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Human Activity Recognition Using Smartphones Sensors for Ambient Assisted Living

CG Igiri[1*], OE Taylor[2], Orji Friday[3]

[1,2,3]Computer Science Department, Rivers State University, Rivers State, Nigeria

Corresponding Author: igiri.chima@ust.edu.ng, Tel: +2348187655182

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Abstract— With the rapid growth in the elderly population, conventional health care system is no longer sufficient to provide personalized healthcare services for the elderly and healthcare givers are looking for a technological based solution. Ambient Assisted Living(AAL) is such a solution and at the heart of AAL is human activity recognition. Modern smartphone embedded with a lot of sensors has become an integral part of our life and is a vital option for collecting data for activity recognition. In this paper we looked at the use of smartphone accelerometer with supervised machine learning algorithm in WEKA framework for monitoring Activity of Daily Living (ADL): standing, walking, lying, walking upstairs and walking down stairs. Sitting, for the elderly in their environment of choice. We examined two common classification algorithms: Random Forest (RF), instance-based learning (KNN), RF gave us the highest accuracy of 94.4% which is considered adequate for activity recognition.

Keywords— Human Activity Recognition, Ambient Assisted Living Smartphone, ReliefF, Sequential Forward Floating Selection.

I. INTRODUCTION

Advancement in technology, public health, medicine, food and nutrition, decline birth rates, infant mortality, rising life expectancy [1] are some factors that contributed to the growing ratio of the aged pollution, especially in developed countries. According to United Nations (2015), world elderly population is estimated to be about two billion by 2050. This growth is expected to place tremendous burden on formal healthcare since it will lead to limitation in physical functions, chronic age related diseases, increase in health care cost, and inadequate professional health care givers [2]. Demand for personalized health care service is expected to increase more rapidly [6], as well as independent Living of the elderly [2]. Since, technology has become an essential and integral part of our daily life [2], there will be need to provide technological based solutions that will complement the present health system to provide adequate health services to enable the elderly live independently in their preferred environment [4, 2].

Ambient Assisted Living(AAL) enables both professional healthcare givers and informal caregivers to monitor patient's physiological signs, activity of daily living, and behaviour pattern [7]. It provides more convenient automated healthcare services at affordable cost [8]. Also promotes collaboration among health care givers, patient, their neighbours, relations and ensure everyone is actively involved [3, 2], and reduces care giver burden.

At the core of AAL is Human Activity Recognition(HAR), which interpret sensor data to classify a set of human activities [5]; and has application in Smart hospitals, smart homes, surveillance, AAL, and public healthcare [9]. HAR is an active research area that can provide valuable information on health, wellbeing, and fitness of monitored persons outside a hospital setting. A collection of studies has proposed various methods to address the activity monitoring problem, ranging from video cameras, wearable sensors and wireless sensor networks. Wearable and camera-based sensors are not very appreciated by the elderly due to inconvenience, computational complexity, and privacy issues [10]. Smartphones are innovative platforms for HAR because of its unobtrusiveness, ease of use, high computing power, storage, and availability of sensors (such as accelerometer, compass, and gyroscope) [5] [6].

The main objective of this paper is to recognize the type of physical activity the elderly is performing accurately, using the sensors embedded in smartphone. We developed and explored six human activity (standing, walking, lying, walking upstairs, walking down stairs. and Sitting) models using the smartphone's inertial sensors with the aim of choosing the most accurate model experiment in AAL environments. Six machine learning classifiers: Multi-Layer Perception(MLP), Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbor (KNN), Random Forest (RF) and Linear Regression(LR) were adopted to test the effectiveness of the model. This research demonstrate that it is possible to perform activity recognition with commonly available equipment and yet achieve highly accurate results. This paper is organized as follows: in Section 1, background on Ambient Assisted Living, Human Activity recognition and Smartphones sensors is presented. Section 2 describes some of the related work in the area of human physical activity recognition using smartphone based sensors in AAL. Section 3: The adopted methodology 4: presents the experimental results obtained and performance evaluation. Section 5: Finally, concludes the paper.

II. REVIEW OF RELATED WORKS

Earlier works explored the use of multiple on-body sensors placed at the waist, arms, knees and ankles for identifying physical activities. A few works have been performed whereby only one tri-axial accelerometer was used. With advancement in the mobile phone technology and emergence of smartphone containing lot of sensors, physical activity monitoring is realized by many mobile applications using acceleration sensor of the smartphone. For continuous and passive identification of smartphone users, [11] used the gyroscope, accelerometer and magnetometers of a smartphone to read sensors data to identify six activities, sitting, walking, standing, running, walking upstairs and walking down stairs. The phone was placed at the right wrist, right upper arm, left thigh, right thigh and waist position. A sample rate of 50HZ, sliding window with 50% overlapping was used to exact both time and frequency features. Bayes Net classifier provided the best accuracy rate of 94.57% and F-measure of 0.94 as compared to KNN and SVM for all phone positions [17] used the DT classifiers to identify activities such as idle, sitting, standing, walking, going upstairs and down stairs, running and cycling, with different phone position. Time and frequency features such as standard deviation, and number of peaks of the accelerometer signal were extracted, and average accuracy of approximately 80% was obtained.

To recognise gait difference between healthy and elderly people with accelerometer embedded in the phone, [12] used NB, SVM, KNN, DT, MLP, Bayesian Network, LR in Weka tool to identify walking, hobby and sticking. Features such as mean, standard deviation, were used alongside with the horizontal and vertical components, with sampling rate of 30Hz. KNN was higher than the other classifiers with accuracy of 95.5% and 81.4% for healthy and elderly respectively.

[13]. also used a smartphone accelerometer for recognizing five basic human activities, i.e. limping, jogging, walking, walking down stairs, and walking up stairs. using a wrapper-based sequential forward selection (SFS), and four different learning methods: Artificial Neural Network, quadratic classifier, SVM, and KNN for classification. SVM gave highest accuracy of 84..4%.
[20] proposed a hybrid method feature selection process, using sequential floating forward search (SFFS), and a multiclass support vector machine (SVM). Data was collected using inertial sensors (accelerometer and gyroscope) mounted on the waist. The hybrid feature selection method containing the filter and wrapper approaches played an important role for selecting optimal features. The selected features are used with SVM to identify the human activities. The proposed system shows 96.81% average classification performance using optimal features, which is around 6% higher improved performance with no feature selection.

To recognize activities such as walking, going upstairs and downstairs, standing, and sitting, [19] used the Nokia N95 smartphones collected accelerometer sensor data. Classifiers were used to test the effectiveness of the reduced feature set, an accuracy up to 94% was obtained.

[18], recognizes activity such as walking, sitting, standing, walking on stairs, jogging, cycling and jumping with the accelerometer data only. Using two feature selection methods in Weka, OneRAttributeEval and ReliefFAttributeEval the most discriminant features were obtained. Several classifiers were used and KNN gave the best accuracy of 93.84% and RF with an accuracy of 93.13%.

This work differs from most prior work in that we use a single device conveniently kept in the user's waist rather than multiple devices distributed across the body. The location where the phone should be placed and the orientation of the phone are predetermined. Also, we plan to make the data generated by our mobile app public in the future. This data can serve as a resource to other researchers, and also demonstrate how raw time series accelerometer data can be transformed into examples that can be used by conventional classification algorithms. M any studies have been proposed in recent years to recognize physical activities based on smartphone accelerometer data using a combination of different reasoning techniques. For such studies our model provided higher accuracy.

III. MATERIALS AND METHOD

In this paper, a set of experiment was conducted to obtain the HAR dataset with 5 Subjects volunteers (5Males, 1 Female). The subjects are between 65-70 years of age. Each of them was informed on the rules for selecting the activities, and how to perform the activity in such situations. Samsung Galaxy S2, was used for this purpose. Each participant places the smartphone on his/her hand, and tied it to his/her waist. Each of the participants performed each of the activities specified for 1 minute, and raw data from the accelerometer sensor readings were taken (recorded on x, y z, axes).

3.1 Experimental Setup

The Samsung Galaxy S II smartphones, with inbuilt accelerometer and gyroscope sensors, were used to conduct this experiment. A mobile sensing application was developed using Android Development tools. Signal pre-processing, feature extraction was implemented using python programming language, while feature selection and classification were implemented using WEKA toolkit. In the experiment, each volunteer was instructed to perform the following activities: sitting, standing, walking, lying, walking upstairs and walking down stairs while wearing a Samsung Galaxy S2 smartphone that contained a tri-axial accelerometer and gyroscope on his/her waist.

3.2 Sensor Data Acquisition

The data collection was controlled by an application we created that executes on the smartphone. On launching the application, the subjects are required to supply their bio data, which is used to build a profile for each users. Basic information like name, age, height, weight, gender is collected; also start and stop time. The activity being performed is then labeled. When activated, the application continuously reads linear accelerometer and gyroscope sensor data from three axes of each sensor and timestamp at about 20Hz and then the data are stored into a local plaintext file. Each activity trace contains data consisting of time series of 3 accelerometers ($a_X[n]$, $a_Y[n]$, $a_Z[n]$) and 3 gyroscopes ($g_X[n]$, $g_Y[n]$, $g_Z[n]$). To avoid mislabeling, subjects were asked to stop and wait a few seconds after an activity before starting the next activity. Besides, since the waist is close to human body's mass center (human body movements originate from this region,) waist- placement for motion sensors is commonly used in many studies. In this experiment the final dataset used is a combination of 50% of data generated in this research and 50% of the standard UCI dataset for AAL [14]. The data generated in this research was generated under the same conditions as in the UCI dataset, and in this work a naming convention similar to that os UCI was adhered to for the purpose of simplicity.

3.3 Pre-Processing: Pre-processing is the second stage of Human Activity Recognition Process. Pre-processing is done using two methods; first is noise removal and second is windowing or segmentation. Standard classifiers do not work well on this raw sensor data; hence it is essential to transform this raw data. Smartphone-based HAR solutions primarily use low-pass, Butterworth, Kalmar, and Moving Average filters for noise removal**.** The raw signal data per window were filtered using a median filter and a 3rd-order low-pass Butterworth filter of 20*Hz* corner frequency.

3.4 Architecture of Human Activity Recognition

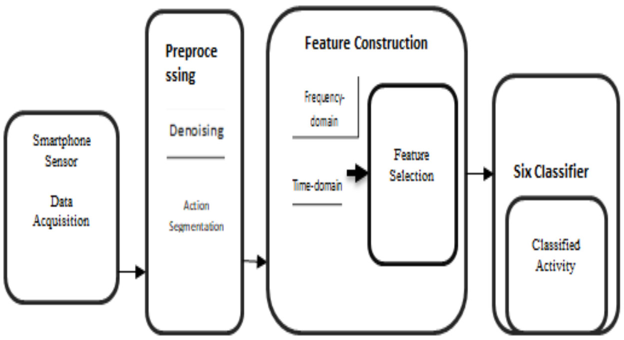

Fig 1: Architecture of proposed HAR

3.5 Feature Construction

This section is made up of feature extraction and feature selection.

3.5.1 Feature Extraction(FE): The purpose of feature extraction is to extract some features that represent the original activity information to the greatest extent. Signal characteristics such as time-domain and frequency-domain features are widely used for feature calculation. Time-domain features include mean, median, variance, skewness, kurtosis, range. Peak frequency, peak power, spectral power on different frequency bands and spectral entropy are generally included in the frequency-domain features. The raw data was sampled with fixed-width sliding windows (has better smoothness property) of 2.56 sec and 50% overlap, since ideal size for fixed windows varies around 2 to 5s considering a frequency of 20 Hz to 50 Hz. From each window, a vector of features is obtained by calculating variables from the accelerometer signals in the time and frequency domain. The dataset consists of vectors that each contain 561 features and represent 2.56 seconds of time. In the following formulas, *ai* is the value of the sensor signal, $x(t)$, $y(t)$, $z(t)$ is the acceleration curve of the *x*-, *y*-, *z*-axis. $a_X(t)$, $a_Y(t)$, $a_Z(t)$ represent the *t*-th acceleration value of the x-, y- and z-axis. Mean: The average value of the signal over the window. Acceleration (x-, y-, and z-axes) $\mathrm{a_x}, \mathrm{a_y}, \mathrm{a_z}$

Table 1: Some formulas for statistical feature selection

Arithmetic mean $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_1$
Root Mean Square $RMS(Y) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} y_1^2}$
Signal magnitude Area:(SMA): $SMA = \frac{1}{t}(\int_0^l \lvert a_x(t)\rvert\, dt + \int_0^l \lvert a_y(t)\rvert\, dt + \int_0^l \lvert a_z(t)\rvert\, dt)$
Variance: A measure of the dispersion $S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(a_i - mean)^2$ degree of a set of data over a window
Standard deviation: The arithmetic $std = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(a_i - mean)^2}$

3.5.2 Feature Selection(FS): [15] affirm that the choice of features is more important than the choice of classification algorithms, since the poor quality of the features can negatively impact the accuracy of any model generated by the conventional machine learning algorithms. The features selection techniques define the subset of features that best discriminate human activities, this work adopts ReliefF and Sequential Floating Selection algorithm (SFS): both Sequential Forward Floating Selection (SFFS) and Sequential Backward Floating Selection algorithms (SBSF). In the present study, first feature selection using ReliefF FS method was first applied to the dataset to first reduce the feature dimensionality. The reduced features set of thirty-nine discriminant features returned by ReliefF, were feed into SFFS and SBFS, to produce a final set of twenty-four features. This final features of twenty-four out of five hundred and sixty-two was passed to the two best classifier for classification, hence the computational burden on the classifier is reduced and accuracy enhanced with the reduced features. Table 2 shows the most important twenty-four features.

Table 2: First 24 most discriminant features for HAR recognition.

tGravityAcc-energy()-X , angle(X-gravityMean), tGravityAcc-mean()-X, tGravityAcc-energy()-Z , tGravityAcc-max()-Z, tGravityAcc-mean()-Z, tGravityAcc-min()-Z, angle(Z-gravityMean) , tBodyAccJerk-entropy()-X, tGravityAcc-min()-Y, tGravityAcc-mean()-Y, fBodyAccJerk-entropy()-Y, tGravityAcc-max()-Y, fBodyBodyAccJerkMag-entropy(), tGravityAcc-energy()-Y, angle(Y-gravityMean), tBodyAccJerk-entropy()-Z, fBodyGyro-entropy()-X , fBodyGyro-entropy()-Z, tBodyGyroJerk-entropy()-Z, fBodyBodyGyroJerkMag-entropy(), fBodyAccMag-entropy(), tBodyGyroMag-entropy(), fBodyGyro-entropy()-Y.

The Sequential Forward Floating Selection (SFFS) [16] procedure consists of applying after each forward step a number of backward steps as long as the resulting subsets are better than previously evaluated ones at that level. The backward counterpart to SFFS is the Sequential Backward Floating Selection (SBFS). Its principle is analogous. Both algorithms allow a 'self-controlled backtracking' so they can eventually find good solutions by adjusting the trade-off between forward and backward steps dynamically. The algorithm for Sequential Forward Floating Selection yielding a subset of d features, with optional search-restricting parameter $\Delta \in [0, H-h]$:

I. Start with $Z_0 = \emptyset$, $i = 0$.
II. $Z_{i+1} = ADD(Z_i)$, $i = i + 1$.
III. Repeat $Z_{i-1} = REMOVE(Z_i)$, $i = i - 1$ as long as it improves solutions already known for the lower i.
IV. If $i < h + \Delta$ go to 2

Algorithm for SBFS search-restricting parameter $\Delta \in [0, h]$:

I. Start with $Z_0 = D$, $i = |D|$.
II. $Z_{i-1} = REMOVE(Z_i)$, $i = i - 1$
III. Repeat $Z_{i+1} = ADD(Z_i)$, $i = i + 1$ as long as it improves solutions already known for the higher i.
IV. If $i > h - \Delta$ go to 2.

3.6 Classification Algorithm

After the data processing in the segmentation and features extraction steps, the next step is to use classification algorithms that are responsible for generating classification models to infer human activities. In this paper, the classification algorithms adopted are the RF and KNN, though we applied NB, SVM, MLP and LR before the feature selection. These other classifiers were not considered further for the sake of space and their results were less than the two we choose.

3.6.1 Random Forests are an ensemble of decision trees, and are based on ensemble learning methods for classification and regression, hence reduces model over-fitting. They are also thought of as form of a nearest neighbor predictor, that construct a number of decision trees at training time and output the mode of the classes as the output class. Random Forests work by training many decision trees on random subsets of the features, then averaging out their predictions. Random Forests have very few parameters to tune and most of the time work very well by simply using them with parameter settings set to default values, this work adopts the default setting in WEKA. Random Forests can handle data with high dimensionality by increasing the number of trees, which is very suitable for the feature vectors extracted in this work. The default value of 100 bagging was adopted.

3.6.2 KNN: The K Nearest-Neighbor classifier models one activity's motion-sensor behavior on the assumption that new feature vectors from the same activity will resemble one or more of vectors in the training data. In our work, we implemented a K-Nearest-Neighbor classifier, which assigns the new vector the label most frequently represented among the k nearest training samples. In the training phase, the classifier calculates the covariance matrix of the training feature vectors, and the nearest-neighbor parameter k is set as 1. In the testing phase, the classifier computes Euclidean distances, and the new sample is assigned to the category most frequently appearing among the k nearest training samples.

3.7 Training:

The activity classifiers are required to be trained before the classification process. Training provides the model feature to be used by the classifiers. The training examples are vectors in a multidimensional feature space, each with a labeled class. The training phase of the algorithm consists of storing the feature vectors and class labels of the training samples. Here we divided our dataset into two, one part (70%) for training the model and the other (30%) for testing the model. In k-fold cross-validation, the original sample is randomly partitioned into k equal size subsamples. A single subsample is selected from the k subsamples as the validation dataset for testing the model, and the remaining k-1 subsamples are used as the training dataset. The cross-validation process repeat for k times, with each of the k subsamples used exactly once as the validation data. The results from the k processes can then be averaged to produce a single estimation. In general, 10-fold cross-validation is commonly used in most of situations. Therefore, 10-fold cross validation was used to optimize the six classifiers in our study.

IV. RESULTS

The experimental results are presented here.

4.1 Performance Measures

Confusion matrix, precision, recall, F1 and accuracy were used to evaluate the performance of the model.

(1) Precision is the weighted average of the fraction of the inferred activity labels that are correctly predicted for each activity class, and can be calculated with (1) where C represent the number of class.

$$\text{Precision} = \frac{1}{C}\sum_{i=1}^{C} \frac{TP_{ii}}{TP_{ii}+\sum_{j=1,j\neq i}^{C} FP_{ij}}, \qquad (1)$$

where TP_{ii} is the number of test samples that are corrected classified for the inferred label i; the denominator shows the total number of test samples that are classified as label *i*,

(2) *Recall* is the weighted average of the fraction of the true activity labels that are correctly classified for each activity class and is measured using (2).

$$\text{Recall} = \frac{1}{C}\sum_{i=1}^{C} \frac{TP_{ii}}{TP_{ii}+\sum_{j=1,j\neq i}^{C} FP_{ji}} \qquad (2)$$

Where *denominator* indicates the number of test samples with true label I.

(3) F1 takes a real number between 0 and 1, and 1 indicates that the classifier can correctly classify all test samples and is given by equation (3).

$$\text{F1} = \frac{2*precision*recall}{precision+recall} \qquad (3)$$

(4) *Accuracy* is the number of samples that are correctly classified and is computed by equation. (4)

$$\text{Accuracy} = \frac{\sum_{i=1}^{C} TP_{ii}}{\sum_{i=1}^{C} TP_{ii}+\sum_{j=1,j\neq i}^{C} FP_{ji}} \qquad (4)$$

4.2 Results

KNN classifier outperformed the other classifiers when all features were used for the classification. However, using all features will increase model building time, place heavy computational burden on the classifier and may lead to model over fitting, hence the need to reduce the feature set. Figure 3 shows the classification accuracy for each activity by classifiers, BN and SVM are the lowest in terms of accuracy. Activities such as sitting, laying were easily confused by the classifiers. Figure 2 shows accuracy of each classifier, where KNN out performed others using the full feature set, while figure 3 gives the accuracy based on the full feature set.

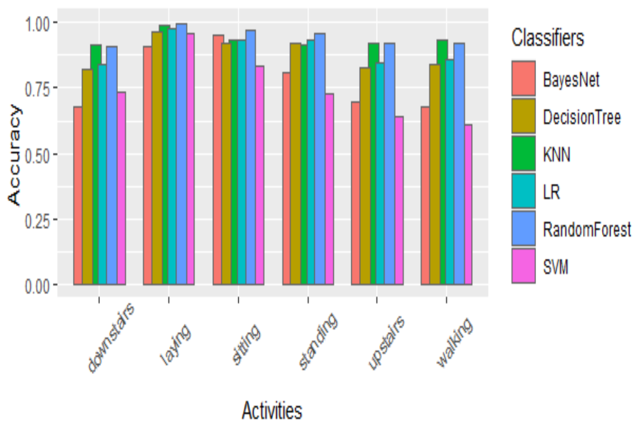

Figure 2: Accuracy Against Activities Base On Six Classifier

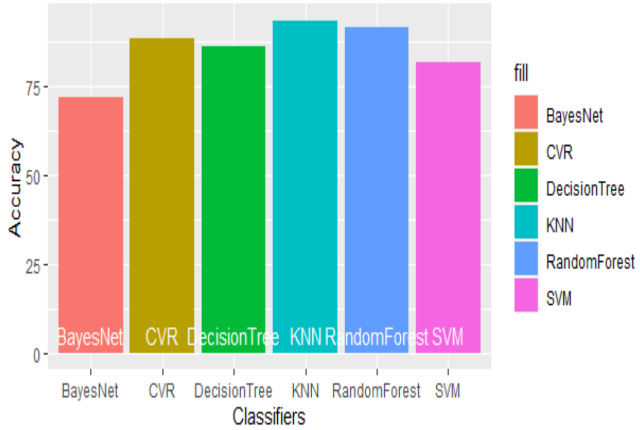

Figure 3: Accuracy Against Classifiers

The F measures are shown in figure 4 and follows almost the same pattern as that of the accuracy.

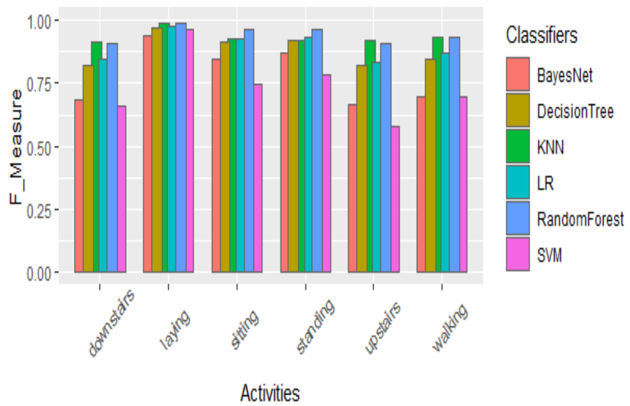

Figure 4: F- Measure Against Activities Base On Six Classifier

A comparison of the performance of the best two classifiers is presented in table 3, the summary statics before and after feature selection is shown. The effect of feature selection can be shown in the reduction of number of features, model building time and accuracy. Table 4 gives the Performance of the classifiers.

Table 3: Summary Statistic for KNN and RF Classifiers

Summary	**FULL FEATURES**		**AFTER FEATURE SELECTION**	
Classifier	**KNN**	**RF**	**KNN**	**RF**
Correctly Classified Instances	3971(93.4 %)	3888(91.5 %)	3961(93.2%)	4012(94.4%)
Incorrectly Classified Instances	280(6.6%)	363(8.5%)	290(6.8%)	239(5.6%)
Kappa statistic	0.9207	0.8972	0.9178	0.9323
Mean absolute error	0.0224	0.0948	0.0231	0.0505
Root mean squared error	0.1481	0.1764	0.1507	0.1304
Relative absolute error	8.0771%	34.2592%	8.36%	18.2539%
Root relative squared error	39.8003%	47.4088%	40.5046%	35.062%
Total Number of Instances	4251	4251	4251	4251
Attributes	562	562	25	25
Time taken to build model (s)	0.03	21.98	0.01	7.12

Table 4: Performance of KNN and RF Classifiers

Precision	Recall	F-Measure	Precision	Recall	F-Measure	Class
KNN			RF			
0.914	0.932	0.923	0.955	0.969	0.962	**STANDING**
0.934	0.914	0.924	0.972	0.951	0.961	**SITTING**
0.989	0.986	0.987	0.993	0.989	0.991	**LAYING**
0.931	0.936	0.934	0.921	0.943	0.932	**WALKING**
0.914	0.919	0.916	0.905	0.913	0.909	**WALKING_DOWNSTAIRS**
0.922	0.917	0.920	0.920	0.898	0.909	**WALKING_UPSTAIRS**
0.932	0.932	0.932	0.944	0.944	0.944	**Weighted Average**

In this research the confusion matrix is one of the main performance measures used to evaluate the performance of our model. Table 5 and Table 6 shows the confusion matrix for RF and KNN classifiers. From the matrixes, the misclassification occurs more in activities such as walking, walking upstairs and down stairs. Also the classifier was not able to distinguish in most cases between standing and Sitting.

Table 5: Confusion matrix for KNN using selected Features

a	B	C	D	e	F	classified as
722	48	0	2	1	2	a = STANDING
64	762	3	1	2	2	b = SITTING
0	3	546	2	1	2	c = LAYING
1	0	0	719	25	23	d = WALKING
1	2	1	32	635	20	e = WALKING_DOWNSTAIRS
2	1	2	16	31	577	f = WALKING_UPSTAIRS

Table 6: Confusion matrix for RF using selected features

a	**b**	**c**	**d**	**E**	**f**	**classified as**
751	18	1	1	1	3	a = STANDING
32	793	2	1	0	6	b = SITTING
0	1	548	0	1	4	c = LAYING
0	0	0	724	24	20	d = WALKING
2	2	0	40	631	16	e = WALKING_DOWNSTAIRS
1	2	1	20	40	565	f = WALKING_UPSTAIRS

V. CONCLUSION

In this paper, we evaluated the use of smartphone sensor to predict human activity using RF and KNN classifiers in an AAL. The effect of feature selection with ReliefF, Sequential floating Search algorithm was considered. The work demonstrates the need for feature selection to reduce the computational burden on the classifiers. The most important features for identifying activities were selected and other irrelevant features were discarded, this in turn reduces the model building time as well. A combination of Relief and SFS algorithm returned a feature set that resulted in the highest accuracy of 94.4% by RF classifier. Other classifiers still perform relatively better with the reduced feature set. This work combined our own generated dataset and publicly available dataset, and demonstrate the successful use of the smartphone for sensing in AAL to enable the elderly live independently in environment of their choice.

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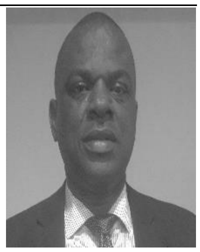
AUTHORS PROFILE



Igiri Chima Godknows holds a Bachelor degree in Computer Science and Engineering, from Enugu State University Enugu, an MSc. In Computer Science from University of Port Harcourt, and is presently a lecturer in the department of computer science, Rivers State University. His research interests are in Big Data, Internet of Things, Intelligent systems, and he has over fifteen years industrial and academic experience.

***Dr.* O. E. Taylor** pursed his B.Sc, M.Sc and Ph.D degrees all in Computer Science from the Rivers State University of Science and Technology, University of Ibadan and University of Port Harcourt, Nigeria respectively. He is currently Senior Lecturer in the Department of Computer science, Rivers State University, Port Harcourt, Nigeria. He is a chartered member of the Computer Professionals (Registration Council) of Nigeria and Nigeria Computer Society. His research focuses on intelligent systems, smart space, context-aware systems, machines learning algorithms and artificial intelligence. He has over ten years of teaching and research experience.

Friday Orji is a lecture in the Department of Computer Science Rivers State University
Port Harcourt, Nigeria.