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Health monitoring catalogue based on human activity classification using machine learning

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ABSTRACT

In recent times, fitness trackers and smartphones equipped with different sensors like gyroscopes, accelerometers, global positioning system sensors and programs are used for recognizing human activities. In this paper, the results collected from these devices are used to design a system that can assist an application in monitoring a person's health. The proposed system takes the raw sensor signals as input, preprocesses it and using machine learning techniques outputs the state of the user with minimum error. The objective of this paper is to compare the performance of different algorithms logistic regression (LR), support vector machine (SVM), k-nearest neighbor (k-NN) and random forest (RF). The algorithms are trained and tested with an original number of features as well as with transformed number of features (using linear discriminant analysis). The data with a smaller number of features is then used to visualize the high dimensional data. In this paper, each data point is mapped in the high dimensional data to two-dimensional data using t-distributed stochastic neighbor embedding technique. Overall, the first high dimensional data is visualized and compared with model's performance with different algorithms and different number of coordinates.

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1. INTRODUCTION

Human activity recognition is a process where sequences of data collected using smartphones or smart-belts are classified using different techniques into movements. Several different fitness trackers incorporated with powerful sensors like acceleration, gyroscope, visual sensors are released in the market every year. The acquired signals are stored in real-time. Traditional devices used pedometers to take step counts. They are cheaper, however, devices that primarily use accelerometers are favored because they give more accurate results. Most devices use the accelerometer to keep track of activity and measure it in three orientations which can be used to estimate activities such as energy estimation, and energy intensity [1], [2]. In addition other sensors such as gyroscope, magnetometers are used to potentially improve the accuracy. Orientation and angular velocity estimated by gyroscope help in better prediction of human activity. Often accelerometers, gyroscopes and magnetometers are combined to form inertial measurement units (IMU) to give more accurate metrics [3].

Human activity data plays an important role in analyzing the overall health of a patient and has fundamental utility in clinical research. Research shows that physical activity plays a substantial role in eliminating the risk for non-communicable diseases (NCD). For a long, physical activity has been studied in epidemiological research to map the relationship between health and human activity. Patients are now required to follow a definite exercise routine and their activities are tracked and analyzed with their health status. Such continuous monitoring has proved to improve the reliability of diagnosis and enhance patient's quality of life. For a good analysis of human activity, it is extremely important to predict the type of activity for a given signal with good accuracy.

Many approaches have been proposed in the task of classifying human activity. In this paper, the human activity recognition task is considered as a supervised problem. The proposed method uses all features for the task of prediction, for feature reduction, paring the data to only those features that enhance the prediction accuracy. Moreover, state-of-the-art did not give importance to data visualization. The proposed work strives to provide a visualization of high dimensional data to track and analyze how different activities are related to each other. This will help in understanding as to why and how it is difficult to separate out some activities from other. The paper is organized as follows: section 2 related work. Section 3 discusses the research method used. Section 4 explains linear discriminant analysis (LDA) with a detailed discussion of algorithms in section 5. Section 6 explains the results obtained with conclusive remarks in section 7.

2. RELATED WORK

This section discusses the work done so far and enumerates some of the classic models of the state-of-the-art. In a study [4], traditional algorithms such as naïve Bayes, hidden Markov model (HMM), hidden semi Markov model (HSMM) and conditional random fields (CRFs) are compared with deep learning models on raw sensory data and validated that those deep learning models outperformed the best result by 40%. Similar deep learning approaches have been previously employed for recognition in [5], [6]. The concept of combining AdaBoost with other classifiers (C4.5, multilayer perceptron and logistic regression (LR)) was introduced in [7]. It was tested that Adaboost combined with C4.5 gave an accuracy of 94.04%. A similar technique with slight modification by combining AdaBoost algorithm with decision stump (DS), Hoeffding tree (HT), random tree (RT), J48, random forest (RF) and reduce error pruning (REP) Tree was discussed to classify six activities of daily life by using the Weka tool [8]. Bayat *et al.* [9] used a single triaxial accelerometer to obtain accurate recognition. Different activities of a person were analyzed using a classification model also using feature selection. The model was trained on different classifiers and finally, it was proposed that overall efficiency of 91.15% was obtained by taking the average of probabilities as a fusion method. Machine learning models including naïve Bayes, support vector machine (SVM), Markov chains are employed for recognition of human activity [10], [11]. Liu *et al.* [12] proposed two methods, first activity recognition is performed using a machine learning model after performing feature extraction on the data collected using accelerometer and gyroscope and using convolution neural network model on raw data. The final result proposes that SVM performs the best among other methods and that accelerometer reading contribute more to recognition than gyro sensor reading. In study [13], a position independent method is proposed where first, raw data were converted into vertical and horizontal acceleration so as to avoid the influence of the orientation of smartphones on prediction. Bao and Intille [14] mentions the use of five biaxial accelerometers that are worn on the wrist, upper-arm, ankle, right hip and thigh and 20 types of activities for monitored and various data mean, entropy, energy and recorded, the model was trained using naïve Bayes classifier, decision trees, C4.5 and instance-based learning.

The work in [15] recognizes activities using a single triaxial accelerometer worn near the pelvic region. Eight sets of activities standing, walking, running, climbing up stairs, climbing down stairs, sit-ups, vacuuming, brushing teeth were performed by two subjects in multiple rounds over different days. The model was trained using level based classifiers-decision tables, decision trees, k-nearest neighbors (k-NN), SVM, naïve Bayes. Plurality voting combining base-level classifiers outperformed other techniques. In a study [16] the approach uses legion: AR, a system for training an arbitrary activity recognition system in real-time using a crowd of workers. Kańtoch and Kańtoch [17] proposed a prototype of a body sensor network (BSN)-based wearable wireless monitoring system optimized to monitor patient's activity and physiological signals. Further, in study [18] a local space-time feature is proposed to represent the human movement observed in a video and recognize motion patterns with SVM classification schemes for recognition. A general kernel method can be employed for recognition with local features. In several study [19]–[21] focuses on group activities where three different approaches are used to model person-person interaction. By exploring person-person interaction in the feature level for which a new feature representation called action contact (AC) descriptor is proposed. The third approach combines the first two. In study [22], improvement to the model is proposed by incorporating high-dimensional features of duration and time block characteristics.

3. RESEARCH METHOD

In this paper, the aim is to compare and analyze the performance of the system using different algorithms with different number of features. The input to the model is a set of pre-processed signals obtained using an accelerometer and gyroscope passed through various noise filters and finally converted to structured data and output is the activity performed while the signals were recorded. Since the data has widely varying dimensionality, t-distributed stochastic neighbor embedding is used to chart the high dimensional data to 2-D plots. Essentially, the main focus is on decreasing the number of features and doing a comparative analysis. LDA is performed several times simultaneously measuring the accuracy, analyzing how many features are concretely required to predict the activity correctly.

3.1. Data

The data consists of 10,299 observations, 561 frequencies and time-domain feature vector and an activity label. The data was collected from 30 people to wear waist-mounted smartphones and were asked to perform various static and dynamic activities and the movement data was recorded. The various activities consisted of laying, sitting, and standing, walking downstairs, and walking upstairs. The model is trained on different numbers of bits k for β estimation. Finally, it is demonstrated that the movement data (the features of the data) is based on 3 axial linear acceleration obtained using accelerometer and 3 axial angular velocities obtained using gyroscope. These sensor signals were passed through noise filters. Windowing approach is used for the segmentation of data. Further, signal frequency components were obtained by applying fast Fourier transform (FFT) [1]. Features set (for example: -mean standard deviation, entropy, skewness, signal magnitude area) therefore are summarized versions of those processed time-domain signals. For modelling the data was split as follows: i) training data: 7,352 and ii) test data: 2,947.

3.2. Visualizing using T-SNE

One of the best and easiest ways to understand the complicated relationship between the data is through data visualization. This is particularly important for high-dimensional data to communicate the findings. There are a variety of techniques that have been proposed for visualization of such high-dimensional data, like mosaic plots, parallel coordinate plots, projection pursuit and grand tour, trellis to display different kinds of data like purely categorical, purely continuous, mixed scaled data respectively [23]. A technique called t-SNE is used that pictures high dimensional data by drafting each data point in high dimension to low dimension i.e. two or three- dimensional map [24].

The objective of t-distributed stochastic neighbor embedding (t-SNE) is to visualize the data by reducing the dimensionality while keeping similar instances close and dissimilar instances apart thus just preserving local structure. In short, the t-SNE algorithm is a similarity measure algorithm between pair of instances in the low dimensional and low dimensional space. Perplexity is the number of nearest neighbors considered when matching original and fitted distribution for each data point. The perplexity is high like 50 or 100 to take more of the big picture into account. From Figures 1 and 2 it is deduced that it is easy to distinguish static and dynamic activities, however, the issue is that both “standing” and “sitting” activities are quite similar to each other, hence it seems that there is relatively little difference between the position and movement of a “sitting” person and “standing” person. A solution to this problem is to use an algorithm to separate only “sitting” and “standing” observations.

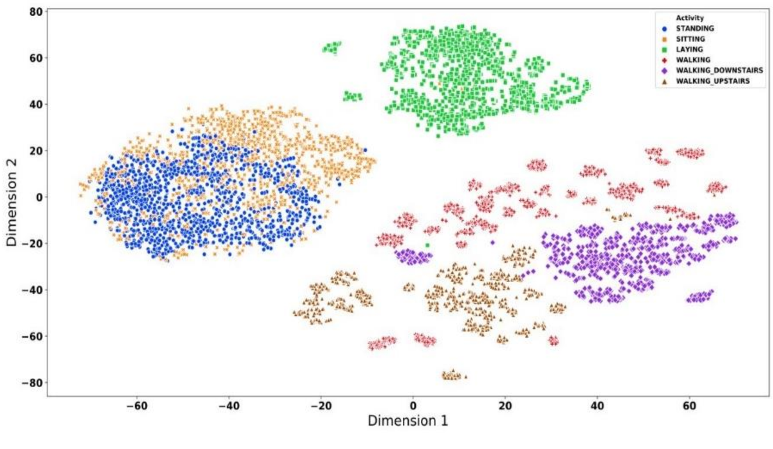

Figure 1. Visualization using t-SNE

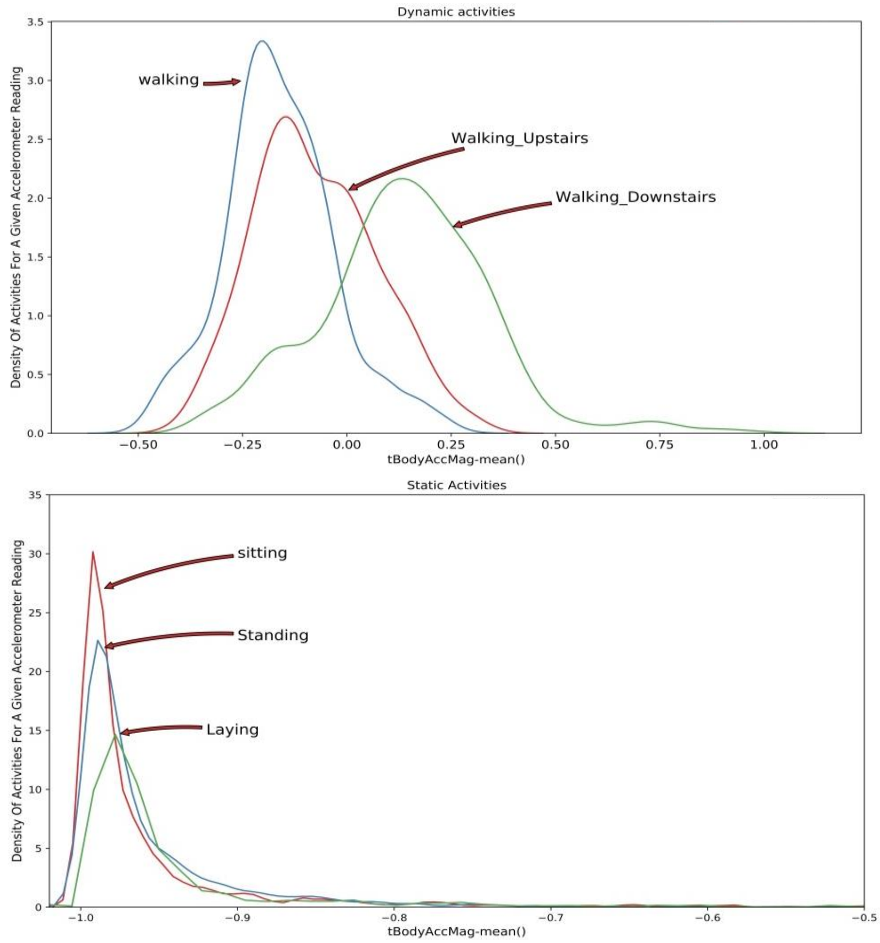

Figure 2. A closer view of static and dynamic activities indicating a difference in static and dynamic activities

Further, another way of dealing with high dimensional data is to reduce the number of features by converting the high dimensional data set into low dimensional data which can then be displayed using a scatterplot. There are many proposed techniques for feature reduction like principle component analysis (PCA), multidimensional scaling (MDS), and locally linear embedding (LLE). In this paper, LDA is used.

4. LINEAR DISCRIMINATE ANALYSIS

LDA is a classification algorithm that learns the most discriminative axes between the classes during training, and these axes can then be used to define a hyperplane onto which data is projected. This algorithm is used to identify m-dimensional summary of the data from d-dimensional space such that within-class variance is minimized while keeping between classes variance maximized. This supervised subspace learning method projects features xi in the high dimensional space, where X=[x_1, …, x_n]∈Rd×nto W∈Rd×m assuming that X has been centered with zero mean, i.e., $\sum_{i=1}^{n} x_i = 0$, i.e.

$$arg\ arg\ max_{w}\ tr\left((W^T S_w W)^{-1} * (W^T S_b W)\right) \quad (1)$$

Where S_w is within class and S_b is between-class scatter matrix respectively.

$$S_w = \sum_{k=1}^{c} \sum_{i \in ck} ((x_i - \mu_k) * (x_i - \mu_k)^T) \quad (2)$$

$$S_b = \sum_{k=1}^{c} n_k \left((\mu_k - \mu) * (\mu_k - \mu)^T\right) \quad (3)$$

C_k = index set of the k^{th} class, μ_k and n_k are mean vector and size of k^{th} class respectively. If $S_t = S_w + S_b$., where S_t is the total scatter matrix, then (2) and (3) can also be modified as (4).

Where, $S_t = \sum_{i=1}^{n}(x_i - \mu)(x_i - \mu)^T$ (4)

When the total class scatter matrix is singular, the solution to (4) consist of top eigenvectors of matrix $S^{\dagger}_t S_b$ corresponding to nonzero eigenvalues, where $S^{\dagger}_t$ is the pseudo inverse of S_t. When the total class scatter matrix is non-singular, the solution to (4) consist of top eigenvectors of matrix $S^{-1}_t S_b$ corresponding to nonzero eigenvalues [25].

The following steps are used for feature reduction and classification algorithm.

Step 1: First, the projection of the dataset is calculated using the LDA and a number of features are selected, which is called LDA transform. LDA transform is performed several times with different numbers of input features and accuracy is calculated each time and the number of features with the best average performance is chosen.

Step 2: Different models are built on the training data on which LDA transformation is performed to find the optimum dimension.

Step 3: Each model obtained after step 2 is used to predict classes in the validation data.

Step 4: Misclassification error is calculated for each model and the model with the least error is used to predict classes in test data.

Step 5: The model is then further optimized by tuning hyper-parameters based on the result obtained after the performance on the validation data.

5. ALGORIMHS

This section explains the preliminaries used in the proposed framework. For brevity, only basic details of logistic regression, k-nearest neighbor, support vector machine and random forest are presented. The specific details of these algorithms, which are used during empirical evaluation of the proposed methodology is also given.

5.1. Logistic regression (LR)

Logistic regression algorithm is used with one-vs-rest (OvR) scheme. This is a parametric method which is trained for each class to predict whether that query belongs to a particular class or not. It follows the assumption that all classes are independent of each other. LDA transform is performed with a different number of dimensions. It has been observed that performance is almost the same for five dimensions and more.

5.2. k-nearest neighbor (k-NN)

k-NN classifier [26] is a nonparametric technique. It gives the probability of a data point belonging to a particular class B based on the probability of its K neighbors' probability of belonging to the same class B. The model is trained for different values of k in the range of the expected k-value and accuracy is calculated each time. The best result is obtained at K=9. Also, it is observed that the model performs best when the number of components is set to 6.

5.3. Support vector machine (SVM)

Support vector machine [27] takes the data points and outputs a hyperplane that best separates the classes. In the SVM model, data points are mapped so that the data points belonging to different categories are divided by a clear gap that is as wide as possible. SVM is one of the most effective algorithms for high dimensional data. One vs all method with a number of coordinates equal to five is implemented.

5.4. Random forest (RF)

Random forest [28] operated by selecting multiple bootstrap samples from the original dataset. In addition to being effective classifiers, this approach can be used for dimensionality reduction by constructing trees against a target attribute. The approach is to construct a classification tree ensemble in which LDA is employed for feature selection.

6. RESULTS AND DISCUSSION

After implementing each algorithm on the original and LDA transformed data, the performance of the proposed model is evaluated using a confusion matrix, learning curves and classification accuracy. Based on the confusion matrix as shown in Figures 3 to 6, it is observed that some activities are difficult to predict than others. For example, ‘sitting’ classes are usually misclassified as ‘standing’, it seems that both ‘sitting’ and ‘standing’ classes have relatively the same accelerometry and gyroscopic pattern.

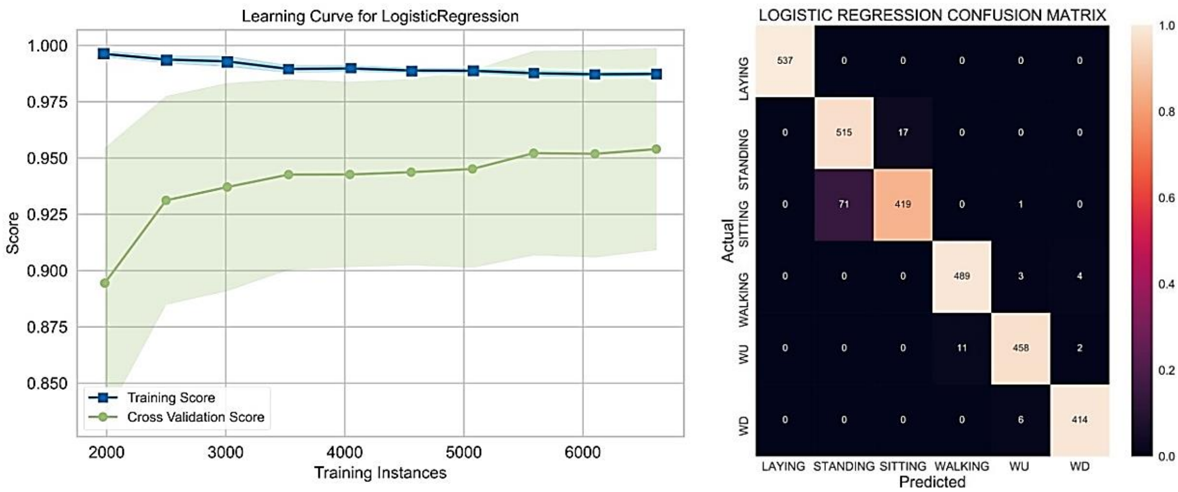

Figure 3. Learning curve and confusion matrix for logistic regression

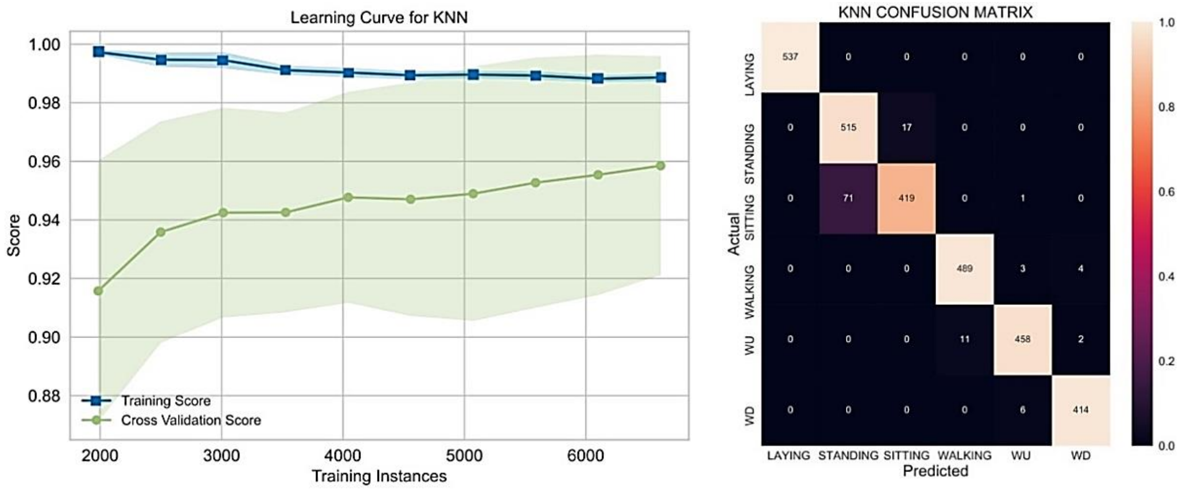

Figure 4. Learning curve and confusion matrix for KNN

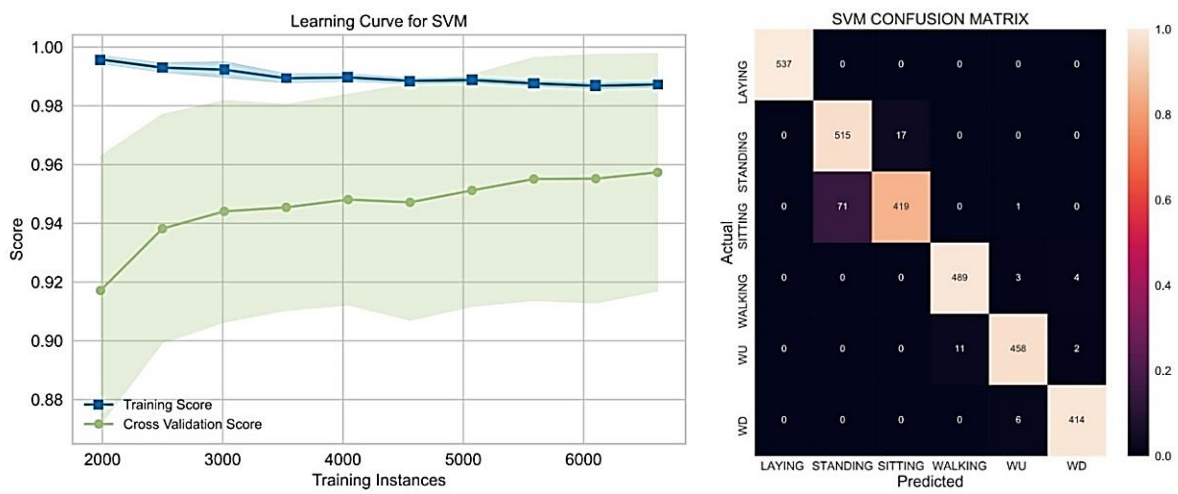

Figure 5. Learning curve and confusion matrix for SVM

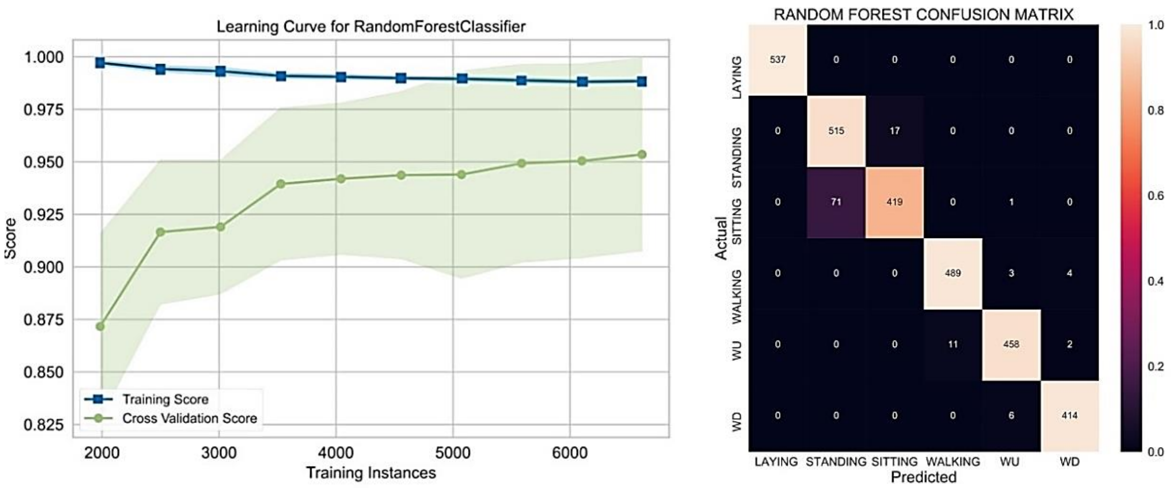

Figure 6. Learning curve and confusion matrix for random forest

Analyzing the learning curves, the trend is almost the same for all the algorithms, the proposed algorithm portrays that the model's performance is proportional to the amount of data that is fed into the system. F1 score in Table 1 is another way for evaluating the empirical performance of algorithms. It can be seen that it is easy to classify 'Lay' from other activities. This is quite obvious from the visualization of data in Figure 1.

Based on the F1 score in Table 1, accuracy scores in Table 2, it is deducted that SVM and RF perform better after applying LDA transformation. Surprisingly, LR and KNN performance did not improve with a smaller number of features as compared to other algorithms in Table 2, hence it can be concluded that feature reduction does not have much impact on the score improvement when predicting using the above mentioned algorithms.

Table 1. F1 scores by class for basic model data and LDA enabled and transformed data using different algorithms

Features	Algo	Sit	Stand	Lay	Walk	Wu	WD
ORIGINAL	LR	0.93	0.92	1.00	0.97	0.98	0.96
	KNN	0.88	0.85	1.00	0.91	0.86	0.89
	SVM	0.91	0.93	1.00	0.96	0.94	0.95
	RF	0.91	0.90	1.00	0.93	0.89	0.90
LDA	LR	0.91	0.93	1.00	0.98	0.97	0.99
	KNN	0.91	0.93	1.00	0.99	0.98	0.99
	SVM	0.92	0.92	1.00	0.99	0.98	0.99
	RF	0.91	0.92	1.00	0.94	0.92	0.96

Table 2. Comparative scores basic vs. LDA enabled model for Logistic regression, k-nearest neighbor, support vector machine and random forest algorithms

Algorithm	Accuracy scores (Basic model)	Accuracy scores (LDA-Enabled)
Logistic regression	0.950	0.963
K-nearest neighbor	0.949	0.96
Support vector machine	0.900	0.967
Random forest	0.923	0.964

The precision score of different algorithms after LDA transformation are shown in Figures 7 and 8. It is analyses the performance capability of each algorithm in classifying each class correctly. It is observed that random forest is able to classify "sitting" and "standing" activity with the highest precision but lags in predicting "walk" and "walking downstairs" activity. On the other hand SVM predicts "walk" and "walk downstairs" activity with the highest precision but lags in predicting "sit and "stand" activity. KNN algorithms can predict "sit" and "walk" with high precision. LR performs the worst compared to other algorithms. All the algorithms are able to predict "lay" class with 1.00 precision.

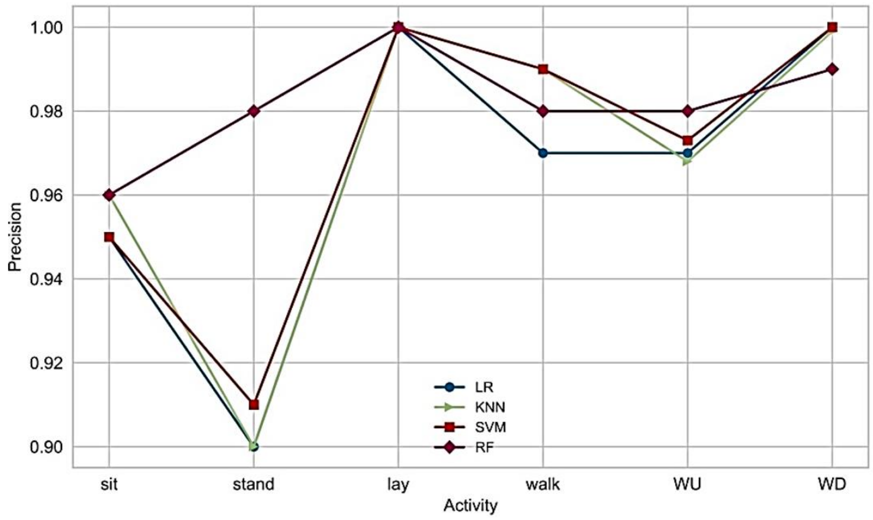

Figure 7. Precision score of different algorithms on LDA transformed data

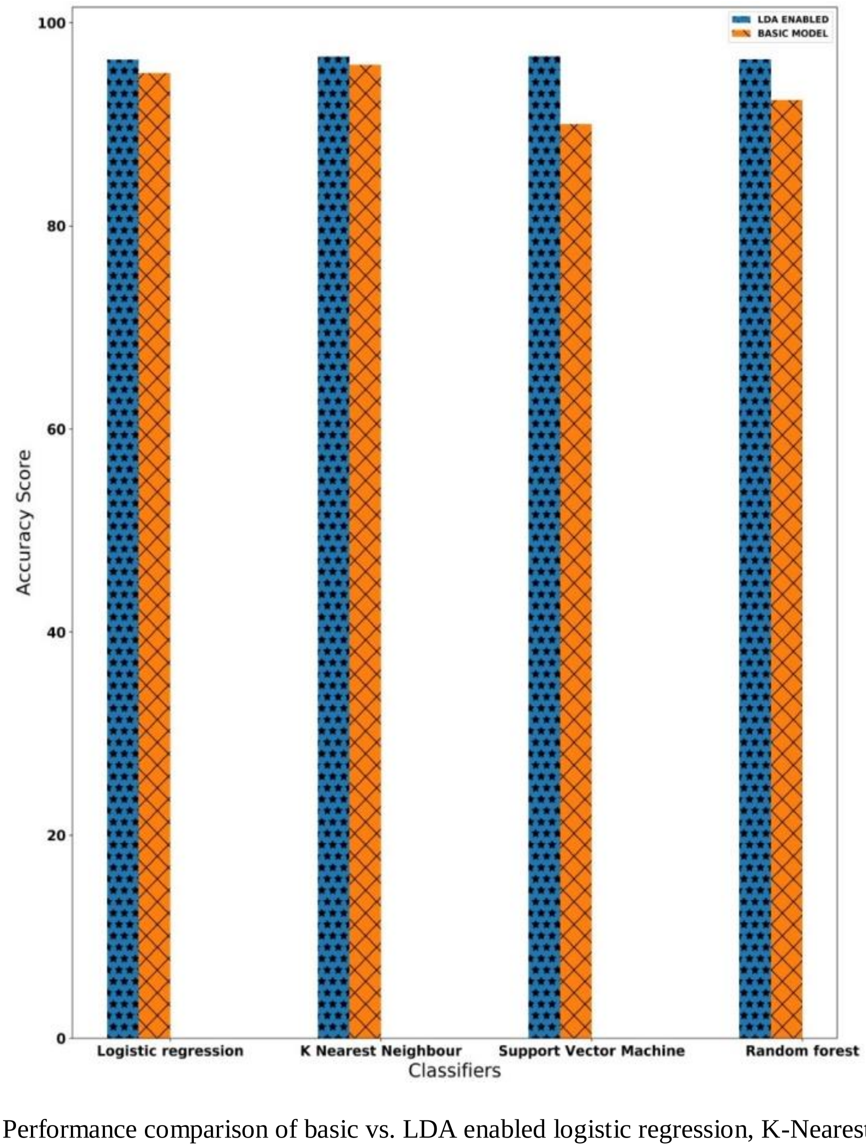

Figure 8. Performance comparison of basic vs. LDA enabled logistic regression, K-Nearest Neighbor, support vector machine and random forest model

7. CONCLUSION AND FUTURE WORK

In this paper, human activity recognition using optimized number of features is used with different machine learning algorithms. For this t-distributed stochastic neighbor embedding technique is used and results are established. The role of feature reduction in decreasing the misclassification error rate by reducing variance due to high feature space is studied and analyzed. The proposed work also emphasizes on data visualization to understand the problem in hand. The proposed methodology obtained 6% less misclassification error using SVM on LDA transformed data when compared with original data. This is because the sparsity of the data is reduced by reducing the number of features that now are less likely to overfit. The algorithm that worked best is the SVM classifier and Random forest with LDA transformation. It is observed that class ‘Laying’ was correctly classified every time, this is mainly due to the difference in the signals of this activity as compared to others. The proposed method deducts that it is easier to distinguish static activities (stand, sit, lay) from dynamic activities (Walk, WU, WD). However, the majority of the misclassification error is due to certain activity labels which are closely related to each other such as ‘stand’, ‘sit’ and ‘walking’, ‘walking downstairs’ resulting in a high error rate for these classifications. In the future work on implementing an algorithm to separate such classes can be investigated more deeply. Also, the issue of variance is reduced but not completely resolved. The proposed work can be extended on reducing the problem of variance by using different techniques such as the introduction of bias, collecting more data, including regularization parameters.

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