Coupling of Dimensionality Reduction and Stacking Ensemble Learning for Smartphone-Based Human Activity Recognition

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ABSTRACT

Human activity recognition (HAR) plays a vital role in the field of ambient assisted living (AAL) for the welfare of the elders who live alone in the home. AAL provides service through ambient sensors, vision systems, smartphone devices, and wearable sensors. Smartphone devices are familiar, portable, cost-effective, and make the process of monitoring easier. Various research works have proposed smartphone-based HAR systems to recognize basic and complex activities. However, the results are not satisfactory for the case of postural transitions such as stand-to-sit, sit-to-sleep, etc. To improve the recognition rate, this paper couples principal component analysis with stacking ensemble learning for dimensionality reduction and classification respectively. Extensive experimentation of UCI repository datasets such as UCI-HAR has been performed and the performances are measured using familiar metrics such as accuracy, precision, and recall.

KEYWORDS

Activity Recognition, Ambient Sensors, Assistive Living, E-Health, Smartphones, Wearable Devices

INTRODUCTION

The percentage of elders’ population over and above the age of 60 is increasing a lot in the last 10 years and this will continue to increase for another 20 years (WHO, 2015). In the year 2015, the elders’ population was around 900 million in the world which is expected to increase triple by 2050 (WHO, 2015). As the age of elders increases, they face more challenges and issues to live independently. This makes the family members to take up the role of informal caregivers to provide them care and help to do their basic daily activities. These challenges attract the researchers of Ambient Assisted Living (AAL) over the last decade to provide some creative solutions for ensuring the safety and
health quality of the senior citizens in various care needs such as Human Activity Recognition, Fall detection, Alzheimer’s disease detection, blind support etc.,

Human Activity Recognition (HAR) now plays a vital role in the field of AAL for the welfare of elders (Zdravevski et al, 2017) as most of the elders live independently. AAL comprises pervasive and ubiquitous hardware components termed as HAR devices that provide services to the elder with disabilities or for adults who cannot or who choose not to live independently. In general, HAR components gather signals from pervasive and ubiquitous devices such as ambient and wearable sensors to be processed through any Machine Learning (ML) algorithms for activity recognition (Ramanujam and Padmavathi, 2019). The HAR system recognizes multiple activities in various domains of applications such as intelligent transportation, education and Healthcare (Wang et al, 2019). In the field of Healthcare, HAR has the greatest impact on recognizing Activities of Daily Living (ADLs) such as basic, complex and postural transitions. These activities are categorized based on the duration of seconds. For instance, basic activities are characterized by a longer duration and can be either dynamic or static (e.g running and reading). Complex activities are the extension of basic activities where the subjects interact with any other physical objects may be like playing sports, etc. Finally, the Postural transitions comprise of transition from one gesture to another gesture such as sit-to-stand, stand-to-sit, etc. More number of research works has been proposed in the last decade for the HAR (Hernandez et al, 2020) with elders.

In the last decade, more research works have been proposed for HAR as reviewed in a survey done by (Hernandez et al, 2020). Mubashir et al, (2013) have categorized HAR systems into three such as Ambient, Wearable, and Vision systems. Many research works (Seneviratne et al, 2017) has suggested that wearable devices are appropriate in most of the emergency situation. The success of this device purely depends on user involvement such as pressing the button of the device, etc. To be specific, the wearable devices have to be worn throughout the day by the elder and need to be charged regularly. The elders may forget to do those due to their age factor. On the other side, ambient sensors (Wang et al, 2019) are costlier and not feasible to install all over the actuation area of the elder. Moreover, the maintenance cost seems to be very high and it makes the elder live only in the controlled environment. In the case of vision systems (Jegham et al, 2020), the surveillance cameras highly interrupt the seniors from their personal privacy and security.

Nowadays, Smartphone has a high impact in the field of HAR which provides better solutions than the other AAL devices (Morales et al, 2017). Smartphone is feasible to implement in HAR as it is cost-effective and has wide response and familiarity among all the persons for communication, social networking, e-commerce, and other baking transactions in a secure manner. Smartphone based HAR system utilizes the embedded inertial sensor such as accelerometer, gyroscopes and magnetometers for the process of activity recognition. The smartphone based HAR performs the operation through various modules such as data collection, data preprocessing, feature extraction, feature selection and classification as shown in Figure 1. In data collection, smartphones are tied in the belt or kept in the trouser pocket of the subject to collect the tri-axial accelerometer, gyroscope, and magnetometer data. In the process of data preprocessing certain filters, and sliding window size has been used as discussed in (Sousa et al, 2017) to convert the time series data to discrete data. Feature extractions extract relevant and expensive features for the better classification. Finally, the classification has been performed through any machine learning classifiers.

Figure 1. General Framework of Smartphone based Human Activity Recognition systems
The performance of Smartphone based HAR depends on the signal-to-noise reduction, feature quality, data fusion, sliding window size, etc (Thakur and Biswas, 2020). Most importantly, feature selection i.e selection of best features has the greatest impact on the classification performance, as false detection creates a pathetic situation among the caretakers and relatives of the elders. The state-of-the-art techniques have proposed various techniques for the purpose of feature selection and those techniques have been evaluated through familiar common performance metrics such as Accuracy, Precision, Recall and F-Measure (Demrozi et al, 2020). Even though, in recent years numerous research works have also been proposed for Smartphone based HAR. There is more provision to improve recognition performance by reducing the false detection rate.

To enhance the recognition performance, this paper couples the concept of dimensionality reduction along with an ensemble of classification process to provide better predictions. To demonstrate the proposed methodology, two familiar HAR datasets such as Human Activity Recognition Using Smartphones Data Set (UCI-HAR) (Anguita et al, 2013) and Smartphone-Based Recognition of Human Activities and Postural Transitions (UCI-HAPT) (Reyes-Ortiz et al, 2016) dataset are utilized from the University of California Machine Learning repository (Dua, and Graff, 2019) and its performances are shown in the following section.

The remainder of this paper is organized as follows. First, the literature on the various study, research works, Smartphone based HAR systems their merits and demerits are provided in order to present the research hypotheses. Next, the proposed methodology is presented, followed by the experimental results and discussions of UCI dataset. Subsequently, conclusions, and suggestions for future research are identified.

RELATED WORK

In the recent years, a large number of research works have been proposed for the purpose of Human Activity Recognition (HAR). Among the techniques, deep learning plays a vital role in the classification and recognition of activities (Wang et al, 2019). However, the deep learning algorithms have more limitations when compared to traditional machine learning algorithm such as:

1. Requires higher-end machines for training the data.
2. Algorithm takes a longer duration to train the data due to a large number of parameters.
3. Lack of domain understanding for feature engineering makes tedious interpretability in parameter optimization.
4. Needs high-end infrastructure to train in a reasonable time.

In addition, the deep learning algorithms are more compatible with vision based human activity recognition systems. As smartphone based system probably generates only time series signals, the traditional machine learning algorithm itself performs well in activity recognition (Liew et al, 2015). The research works have mostly utilized traditional machine learning algorithm such as k-Nearest Neighbor (k-NN) classifier, Support Vector Machine (SVM), Multilayer Perceptron (MLP), Decision Tree (DT) classifier for the classification and activity recognition. Mannini and Sabatni, 2010 has proposed an advanced classification algorithm termed Gaussian Continuous Emission Hidden Markov Model (HMM), and threshold-based classifier by Ermes et al, 2008 etc for their performance evaluations.

Recently, researchers have concentrated more on feature selection rather than machine learning algorithms. As more number of features drastically increases the computational cost of the classification process. In the process of feature selection, Nurhanim et al, 2019 has compared different filter-based feature selection for the purpose of multiclass classification problem on HAR. An ensemble method of random subspace feature selection along with SVM classification achieved 98.89% accuracy for selected 198 features of the HAPT dataset using the 10-fold cross-validation process. However, the
randomness may cause a reduction of final ensemble decision performance because of contributions of classifiers trained by subsets with low class seperability. Similarly, Karagiannaki et al, 2016 has analyzed the performances of benchmark feature selection techniques for the HAR dataset. In this approach, a new dataset and framework termed FORTH-TRACE has been derived from various features selected from other HAR datasets. The FORTH-TRACE has shown better performance, as highly relevant features are selected from various HAR dataset. Further, this dataset is not compatible for fair comparison. Using the extended dataset, various evaluation performances are performed by varying the sliding window size, noise filters, training and testing data ratio, etc.

To optimize both the feature selection and classification process, Rosati et al, (2018) has proposed a Genetic Algorithm based optimization technique. The author generates two different feature set of HAR dataset that has time, frequency, time-frequency domain features, and classified using SVM, DT, and NN. Experimentation on these two feature sets achieved a maximum accuracy of 97.1% and 96.7% for the proposed Genetic Algorithm. In this approach, Genetic Algorithm consumes more time in the selection of features, however there is no computational complexity analysis provided in the paper. Doewes et al, 2017 has proposed a feature selection technique on the HAPT dataset using a traditional feature selection technique named minimum redundancy and maximum relevancy (mRMR). The proposed technique selects 201 features out of 561 features and achieved an accuracy of 95.15% and 94.23% accuracy for SVM and MLP classifier. In this case, the reporting time for the recognition of activity will be high as it considers more number of features for recognition.

Wu et al, 2015 has demonstrated the importance of time-domain features of HAPT dataset using machine learning classifiers and achieved the highest accuracy of 94.50% using SVM on 90%-10% training and testing. In addition, Sousa et al, 2017 have demonstrated the performance of time, and frequency domain features using machine learning algorithms such as SVM and Random Forest (RF). This approach has achieved a higher accuracy of 88% for SVM and RF for time-domain features. Fast Fourier Transformation (FFT) and wavelet domain feature achieved an accuracy of 72% and 78% using RF respectively. Uddin et al, 2016 measures the feature importance score using RF and selected 20 important features and classified using RF. The proposed technique uses 5-fold cross-validation for measuring the importance score and achieved better performance in terms of Precision and Recall.

Bustoni et al, 2020 have compared the performances in terms of precision and recall of various classifiers such as k-NN, Artificial Neural Network (ANN), SVM, and RF. The authors in this approach have introduced Support Vector Classifier (SVC) and Radial Basis Function (RBF) kernels to improve the performance of SVM and achieved Precision of 87% and Recall of 85%. The proposed model has also constructed the RF with a maximum depth of 100 and a height of 300 trees to achieve an accuracy of 96% by considering the entire 561 features.

The state-of-the-art feature selection techniques have selected specifically, the time or frequency domain features for better performances. In the case of specific selection there may be more noise prone to activity recognition. Moreover, all the recognition system has justified their performances in terms of Accuracy. In the process of life threatening activity recognition, the Precision and Recall plays a vital role. More the value of Precision and Recall have good recognition activity than the better accuracies. However, the state-of-the-art techniques have better accuracy but the Precision and Recall values are low. In some cases, the robust feature selection such as Genetic Algorithm along with ensemble classification process such as Random Forest etc have been used. This motivated us to use dimensionality reduction technique to reduce the dimensions of dataset for earlier prediction using linear classification technique. However, to analyze the liner prediction of data, the propose approach utilizes various stacking principles.

The performances of the proposed technique can also be improved by concentrating more in terms of feature selection and classification. As a very critique selection of features may linearly improve the performance of classification technique. This motivated us to propose this paper by coupling dimensionality reduction and ensemble classification approach to improve the performances in recognition of activities of two familiar HAR datasets.
PROPOSED METHODOLOGY

The proposed Human Activity Recognition follows a sequence of steps from data collection to the classification of activities as shown already in Figure 1. In this proposed approach, Smartphone based Human activity recognition dataset from UCI repository – Human Activity Recognition using Smartphone (UCI – HAR) and Smartphone based recognition of Human Activities and Postural Transitions (UCI – HAPT) has been used. There are also other Smartphone based Human Activity Recognition datasets; however, these datasets only contain static, dynamic and Postural transitions. The dataset is already preprocessed to form a feature vector that characterizes certain aspects of sensors. Both the dataset contains 561 features along with the activity labels and the entire dataset has been reduced dimensionally using Principal Component Analysis (PCA). Then the efficient Principal Components (PCs) are divided into training and test data with a ratio of 70% and 30% respectively. Initially, the proposed model has been applied for the training data to generate the trained ensemble model. During the testing phase, the trained ensemble method is used to test with the test data for the recognition of activities as shown in Figure 2. Actually, the proposed approach transforms the raw feature vector to a model that recognizes basic, complex, and postural transitions.

Dataset Collection

The proposed approach uses two familiar HAR datasets from UCI repository – Human Activity Recognition using Smartphone (UCI – HAR) and Smartphone based recognition of Human Activities and Postural Transitions (UCI – HAPT). The datasets are originally collected through the Smartphone kept in the trouser pocket or belt pouch of various subjects during experimentation in the controlled environment (Anguita et al, 2013; Reyes-Ortiz et al, 2016; Ramanujam et al, 2019). The HAPT dataset is an extension of the HAR dataset. The detailed description of the subjects involved and the number of activities recorded are described in Table 1.

Principal Component Analysis – Dimensionality Reduction

The HAR dataset contains the features set \( f = \{f_1, f_2, \ldots, f_{561}, C_i\} \) where \( f_i \) represent the feature and \( C_i \) represents the activity label. As, the generated dataset has more number of features, Principal Component Analysis (PCA) (Wold et al, 1987) has been used to reduce the dimensionality of the datasets. As, large datasets often difficult to interpret and consumes more time in classification. PCA reduces the dimensionality of the datasets linearly and increases the interpretability and at the same time minimizes the information loss. It computes the new variables termed Principal Components (PCs) which are the basics vectors of directions in the decreasing order of variability. The first PC may have the highest variability and the second PC may variability less than the first and it is an orthogonal transformation of the first PC. Further PC is sorted in the same fashion. Actually, the computation of PC involves covariance matrix computation of data, its eigenvalue decomposition, sorting of eigenvectors in the decreasing order of eigenvalues. Finally, the projection of data has been

Figure 2. Architecture of the proposed approach
taken by the inner product of signals and their sorted eigenvector as defined by PCs. Then the PCs with the highest variability will be considered for the process of classification.

Stacking Ensemble Learning

To improve the performance of traditional machine learning algorithm in activity recognition, the heterogeneous ensemble of machine learning algorithm using stacking (Homayouni et al, 2010) has been proposed. The main objective of Stacking is, it produces strong models with less bias than their components. Stacking is an ensemble learning technique that combines multiple heterogeneous weak classifiers via a Meta-classifier. In the proposed model, the Naïve Bayes and Support Vector Machine (SVM) are considered as base-level classifiers and are trained based on the complete training data set. Then the Meta-classifier is trained using the output of the base level models as features. In this approach, Linear Discriminant Analysis (LDA) has been considered as a Meta-classifier. This process generates a trained ensemble model as shown in Figure 2. Then the test data has been used to test for activity recognition. For performance comparison, various stacking ensemble learning has also been proposed using Decision Tree, Naïve Bayes and SVM classifier.

Table 1. Specifications of Human Activity Recognition dataset from UCI repository

| Specifications | Human Activity Recognition using Smartphone (UCI – HAR) | Human Activity and Postural Transition (UCI – HAPT) |
|----------------|----------------------------------------------------------|--------------------------------------------------|
| # of Subjects  | 30                                                       | 30                                              |
| Age bracket    | 19-48                                                    | 19-48                                           |
| Device Used    | Samsung Galaxy SII                                      | Samsung Galaxy SII                              |
| Place of Device| Waist                                                    | Waist                                           |
| Source of Signals | 3-axial linear acceleration + 3-axial angular velocity @ constant rate of 50Hz | 3-axial linear acceleration + 3-axial angular velocity @ constant rate of 50Hz |
| Pre-processing | Noise filters                                            | Noise filters                                   |
| Sliding window | 2.56s of 50% overlap                                     | 2.56s of 50% overlap                            |
| Segregation of signals from gravitational and body motion | Butterworth low-pass filter                           | Butterworth low-pass filter                     |
| Cut-off frequency (Gravitational Force) | 0.3Hz                                                    | 0.3Hz                                           |
| Feature vector | Time and frequency domain of each window                 | Time and frequency domain of each window        |
| # of features in feature vector | 561                                                      | 561                                             |
| # of Observations | 10299                                                    | 10929                                           |
| # of Activities | 6                                                        | 12                                              |
| Categorization of Activities | Static Postures – 3 Dynamic Activity – 3                  | Static Postures -3 Dynamic Activity – 3 Postural Transitions – 6 |
| Static Postures – 3 | Sitting, Standing, Laying                                | Sitting, Standing, Laying                        |
| Dynamic Activity – 3 | Walking, Walking_Upstairs, Walking_Downstairs, | Walking, Walking_Upstairs, Walking_Downstairs   |
| Postural Transition | NIL                                                      | stand-to-sit, sit-to-stand, sit-to-stand, lie-to-sit, stand-to-lie, and lie-to-stand |
| Training and Testing set | 70%-30%                                                  | 70%-30%                                         |
**Naïve Bayes Classifier**

Naïve Bayes classifier (Lewis, 1998) belongs to a family of simple probabilistic machine learning used for classification. The classifier applies Bayes theorem with the assumption of strong independence between the features which means that the probability of one attribute doesn’t affect the probability of another attribute. Hence so it is named Naïve. The classifier model assigns a class label to the predictor set where the class labels are drawn from the probability of finite training set. Naïve Bayes classifier is easy to build and particularly requires only a small number of training data to estimate the parameters necessary for predicting the class variable. In addition, the classifier is capable to classify large datasets and performs well for multiclass classification problems.

**Decision Tree Classifier**

Decision tree classifier (Quinlan et al, 1996) is a supervised machine learning model can be used for both classification and prediction depending upon the features. It is a flowchart like tree structure where an internal node represents the feature, leaf node represents the outcome and the branches/edges represent the decision rule. The root node is the topmost node of the tree. The decision tree can be learned/ trained by splitting the source set into subsets on the basis of the attribute value and it partitions the tree using recursive partitioning. The recursion will be completed when splitting no longer adds value to the predictors. The construction of the decision tree doesn’t require any domain knowledge or parameter optimization and therefore it is appropriate for any data exploratory operations. The advantage is it handles high dimensional data and has good accuracy.

**Support Vector Machine**

In machine learning, Support Vector Machine (SVM) (Bennett and Demiriz, 1999) is a supervised learning model that can be used for both classification and prediction. SVM is preferred in many research works due to its significant accuracy with less computation power. The objective of SVM is to identify the hyperplane in N-dimensional space (N-number of features) to distinctly categorize the data points. There is more possible hyperplane to categorize the data points however the SVM finds a plane that has a maximum margin. Maximizing the margin distance provides some reinforcement so that the future points can be classified with more confidence. Data points falling on either side of the hyperplane can be attributed to different classes, and the dimension of the hyperplane depends on the number of features. If it is binary (only 2 features) then it may be a line, if more features than it may be a 2-dimensional plane. Support vectors are data points that are close to the hyperplane which are used to influence the position and orientation of the hyperplane. Using these support vectors, the classifier maximizes the margins.

**Linear Discriminant Analysis**

Linear Discriminant Analysis (LDA) (Balakrishnama and Ganapathiraju, 1998) is a generalization of fishers’ linear Discriminant analysis, a method mostly used in pattern recognition and classification. This method finds a new feature space using a linear combination of features. This is the first step in LDA to find a way to measure the capacity of separation of each new feature space candidate. The projected feature space characterizes and separates two or more classes of objects or events in order to maximize class seperability. Maximization refers to maximize the distance between the mean of each class and to minimize the variability within the class itself. It is measured using within-class and between-class variability as the econd step in LDA. The basic assumption of data is the normalized distribution of the feature vector set, and LDA doesn’t perform well for non-Gaussian data. The resultant combination can be used for both classifications or in dimensionality reduction. In this proposed approach, the LDA has been used as a Meta-classifier to improve the classification performance.
RESULTS AND DISCUSSIONS

To analyze and demonstrate the performance of the proposed Stacking ensemble learning of machine learning algorithms coupled with dimensionality reduction, two HAR datasets from UCI – HAR and UCI – HAPT has been used. The detailed description of the attributes, activities, number of observations and size of the dataset is already shown in Table 1. Both the datasets contains 561 features as feature vector along with activity labels. Initially the Principal Component Analysis (PCA) has been applied to reduce the features and the selection of best features using variances of PCs as shown in Figure 3. From Figure 3, the variance started degrades at 100th PC. Hence, the first 100 PCs are considered for the process of classification (both the datasets) using the stacking ensemble learning method. The proposed stacking ensemble learning method uses SVM and Naïve Bayes as weak learners and Linear Discriminate Analysis as Meta-model. In addition to performance analysis, additional stacking ensemble learning such as various combinations of SVM, Decision Tree, Naïve Bayes and LDA is also considered as shown in Table 2. However, the proposed method considers the performance of Stacking 3 as shown in Table 2 and the other Stacking 1, 2, and 4 are only for performance analysis. The performance of the methods are compared using familiar performance metrics Accuracy, Precision, Recall and F-Measure which are measured as described in Wang et al, 2019. Further, this section demonstrates the performance of the proposed stacking ensemble learning method in two scenarios, first describes for the performance analysis of the proposed method for UCI - HAR dataset and the next one describes for UCI - HAPT dataset.

Figure 3. Extraction of Principal Components for the feature vector of 561 features

Table 2. Proposed Stacking Ensemble Learning methods

| Proposed Method | Base Models 1 | Base Model 2 | Base Model 3 | Meta Model         |
|-----------------|---------------|--------------|--------------|--------------------|
| Stacking 1      | Naïve Bayes   | Decision Tree| -            | SVM                |
| Stacking 2      | Naïve Bayes   | Decision Tree| -            | Linear Discriminant Analysis |
| Stacking 3      | Support Vector Machine | Naïve Bayes | -            | Linear Discriminant Analysis |
| Stacking 4      | Naïve Bayes   | Decision Tree| Support Vector Machine | Linear Discriminant Analysis |
UCI - HAR Dataset

Initially, the HAR dataset has been dimensionally reduced and the selected Principal Components are used for performance analysis using the proposed Stacking ensemble classification (Stacking 3). In addition, for performance comparison, the selected Principal Components (PCs) are also classified using traditional machine learning classifiers such as SVM, Decision Tree and Naïve Bayes classifier. The performance analysis of the proposed stacking ensemble learning method for the selected PC is shown in Table 3. The performances of the proposed method have been measured using Accuracy, Precision, Recall and F-Measure. Table 3 shows the performances of the proposed method for the selection of the first 50, 100 and 200 PCs. PCA 50 and PCA 200 are shown only for its performances. On comparing the performance PCA 50 with other traditional machine learning algorithms and the Stacking ensemble method, there is no much difference in the performance of the proposed Stacking 3. The Accuracy of Stacking 3 is 82.34 whereas the Naïve Bayes is very nearer and shows the accuracy of 81.24. Further, Precision and Recall also shows the maximum performances very nearer to Naïve Bayes classifier. On comparing to Naïve Bayes, proposed Stacking 3 may consume more time for the execution. As it have base models and Meta-model for recognition.

On comparing the performance of PCA 100, the proposed Stacking 3 outperforms other techniques in terms of all the performance metrics. It shows the highest accuracy value of 98.30% which is greater and no other learning algorithms have shown equal performances. In the case of Precision and Recall, the proposed Stacking 3 shows the value of 94.97% and 94.98% which is nearer to Stacking 1 as it is also an ensemble Stacking method. However, the minor change in the Precision and Recall may show a greater deviation in the performance of the model in activity recognition systems. The detailed performance of the proposed stacking ensemble method in identifying the individual activity of the UCI-HAR dataset is shown as a confusion matrix in Table 3. In Table 3, Accuracy is shown in the right corner marked as accuracy in the brackets; Recall and Precision are shown for individual activities. The overall Precision and Recall shown in Table 3 is the average of all the individual activities. Table 3 justifies the efficiency of the proposed stacking model (Stacking 3). The model performs better for selected 100 PC as its variance started to saturate after 100th component as shown in Figure 3. Further to analyze the performance on PCA 200, the proposed method has also been executed and tested for its performances. However, the PCA 200 doesn’t show better performance than PCA 100.

UCI-HAPT Dataset

To analyze the performance of the proposed Stacking ensemble method along with dimensionality reduction, the UCI-HAPT dataset has been used. This dataset has more complex and postural transitions than the UCI-HAR dataset and it has 12 activity labels. The performance of any classification method can be validated only using more number of class variables. Accordingly, the UCI-HAPT dataset has

| UCI – HAR dataset | Standing | Sitting | Laying | Walking | W. Downstairs | W. Upstairs | Recall (%) |
|-------------------|----------|---------|--------|---------|---------------|-------------|------------|
| Sitting           | 527      | 0       | 0      | 10      | 4             | 0           | 97.41      |
| Standing          | 3        | 479     | 11     | 0       | 0             | 0           | 97.16      |
| Laying            | 0        | 7       | 511    | 0       | 0             | 0           | 98.65      |
| Walking           | 0        | 0       | 3      | 441     | 6             | 0           | 98.00      |
| W. Upstairs       | 7        | 5       | 4      | 45      | 396           | 24          | 82.33      |
| W. Downstairs     | 0        | 0       | 3      | 0       | 14            | 447         | 96.34      |
| Precision (%)     | 98.14    | 97.56   | 96.05  | 88.91   | 94.29         | 94.90       | 98.30 (Accuracy) |

Table 3. Performance of the proposed Stacking ensemble method in identifying the individual activity of UCI – HAR dataset
been tested and its performances in terms of Accuracy, Precision, Recall and F-Measure are shown in Table 5 for the selected Principal Components of 50, 100 and 200. However, the proposed Stacking Ensemble method (Stacking 3) is the combination of SVM and Naïve Bayes as base classifiers and LDA as Meta-classifier the other stacking and traditional machine learning algorithms are used only for performance comparisons.

On comparing the performance of the selected 50 PC, the Proposed Stacking ensemble method shows maximum accuracy and precision of 83.22% and 58.01% respectively. In the case of Recall, Decision tree shows a better performance of 61.31%. For the selected 100 PCA components, the proposed Stacking ensemble method performs better than other stacking and machine learning algorithms in terms of Accuracy, Precision and Recall of 97.49%, 77.04% and 67.58%. In addition, the performance of Recall is very closer to Decision tree performance. This shows the complexity of handling the multi-class classification problems. As the target class variables increase the performances may degrade accordingly to all the ensemble machine learning classifiers due to the performance of weak learners.

The detailed performances of the proposed stacking ensemble learning method in identifying individual activity are shown in Table 4. The accuracy is shown in the right corner of the table indicated as accuracy in the bracket. Recall and F-measure are shown with respect to individual activities. To the worst case, the proposed stacking ensemble method shows very poor performance when compared to other algorithms for PCA 200 components. This justifies the use of statistical inference of using variance and bias as referred in Figure 3 for earlier and better recognition of activities. In the future, the proposed method has to concentrate more on improving the precision and recall i.e accurate detection of activities for the multi-class recognition problems.

Further to compare the performance of the proposed stacking ensemble learning method with other state-of-the-art techniques, the comparison has been made as shown in Table 5. The entire

**Table 4. Performance of the proposed Stacking ensemble method in the identifying individual activity of UCI – HAPT dataset**

| HAPT dataset | Walking | W. Upstairs | W. Downstairs | Sitting | Standing | Laying | Stand to Sit | Sit to Stand | Sit to Lie | Lie to Sit | Stand to Lie | Lie to Stand | Recall (%) |
|--------------|---------|-------------|---------------|---------|----------|--------|-------------|-------------|-----------|-----------|-------------|-------------|------------|
| Walking      | 470     | 52          | 29            | 0       | 0        | 0      | 0           | 0           | 0         | 2         | 0           | 0           | 84.99      |
| W. Upstairs  | 3       | 391         | 32            | 0       | 0        | 0      | 0           | 0           | 0         | 2         | 0           | 0           | 91.36      |
| W. Downstairs| 21      | 19          | 350           | 0       | 0        | 0      | 0           | 0           | 0         | 0         | 0           | 0           | 89.74      |
| Sitting      | 0       | 0           | 0             | 357     | 22       | 0      | 0           | 0           | 0         | 0         | 1           | 0           | 93.95      |
| Standing     | 0       | 0           | 0             | 131     | 527      | 0      | 0           | 0           | 0         | 0         | 0           | 0           | 80.09      |
| Laying       | 0       | 0           | 0             | 530     | 0        | 0      | 0           | 0           | 0         | 0         | 0           | 0           | 100        |
| Stand to Sit | 0       | 2           | 0             | 6       | 13       | 0      | 20          | 0           | 0         | 8         | 0           | 0           | 88.56      |
| Sit to Stand | 0       | 0           | 0             | 9       | 1        | 0      | 2           | 7           | 0         | 0         | 0           | 0           | 36.84      |
| Sit to Lie   | 0       | 0           | 0             | 3       | 0        | 0      | 0           | 28          | 1         | 7         | 0           | 0           | 71.79      |
| Lie to Sit   | 0       | 0           | 0             | 0       | 6        | 0      | 0           | 28          | 1         | 22        | 1           | 24          | 41.51      |
| Stand to Lie | 0       | 7           | 0             | 2       | 4        | 0      | 1           | 0           | 3         | 0         | 28          | 0           | 62.22      |
| Lie to Stand | 0       | 0           | 0             | 9       | 0        | 0      | 1           | 0           | 1         | 2         | 0           | 3           | 20.00      |
| Precision (%)| 95.14   | 83.01       | 85.16         | 70.28   | 92.95    | 97.25  | 86.96       | 70.00       | 87.50     | 88.00     | 57.14       | 11.11       | 97.49      |

(Accuracy)
comparison is completely based on UCI – HAPT dataset, as UCI-HAPT is an extension of the UCI-HAR dataset. Wu et al, 2015 has focused on dimensionality reduction as like the proposed and selects only 30 Principal Components and achieved an Accuracy of 84.56%. However, the proposed method has additionally used the Stacking ensemble learning method to improve performance and achieved an accuracy of 97.49%. Uddin et al, 2016 ranked the feature importance score using RF an ensemble decision tree classifier and achieved the Precision and Recall of 100%. The performance of Uddin et al, 2016 completely depends on RF, as it has been used for both feature selection and classification. The proposed RF based HAR is very costlier in terms of computation cost as it takes more time for the selection of decision tree parameters and split-up. Later, Sousa et al 2017 has used Time and Frequency domain features to achieve a maximum Accuracy of 88% which is less compared to the proposed stacking ensemble learning classifier. Reyes-Ortiz et al, 2016 has utilized the entire 561 feature and achieved a Precision rate of 94.2% which performs better than the proposed due to the entire usage of 561 features. Further, Bustoni et al, 2019 has achieved an accuracy of 96% for the RF with breadth and depth of 100 and 300. The performance of Bustoni et al, 2019 and Reyes-Ortiz et al, 2016 is high due to the selection of ensemble Decision tree classifier. However, the proposed technique uses an ensemble of weak and Meta learners to achieve these performances. Table 5 shows still there are more provisions to achieve better performances of the UCI-HAPT dataset. In the future, the proposed Stacking ensemble learning method can be modified using an optimization technique to achieve better performances.

**CONCLUSION**

Ambient Assisted Living supports the elders through pervasive and Ubiquitous computing facilities such as ambient sensors, wearable devices, Smartphone and Vision systems. Smartphones are nowadays familiar and much attracted to use in Human Activity Recognition.

| S.No | Model            | Feature Selection | No of Features | Classification Algorithm | Performance Measure | Performance Value |
|------|------------------|-------------------|----------------|--------------------------|---------------------|-------------------|
| 1    | Wu et al, 2015   | PCA               | 30             | k-NN                     | Accuracy            | 84.56%            |
| 2    | Uddin et al, 2016| Feature Importance Score using RF | 20             | RF                       | Precision | 100               |
|      |                   |                   |                |                          | Recall               | 100               |
| 3    | Sousa et al, 2017| Time features     | 28             | RF                       | Accuracy            | 88%               |
|      |                   | FFT of frequency domain features | -              | RF                       |                     | 72%               |
|      |                   | Wavelet of frequency domain features | -              | RF                       |                     | 78%               |
| 4    | Reyes-Ortiz et al, 2016 | - | 561 | SVM | Precision | 94.2% |
| 5    | Bustoni et al, 2019 | - | 561 | SVC + RBF - SVM | Precision | 87% |
|      |                   | RF (100, 300)     |                |                          | Recall               | 85%               |
| 6    | Proposed         | PCA               | 100            | Stacking Ensemble Learning | -Accuracy            | 97.49%            |
|      |                   |                   |                |                          | Precision            | 77.04%            |
|      |                   |                   |                |                          | Recall               | 67.58%            |
|      |                   |                   |                |                          | F-Measure            | 72.001%           |
Various research works have already proposed certain Smartphone based HAR models to recognize basic and complex activities. However, the state-of-the-art techniques have drawbacks in handling postural transitions (dynamic postures), and the performance in recognition of postural transitions is low. Most of the state-of-the-art technique have used ensemble classifiers or specific feature selection technique to improve their performances and this may increase the computational power for recognition.

To improve the recognition rate of Postural transitions this paper coupled Dimensionality reduction with Stacking ensemble learning method for better performances. In this proposed method, SVM and Naïve Bayes have used as weak learners and Linear Discriminate Analysis is used as Meta-model for experimentation using UCI-HAR and UCI-HAPT datasets. The proposed technique requires a minimal computational cost when compared with state-of-the-art techniques as it uses only a stacked learning rather ensemble learning techniques. Moreover, the classifiers utilized in the stacked learning are linear in nature.

The experimental results and discussions have shown that the proposed method has better performance than state-of-the-art Smartphone based HAR techniques in particular recognizing the postural transitions. When compared with other state-of-the-art techniques, the precision and recall value for postural transitions recognition are high and accurate.

The proposed technique has certain limitations in addressing more number of postural transitions to the maximum of six. In future, the technique can be extended to address this issue. Moreover, the Smartphone based HAR has to be introduced for the process of outdoor activities and even during night time.
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APPENDIX

Table 6. Performance analysis of proposed method for the selected Principal Components of UCI – HAR Dataset

| Performance Metrics | SVM         | DECISION TREE | NAIVE BAYES | STACKING 1 | STACKING 2 | STACKING 3 | STACKING 4 |
|---------------------|-------------|---------------|-------------|------------|------------|------------|------------|
| Accuracy (%)        | 76.59       | 73.50         | 81.24       | 68.24      | 77.94      | 82.34      | 78.62      |
| Precision (%)       | 93.86       | 73.49         | 80.22       | 94.6       | 90.91      | 98.30      | 93.28      |
| Recall (%)          | 76.52       | 78.79         | 71.73       | 75.03      | 74.65      | 92.94      | 81.13      |
| F-Measure (%)       | 76.65       | 72.67         | 80.39       | 67.77      | 77.14      | 81.29      | 78.62      |

Table 7. Performance analysis of proposed method for the selected Principal Components of UCI – HAPT dataset

| Performance Metrics | SVM         | DECISION TREE | NAIVE BAYES | STACKING 1 | STACKING 2 | STACKING 3 | STACKING 4 |
|---------------------|-------------|---------------|-------------|------------|------------|------------|------------|
| Accuracy (%)        | 72.15       | 79.60         | 80.61       | 70.54      | 72.36      | 83.22      | 68.96      |
| Precision (%)       | 92.38       | 84.98         | 85.0        | 91.46      | 88.36      | 97.49      | 72.11      |
| Recall (%)          | 72.45       | 78.68         | 68.93       | 69.34      | 69.34      | 80.65      | 76.84      |
| F-Measure (%)       | 53.52       | 58.75         | 58.74       | 53.22      | 58.82      | 58.01      | 52.36      |

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