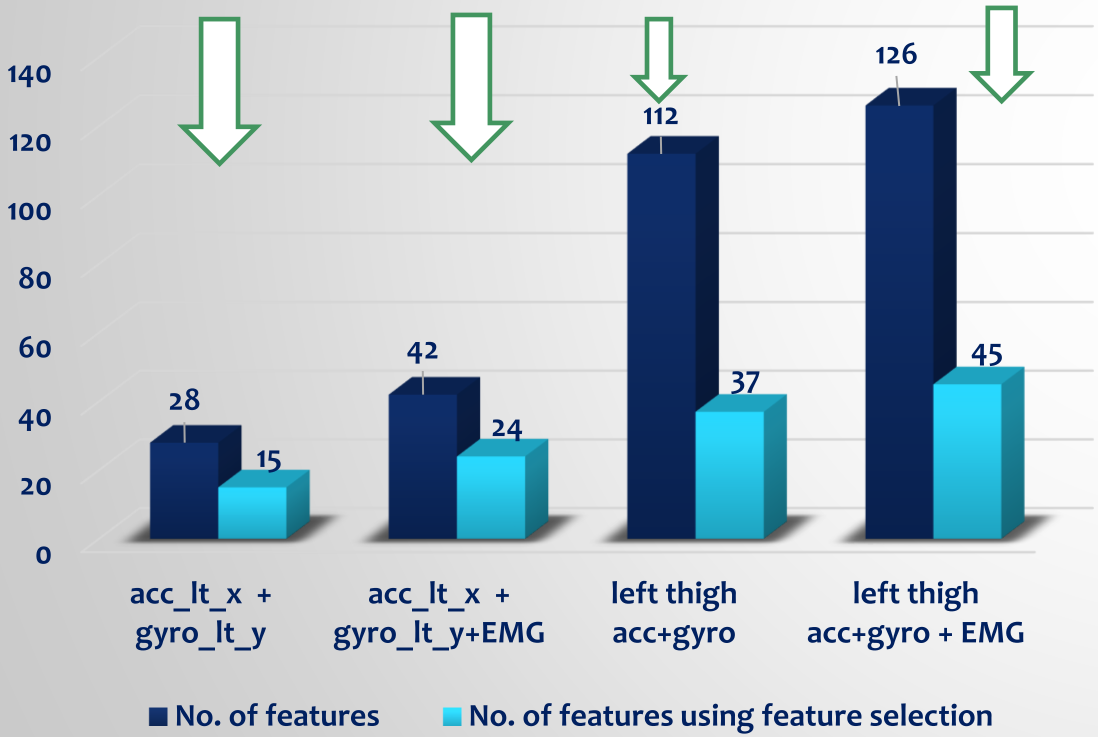
Table I Comparison between single axis vs triple axis for gyroscope and electromyography signals before using feature selection.

sensor/algorithm	DT	SVM	RF	kNN	No. of features
gyro_lt_y	88.10%	85.20%	88.70%	87.80%	N=8
EMG	78.00%	80.30%	84.30%	70.10%	N= 11
gyro_lt_y + EMG	90.11%	91.78%	**94.91%**	75.23%	**N=18**
Left thigh gyro. ALL	89%	90.10%	94.40%	82.90%	N=26
left thigh gyro All + EMG	93.13%	92.83%	**97.60%**	76.32%	**N=32**

Table II Comparison between single axis vs triple axis for gyroscope and electromyography signals after using sequential forward floating feature selection.

FUSION OF THE THREE SENSORS

3- Accelerometer, Gyroscope, and Electromyography:



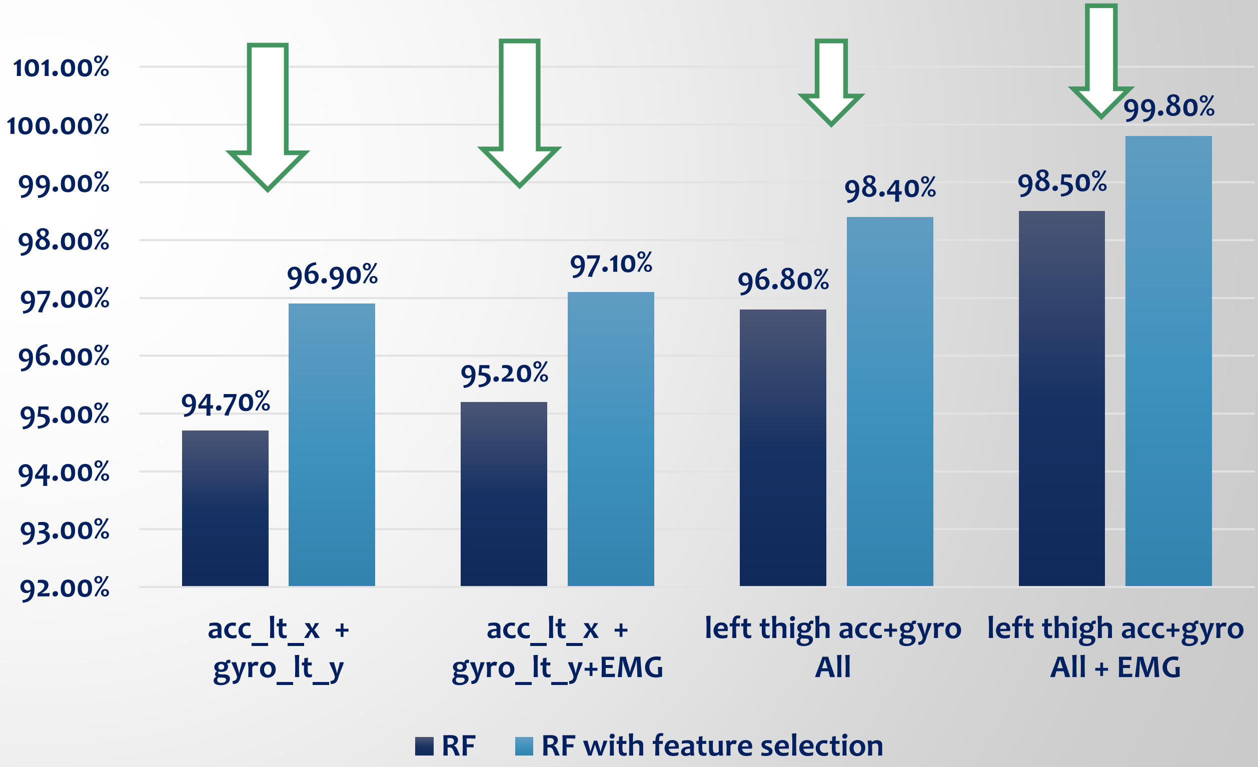


Fig I The variance in the number of features before and after using feature selection for different fusion between the sensors.

Fig II The variance in accuracies before and after using feature selection for different fusion between the sensors

CONCLUSION

- **We used machine learning techniques to classify human activities from three wearable sensors placed on six different positions.**
- **The machine learning techniques we apply have proven the most effective in the literature, and we were able to identify, for each type of sensor, the position and the sensor placement that yields the highest accuracy of activity recognition.**
- **We further investigate the most effective classifier on the dataset at hand (Random Forest classifier) and we report the impact of parameter variation on the classification performance.**

CONCLUSION

- We showed that using the best single axis position with the right classification, features extracted and selected can lead to a competitive accuracies with the 3-axis sensor.
- We showed that using optimal feature selection, higher recognition accuracies can be attained with an average of half the number of features that were originally acquired.
- We proved that sensor fusion between accelerometer, gyroscope, and EMG can lead to significant results (99.8%).

CONCLUSION: PUBLICATIONS

- **A. Badawi, A. Al-Kabbany, and H. Shaaban, "Multimodal human activity recognition from wearable inertial sensors using machine learning," Submitted to IECBES, 2018 (Accepted).**

- **A. Badawi, A. Al-Kabbany, and H. Shaaban, "Enhancing Multimodal Human Activity Recognition Using Feature Selection on Wearable Sensors," Submitted to ICCES, 2018 (Accepted).**

CONCLUSION: FUTURE WORK

- Design a mobile application to collect the data from users and predict the movement using fusion of sensors to predict the activity more accurately.
- Comparing our dataset with an unhealthy dataset to extract the differences between the signals to detect the diseases symptoms.
- Investigate other effective feature selection techniques such as sparse coding to reach the same accuracies with less number of features.

Thank you