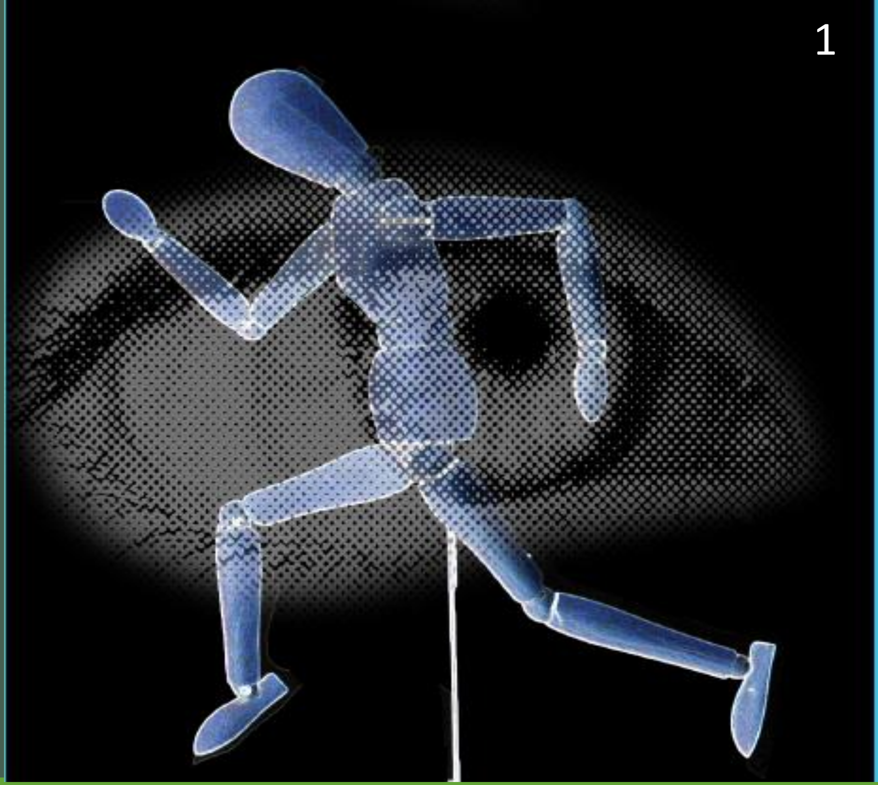
Dynamic Activity Recognition Using Smartphone Sensor Data



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Overview

- Introduction and Motivation
- Methodology
- Data Processing and Classification
- Conclusion and Outlook

Introduction and Motivation

"Dynamic Activity recognition using smartphone sensor data"

Why activity recognition?

- Patient monitoring
- Sport trainers
- Emergency detectors
- Diary builders
- Location systems

How to perform activity recognition?

Video processing

Wearable sensors

- Ad-Hoc sensors
- Personal mobile embedded sensors
  - Accelerometers, gyroscopes, compass, camera, microphone, etc.
  - Mainly infrastructure-based
    - Network coverage, latency, privacy, etc.

What about using smartphones processing capabilities for activity recognition?

- Their use on a daily basis
- Processing capabilities are growing spectacularly

Focus

- How smart phones can be used to recognize dynamic human activities
- Investigates the best machine learning model for classifying the investigated activities from the acceleration data.

Proposed System

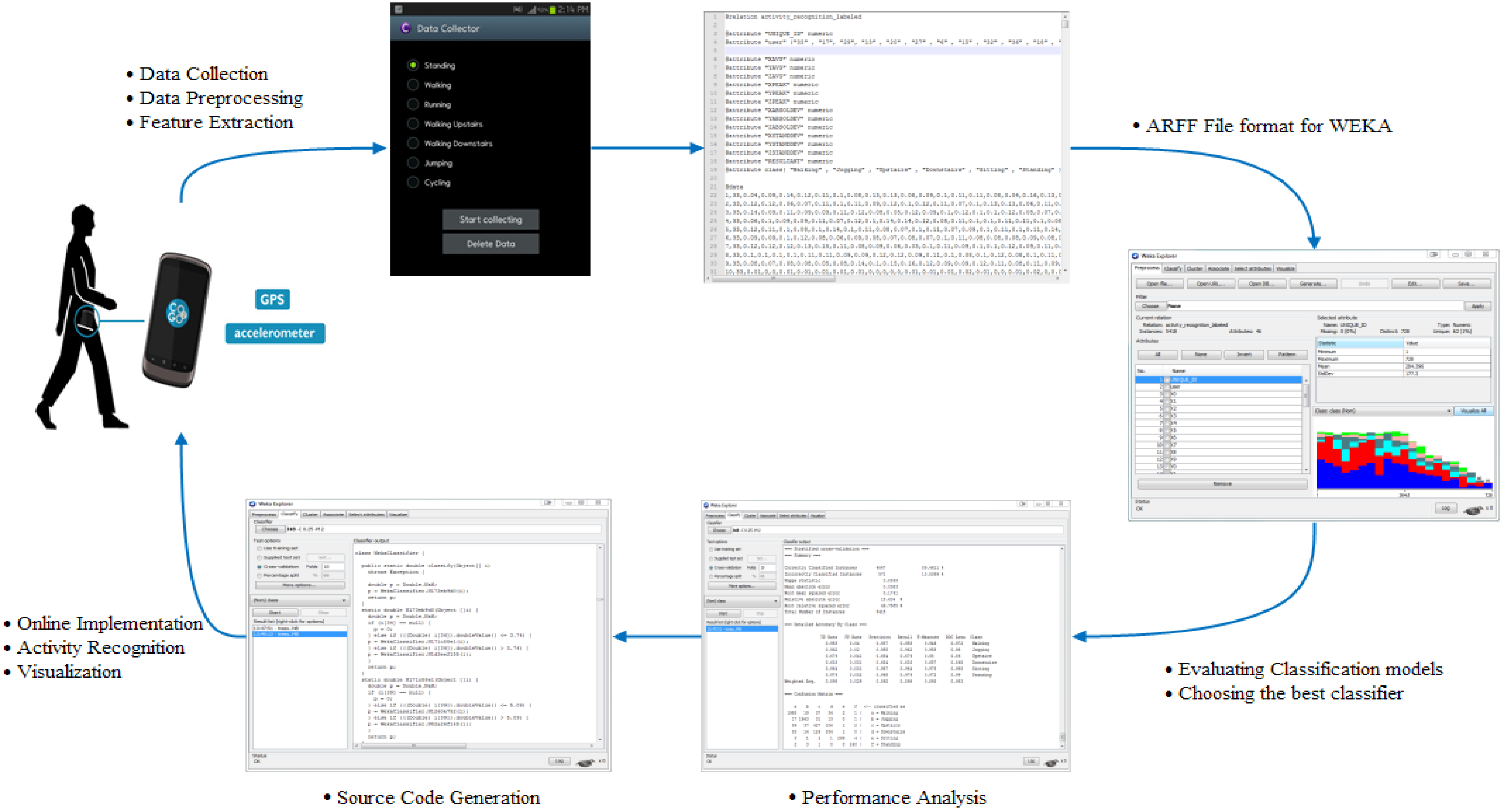


Figure 1. System overview

Architecture Details

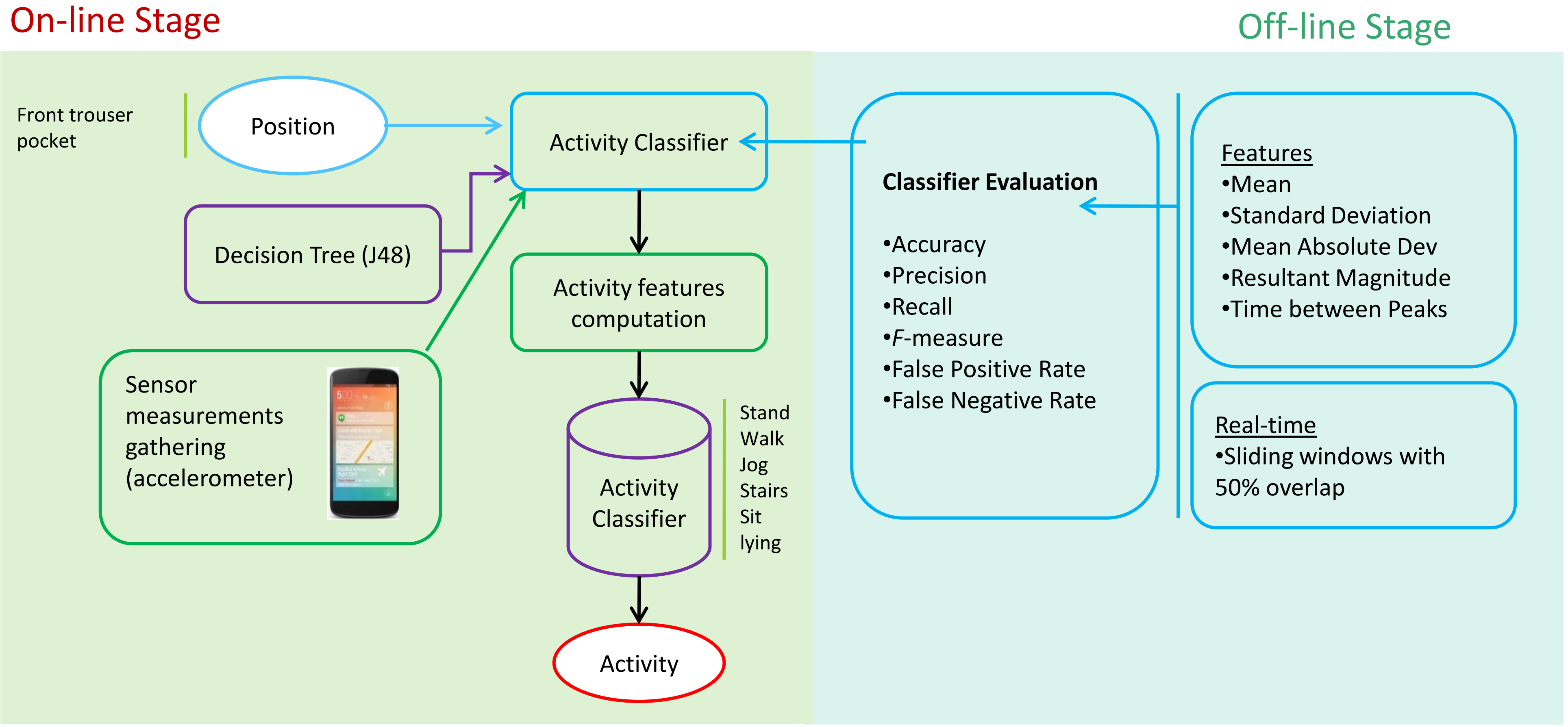


Figure 2. System Architecture

Methodology

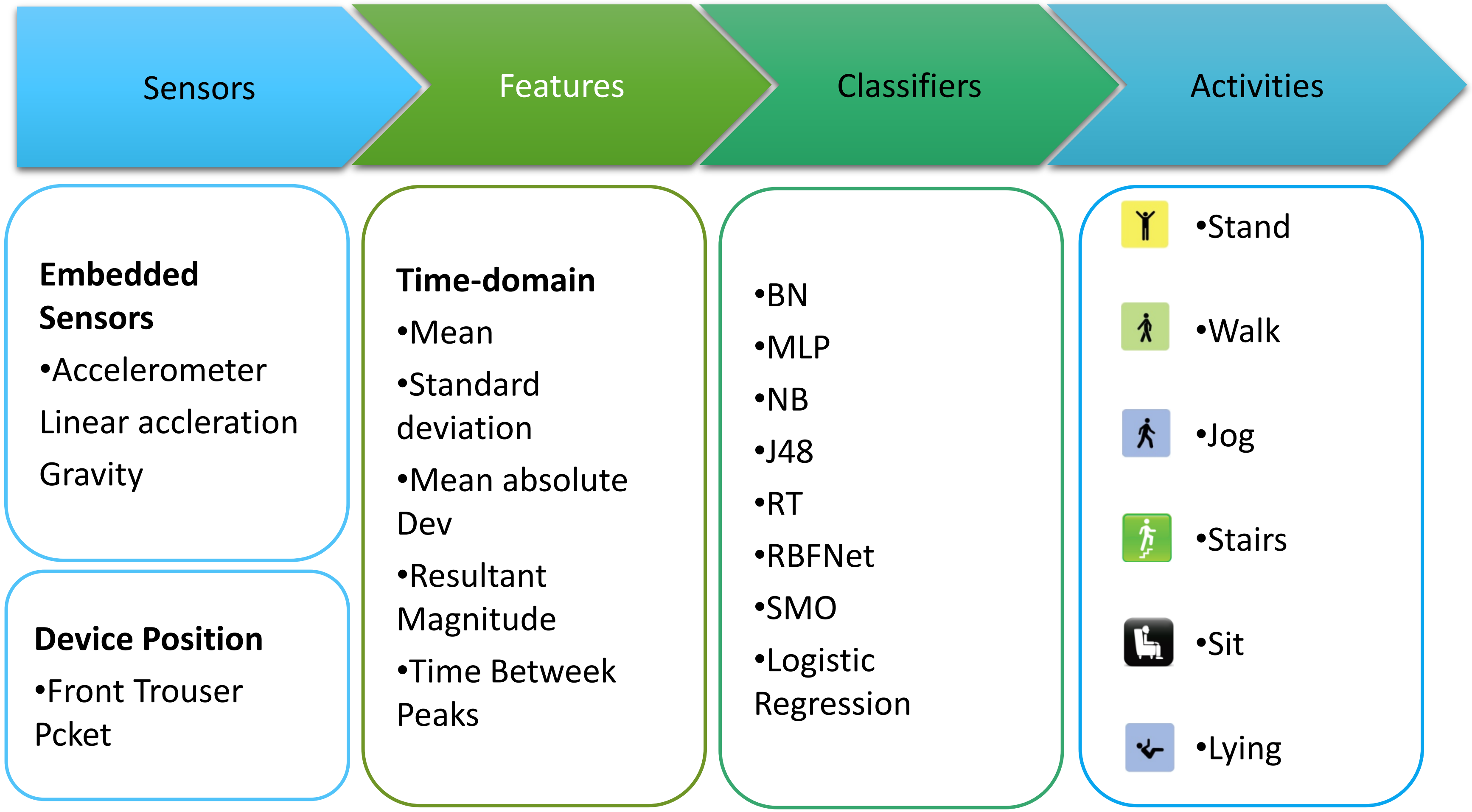


Figure 3. Classifier Evaluation Module

Methodology

- **Data Collection**

  - Smartphone Sensor: **3D accelerometer @ 20 Hz**
  - Cell phone in **front pants leg pocket**
  - Participants:**50 healthy subjects (30 males and 20 females)**
  - Dynamic Activities: **walking, jogging, using stairs, walking downstairs, sitting, standing** and **lying down**-total of 6 activities
  - Data was collected in a **naturalistic fashion** rather than lab environment

Methodology (cont)

Data Collection App

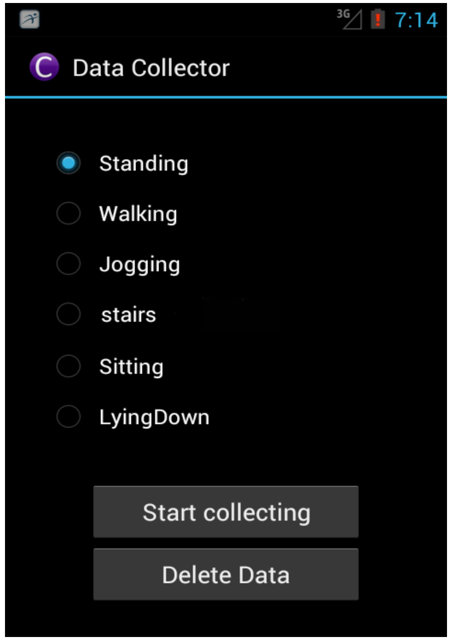


Figure 3. Smartphone interface for Data collection

Participants Characteristics

Table 1. Summary of Physical characteristics of the participants.

	Avg.	Min	Max
Age (*years*)	23	21	35
Weight (*kg*)	67	53	85
Height (*cm*)	172	142	187
BMI (*kg/m^2*)	24.9	18.5	29.9

Feature Extraction

- Simple time domain statistical features using a window size of 512 samples with 256 samples overlapping between consecutive windows.
- Five features from each window, with a total of 13 attributes.

Table 2. Summary of the set of features extracted.

No.	Feature	No. of features generated	Formula
1	Mean	3	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
2	Standard Deviation	3	$\sigma_x = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$
3	Mean Absolute Deviation	3	$MAD_x = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\lvert x_i - \bar{x}\rvert}$
4	Magnitude	1	$mag = \sqrt{x^2 + y^2 + z^2}$
5	Time between peaks	3	

Evaluation

- **Classification Models**
  - BN (Bayesian Network),
  - MLP (Multilayer Perceptron),
  - NB (Naïve Bayes),
  - J48 (C4.5 Decision Tree),
  - RT (Random Tree),
  - RBFNet (Radial Basis Function Network),
  - SMO (Sequential Minimal Optimization) and
  - Logistic Regression.

Evaluation

- **Classification Models (cont)**

1. To determine whether a classifier is superior than another, a 5x2 fold cv was performed using the WEKA.
2. A paired t-test

In practice, a 10-fold cross validation is the most widely used methodology to calculate the accuracy of a classifier. However, in order to choose the most accurate one by comparing the two classifiers, a 5x2-fold cross validation along with a paired *t*-test is recommended[1].

[1]T. G. Dietterich, "Approximate statistical tests for comparing supervised classification learning algorithms," *Neural computation,* vol. 10, pp. 1895-1923, 1998.

Performance Measures

- F-measure was used as a performance index to evaluate the different classifiers ability to classify each of the activities.

$$\Pr ecision = \frac{TP}{TP + FP}$$

Precision is a measure of the accuracy provided that a specific class has been predicted

$$\operatorname{Re} call = \frac{TP}{TP + FN}$$

Recall is a measure of the ability of a prediction model to select instances of a certain class from a data set. (Sensitivity)

$$F - measure = 2 \times \frac{\Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call}$$

A higher F-measure value indicates improved detection of the investigated activity.

Results

- **Offline analysis using WEKA *(subject-independent)***
  - 8 classifiers with five different random seeds

$$s_i = \{1,128,255,1023,4095\}$$

Table 3: Percentage Classification accuracy given by the 5x2-fold cross validation

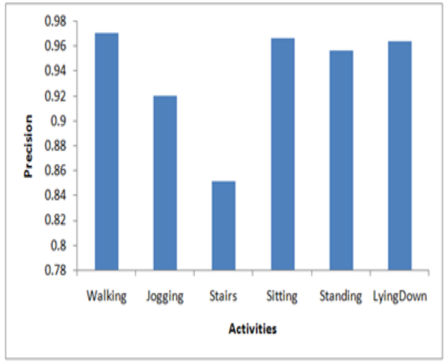
	s_1	s_2	s_3	s_4	s_5	**Avg.**	***p*-value**
BN	76.8211	77.8112	77.1924	77.3868	77.2984	77.302	<0.001
MLP	93.9003	94.4484	93.8649	93.8649	94.1478	94.045	0.001
NB	58.0622	57.6025	57.4257	57.7086	56.4887	57.457	<0.001
J48	**94.9788**	**95.1556**	**95.0318**	**95.4031**	**95.2086**	**95.156**	-
RT	93.6704	94.4031	94.4837	94.6782	94.5191	94.351	0.004
RBFNet	72.0297	71.7999	71.0396	73.0375	72.7723	72.136	<0.001
SMO	89.4802	89.7808	90.1167	90.2758	89.71	89.872	<0.001
Logistic	91.9024	92.6096	92.4505	92.7157	91.7786	92.291	<0.001

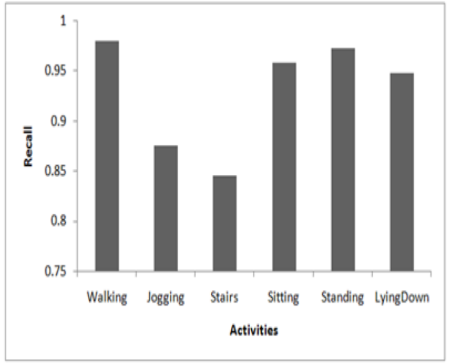
Results

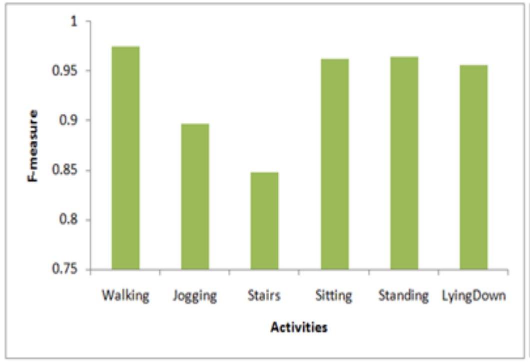
- ***Subject-independent Analysis (5x10-Fold cv)***

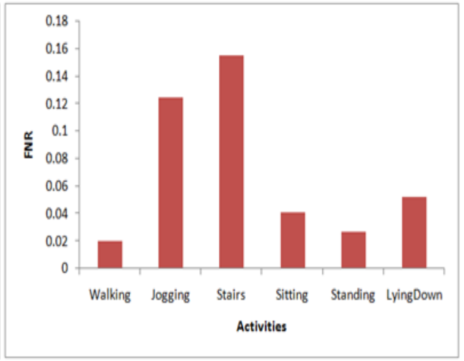
Table 4: Evaluation metrics for the best classifier: precision, recall, F-measure, FPR, FNR for J48.

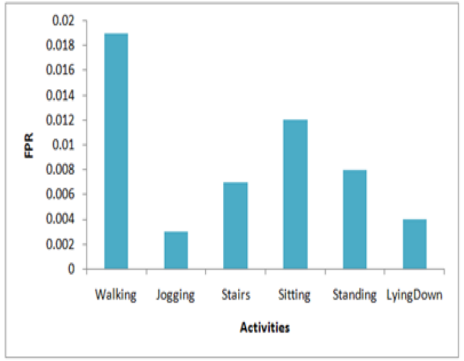
Overall Accuracy: 96.0219%						
J48	**Walking**	**Jogging**	**Stairs**	**Sitting**	**Standing**	**LyingDown**
Precision	0.971	0.92	0.851	0.967	0.957	0.964
Recall	0.98	0.875	0.845	0.958	0.973	0.948
F-measure	0.975	0.897	0.848	0.963	0.965	0.956
FPR	0.019	0.003	0.007	0.012	0.008	0.004
FNR	0.020	0.125	0.155	0.041	0.027	0.052











Results

- **Online Recognition via 2 new subjects *(subject-dependent)***

Table 5: Confusion matrix for Individuals *A* and *B*

		Individual A-Predicted Class (Overall Accuracy: 92.36%)					
		Walking	Jogging	Stairs	Sitting	Standing	LyingDown
Actual Class	Walking	30	0	1	0	0	0
	Jogging	0	19	0	0	0	0
	Stairs	0	1	39	0	0	0
	Sitting	1	0	0	7	5	0
	Standing	0	0	0	3	62	0
	LyingDown	0	0	0	2	0	0

		Individual B- Predicted Class (Overall Accuracy 97.30%)					
		Walking	Jogging	Stairs	Sitting	Standing	LyingDown
Actual Class	Walking	60	0	0	0	0	1
	Jogging	0	12	0	1	0	0
	Stairs	0	0	4	0	0	0
	Sitting	0	0	0	18	0	0
	Standing	0	0	0	0	0	0
	LyingDown	0	0	0	1	0	14

Results

- **HAR Application Interface**

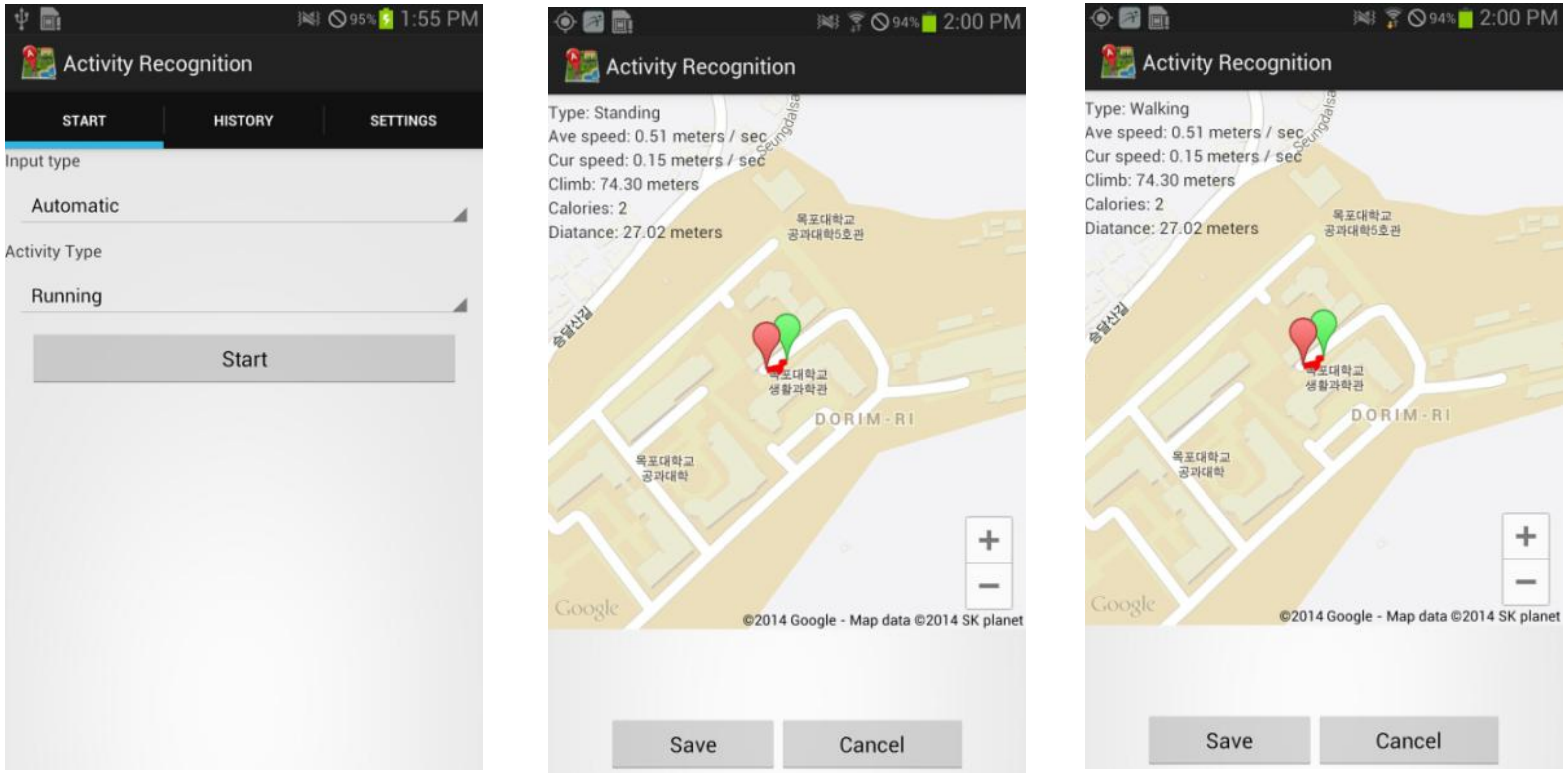


Figure 4: Mobile application User interface

This work vs. other state of the art

Table 6: Comparison of this work with other state-of-the-art HAR systems

	Awan et al[2]	Kwapisz[3]	Centinela[4]	eWatch[5]	This Work
walking	100	90.6	94.28	92	97.96
running	-	-	100	93	-
stairs	-	77.6	92.1	68	84.46
sitting	94.73	96.5	100	99	95.83
jogging	96.15	96.9	-	-	87.5
standing	98.01	93.7	-	-	97.34
Lying down	-	-	-	-	94.83
Total (%)	97.13	92	95.7	92.8	96.02

*Values marked with (-) indicate that the particular activity was not considered.

[2]M. A. Awan, Z. Guangbin, and S.-D. Kim, "A Dynamic Approach to Recognize Activities in WSN," *International Journal of Distributed Sensor Networks,* vol. 2013, 2013.

[3]J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SIGKDD Explorations Newsletter,* vol. 12, pp. 74-82, 2011.

[4]Ó. D. Lara, A. J. Pérez, M. A. Labrador, and J. D. Posada, "Centinela: A human activity recognition system based on acceleration and vital sign data," *Pervasive and Mobile Computing,* vol. 8, pp. 717-729, 2011.

[5]U. Maurer, A. Smailagic, D. P. Siewiorek, and M. Deisher, "Activity recognition and monitoring using multiple sensors on different body positions," in *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on*, 2006, pp. 4 pp.-116.

Conclusion

- J48 provided the most accurate classification results (up to 96.02%)
- Most activities being recognized correctly over 95% of the time
- System does not require a server for feature extraction and processing, thus, reducing the energy expenditures and making it more robust and responsive.

Outlook

Focus on identifying the best machine learning algorithm for finer grain activities such as fall detection, sitting reading or sitting eating.

Effects on the classification accuracy from sensors such as gyroscopes and magnetometers

Thank you for your time.