PERFORMANCE ANALYSIS OF MLP AND SVM BASED CLASSIFIERS FOR HUMAN ACTIVITY RECOGNITION USING SMARTPHONE SENSORS DATA

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Abstract

Days have gone when Mobile Phone used to be matter luxury, it has become a significant need for rapidly evolving fast track world. Intelligent aspects of the computing device enhance the importance of the interface development since; efficient collaboration always relies on the good communication between man and machine. The information about mobile device and user activity, environment, other devices, location and time can be utilized in different situations to enhance the interaction between the user and the device. Here, we presented our work in which certain types of human physical activities using accelerometer and gyroscope data generated by a mobile device. The benchmark Human Activity Recognition dataset is considered for this work is acquired from UCI Machine Learning Repository which is available in public domain. MLP and SVM Classifiers were tested using various time domain and frequency domain features. We found the using Multi Layer Perceptron with Processing Element 6, Learning rate 0.05, Momentum 0.1 reach an overall accuracy of 98.11%.

Keywords— *Context; Framework; Adaptive User Interfaces; Classifier, Multilayer Perceptron, Support Vector Machine*

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1. INTRODUCTION

Days have gone when Mobile Phone used to be matter luxury, it has become a significant need for rapidly evolving fast track world[1]. Intelligent aspects of the computing device enhance the importance of the interface development since; efficient collaboration always relies on the good communication between man and machine[2]. The information about mobile device and user activity, environment, other devices, location and time can be utilized in different situations to enhance the interaction between the user and the device[3]. Human activity has enabled applications in various areas in healthcare, security, entertainment, personal fitness, senior care and daily activities[4].

2. RELATED WORK

While studying the related literature within past few decades, we found many researchers have been presented literature through proposing and investigating various methodologies for human activity recognition. Methodologies for activity recognition from video, or from on body wearable sensors data or from sensors data on mobile device found in literature.

Human Activity Recognition through environmental sensors is also one of the promising approach because this approach is successful to recognise activities which are not easy to recognize with body movement alone. Different kind of sensors like motion sensors, video cameras, RFID tags, door contact sensors are use to gather activity related information. This method have high recognition rate and more useful in indoor environments. But this requires costly hardware infrastructures [5,6].

Another effective approach in which multiple sensors are placed on different parts of the body to recognise human activity.This type of sensing having drawbacks that user has to wear lot of sensors on his body [5].

In the literature, extensive study found on approach in which mobile phone is used to collect human activity related data for recognition and adapt the interfaces to provide better usability experience to mobile users [7,8]. Today's Mobiles are well equipped with mores sensors offer a number of advantages including not requiring any additional hardware for data collection or computing. This make mobile device an attractive platform for activity recognition. These devices saturate modern culture, they continue to grow in functionality increases the security and privacy issues[9].

3. METHOD

After surveying the extensive literature, the methodology adopted for the system. The system consists of data acquisition, preprocessing, feature extraction, feature selection, classification, knowledge base, inference engine, action base and finally user interface adaptation.

The feature extraction, we have used statistical and transformed based features extracted. The Classifier are designed with the help of Neural Network like Multi Layer Perceptron (MLP) and Support Vector Machine (SVM).

3.1 Experiment

- Acquisition of benchmark HAR Dataset for Human Activity Recognition through mobile device.
- Processing data for missing values, randomization tagging into input-output.
- Partitioning dataset into training, testing and cross validation.
- Selection of appropriate neural network structure for classification with variation in transfer function, learning rules.
- Variation of parameters to arrive at the optimal model.
- Examination of each NN model on test and cross validation dataset.
- Comparison of classifiers on performance measures such as, classification accuracy, area under ROC curve and minimum MSE.
- Comparative analysis of all models on the basis of classification accuracy, complexity, minimum train time.
- Selection of optimal NN model.
- Simulation also realized using Samsung Galaxy Note3 and MyWeka version 1.1 application using Machine Learning Weka library.

3.2 Benchmark Data Set

The benchmark dataset is considered for this work is acquired from UCI machine learning repository which is available in public domain[9]. Here data was gathered from a group of 30 volunteers. Each volunteer performed the 6 activities keeping a smartphone (Samsung Galaxy SII) on the waist. With the sampling rate of 50Hz, the raw data from built-in 3-axial accelerometer and gyroscope captured. These activities recognition has modeled as a six-class classification problem. The six classes for benchmark are:

1. Walking 2. Sitting 3. Standing 4.Stair-Up
5. Stair-Down 6. Laying

1) Attribute Information:
In each record of the dataset following attributes are included:

- Raw acceleration value in X, Y, Z axis direction from the accelerometer (total acceleration)
- The body acceleration estimated from raw acceleration.
- Raw Angular velocity value in X, Y, Z axis direction from the gyroscope.
- Total 561features generated from raw data in time and frequency domain.
- Label for corresponding activity
- Features vector are normalized and bounded within [-1,1].
- Each row form a feature vector.

3.3 Feature Extraction:

Features selected for this dataset come from raw data captured from the accelerometer and gyroscope raw signals. These 3-axial raw signals are time domain signals prefix 't' to denote time. Before selecting features, raw sensor signals were pre-processed. To remove the noise from raw signals median filter is used and raw signal passed through a 3rd order low-pass Butterworth filter with a corner frequency of 20Hz. Another low pass Butterworth filter with a corner frequency of 0.3 Hz has been used to obtained body acceleration and gravity acceleration signals from the acceleration signal. Jerk Signals has been obtained the body linear acceleration and angular velocity were derived in time. Finally, frequency domain signals are produced by applying a fast fourier transform (FFT) [10].

These time domain and frequency domain signals were used to estimate variables of the feature vector for each pattern: '-XYZ' is used to denote 3-axial signals in the X, Y and Z directions. The set of variables that were estimated from these signals are as shown in table 1:

Table 1: Summary of Features Extraction Methods used for Accelerometer and Gyroscope signals

Group	Methods
Time-Domain	Mean, SD, MAD,Max, Min, SMA, Energy, Entropy, IQR, Auto Regression Coeffient, Correleration, Linear Acceleration, Angular Velocity, kurtosis, skewness,
Frequency Domain	FFT, mean frequency, Index of Frequency component with largest magnitude

3.4 Performance Measures

1) Confusion Matrices:
The most common way to express classification accuracy is the formation of the confusion or contingency matrix. A confusion matrix is a simple methodology for displaying the degree of accuracy of classification results of a network.

2) Overall Accuracy:
The overall accuracy can computed as the ratio between the total number of correctly classified instances and the test set size. We have used average class accuracy which is more informative measure than overall accuracy on unbalanced dataset in order to make objective assessment of classifier quality.

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative} \quad (1)$$

3) Precision:
The *precision is the* ratio of correctly classified positive instances to the total number of instances classified as positive:

$$precision = \frac{TruePositive}{TruePositive + FalsePositive} \quad (2)$$

4) Recall:
The *recall* is the ratio of correctly classified positive instances to the total number of positive instances. This is also called *true positive rate*.

$$recall = \frac{TruePositive}{TruePositive + FalseNegative} \quad (3)$$

5) F-measure:
The *F-measure* combines precision and recall in a single value:

$$f-measure = 2 * \frac{precision \cdot recall}{precision + recall} \quad (4)$$

4. EXPERIMENT RESULTS

In this experiment, we have used WEKA tool to assess the performance of the classifiers. Activity recognition on these features was performed using the SVM and MLP classifiers. Classifiers were trained and tested with 10-fold cross-validation. As shown in table 2 and table 4, we computed the different measures for both SVM and MLP Classifiers. We tested the performance of Support Vector Machine and Multi-Layer Perceptron classifiers.

The confusion matrix shown in table 3 and table 5 of SVM and MLP classifier. It observed from the confusion matrix that for the activity 4 and 5 there is increased in misclassifications.

Table 2: Detailed Accuracy by SVM Classifier

TP-Rate	**FP-Rate**	**Precision**	**Recall**	**F-Measure**	**MCC**	**ROC Area**	**PRC Area**	**Class**
0.989	0.002	0.99	0.989	0.989	0.987	0.993	0.98	1
0.982	0.006	0.965	0.982	0.973	0.969	0.988	0.95	2
0.964	0.003	0.98	0.964	0.972	0.968	0.981	0.95	3
0.886	0.019	0.908	0.886	0.897	0.876	0.934	0.824	4
0.916	0.022	0.903	0.916	0.91	0.889	0.947	0.843	5
1	0.001	0.994	1	0.997	0.996	0.999	0.994	6
0.955	0.009	0.955	0.955	0.955	0.946	0.973	0.922	W. Avg

Table 3: Confusion Matrix for SVM Classifier

Output/ Desired	**Walking**	**Sitting**	**Standing**	**Stair-Up**	**Stair-Down**	**Laying**	**% Correctly Classified**
Walking	**1703**	13	6	0	0	0	0.989
Sitting	7	**1516**	21	0	0	0	0.982
Standing	11	39	**1356**	0	0	0	0.964
Stair-Up	0	3	0	**1575**	187	12	0.886
Stair-Down	0	0	0	160	**1746**	0	0.916
Laying	0	0	0	0	0	**1944**	1

As shown in table 4 % of Correctly classification accuracy is 95.5% in case SVM and in case MLP it is 98.11% . In case % of misclassified 4.46% and 1.89% with SVM and MLP respectively. While experimentation with MLP classifier, we got optimum performance of classifier with 6 processing elements. We checked the performance of classifiers with 6 processing elements and varied learning rate. For learning rate 0.05 the Root Mean Square Error (RMSE) is less. Finally with 6 processing elements, Learning rate 0.05, we checked the performance of classifier with various momentum. We got minimum 0.0737 RMSE with 0.1 momentum where overall classification accuracy is found 98.11% while for the similar simple activities the performance was found over 93% using Multi-Layer Perceptron[6].

Table 4: Detail Accuracy by MLP Classifier

TP-Rate	FP-Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.994	0.001	0.995	0.994	0.994	0.993	1	1	1
0.993	0.001	0.992	0.993	0.993	0.991	1	1	2
0.994	0.001	0.993	0.994	0.993	0.992	1	0.999	3
0.956	0.01	0.951	0.956	0.954	0.944	0.994	0.973	4
0.955	0.009	0.96	0.955	0.957	0.948	0.995	0.98	5
1	0	0.999	1	0.999	0.999	1	1	6
0.981	0.004	0.981	0.981	0.981	0.977	0.998	0.991	W. Avg

Table 5: Confusion Matrix for MLP Classifier

Output/ Desired	Walking	Sitting	Standing	Stair-Up	Stair-Down	Laying
Walking	**1711**	6	5	0	0	0
Sitting	4	**1533**	5	1	1	0
Standing	4	5	**1397**	0	0	0
Stair-Up	0	1	0	**1699**	75	2
Stair-Down	0	0	0	86	**1820**	0
Laying	0	0	0	0	0	**1944**

Table 6: Performance of Classifier

Performance Measures	LibSVM	MLP
% Correctly Classified Instances	95.54%	98.11%
% Incorrectly Classified Instances	4.46%	1.89%
Kappa statistic	0.9464	0.9772
Mean absolute error (MAE)	0.0149	0.0097
Root mean squared error (RMSE)	0.1219	0.0737
Relative absolute error (RAE)	5.36%	3.49%
Root relative squared error (RRSE)	32.75%	19.79%
Coverage of cases (0.95 level)	95.54%	99.04%
Mean rel. region size (0.95 level)	16.67%	17.23%
Total Number of Instances	10299	10299
Time Taken to build model	54.92	658.53

Table 7: % Classification accuracy and ROC Area for Classifiers

	% Classification Accuracy		ROC Area	
Class	**SVM**	**MLP**	**SVM**	**MLP**
1	98.9	99.4	0.993	1
2	98.2	99.3	0.988	1
3	96.4	99.4	0.981	1
4	88.6	95.6	0.934	0.994
5	91.6	95.5	0.947	0.995
6	100	100	0.999	1
W. Avg	**95.5**	**98.1**	**0.973**	**0.998**

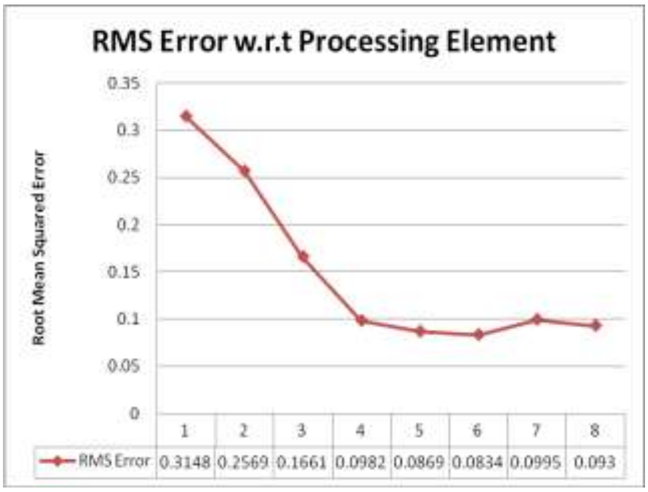

Fig 1: Variation of RMS Error with Processing Elements

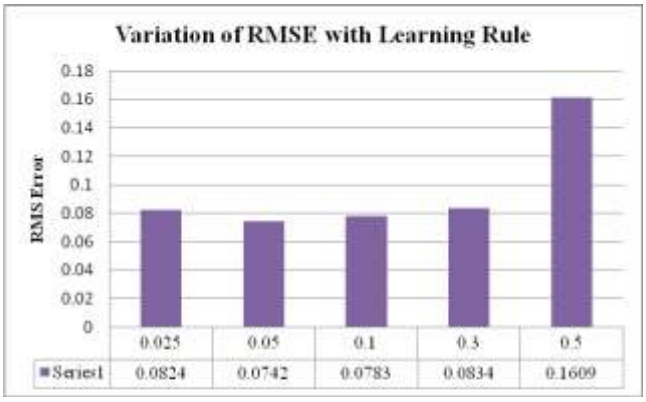

Fig 2: Variation of RMS Error with Learning Rule

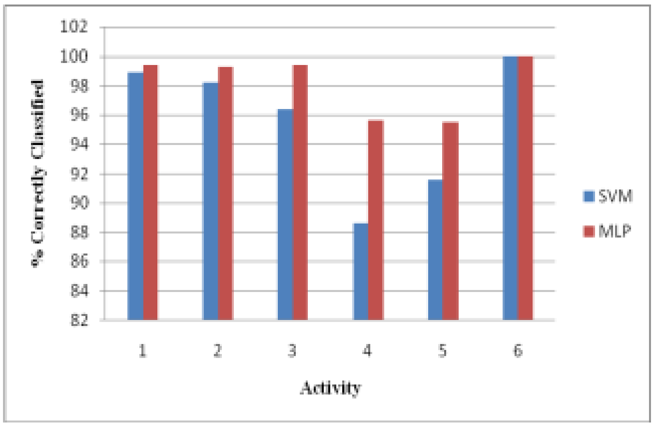

Fig 3: %of Correctly classified activities by using SVM and MLP

5. CONCLUSION

In this paper, we have investigated human activity recognition by using built-in accelerometer and gyroscope data. For this purpose, we have designed optimized MLP and SVM based classifiers. The recognition accuracy 98.11% is obtained by using Multi-Layer Perceptron while the recognition accuracy for Support Vector Machine 95.5% is obtained. Though the classification accuracy for the MLP is higher than SVM but time to build the MLP model is 10 times higher than the SVM. So, we conclude that overall it is tradeoff to select the classifier.

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