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Towards human activity recognition for ubiquitous health care using data from a waist-mounted smartphone

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Abstract: Understanding human activities is a newly emerging paradigm that is greatly involved in developing ubiquitous health care (u-Health) systems. The aim of these systems is to seamlessly gather knowledge about the patient's health and, after collecting knowledge, make suggestions to the patient according to his/her health profile. For this purpose, one of the most important ubiquitous communication trends is the smartphone, which has drawn the attention of both professionals and caregivers for monitoring the aging population, childcare, fall detection, and cognitive impairment. Recognizing human actions in a ubiquitous environment is very challenging and researchers have extensively investigated different methods to recognize human activities in the past decade. However, this field of research still needs further exploration in order to improve the accuracy and reduce the computational cost of these health care systems. Therefore, for expediting the existing system, this research work investigated a novel approach based on feature selection and classification. In the proposed work, sparse Bayesian multinomial logistic regression (SBMLR) is used for feature subset selection and a multiclass support vector machine (SVM) is adapted for the classification of six human daily activities (laying down, walking up stairs, walking down stairs, sitting, standing, and walking). For identifying the best features among the features returned by the SBMLR, a tuned threshold value is used for the selection of the features. Further, other classification algorithms including K-nearest neighbor, decision tree, and naive Bayes and different feature selection methods such as principal component analysis and random subset feature selection are also used for evaluation and comparison. The dataset used for testing is obtained from the UCI Machine Learning Repository. It is collected by using a smartphone embedded with an accelerometer and gyroscope. The experimental results show that the highest accuracy of 99.40% can be achieved by using the proposed method. Moreover, the paired sample two-tailed t-test over the significance level of 0.05 reveals that the performance difference between the proposed technique and a competing technique is statistically significant.

Key words: Health care, activity recognition, feature selection, multiclass support vector machine, radial basis function, loose grid search, linear kernel

1. Introduction

Monitoring physical activities plays a significant role in healthy living. It is a key research area and one whose importance has notably increased in various related fields such as robotics, ubiquitous computing, artificial intelligence, ambient assisted living, human–computer interaction, and health care. Recognizing human physical

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activities can be classified into vision-based and sensor-based recognition[1]. Vision-based systems aim to allow machines to be able to achieve a human-like capability of seeing through acquiring, processing, analyzing, and understanding digital images. The images can be acquired from a 3-D scanner, video sequences, or multiple cameras. Various novel approaches[2–4] have been proposed to perform analysis on video sequences to identify the pattern of ongoing patient activities. However, the adoption of these systems is raising privacy issues due to the installation of unwelcoming devices, particularly the use of cameras.

In sensor-based recognition different ubiquitous sensing technologies such as eWatch [5], radio-frequency identification (RFID) [6], microphones [7], pyroelectric infrared sensors (PIRs) [8], and smartphones equipped with an accelerometer and gyroscope [9] are used for continuously monitoring patients without affecting his/her normal activity patterns. Among the mentioned technologies, the use of accelerometers is the most preferred option for tracking various activities due to their low cost, ease of installment, and small size. These accelerometers can be placed on different locations of human body such as the waist [10, 11], the wrist [12–14], the chest [15] the lower back [16], the thigh [14, 17], near the pelvic region [18], the hip [12, 14] and the foot [15] to identify different human activities like sitting, climbing, walking, sleeping, driving, and running. The recognition of these activities helps to enable the development of different humancentric applications. These applications include but are not limited to smart hospitals [19], childcare [10], smart homes [20], surveillance [21], mobile health [22], fall detection [11, 23], assembly tasks [7], pulse rate [24], unobtrusive sleep [25], and elderly care [6].

The raw data acquired from the above-mentioned technologies are firstly preprocessed [26], in which filtering is performed, missing values are replaced, outliers are identified, and different features are extracted. There are different types of windowing techniques for extracting features that include activity-defined [22], sliding[10], and event-defined windows[7]. In these techniques, features are computed from each window and then these features are used for training and testing purposes. The preprocessing step is followed by the feature selection and classification steps. In the feature selection step, a features subset is selected from the candidate's feature set. There are a large number of studies [27–30] in which different feature selection techniques have been adapted for supporting the health care, early stroke diagnosis, elderly care, and other medical monitoring applications. In these studies, different techniques such as genetic algorithm [31], sequential forward floating search (SFFS) [32], iterative search margin based algorithm (Simba) [33], minimal redundancy maximal relevance criterion (mRMR) [34], and Relief [35] were used for feature selection. Although all available features can be used for classification, the problem with this approach is that utilizing all features does not improve the classification accuracy of diagnosing the patients due to the inclusion of irrelevant features. Therefore, for reducing the dimensionality in the feature selection step, irrelevant features are detected and discarded. As a result, this increases robustness and reduces computation time.

The main contribution of the present paper is the adaption of an efficient wrapper-based feature selection method and classification technique for improving the accuracy of a health care system. First, sparse Bayesian multinomial logistic regression (SBMLR) is used to reduce the feature dimension; then the tuned threshold value is used for selection of the best features. Next, a multiclass support vector machine (SVM) is employed for the classification of six different physical activities, which include sitting, standing, laying down, walking, walking up stairs, and walking down stairs. During the model selection procedure, a loose grid search was applied in the parameter space to identify the region containing the optimal parameter value. After that, a fine grid search was performed in the identified region in order to determine the optimal parameters. The best-suited parameters found by this search were $\gamma : -4.5$ and C: 4, which were then used as input to the radial basis function (RBF) kernel. Different classification algorithms and feature selection methods are also used for evaluation and comparison.

The rest of the paper is organized into the following sections. In the next section, a review of related research is presented. Section 3 explains the methodology adapted for improving the HAR process and details of the dataset used. Section 4 presents the experimental results and discussions. The conclusion and future directions are given in Section 5.

2. Related Work

There are different machine and nonmachine learning techniques available for identifying the physical activities of the user. In machine learning techniques, features are extracted from the raw signals, models are defined for each activity, and classification is performed on the basis of these models. These physical activities can be static such as standing, sitting, and lying and dynamic like walking, walking up stairs, and walking down stairs [36]. Our literature survey showed that researchers have done a lot of work in this field using different feature selection techniques and classification methods. Maurer et al. [5] designed the eWatch to monitor the same activities that have been used in the present study (walking up stairs, walking down stairs, walking, running, sitting, and standing). Experiments were performed by wearing the designed eWatch in different locations such as the neck and trouser and shirt pockets. They used a filter-based approach (correlation-based feature selection) [37] to find feature sets containing features that were highly correlated within the particular class and uncorrelated with each other. There were different classifiers evaluated, namely DT, NB, KNN, and DT, with a five-fold cross validation method. Overall they reported 16% to 92% classification accuracy in their work [5] by wearing the eWatch in different locations on the body.

Atallah et al. [30] also indicated the importance of activity recognition for health monitoring by grouping activities into low, medium, high, and transitional categories. Feature selection was performed by using different filter methods such as Relief-F [35], Simba [33], and mRMR [34]. The authors used these methods to rank features from most relevant to least relevant and assigned weights according to this ranking. They performed experiments with the help of 11 subjects who performed 15 different activities such as lying down, reading, preparing food, and getting dressed. These activities were performed by wearing the sensors at 7 different positions: knee, ear, chest, wrist, waist, ankle, and arm. During classification, the one-versus-all approach was used in which each subject was used for testing and the other subjects for training. The classifiers used were KNN with k=5 and 7 and the Bayesian classifier with Gaussian priors. They divided the activities into different groups and the precision rate was more than 85% in the case of very low level activities [30].

Mannini and Sabatini [36] used a wrapper-based approach SFFS [32] for feature subset selection. Experiments were conducted with the help of 13 users wearing five triaxial accelerometers on the thigh, arms, ankle, wrist, and hip. There were various learning methods used, namely SVM, NB, and cHMM, to identify bicycling, running, standing, walking, stair climbing etc. The highest accuracy among the mentioned classifiers was obtained by cHMM. During the literature survey, it was also found that instead of wearing the sensors the researchers used environment sensors for ambient-assisted living. There are a good number of research projects in which environment sensors have been placed. These include CASAS [38], MavHome [39], ARAS [40], and CARE [41]. In these projects the data collected from the environment sensors were used to recognize the different complex activities of the residents, such as bathing, cooking, and eating.

Although these mentioned approaches performed well, some of them were dependent on installing more than one sensor in a home. Furthermore, some of the approaches required wearing multiple sensors in a particular orientation, and when the number of sensors was reduced the accuracy of the system decreased as well [15]. Currently, many applications related to fall detection [42], diagnosing Parkinson disease [43], and Alzheimer disease rehabilitation [44] have been designed using smartphones to improve patients' quality of life. These smartphones can also be used for identifying simple as well as complex activities [45].

Anguita et al. [46] introduced a HAR dataset using a smartphone, which was also used for the evaluation of the present work. There were 561 features extracted with frequency and time domain variables. They used a multiclass SVM (MC-SVM), which achieved an accuracy of 96%. They compared their approach with existing wearable sensor-based approaches. The authors argued that their work had the same accuracy as in the case of chest- [47] and waist- [48] mounted approaches. Therefore, it is recommended to use a smartphone instead of wearing sensors.

Rasekh et al. [49] also used a smartphone accelerometer for recognizing five basic human activities, i.e. limping, jogging, walking, walking down stairs, and walking up stairs. The feature dimensionality reduction was performed using a wrapper-based sequential forward selection (SFS). There were four different learning methods used, namely ANN, quadratic classifier, SVM, and KNN. The method with the highest accuracy, with 84.4%, was SVM [49]. During these studies, it was observed that there is no fixed classification model and feature set for these systems. In every approach, there are different feature selection techniques and classification models.

3. Methodology

This section presents the details of the proposed methodology based on well-known steps, which include feature selection and classification. The basic techniques for the feature selection process are filter [30], wrapper [50], and hybrid methods [51]. Filter methods do not use any classifier during the feature selection process as they apply statistical measures for assigning a score to each feature. Removal and selection of features from the dataset are performed by ranking of the features using these scores. Filter methods are mostly suitable for real-time applications as they do not invoke a learning algorithm repeatedly. In contrast, wrapper methods use a classifier. Features are evaluated and scored based on model accuracy. Wrapper methods are sometimes more efficient compared to filter methods, because they use a classifier hypothesis [52]. Finally, the hybrid methods combine the features of both filter and wrapper methods[51]. After feature selection, the last step is the adaption of machine learning algorithms such as NB, DT, and SVM for classifying human activities.

In the present study, first feature selection (using SBMLR) was applied to a well-known UCI HAR dataset [46] in order to reduce feature dimensionality. After identifying and removing the unneeded features, a multiclass SVM was employed for dealing with the best-selected features as shown in Figure 1.

The preprocessing and feature extraction part of Figure 1 was available in a dataset [46]. During model selection, the optimal region was identified by a loose search algorithm, and then the optimal parameter was identified using a fine grid search. The evaluation was performed using a 10-fold cross-validation method. The features returned by SBMLR were further processed for identifying the best features based on their weight values. For this purpose, a tuned threshold value was used on the weights for selecting only the best features as returned by SBMLR.

During experiments for a fold, the 9 folds of the data are further split into 70% (called the training set) and 30% (called the validation set). SBMLR along with LIBSVM is applied to 70% of the data for training and selection of features (F), respectively. Tuning of the threshold value on the weights of features is accomplished over the 30% of the data (validation set) for identifying only the best features. A loose grid search is applied

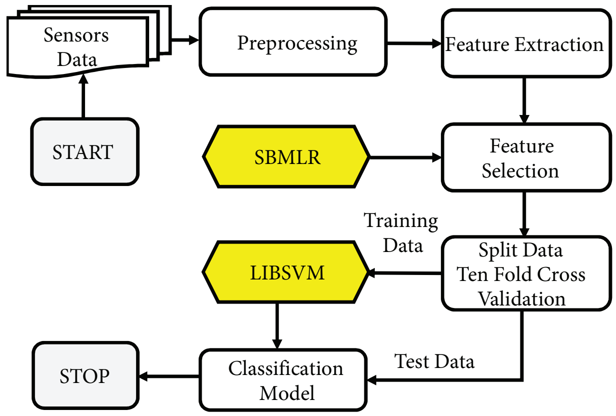

Figure 1. Structure diagram.

between the region of minimal and maximal values of the weights of features returned by SBMLR. Later, the region identified by the loose grid search is further explored using a fine grid search to find near optimum threshold value of the feature weights. Finally, the tuned threshold value is used for selection of only the best features of the tested fold and results are generated with the SVM model having the same tuned parameter values of the kernel as found during the training phase. The entire process of thresholding is illustrated in Figure 2.

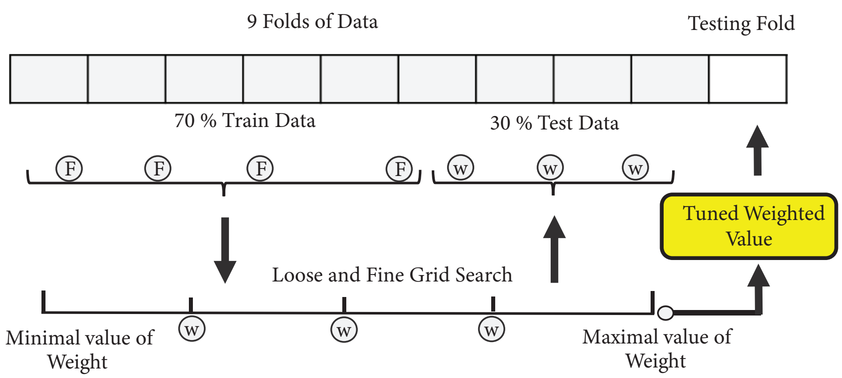

Figure 2. Thresholding for feature selection.

3.1. Dataset

In the present study, the HAR Dataset [46] was used, available at the UCI Machine Learning Repository. The dataset was obtained from 30 volunteers between the ages of 19 and 48 years. The dataset consisted of 10,299 labeled instances, which were recorded through the use of an accelerometer- and gyroscope-enabled smartphone (Samsung Galaxy S II) attached to the waist of each volunteer. A video was made of each volunteer performing each of the six activities, which included sitting, standing, lying down, walking, climbing up stairs, and climbing down stairs. The videos were reviewed and the data were manually labeled for each of the activities.

3.2. Data preprocessing

Anguita et al. [46] 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 rate of 50 Hz. For preprocessing, a noise filter was applied to the recorded signals. The sampling of the signals was performed by using a sliding window of 2.56 s and overlap of 50%. There were 128 readings per window. Furthermore, a Butterworth low-pass filter was used to separate the body and gravitational motion from the sensor signals. Only low frequency of the gravitational force was considered and cutoff frequency for the filter was 0.3 Hz.

3.3. Feature extraction

There were a total of 561 features with frequency-domain and time-domain variables [46]. The frequency-domain variables included skewness, the largest magnitude of frequency components, the weighted average of frequency components, kurtosis, etc. The time-domain variables included interquartile range, magnitude, median, absolute deviation, mean, maximum, minimum, autoregression coefficients, standard deviation, energy, entropy, etc. The mentioned features were used for both accelerometer and gyroscope signals.

3.4. Feature selection by SBMLR

The presence of redundant or irrelevant features in the feature space causes an unnecessary increase in the computation time and affects the accuracy. Machine learning techniques used for modeling data can be affected by the noise in data [53]. Therefore, an SBMLR algorithm [54] was used in the present research in order to make the generalization process simpler. SBMLR uses a simple but efficient training algorithm to determine the model parameters [55]. It returns selected features, along with their corresponding weight, according to the information obtained in the original feature space. The features obtained after applying the SBMLR algorithm did not require any further processing [56]. Suppose that the training sample $\mathcal{D} = \{(x^n,\ t^n)\}_{n=1}^{\ell}$, where x^n is the input feature vector having i number of features and t^n is the class vector. The probability of the training instance x^n belonging to the class vector instance t^n can be defined as follows:

$$p\left(t_i^n|\boldsymbol{x}^n\right) = y_i^n = \frac{\exp\left\{a_i^n\right\}}{\sum_{j=1}^{c}\exp\left\{a_j^n\right\}} \quad \text{where} \quad a_i^n = \sum_{j=1}^{d} w_{ij}x_j^n, \tag{1}$$

where x_j^n is the j^{th} value of the x^n and t_i^n is the ith class label belonging to this instance. The parameter w_{ij} of the multinomial logistic regression model is for the j^{th} feature and i^{th} class label, and it can be calculated by minimizing the value of negative log-likelihood for the training samples. Assuming that D represents the identically distributed and independent sample from a conditional multinomial distribution, then the negative likelihood will be as follows:

$$E_{\mathcal{D}} = \sum_{n=1}^{\ell} E_{\mathcal{D}}^n = -\sum_{n=1}^{\ell}\sum_{i=1}^{c} t_i^n \log\left\{y_i^n\right\} \tag{2}$$

w of the multinomial logistic regression model can be computed by reducing the penalized maximum-likelihood as follows:

$$Z = E_{\mathcal{D}} + \alpha E_{\mathcal{W}} \quad \text{where} \quad E_{\mathcal{W}} = \sum_{i=1}^{c}\sum_{j=1}^{d} |w_{ij}| \tag{3}$$

In the preceding Eq. (3), α is a regularization parameter for introducing sparseness and is used in the model related to Laplace prior to the parameter. The partial derivatives of Z, according to the model parameters, will be zero and are stated as follows:

$$\left|\frac{\partial E_{\mathcal{D}}}{\partial w_{ij}}\right| = \alpha \quad \text{if } |w_{ij}| > 0 \quad \text{and} \quad \left|\frac{\partial E_{\mathcal{D}}}{\partial w_{ij}}\right| < \alpha \quad \text{if } |w_{ij}| = 0 \tag{4}$$

The above Eq. (4) states that when model parameter w_{ij} falls below α, then zero will be assigned to that parameter and the corresponding input feature against that value is also removed from the model.

3.5. Classification using SVM

In the present study, activity recognition is basically a classification problem. Therefore, the Library for Support Vector Machines (LIBSVM) [57] was used for classification purposes. Using a SVM allowed for the separation of classes by finding the hyperplane, which is the maximum distance to the closest point of every class. These closest points are known as support vectors. Let N be the number of training examples in the set that has x_i data points and y_i is the class label $y_i \in \{\text{-}1, +1\}$. Finding an optimal hyperplane with the maximum margin is basically solving the optimization problem by using quadratic programming and can defined by the following equation:

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i k(x_i, x) + b, \tag{5}$$

where the sign of $f(x)$ denotes the membership class of x, α_i is the Lagrange multiplier, and $k(x_i, x)$ is the kernel, which is the dot product of these points for a linearly separable problem. In the case of nonlinearly separable problems, a kernel trick can be used for mapping the original input space to a higher dimensional space, which makes the data linearly separable. Different kernel tricks can be used such as polynomial, linear, radial basis functions, and sigmoid. In this research, the RBF kernel was used as it gave the most promising results. Both parameters of RBF, γ (width of kernel function) and C (soft slack variable), were tuned in order to achieve a better hypothesis. During the model selection procedure, the region containing the optimal parameter values was identified by applying the loose gird search in the parameter space and then a fine grid search was performed in the region to find the optimal parameters. The values in the present study were found to be $\gamma = -4.5$ and C=4, and they were subsequently inputted into the RBF kernel.

The SVM by nature is a binary classifier; however, in the present study, the dataset contained six classes, and therefore its extension was used for solving the multiclass problem. The most commonly used methods for solving this problem are one-against-all and one-against-one techniques. In one-against-all, the N-class problem is considered two-class by training N binary classifiers, which can then distinguish one class from another. In the case of one-against-one, there are pairwise combinations of the N classes. In the present study, the one-against-all method was used due to its high accuracy and less memory usage as compared to the one-against-one method. Further training and test sets were generated by using a 10-fold cross-validation method. The model was trained by using the training set and during testing the classes estimated by the classifier were compared with true classes.

3.6. Performance evaluation

The evaluation of the proposed method was performed using different metrics. Predictions made by the trained model were measured on the test data. The confusion matrix, also known as the error matrix, was used for identifying different types of errors, such as false positives and false negatives, and correctly identifying true positives and true negatives. Table 1 shows the various other metrics deduced from the confusion matrix such as accuracy, recall, precision, and F-measure.

Table 1. Performance metrics.

Definition	Formula
Accuracy: It is the proportion of the true results, i.e. true positive and true negative to the total number of values in the dataset	$\frac{T_p+T_n}{T_p+T_n+F_p+F_n}$
Error: It reflects the overall performance of classifier, i.e. how often it was wrong, and is also known as error rate	$1 - accuracy$
Recall or sensitivity: It is the true positive rate, i.e. how many times the classifier correctly predicted actual positives values	$\frac{T_p}{T_p+F_n}$
Precision: It is the true positive rate with respect to all the predicted positives	$\frac{T_p}{T_p+F_p}$
F1 score: or **F-measure:** It is a measure of the classifier's accuracy by the weighted average of true positive rate and precision	$2 * \frac{precision*recall}{precision+recall}$

4. Experimental results and discussion

The experiments were conducted using the MATLAB platform and a 2.40 GHz Intel Core i3-3110 M system. During the experiments, the evaluation was performed using a 10-fold cross-validation method. The entire dataset (10,299 instances = training + testing instance) was randomly partitioned into ten equal sample sets. Next, each sample set was considered for testing while the remaining nine were used for training. The entire process was repeated ten times. Finally, the performance of the algorithms was measured using the evaluation metrics explained in Table 1. In the present study, the following experimental cases were considered for the results.

4.1. Case 1: Raw data

In the first case, only classification techniques were applied to the raw data in order to make a comparison of the raw data results with applied feature selection technique results. Tables 2, 3, 4, and 5 show the average of the confusion matrix for SVM, NB, DT, and KNN, respectively. The summary of overall results in the case of raw data is presented in Table 6. Each confusion matrix is the average of the ten-fold cross-validation. The rows of each confusion matrix represent the actual class and the columns represent the predicted class. For detailed analysis, the performance of each class is also given in the form of precision and recall. The percentage at the end of each row shows the recall rate, whereas the percentage at the bottom of each column represents the precision.

Table 6 shows that KNN achieved the highest classification rate of 89.77%, followed by SVM (87.73%), DT (79.99%), and NB (75.82%). The confusion matrix for SVM in Table 2 shows that it has a lower performance due to the walking and walking up stairs activities frequently being incorrectly classified. Furthermore, SVM also did not perform well on the large dataset. However, the error difference between SVM and KNN is

Table 2. Confusion matrix for SVM using raw data.

Activity	Walking	Walking up stairs	Walking down stairs	Sitting	Standing	Lying	Recall%
Walking	1304	15	403	0	0	0	75.73%
Walking up stairs	3	1155	386	0	0	0	74.81%
Walking down stairs	28	9	1369	0	0	0	97.37%
Sitting	3	0	4	1605	165	0	90.32%
Standing	6	6	0	222	1672	0	87.72%
Lying	0	0	14	0	0	1930	99.28%
Precision%	97.02%	97.47%	62.91%	87.85%	91.02%	100.00%	87.73%

Table 3. Confusion matrix for NB using raw data.

Activity	Walking	Walking up stairs	Walking down stairs	Sitting	Standing	Lying	Recall%
Walking	1230	311	181	0	0	0	71.43%
Walking up stairs	505	848	191	0	0	0	54.92%
Walking down stairs	213	199	994	0	0	0	70.70%
Sitting	81	5	1	1057	589	44	59.48%
Standing	77	5	0	66	1758	0	92.24%
Lying	0	0	22	0	0	1922	98.87%
Precision%	58.40%	61.99%	71.56%	94.12%	74.90%	97.76%	75.82%

Table 4. Confusion matrix for DT using raw data.

Activity	Walking	Walking up stairs	Walking down stairs	Sitting	Standing	Lying	Recall%
Walking	1158	275	232	31	26	0	67.25%
Walking up stairs	257	1108	146	8	22	3	71.76%
Walking down stairs	284	199	877	21	14	11	62.38%
Sitting	16	10	7	1522	222	0	85.65%
Standing	25	15	4	229	1633	0	85.68%
Lying	0	1	3	0	0	1940	99.79%
Precision%	66.55%	68.91%	69.11%	84.04%	85.19%	99.28%	79.99%

approximately 2%. The confusion matrix of NB in Table 3 also shows that it has the lowest accuracy due to the maximum misclassification of walking up stairs and sitting activity having a recall rate of 54.92% and 59.48%, respectively. In the case of walking up stairs, the activity was frequently incorrectly classified as walking and walking down stairs activity. Sitting was frequently incorrectly classified as standing activity. Properly classifying these activities was very difficult due to the fact that they frequently generated the same signal. In the case of DT, Table 4 also shows that the lowest recall rate recorded was also for walking down stairs, and this activity was frequently misclassified as the walking and walking up stairs activities. Overall the highest recall and precision were found to be for the lying down activity.

Table 5. Confusion matrix for KNN without using raw data.

Activity	Walking	Walking up stairs	Walking down stairs	Sitting	Standing	Lying	Recall%
Walking	1588	8	1	20	105	0	92.22%
Walking up stairs	10	1373	0	19	142	0	88.92%
Walking down stairs	31	15	870	76	414	0	61.88%
Sitting	0	0	0	1696	81	0	95.44%
Standing	0	0	0	132	1774	0	93.07%
Lying	0	0	0	0	0	1944	100.00%
Precision%	97.48%	98.35%	99.89%	87.29%	70.51%	100.00%	89.77%

Table 6. Detailed accuracy per classifier using raw data.

	Precision ± std	Recall ± std	F-measure ± std	Accuracy ± std
SVM	89.41% ± 0.66%	87.54% ± 0.95%	87.35% ± 0.96%	87.73% ± 0.93%
NB	76.51% ± 1.14%	74.61% ± 1.42%	74.56% ± 1.39%	75.82% ± 1.35%
DT	78.90% ± 1.57%	78.75% ± 1.56%	78.75% ± 1.55%	79.99% ± 1.44%
KNN	92.27% ± 0.47%	88.59% ± 0.89%	89.32% ± 0.89%	89.77% ± 0.77%

4.2. Case 2: Feature subset selected using SBMLR

In order to improve the accuracy of Case 1 and to reduce the computational costs, a feature subset selection was performed using SBMLR. It returned a subset of selected features that were identified by the index of the feature. There were a total of 561 features with frequency and time domain variables as explained in Section 3.3. Among these 561 features, SBMLR had the best accuracy with the top 179 selected features. Tables 7 through 10 show the averages of ten-fold cross-validation for each classifier, and Table 11 shows the overall comparison of each classifier for the feature subset. In addition, the percentage and recall rate for each activity are also given in each confusion matrix.

Table 7. Confusion matrix for SVM using selected features.

Activity	Walking	Walking up stairs	Walking down stairs	Sitting	Standing	Lying	Recall%
Walking	1722	0	0	0	0	0	100.00%
Walking up stairs	0	1544	0	0	0	0	100.00%
Walking down stairs	0	0	1406	0	0	0	100.00%
Sitting	0	1	0	1754	21	1	98.71%
Standing	0	0	0	39	1867	0	97.95%
Lying	0	0	0	0	0	1944	100.00%
Precision%	100.00%	99.94%	100.00%	97.82%	98.89%	99.95%	99.40%

As discussed in the related work (Section 2), there are different relevant studies [5, 30, 36, 46–49] that have used different experimental setup, feature selection, and classification methods. In addition, some of these approaches used wearable sensors [5, 30, 36, 47, 48], while others used smartphones [46, 49]. Furthermore,

Table 8. Confusion matrix for NB using selected features.

Activity	Walking	Walking up stairs	Walking down stairs	Sitting	Standing	Lying	Recall%
Walking	1550	95	77	0	0	0	90.01%
Walking up stairs	22	1456	66	0	0	0	94.30%
Walking down stairs	28	135	1243	0	0	0	88.41%
Sitting	0	15	0	1383	376	3	77.83%
Standing	1	22	0	186	1697	0	89.03%
Lying	0	11	0	0	0	1933	99.43%
Precision%	96.81%	83.97%	89.68%	88.15%	81.86%	99.85%	89.93%

Table 9. Confusion matrix for DT using selected features.

Activity	Walking	Walking up stairs	Walking down stairs	Sitting	Standing	Lying	Recall%
Walking	1631	55	36	0	0	0	94.72%
Walking up stairs	68	1404	72	0	0	0	90.93%
Walking down stairs	44	67	1295	0	0	0	92.11%
Sitting	1	1	0	1599	176	0	89.98%
Standing	0	0	0	187	1719	0	90.19%
Lying	0	0	0	0	0	1944	100.00%
Precision%	93.52%	91.94%	92.30%	89.53%	90.71%	100.00%	93.14%

Table 10. Confusion matrix for KNN using selected features.

Activity	Walking	Walking up stairs	Walking down stairs	Sitting	Standing	Lying	Recall%
Walking	1720	0	2	0	0	0	99.88%
Walking up stairs	4	1537	3	0	0	0	99.55%
Walking down stairs	5	6	1395	0	0	0	99.22%
Sitting	0	2	0	1643	130	2	92.46%
Standing	0	0	0	129	1777	0	93.23%
Lying	0	0	0	4	0	1940	99.79%
Precision%	99.48%	99.48%	99.64%	92.51%	93.18%	99.90%	97.21%

Table 11. Detailed accuracy per classifier using selected features.

	Precision $\pm$ std	Recall $\pm$ std	F-measure $\pm$ std	Accuracy $\pm$ std
SVM	$99.44 \pm 0.16\%$	$99.44 \pm 0.17\%$	$99.44 \pm 0.17\%$	$99.40 \pm 0.18\%$
NB	$90.10 \pm 0.62\%$	$89.84 \pm 0.68\%$	$89.79 \pm 0.68\%$	$89.93 \pm 0.65\%$
DT	$93.03 \pm 1.27\%$	$92.99 \pm 1.25\%$	$92.99 \pm 1.25\%$	$93.14 \pm 1.21\%$
KNN	$97.38 \pm 0.65\%$	$97.36 \pm 0.66\%$	$97.36 \pm 0.66\%$	$97.21 \pm 0.69\%$

studies have shown that smartphones [46] can perform as well as wearing multiple sensors. Therefore, in Case 2, the proposed approach is applied to a publicly available dataset [46] collected using smartphones instead of using a wearable sensor-based approach. Our proposed approach showed significant feature reduction and improvement in the F-measure. The results of the experiments in Table 12 show that initially there was 76.42% F-measure when only the SVM was used with default settings. After applying the SVM with parameter tuning, the F-measure was increased to 87.35%. When SBMLR without any threshold value was applied, the F-measure was 93.82%. Finally, when we applied thresholding with SBMLR and SVM with parameter tuning, the highest F-measure of 99.44% was achieved. The results of the proposed approach are comparable with those of existing approaches for the same UCI dataset [46]. Murad and Pyun [58] used deep recurrent neural networks(DRNNs) and achieved accuracy of 96.7%. Ronao et al. [59] used a deep convolutional neural network and reported accuracy of 94.79%. After adding the fast Fourier transform (FFT) of the dataset the accuracy was improved to 95.75%. In another study [60] the authors achieved accuracy of 91.76% using hidden Markov models. Hernandez et al. [61] used bidirectional long short-term memory and reported overall accuracy of 92.67%. Yu et al. [62] used the same technique of bidirectional LSTM and achieved accuracy of 93.79%. In order to compare with other feature selection techniques we used principal component analysis (PCA) [63] and random subset feature selection (RSFS) [64] and reported the results in Table 13.

Table 12. F-measure comparison using different test cases.

Number	Classifier	Feature selection	F-measure
1	SVM with default settings	None	76.42%
2	SVM with parameter tuning	None	87.35%
3	SVM with parameter tuning	SBMLR without thresholding	93.82%
4	SVM with parameter tuning	SBMLR with thresholding	99.44%

Table 13. F-measure comparison using different feature subset selection methods.

Number	Classifier	Raw dataset	PCA (105)	SBMLR (179)	RSFS (282)
1	SVM	87.35%	96.65%	99.44%	99.17%
2	NB	74.56%	81.80%	89.79%	75.77%
3	DT	78.75%	84.22%	92.99%	93.62%
4	KNN	89.32%	92.25%	97.36%	96.14%

The minimum number of features that were selected was by PCA (105) followed by SBMLR (179) and RSFS (282). The difference between the PCA and SBMLR was only 74 features but the F-measure for all the four classifiers in the case of SBMLR was better, which can be seen in Figure 3. On the other hand, RSFS increased the feature size compared to both PCA and SBMLR, but the performance was similar to that of SBMLR and was better than that of PCA. The maximum classification rate was 99.40% when multiclass SVM was used with SBMLR with a reasonable number of features.

The amount of time required to train the SVM model for 561 features was 212.14 s. SBMLR required 166.84 s to select a feature subset, which reduced the time for training the SVM model to 50.18 s. In addition, the RBF kernel was utilized and the time complexity was between $O(n^2)$ and $O(n^3)$, where n is the number of training data points. The confusion matrix of SVM, as indicated in Table 7, shows that there was a 100% recall

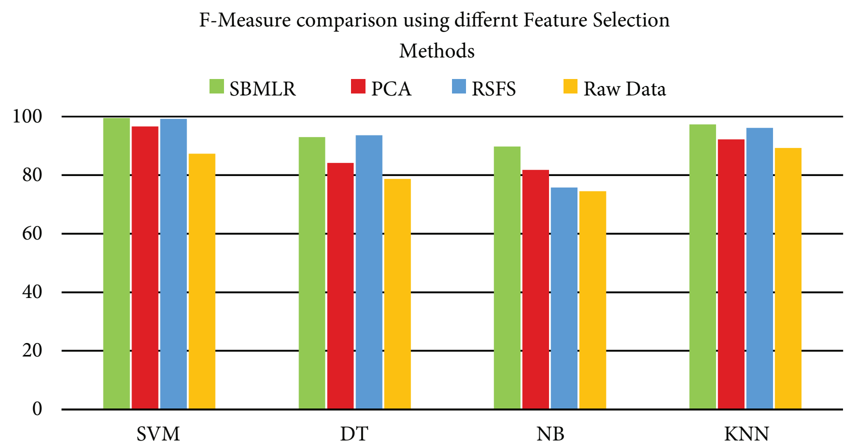

Figure 3. F-measure comparison for SBMLR, PCA, RSFS, and raw data.

rate for walking, walking up stairs, walking down stairs, and lying down. There was a very negligible error rate (0.60%), which was primarily due to a small number of sitting instances that were incorrectly classified as standing and standing being misclassified as sitting. The number of times sitting was misclassified as standing was only 21 times out of 1776 instances, and the number of times standing was misclassified as sitting was 39 times out of 1906 instances. These are the only errors that account for the decrease in accuracy.

In the case of NB, Table 8 shows that the accuracy was improved from 75.82 % to 89.93% as a result of the improvement in the classification of walking, sitting, and standing instances. The recall rate of walking up stairs instances was improved from 54.92% to 94.30%, whereas for sitting instances, the recall rate increased from 59.48% to 77.83%. Furthermore, the precision for classifying walking instances improved from 58.40% to 96.81%. For DT, as indicated in Table 9, the recall rate for walking improved from 67.25% to 94.72%, and for the walking down stairs activity the recall rate improved from 62.38% to 92.11%. The KNN confusion matrix shown in Table 10 clearly indicates that there was a significant improvement from 61.88% to 99.22% in the case of walking down stairs activity. Table 11 shows the summary of the classifiers after removing the misguided features. Overall, all of the classifiers achieved a significant improvement in the classification rates for all the activities. To further test the statistical significance in Case 2, a paired sample two-tailed t-test (also called Student s t-test [65]) was conducted and the results are reported in the following table.

Table 14. Statistical comparison based on 2-tailed t-test at 0.05 significance level (accuracy).

Method	Accuracy ± std	P-val	If(P-val< 0.05)	H_0
SVM-SBMLR SVM-NONSBMLR	99.40 ± 0.18% 87.73 ± 0.93%	3.75×10^{-13}	yes	Reject ▲
NB-SBMLR NB-NONSBMLR	89.93 ± 0.65% 75.82 ± 1.35%	9.60×10^{-10}	yes	Reject ▲
DT-SBMLR DT-NONSBMLR	93.14 ± 1.21% 79.99 ± 1.44%	4.65×10^{-11}	yes	Reject ▲
KNN-SBMLR KNN-NONSBMLR	97.21 ± 0.69% 89.77 ± 0.77%	7.31×10^{-09}	yes	Reject ▲

Table 14 presents the comparisons between four different classifiers based on feature selection (represented as classifier name followed by SBMLR) and without feature selection (represented as classifier name followed by NONSBMLR) at significance of 0.05. In each comparison, the average accuracy of 10-fold cross-validation was used to determine the statistical significance. The null hypothesis for each case states that the difference between the means of competing techniques is zero, i.e. $(H_0 = 1 - 2 = 0)$. This null hypothesis is rejected if the computed P-value $\leq$ significance level. The smaller the P-value the more the difference will be between the means of the techniques. When the null hypothesis is rejected, a ▲ symbol is used for indicating that the proposed technique has performed better than the competing technique. Alternatively a ▼ symbol is placed if the competing technique performs better on the raw data. All P-values are less than 0.05, which indicates that the differences are highly significant.

5. Conclusion and future work

The major contribution of this study is the adaption of SBMLR, which showed remarkable ability to reduce the dimension of features. There were a total of 561 features in the dataset and SBMLR was able to select the top 179 features, which played an important role in improving accuracy. For comparison, other feature subset selection techniques such as PCA and RSFS were also used. Although PCA reduced the features up to 105, the performance of classifiers was not satisfactory. RSFS performed similar to SBMLR, but the feature size was 282. Furthermore, in the case of NB the performance was also not good. In addition to the feature selection technique, different well-known machine learning algorithms (NB, SVM, DT, and KNN) were applied to achieve the best results. For SVM, its extension was used because by nature it is a binary classifier. Therefore, to solve the multiclass problem, the one-against-all method was utilized as it allowed for higher accuracy and less memory consumption. The results of the experiments show that the multiclass SVM together with SBMLR achieved the highest accuracy with a rate of 99.40% as compared to the three other classifiers used. Although the present study accurately identified both static and dynamic activities, future work should include a higher number of activities. The dataset used in this work was collected by attaching the smartphone to the waist. It will be interesting to explore the same activities by placing the smartphone in shirt or pants pockets. Wearing a smartphone during cooking, eating, and bathing activities can be very difficult. Currently, we are also working on identifying the human activities by using Meta Motion R (MMR), which is a 9-axis IMU for performing a comparison with smartphone-based approaches.

References

[1] Ponce H, Martínez-Villaseñor M, Miralles-Pechuán L. A novel wearable sensor-based human activity recognition approach using artificial hydrocarbon networks. Sensors 2016; 16 (7): 1033. doi: 10.3390/s16071033

[2] Jalal A, Kamal S, Kim D. A depth video-based human detection and activity recognition using multi-features and embedded hidden markov models for health care monitoring systems. International Journal of Interactive Multimedia & Artificial Intelligence 2017; 4 (4): 54-62. doi: 10.9781/ijimai.2017.447

[3] Braeken A, Porambage P, Gurtov A, Ylianttila M. Secure and efficient reactive video surveillance for patient monitoring. Sensors 2016; 16 (1): 32. doi: 10.3390/s16010032

[4] Hsu SC, Chuang CH, Huang CL, Teng R, Lin MJ. A video-based abnormal human behavior detection for psychiatric patient monitoring. In: International Workshop on Advanced Image Technology (IWAIT); Chiang Mai, Thailand; 2018. pp. 1-4. doi: 10.1109/IWAIT.2018.8369749

[5] Maurer U, Smailagic A, Siewiorek DP, Deisher M. Activity recognition and monitoring using multiple sensors on different body positions. In: International Workshop on Wearable and Implantable Body Sensor Networks (BSN'06); Cambridge, MA, USA; 2006. pp. 113-116. doi: 10.1109/BSN.2006.6

[6] Wang L, Gu T, Tao X, Lu J. Toward a wearable RFID system for real-time activity recognition using radio patterns. IEEE Transactions on Mobile Computing 2017; 16 (1): 228-242. doi: 10.1109/TMC.2016.2538230

[7] Ward JA, Lukowicz P, Troster G, Starner TE. Activity recognition of assembly tasks using body-worn microphones and accelerometers. IEEE Transactions on Pattern Analysis and Machine Intelligence 2006; 28 (10): 1553-1567. doi: 10.1109/TPAMI.2006.197

[8] Luo X, Guan Q, Tan H, Gao L, Wang Z et al. Simultaneous indoor tracking and activity recognition using pyroelectric infrared sensors. Sensors 2017; 17 (8): 1738. doi: 10.3390/s17081738

[9] Tran DN, Phan DD. Human activities recognition in android smartphone using support vector machine. In: 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS); Bangkok, Thailand; 2016. pp. 64-68. doi:10.1109/ISMS.2016.51

[10] Nam Y, Park JW. Physical activity recognition using a single triaxial accelerometer and a barometric sensor for baby and child care in a home environment. Journal of Ambient Intelligence and Smart Environments 2013; 5 (4): 381-402. doi: 10.3233/AIS-130217

[11] Chen J, Kwong K, Chang D, Luk J, Bajcsy R. Wearable sensors for reliable fall detection. In: 27th Annual International Conference of the IEEE; Shanghai, China; 2006. pp. 3551-3554. doi: 10.1109/IEMBS.2005.1617246

[12] Zheng Y, Wong WK, Guan X, Trost S. Physical activity recognition from accelerometer data using a multi-scale ensemble method. In: Proceedings of the Twenty-Seventh AAAI Conference on Artificial Intelligence; Bellevue, Washington; 2013. pp. 1575-1581.

[13] Garcia-Ceja E, Brena RF, Carrasco-Jimenez JC, Garrido L. Long-term activity recognition from wristwatch accelerometer data. Sensors 2014; 14 (12): 22500-22524. doi:10.3390/s141222500

[14] Bao L, Intille SS. Activity recognition from user-annotated acceleration data. In: International Conference on Pervasive Computing; Berlin, Germany; 2004. pp. 1-17. doi:10.1007/978-3-540-24646-6_1

[15] Reiss A, Stricker D. Introducing a modular activity monitoring system. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society; Boston, MA, USA; 2011. pp. 5621-5624. doi:10.1109/IEMBS.2011.6091360

[16] Bonomi AG, Goris A, Yin B, Westerterp KR. Detection of type, duration, and intensity of physical activity using an accelerometer. Medical Science Sports Exercise 2009; 41 (9): 1770-1777. doi: 10.1249/MSS.0b013e3181a24536

[17] Muhammad SA, Klein BN, Van Laerhoven K, David K. A feature set evaluation for activity recognition with body-worn inertial sensors. In: International Joint Conference on Ambient Intelligence; Berlin, Germany; 2011. pp. 101-109. doi: 10.1007/978-3-642-31479-7_17

[18] Ravi N, Dandekar N, Mysore P, Littman ML. Activity recognition from accelerometer data. In: Proceedings of the 17th Conference on Innovative Applications of Artificial Intelligence; Pittsburgh, PA, USA; 2005. pp. 1541-1546.

[19] Sánchez D, Tentori M, Favela J. Activity recognition for the smart hospital. IEEE Intelligent Systems. 2008; 23 (2): 50-57. doi:10.1109/MIS.2008.18

[20] Noury N, Poujaud J, Fleury A, Nocua R, Haddidi T et al. Smart sweet home...A pervasive environment for sensing our daily activity. In: Noury N, Poujaud J, Fleury A, Nocua R, Haddidi T, Rumeau P (editors). Activity Recognition in Pervasive Intelligent Environments. Paris, France: Atlantis Press, 2011, pp. 187-208. doi:10.2991/978-94-91216-05-3_9

[21] Assaf MH, Mootoo R, Das SR, Petriu EM, Groza V et al. Sensor based home automation and security system. In: IEEE Instrumentation and Measurement Technology Conference (I2MTC); Graz, Austria; 2012. pp. 722-727. doi: 10.1109/I2MTC.2012.6229153

[22] Hong YJ, Kim IJ, Ahn SC, Kim HG. Mobile health monitoring system based on activity recognition using accelerometer. Simulation Modelling Practice and Theory 2010; 18 (4): 446-455. doi: 10.1016/j.simpat.2009.09.002

[23] Lustrek M, Kaluza B. Fall detection and activity recognition with machine learning. Informatica 2009; 33 (2): 197-204.

[24] Ahmed MU, Loutfi A. Physical activity identification using supervised machine learning and based on pulse rate. International Journal of Advanced Computer Sciences and Applications 2013; 4 (7): 210-217.

[25] Hao T, Xing G, Zhou G. iSleep: unobtrusive sleep quality monitoring using smartphones. In: Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems; Rome, Italy; 2013. pp. 4. doi:10.1145/2517351.2517359

[26] Fida B, Bernabucci I, Bibbo D, Conforto S, Schmid M. Pre-processing effect on the accuracy of event-based activity segmentation and classification through inertial sensors. Sensors 2015; 15 (9): 23095-23109. doi: 10.3390/s150923095

[27] AlNuaimi N, Masud MM, Mohammed F. Examining the effect of feature selection on improving patient deterioration prediction. International Journal of Data Mining & Knowledge Management Process (IJDKP). 2015; 5: 1-33. doi: 10.5121/ijdkp.2015.5602

[28] Villar JR, González S, Sedano J, Chira C, Trejo JM. Human activity recognition and feature selection for stroke early diagnosis. In: International Conference on Hybrid Artificial Intelligence Systems; Berlin, Germany; 2013. pp. 659-668. doi: 10.1007/978-3-642-40846-5_66

[29] Gupta P, Dallas T. Feature selection and activity recognition system using a single triaxial accelerometer. IEEE Transactions on Biomedical Engineering 2014; 61 (6): 1780-1786. doi: 10.1109/TBME.2014.2307069

[30] Atallah L, Lo B, King R, Yang GZ. Sensor positioning for activity recognition using wearable accelerometers. IEEE Transactions on Biomedical Circuits and Systems 2011; 5 (4): 320-329. doi: 10.1109/TBCAS.2011.2160540

[31] Koza JR. Genetic Programming: On the Programming Of Computers by Means of Natural Selection. Cambridge, MA, USA: MIT Press, 1997.

[32] Pudil P, Novovičová J, Kittler J. Floating search methods in feature selection. Pattern Recognition Letters 1994; 15 (11): 1119-1125. doi: 10.1016/0167-8655(94)90127-9

[33] Gilad-Bachrach R, Navot A, Tishby N. Margin based feature selection-theory and algorithms. In: Proceedings of the Twenty-First International Conference on Machine learning; Banff, Alberta, Canada; 2004. pp. 43. doi: 10.1145/1015330.1015352

[34] Peng H, Long F, Ding C. Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2005; 27 (8): 1226-1238. doi: 10.1109/TPAMI.2005.159

[35] Kira K, Rendell LA. A practical approach to feature selection. In: Proceedings of the Ninth International Workshop on Machine learning; Scotland, United Kingdom; 1992. pp. 249-256. doi:10.1016/B978-1-55860-247-2.50037-1

[36] Mannini A, Sabatini AM. Machine learning methods for classifying human physical activity from on-body accelerometers. Sensors 2010; 10 (2): 1154-1175. doi: 10.3390/s100201154

[37] Hall MA, Smith LA. Feature selection for machine learning: comparing a correlation-based filter approach to the wrapper. In: Proceedings of the Twelfth International Florida Artificial Intelligence; Orlando, FL, USA; 1999. pp. 235-239.

[38] Rashidi P, Cook DJ. Keeping the resident in the loop: adapting the smart home to the user.IEEE Transactions on Systems, Man, and Cybernetics 2009; 39 (5): 949-959. doi: 10.1109/TSMCA.2009.2025137

[39] Cook DJ, Youngblood M, Heierman EO, Gopalratnam K, Rao S et al. MavHome: an agent-based smart home. In: Proceedings of the First IEEE International Conference on Pervasive Computing and Communications; Fort Worth, TX, USA; 2003. pp. 521-524. doi: 10.1109/PERCOM.2003.1192783

[40] Alemdar H, Ertan H, Incel OD, Ersoy C. ARAS human activity datasets in multiple homes with multiple residents. In: 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops; Venice, Italy; 2013. pp. 232-235. doi: 10.4108/icst.pervasivehealth.2013.252120

[41] Kröse B, Van Kasteren T, Gibson C, Van den Dool T. Care: context awareness in residences for elderly. In: International Conference of the International Society for Gerontechnology; Tuscany, Italy; 2008. pp. 101-105. doi: 10.4017/gt.2008.07.02.083.00

[42] Colon LNV, DeLaHoz Y, Labrador M. Human fall detection with smartphones. In: IEEE Latin-America Conference on Communications (LATINCOM); Cartagena de Indias, Colombia; 2014. pp. 1-7. doi: 10.1109/LATINCOM.2014.7041879

[43] Sahyoun A, Chehab K, Al-Madani O, Aloul F, Sagahyroon A. ParkNosis: diagnosing Parkinson's disease using mobile phones. In: IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom); Munich, Germany; 2016. pp. 1-6. doi: 10.1109/HealthCom.2016.7749491

[44] Zmily A, Abu-Saymeh D. Alzheimer's disease rehabilitation using smartphones to improve patient's quality of life. In: 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops; Venice, Italy; 2013. pp. 393-396. doi: 10.4108/icst.pervasivehealth.2013.252248

[45] Dernbach S, Das B, Krishnan NC, Thomas BL, Cook DJ. Simple and complex activity recognition through smart phones. In: Eighth International Conference on Intelligent Environments; Guanajuato, Mexico; 2012. pp. 214-221. doi: 10.1109/IE.2012.39

[46] Anguita D, Ghio A, Oneto L, Parra X, Reyes-Ortiz JL. A public domain dataset for human activity recognition using smartphones. In: European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN); Bruges, Belgium; 2013. pp. 437–442.

[47] Hanai Y, Nishimura J, Kuroda T. Haar-like filtering for human activity recognition using 3d accelerometer. In: IEEE 13th Digital Signal Processing Workshop and 5th IEEE Signal Processing Education Workshop; Marco Island, FL, USA; 2009. pp. 675-678. doi: 10.1109/DSP.2009.4786008.

[48] Karantonis DM, Narayanan MR, Mathie M, Lovell NH, Celler BG. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE Transactions on Information Technology in Biomedicine 2006; 10 (1): 156-167. doi: 10.1109/TITB.2005.856864

[49] Rasekh A, Chen CA, Lu Y. Human activity recognition using smartphone. arXiv preprint arXiv:14018212. 2014.

[50] Kohavi R, John GH. Wrappers for feature subset selection. Artificial Intelligence 1997; 97 (1-2): 273-324. doi: 10.1016/S0004-3702(97)00043-X

[51] Das S. Filters, wrappers and a boosting-based hybrid for feature selection. In: Proceedings of the Eighteenth International Conference on Machine Learning (ICML 2001); Williamstown, MA, USA; 2001. pp. 74-81.

[52] Suto J, Oniga S, Sitar PP. Comparison of wrapper and filter feature selection algorithms on human activity recognition. In: 6th International Conference on Computers Communications and Control (ICCCC); Oradea, Romania; 2016. pp. 124-129. doi: 10.1109/ICCCC.2016.7496749

[53] Atla A, Tada R, Sheng V, Singireddy N. Sensitivity of different machine learning algorithms to noise. Journal of Computing Sciences in Colleges 2011; 26 (5): 96-103.

[54] Cawley GC, Talbot NL, Girolami M. Sparse multinomial logistic regression via bayesian l1 regularisation. In: Advances in Neural Information Processing Systems; Vancouver, BC, Canada; 2007. pp. 209-216.

[55] Hussain M, Jibreen A, Aboalsmah H, Madkour H, Bebis G et al. Feature selection for hand-shape based identification. In: Computational Intelligence in Security for Information Systems; Burgos, Spain; 2015. pp. 237-246. doi: 10.1007/978-3-319-19713-5_21

[56] Khan S, Khan A, Maqsood M, Aadil F, Ghazanfar MA. Optimized gabor feature extraction for mass classification using cuckoo search for big data e-healthcare. Journal of Grid Computing 2019; 17 (2): 239-254. doi: 10.1007/s10723-018-9459-x

[57] Chang CC, Lin CJ. LIBSVM: a library for support vector machines. ACM Transactions on Intelligent Systems and Technology (TIST) 2011; 2 (3): 27.

[58] Murad A, Pyun JY. Deep recurrent neural networks for human activity recognition. Sensors 2017; 17 (11): 2556. doi: 10.3390/s17112556

[59] Ronao CA, Cho SB. Human activity recognition with smartphone sensors using deep learning neural networks. Expert Systems with Applications 2016; 59: 235-244. doi: 10.1016/j.eswa.2016.04.032

[60] Ronao CA, Cho SB. Human activity recognition using smartphone sensors with two-stage continuous hidden Markov models. In: 10th International Conference on Natural Computation (ICNC); Xiamen, China; 2014. pp. 681-686. doi: 10.1109/ICNC.2014.6975918

[61] Hernández F, Suárez LF, Villamizar J, Altuve M. Human activity recognition on smartphones using a bidirectional LSTM network. In: XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA); Bucaramanga, Colombia; 2019. pp. 1-5. doi: 10.1109/STSIVA.2019.8730249

[62] Yu S, Qin L. Human activity recognition with smartphone inertial sensors using bidir-LSTM networks. In: 3rd International Conference on Mechanical, Control and Computer Engineering (ICMCCE); Huhhot, China; 2018. pp. 219-224. doi: 10.1109/ICMCCE.2018.00052

[63] Wold S, Esbensen K, Geladi P. Principal component analysis. Chemometrics and Intelligent. Laboratory Systems 1987; 2 (1-3): 37-52. doi: 10.1016/0169-7439(87)80084-9

[64] Räsänen O, Pohjalainen J. Random subset feature selection in automatic recognition of developmental disorders, affective states, and level of conflict from speech. In: Proceedings of the Annual Conference of the International Speech Communication Association Interspeech; Lyon, France; 2013. pp. 210-214.

[65] Dietterich TG. Approximate statistical tests for comparing supervised classification learning algorithms. Neural Computation 1998; 10 (7): 1895-1923. doi: 10.1162/089976698300017197