ACTIVITY RECOGNITION USING SMARTPHONE EMBEDDED SENSORS WITH K-NEAREST NEIGHBOR ALGORITHM

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Abstract: Human Activity Recognition(HAR) is behind many human-centric applications such as Smart Homes, and public healthcare. This paper presents a way of detecting six basic physical human activities (Sitting, Laying, Standing, Walking, Walking Downstairs, Walking Upstairs), with accelerometer embedded in an android smartphone. K-Nearest Neighbor (KNN) algorithm, and Relief F feature selector in WEKA Machine Learning Toolkit were adopted to recognize these activities on a publicly available dataset. The average recognition accuracy of 95.2% demonstrated the feasibility of the proposed solution, and can be considered adequate for HAR. This work is significant because it can provide contextual information about the habits of users passively.

Keywords—Smartphone, Human Activity Recognition, Accelerometer, Relief, KNN, Machine Learning.

1.0 INTRODUCTION

Smartphones have evolved from just communication devices to sophisticated personal computer embedded with a lot of sensors (such as audio sensors, light sensors, motion sensors) (Aigwo. *et al*. 2016). These sensors are now being used in various fields for human-centric applications (such as, Smart Homes, Ambient Assisted Living (AAL), public healthcare, and HAR), which are opening the doors to new areas of research and significantly impacting our daily life (Alvina & Muhammad, 2013). HAR is behind many human-centric applications such as, smart homes, surveillance, fall detection, and AAL. (Umar et al. 2020). HAR involves identifying the physical activity a user is performing, and is immensely useful in healthcare applications**.** Understanding human activities is creating a demand in health-care domain, especially in rehabilitation assistance, physiotherapist assistance, elder care support services and cognitive impairment (Usharani & Usha, 2014)**.** There is a need for a proper health and lifestyle monitoring that detects user's activity, situation, and provides people with right motivational feedback. Such system, can provide contextual information, (Fen et al. 2015), reduce cost for people's ill health and unhealthy lifestyle, and at the same time it can help to improve people's wellbeing.

Collections of studies have used vision based technology such as camera for HAR. However, such methods are plagued with privacy issue, the quality of lighting in the environment **(**Aigwo. Et al. 2016), and requires complex computation, and installation cost **(**Usharani & Usha, 2014**).** Wearable sensors (such as accelerometer), were used to overcome the limitations of cameras. The user is made to wear these sensors on various positions of the body depending on the type of activity being performed. However, they are inconveniencing, expensive, obstructive, none-pervasive and can be irritating (when worn for a long time), which render them non practicable in real life scenarios.

Smartphone embedded sensors don't require technical skills for installation, configuration and maintenance, as a result, smartphones are becoming a viable option for monitoring of activity of daily living (Fen et al. 2015). Due to its unassertive, non-obstructive, pervasive nature, none installation cost and easy-to-use, smartphones are becoming the main platform for human activity recognition (Usharani & Usha, 2014)**.** This paper presents a way of detecting daily six basic physical human activities (Sitting, Laying, Standing, Walking, Walking Downstairs, Walking Upstairs), with acceleration sensors data obtained from using android smartphones. KNN algorithm in the Waikato Environment for Knowledge Analysis(WEKA) Machine Learning Toolkit was used to recognize these activities. The rest of the paper is organized as follows: Section 2 briefly describes related works. Section 3 presents proposed architecture and other relevant concept, Section 4 explains the experimental results, discussion, while Section 5 presents the conclusion.

2.0 RELATED WORKS

A number of works have been done on activity recognition using accelerometer, earlier works explored the use of multiple on-body sensors placed at different body location for identifying physical activities. Bao & Intille (2004) used five small biaxial accelerometers that were worn simultaneously on different parts of the body to collect sensor data. The authors extracted various features and constructed a classification model to recognize twenty activities. Decision Tree(DT) classifier obtained the best performance with an accuracy of 84.0%.

Kwapisz *et al.* (2011) used Logistic Regression(LR), Decision Tree(J48), and Multilayer Perceptron(MLP), to recognize Walking, Jogging, Stairs-Up, Stairs-Down, Sitting, and Standing. According to their results, the overall accuracy is above 90%, except for the case Stairs-Up versus Stairs-Down that poses greater difficulty.

Ling & Wang, (2015) extracted features such as the mean, median, variance, standard deviation, and recognized standing, walking, running and going up stairs and going down stairs, with DT and reported an accuracy between 73.72% to 88.32%.

Fenet et al. (2015) extracted features from data collected from embedded smartphone sensors such as accelerometer. The J48, Naïve Bayes(NB), and Sequential Minimal Optimization (SMO) were employed to recognize activities such as walking, running, walking upstairs, and walking downstairs. The result demonstrated that J48 classifier produced the best performance with an average accuracy of 89.6% while other classifiers also produced high accuracy as well.

Using smartphone accelerometer data at a sampling rate of 50hz, sliding widows of 2.56s with 50% overlapping Ginja, Mathew & Farmer, (2015) classified the following activities: walking on flat ground, up and down stairs, sitting, standing and lying down. DT, Random Forest(RF), Random Committee, Bayes Classifier, k means clustering and KNN algorithms were applied for classification, and NB reported an accuracy of 79%, RF reported accuracy of 96.3%.

Walking on stairs, walking, jogging and jumping activities are also recognized in (Chen & Shen ,2017) with the accelerometer and gyroscope data, implementing several methods, such as the k-NN, which reports a minimum accuracy of 73.94%, the RF reports accuracy of 83.59%, and the Support Vector Machine(SVM), which reports a minimum accuracy of 69.21%.

Maurer et al. (2006) with an eWatch collected sensor data for recognizing the following activities, walking, running, sitting, standing, walking up stairs, and walking down stairs. Correlation-based feature selection algorithm was used to obtain ranked feature sets. DT, NB, KNN, classifiers were used, overall they reported 16% to 92% classification accuracy in their work by wearing the eWatch in different locations on the body.

Jarraya et al.(2017) selected 280 features from a total of 561 by means of a nonlinear Choquet integral feature selection approach, classified six basic actions by using the random forest, and finally obtained a better classification. However, the large number of selected features affected the performance of the classifier.The literature review showed that researchers have done a lot of work in this field of HAR using different techniques and classification methods. However, these solutions rely on additional body sensors. Recently, attempts have been made to implement HAR using smartphones, however, there is need to improve on the accuracies of such studies. This study tries to improve on the accuracy levels by applying Relief F Feature selection algorithm to obtain most discriminant feature for optimal solution.

3.0 MATERIALS AND METHODS

The method used in this paper, is based on data acquisition using smartphone sensors (accelerometer, gyroscope), preprocessing, extracting features, selecting features and training classifiers. K-NN algorithm was implemented using the WEKA framework for the data analysis. The experiments are performed by acquisition of standard UCI HAR Dataset, and performed feature selection with Relief F in WEKA.

3.1 Dataset

For this study, an existing dataset courtesy of the UCI Machine Learning Repository (Anguita et al. 2013) was used for the experiment. The dataset contained data of 30 participants, for six different physical activities including walking, sitting, standing, laying, walking upstairs and walking downstairs. Each activity was performed by a participant wearing a waist mounted smartphone (Samsung Galaxy S II) for 3-5 minutes, and the data contain 10,299 observations with about 300-400 observations per subject.

3.2 Architecture

The physical activity recognition includes six steps: Sensing, preprocessing (noise removal), feature extraction, feature selection, training and classification.

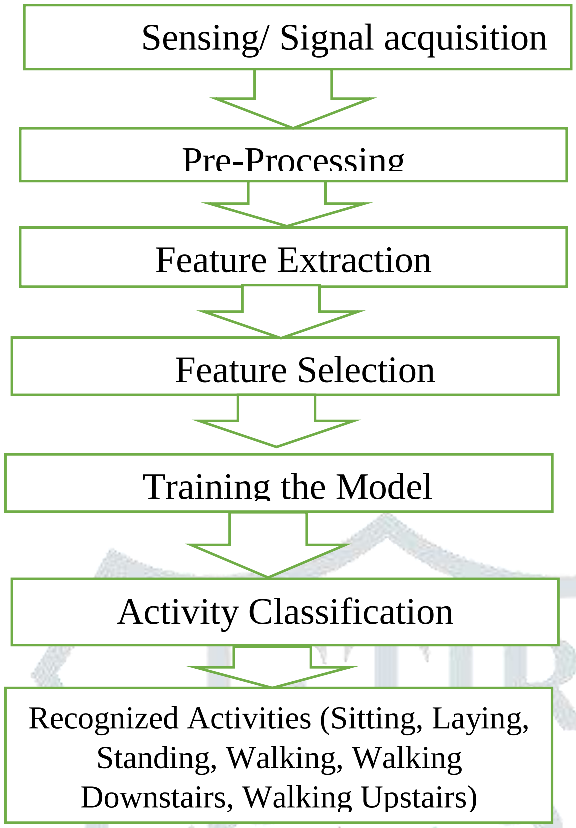

Figure 1: *Human Activity Architectural Diagram.*

3.2.1 Data Acquisition/Sensing

Anguita et al. (2013) recorded the data using a smartphone equipped with an accelerometer and gyroscope sensors. The sensors recorded triaxial angular velocity and linear acceleration at a constant sampling rate of 50 Hz.

3.2.2 Data preprocessing

Anguita et al. (2013) preprocessed the sensor signals by applying noise filters, since the data collected contained noise generated from the participants and the sensors themselves. The sensor acceleration signal, which has gravitational and body motion components, was separated using a Butterworth low-pass filter (with 0.3 Hz cutoff frequency) into body acceleration and gravity.

3.2.3 Feature Extraction

Anguita et al. used a fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window) to extract features. A total of 561 features (such as skewness, the largest magnitude of frequency components, magnitude, mean, standard deviation) with frequency-domain and time-domain were extracted. Mathematical representation of most features extracted is shown in table 1 :

Table 1: Mathematical Formula for some features

Description	**Equation(notation)**
Acceleration (x-, y-, and z- axes)	a_x, a_y, a_z
Gyroscope (x-, y-, and z- axes)	g_x, g_y, g_z
Moving Variance of 100 samples of acceleration and gyroscope data (var)	var=$\frac{1}{N(N-1)}\left(N \sum_{i=1}^{N} x_i^2 \left(\sum_{i=1}^{N} x_i\right)^2\right)$, $here\ x = a_x, a_y, a_z, g_x, g_y, g_z$
Movement intensity of acceleration (MI_a)	$MI_a = \sqrt{a_x^2 + a_y^2 + a_z^2}$
Simple moving average of acceleration data (SMA_a)	$SMA_a = \frac{1}{N}\left(\sum_{i=1}^{N}\lvert a_x\rvert + \sum_{i=1}^{N}\lvert a_y\rvert + \sum_{i=1}^{N}\lvert a_z\rvert\right)$

Variance: A measure of the dispersion degree of a set of data over a window (S)	$S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(a_i - mean)^2$
Standard deviation: The arithmetic square root of the variance (std)	$std = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(a_i - mean)^2}$

3.2.4 Feature selection by Relief F Feature selection algorithm

In this study, Relief F feature selection algorithm was adopted to rank the features in order of relevance. For each instance, the algorithm finds the nearest data point from same class and nearest data points from different classes. Feature relevance is based on how well instances from different classes and instances from the same class are distinguished (Nicole et al. 2015). Relief F weights all features according to relevance. The formula used to update the weight of each feature is eqauction 1.

$$w_i = \sum_{j=i}^{n}\left(x_i^j - Nm\left(x^j\right)_i\right)^2 - \left(x_i^j - Nh\left(x^j\right)_i\right)^2 \qquad (1)$$

where w is the weight of the i th feature, $x^j{}_i$ is the value of the i th feature for point x_j , and N is the total number of data points. Nh x^j and Nm x^j are the nearest data point to x_j in the same and different classes, respectively (Nicole et al. 2015). The Feature selection reduced the computational complexity, improve model interpretability, reduce training time, and enhance generalization by reducing over fitting. In this work we tried several number of ranked features and found that the first twenty-one (21) produced the best accuracy, hence we set a thresh hold for the first twenty-one features. Table 2, shows the selected features.

Table 2: selected features

S/N	Relief Feature Selector	Ranked Attributes
1	**tGravityAcc-energy()-X,**	0.335
2	**fBodyAccJerk-entropy()-X,**	0.273
3	**fBodyAccJerk-entropy()-Y,**	0.251
4	**fBodyAcc-entropy()-X,**	0.250
5	**tBodyAccJerkMag-entropy(),**	0.246
6	**tGravityAcc-max()-Y,**	0.243
7	**angle(X-gravityMean)**	0.241
8	**tGravityAcc-min()-X,**	0.237
9	**tGravityAcc-mean()-X ,**	0.233
10	**tGravityAcc-mean()-Y,**	0.232
11	**tBodyAccJerk-entropy()-X,**	0.230
12	**fBodyAcc-entropy()-Y,**	0.217
13	**tGravityAcc-max()-X,**	0.215
14	**tBodyAccJerk-entropy()-Y ,**	0.213
15	**tGravityAcc-min()-Y,**	0.212
16	**fBodyBodyAccJerkMag-entropy() ,**	0.211
17	**fBodyAccMag-entropy(),**	0.211
18	**tBodyAcc-max()-X ,**	0.207
19	**tBodyGyroJerkMag-entropy(),**	0.206
20	**fBodyAccJerk-entropy()-Z,**	0.202
21	**tBodyAccJerk-entropy()-Z,**	0.200

3.2.5 Training:

The training of the classifier was done in WEKA, and it consists of storing the feature vectors and class labels of the training samples. The training examples are vectors in a multidimensional feature space, each with a labeled class. The dataset was divided into two, one part (70%) for training the model and the other (30%) for testing the model. Training provides the model feature to be used by the classifiers.

3.2.6 Classification using KNN

It is the final step in which the trained classifiers are used to recognize the different physical activities. The KNN algorithm in WEKA was used for the classification. It is a supervised learning algorithm where the result of new instance query is classified based on majority of K-Nearest Neighbor category and it is one of the most popular algorithms for activity recognition. The purpose of KNN algorithm is to stores all available objects and classifies a new object based on attributes and training samples. KNN algorithm used neighborhood classification as the prediction value of the new query instance. The best choice of k depends upon the data; generally, larger values of k reduce the effect of noise on the classification, but make boundaries between classes less distinct. The classification rules are generated by the training samples themselves without any additional data. In the classification phase of activity recognition system, k is a user-defined constant, and an unlabeled vector is classified by assigning most frequent label among the k training samples. Usually Euclidean distance is used as the distance metric for continuous variables. Suppose we have two points x, y where each point is an n-dimensional vector as represented in equation 2.

$$x = \{x_1, x_2, \dots, x_n\}, \qquad y = \{y_1, y_2, \dots, y_n\} \tag{2}$$

Distance function gives the distance between two points by measuring their distance according to Euclidean formula using formula in equation 3

$$d_E(x, y) = \sqrt{\sum_{i=1}^{n}(x_1 - y_1)^2} \tag{3}$$

4.0 Experimental results and discussion

The experiments were conducted using the WEKA machine learning toolkit, the evaluation was performed using a 10-fold cross-validation method. The performance measures used in this study is based on classification accuracy, the F-measure, and the Receiver Operating Characteristics (ROC). For a true positive (TP), a true negative (TN), a false positive (FP), and false negative (FN). Table 3 contains the formula for calculating the evaluation metrics.

Table 3: Evaluation metric

Definition	**Formula**
Accuracy	$\frac{TP + TN}{TP + FN + TN + FP}$
Error	1-accuracy
Recall	$\frac{TP}{TP + FN}$
Precision	$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$
F-measure	$\frac{2\ Precison \times Recall}{Precision + Recall}$

4.1 Results

The summary results for our activity recognition experiments are presented in Table 4(confusion matrix).

Table 4: Confusion Matrix for KNN

		Predicted Class					
Actual Class	**Activity**	**Standing**	**Sitting**	**Laying**	**Walking**	**Walking Down Stairs**	**Walking Up Stairs**
	Standing	**1276**	**98**	**0**	**0**	**0**	**0**
	Sitting	114	**1171**	0	1	0	0
	Laying	0	0	**1407**	0	0	0
	Walking	0	0	0	**1188**	19	19
	Walking Down Stairs	0	0	0	16	**947**	23
	Walking Up Stairs	0	0	0	44	21	**1008**

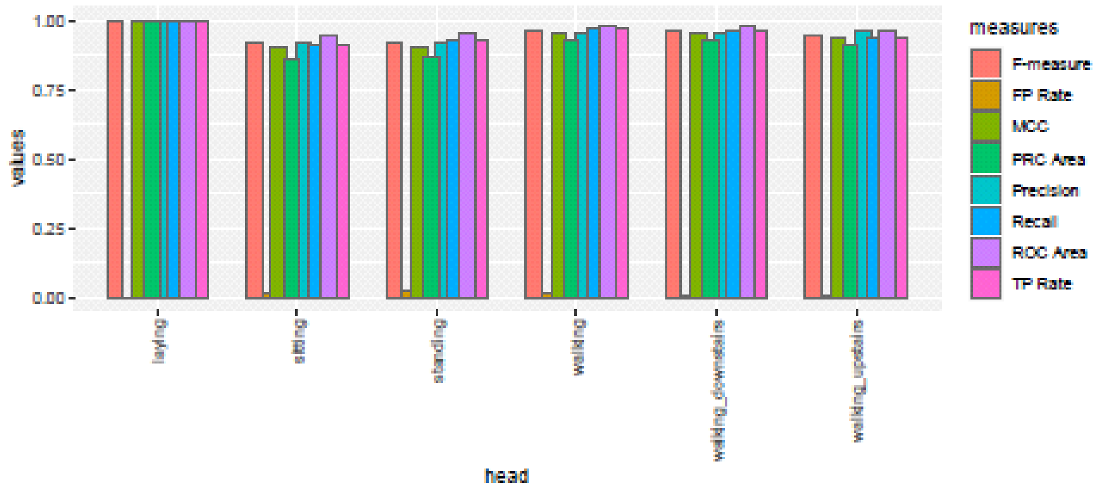

Figure 2: Summary Statistic Per Class

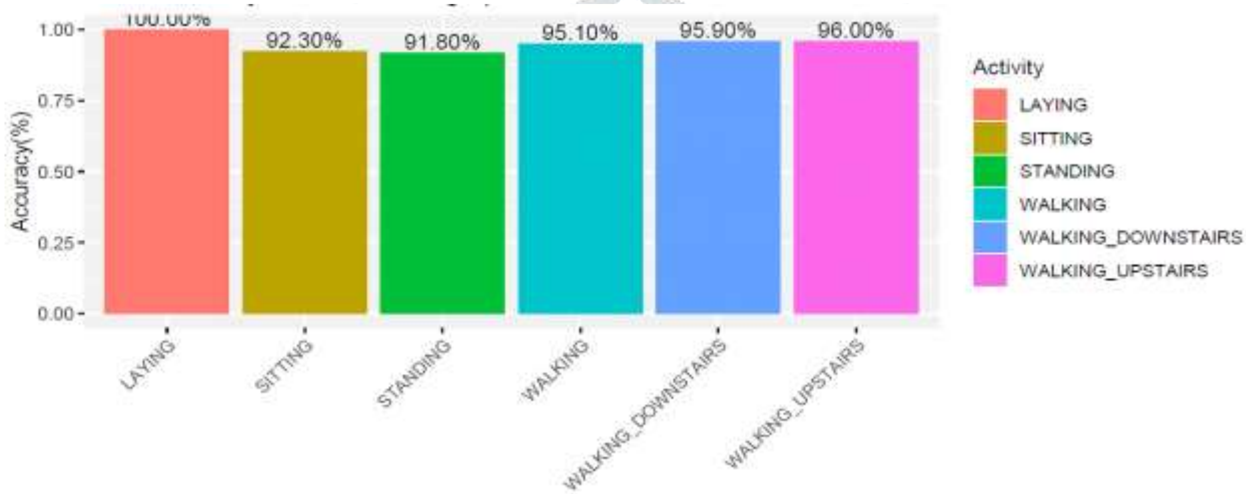

Figure 3: Bar chart of Accuracy versus Activities

From the confusion matrix 1276 instances of Standing were classified correctly, the classifier confused 98 instances for Sitting. The classifier predicted correctly 1171 instances of sitting and confused 114 instances for Standing, and one instance for walking. No instance for laying was predicted wrongly, the classifier predicted 1407 instances of laying correctly. Also 1188 instances of walking were classified correctly, while 19 instance were confused for walking upstairs and 19 for walking downstairs. The model predicted correctly 947 instances of walking down stairs, and confused 16 instances for walking and 23 for walking upstairs. Finally, 1008 instances of walking upstairs were classified correctly, while 21 instance were confused for walking down stairs and 44 for walking. In most cases we can achieve high levels of accuracy (above 90%) for most activities. The confusion matrix indicate that many of the prediction errors are due to confusion in walking up stairs, walking and walking down stairs, since the patterns in acceleration for them are somewhat similar (similar movements and frequencies at the lower limbs). From the result, correctly classified instances are 6997 which gives an overall accuracy of 95.1714 %, incorrectly classified instances is 355 and accounts for 4.8286 %. Also, Kappa statistic is 0.9419, Mean absolute error is 0.0163, Root mean squared error is 0.1268. The result of the proposed approach when compared with those of existing approaches (UCI dataset and others) is shown in table 5.

Table 5: Sumary of Related Works in HAR domain

Related Studies	**Features**	**Implemented Classifier**	**Accuracy**
Fenet et al. (2015)	-	J48, NB, and SMO	89.6%
Atallah et al. (2011)	*ReliefF*, Simba, and MRMR	kNN, Bayesian classifier	90%
Bayat et al. (2014)	Feature Clustering	Multilayer perceptron, SVM, Random Forest, and Logit Boost	81-91%
Maurer et al.(2006)	Correlation based Feature Selection (CFS)	Decision trees (C4.5), KNN, NB and Bayes Net	80-92%

This Study	Relief F	KNN	95.2%

The present work out performed most previous works in terms of accuracy, reduced feature sets, and reduced computational requirements.

5.0 Conclusion

In this paper, we proposed an activity recognition system working on Android platforms while using only the accelerometer data for classification. The KNN gave an accuracy of 95.2% with a reduced feature sets, and is considered reliable for recognizing basic human activities. This indicates that the features eliminated in the feature selection process were redundant and did not significantly contribute to classifier accuracy. Thus, with appropriate feature selection, equivalent classifier performance can be obtained with a reduced feature set, effectively reducing computation burden on the HAR systems.

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