IJCSC 0973-7391 Vol 6 • Number 2 April - Sep 2015 pp. 102-107 **Impact Factor: 2.5** **Available at www.csjournals.com**

# Accelerated Plethysmography based Enhanced Pitta Classification using LIBSVM

Mandeep Singh[1] Mooninder Singh[2]Sachpreet Kaur[3]
[1,2,3]Department of Electrical & Instrumentation Engineering, Thapar University, Patiala, INDIA
[1] mandy_tiet@yahoo.com, [2]mooninder@gmail.com [3]sachpreetkaur7433@gmail.com

**Abstract:** The Accelerated Plethysmography is a non-invasive optical technique developed for its experimental usage in cardio vascular diseases. The existing traditional cardio vascular diagnostics tools might be replaced by this technique. In this study we have designed a high pitta classifier, using the features extracted from the accelerated plethysmography waveform. A classifier achieving an accuracy of 75% for Comparative Group 1, 75% for Comparative Group 2 and 68.75% for Comparative Group 3 is developed effectively.Comparative Group 1 comprises of data recorded after breakfast and before lunch, Comparative Group 2 comprises of data recorded after breakfast and after lunch, Comparative Group 3 comprises of data recorded before lunch and after lunch.

## 1. INTRODUCTION

According to Ayurveda, health is a perpetual and a participatory process that include all aspects of life i.e. physical, spiritual, emotional, mental, social, behavioral, familial and universal. Attaining harmony among all these aspects is the correct determination of vibrant health [1]. Regardless of its inclusive foundation, Ayurveda has not obtained scientific recognition in the twenty-first century. This might be due to absence of a quantitative beginning in its experimental research. Since the need for a well-organized and non-invasive substitute to the advanced medical system is increasing day by day, research in Ayurvedic science and traditional medical sciences has experienced a new drift [2]. In early research, researchers detected the ayurvedicdoshas by finding correlation between finger pulse profiles [3-4]. The features extracted from the second derivative of finger pulse profile were used by some researchers to detect pitta Dosha [5-7].

Our body is composed of three dynamic energies: Vata, Pitta, and Kapha that vary continually in response to our actions, emotions, the seasons, the foods we consume, and other sensory inputs that feed our body and mind. In our study we have given emphasis on the Pitta Dosha. Pitta Dosha is the energy of metabolism and digestion in the body which operates through carrier substances such as enzymes, bile, organic acids and hormones[1].

## 2.DATA COLLECTION

Finger pulse profile of 25 healthy subjects was recorded using MP150 BIOPAC system and Acknowledge software. This data was acquired from index, middle and ring fingers of both hands at three different instances of the day. The obtained waveform was differentiated twice to obtain accelerated plethysmography which interprets the original wave easily and leads to the recognition of inflection points more precisely. Five distinctive peaks a, b, c, d and e were extracted using a computer algorithm. The height from the baseline to the peak of each wave is considered as the value for each wave. The most appropriate waveform for heart rate calculations is ‘a’ wave because of its steepness and amplitude. The pattern of APG waveform is determined by proportion of ‘b’, ‘c’,‘d’ and ‘e’ waves to ‘a’ wave[8].The accelerated plethysmography waveform is shown below in Figure 1.

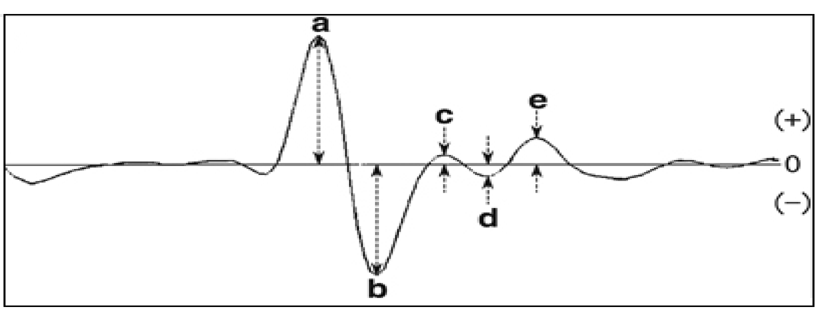


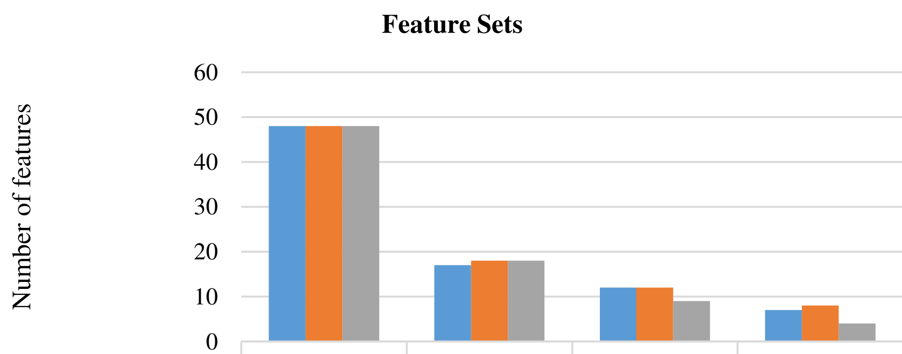

Figure 1:Accelerated Plethysmography waveform [9]

Average and standard deviation was found for each proportion.8 features were extracted from each finger, thus a total of 48 features were obtained for each subject.The entire process of feature extraction was done using a computer algorithm [10].

For our suitability we referred these 48 features as **"Gross Feature Set".**The data has been divided into three comparative groups namely:

- Comparative Group1 of After Breakfast (Class A) and Before Lunch (Class B)
- Comparative Group2 of After breakfast (Class A) and After lunch (Class C)
- Comparative Group3 of Before Lunch (Class B) and After Lunch (Class C)

Further the feature setsarereduced optimally. For this fisher linear discriminant analysis and Correlation has been employed [11].The graphical description of number of features selected in each Comparative Group is given below in Figure 2.




| | Gross Feature Set | Truncated Feature Set | Reduced Feature Set | Super Reduced Feature Set |
|---|---|---|---|---|
| Number of Features | 48 | 17 | 12 | 7 |
| Number of Features | 48 | 18 | 12 | 8 |
| Number of Features | 48 | 18 | 9 | 4 |

Figure 2: Graphical representation of Feature Sets

## 3. PROBLEM DEFINITION

The objective of this research is to design and validate a High Pitta classifier. For this purpose different feature sets shall be consideredas mentioned in Figure 2 and these feature sets shall be classified using a classification technique LIBSVM. We shall also find the suitability of "Truncated Feature Set", "Reduced Feature Set" or "Super Reduced Feature Set" for obtaining finest results.

## 4. CLASSIFICATION

The data has been classified into two separate classes namely: High Pitta and Low Pitta. For this classifier has been used. Each Comparative Group has been classified independently using LIBSVM.The three feature sets considered for classification are:

- Truncated Feature Set
- Reduced Feature Set
- Super Reduced Feature Set

### 4.1 LIBSVM

LIBSVM is an integrated software that is being used for support vector classification, distribution estimation and regression. It has various features like efficient multi-class classification,cross-validation for the selection of best model, availability of various inbuilt kernels like linear kernel, polynomial kernel, RBF kernel etc. [12].

The support-vector network is the learning machine for classifying the data in two groups. The conceptual idea implemented by the machine is that the input vectors are mapped non-linearly into a very large dimension feature space. The linear decision surface is being constructed in the feature space. High generalization ability of the support vector machine is ensured by this decision surface [13]. Figure 3 shows the basic classification criteria of support vector machine.

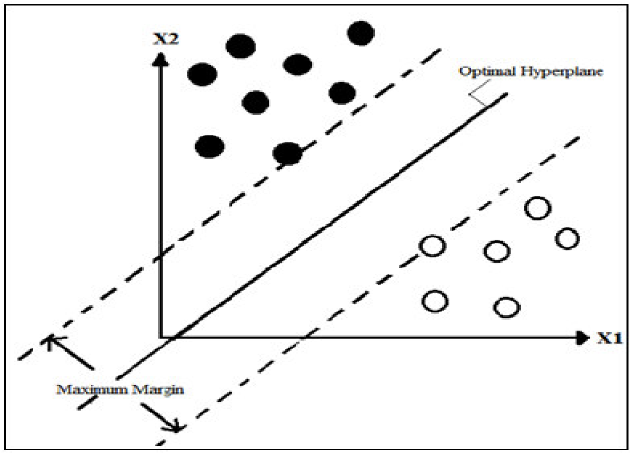



Figure 3: General Support Vector Classification

Out of a total of 50 samples,training wasperformed on 68% of data .Two different kernels i.e. Radial Basis Function (RBF) kernel and Polynomial Kernel have been used. Best values of cost factor and gamma is determined and the best model has been developed under observation. The best model obtained was tested on remaining 32% to test the performance of the network.

## 5. RESULTS AND DISCUSSION

LIBSVM is widely used for data classification. Firstly,radial basis function kernel (default order 3) has been used and two fold cross-validation isperformed. Secondly data is classified using low orderpolynomial kernel. The order of polynomial kernel is varied i.e. order 2 and order 3. Each feature set is classified using these kernels. The accuracies achieved while classifying different Comparative groups are listed below. Table 1 shows the accuracies achieved while classifying Group 1, Table 2 shows accuracies achieved while classifying Group 2 and Table 3 shows the accuracies achieved while classifying Group 3.The attained accuracies are represented graphically in Figure 4,Figure 5 and Figure 6.

Table 1:Accuracies achieved while classifying Comparative Group 1

| Feature Set | Accuracy achieved using different kernels (%) | | |
|---|---|---|---|
| | **Radial Basis Function** | **Polynomial (order 2)** | **Polynomial (order 3)** |
| Truncated Feature Set | 68.75 | 68.75 | 75 |
| Reduced Feature Set | 75 | 62.5 | 68.75 |
| Super Reduced Feature Set | 62.5 | 68.75 | 62.5 |

Table 2: Accuracies achieved while classifying Comparative Group 2

| Feature Set | Accuracy achieved using different kernels (%) | | |
|---|---|---|---|
| | **Radial Basis Function** | **Polynomial (order 2)** | **Polynomial (order 3)** |
| Truncated Feature Set | 68.75 | 62.5 | 68.75 |
| Reduced Feature Set | 75 | 68.75 | 62.5 |
| Super Reduced Feature Set | 68.75 | 62.5 | 68.75 |

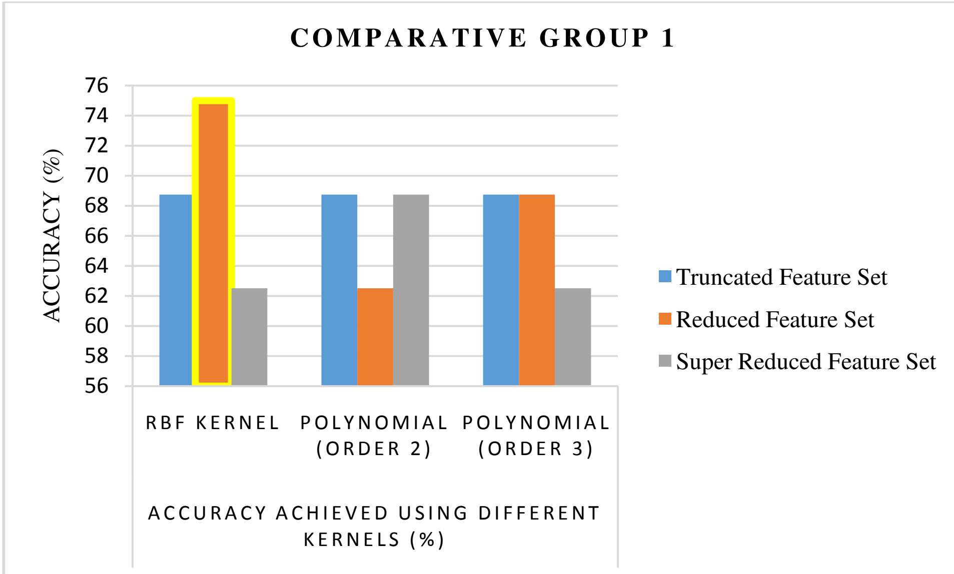



Figure 4:Graphical representation of accuracies achieved while classifying Comparative Group 1

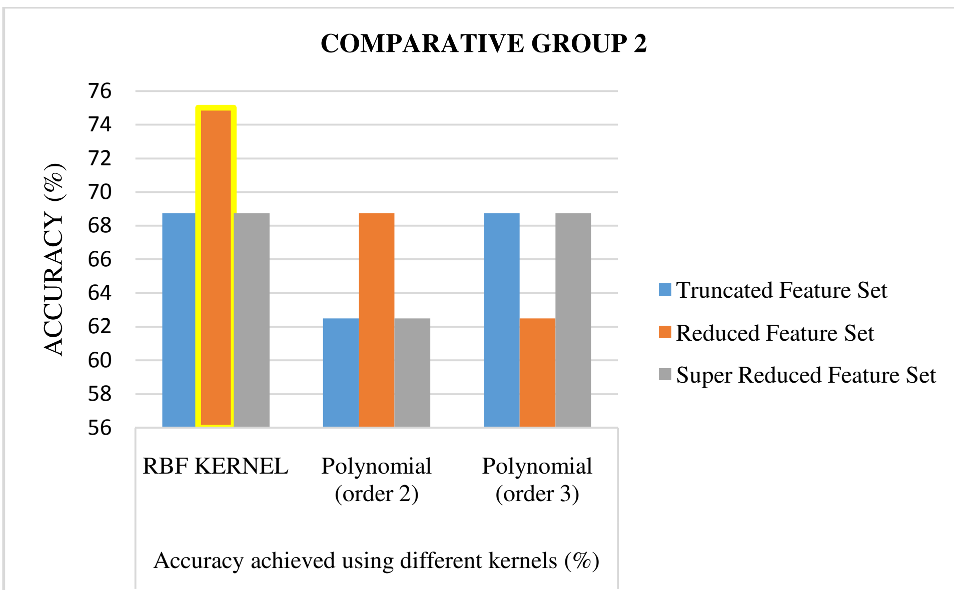



Figure 5: Graphical representation of accuracies achieved while classifying Comparative Group 2

Table 3: Accuracies achieved while classifying Comparative Group 3

| **Feature Set** | **Accuracy achieved using different kernels (%)** | | |
|---|---|---|---|
| | **Radial Basis Function** | **Polynomial (order 2)** | **Polynomial (order 3)** |
| Truncated Feature Set | 62.5 | 62.5 | 62.5 |
| Reduced Feature Set | 68.75 | 68.75 | 68.75 |
| Super Reduced Feature Set | 62.5 | 62.5 | 62.5 |

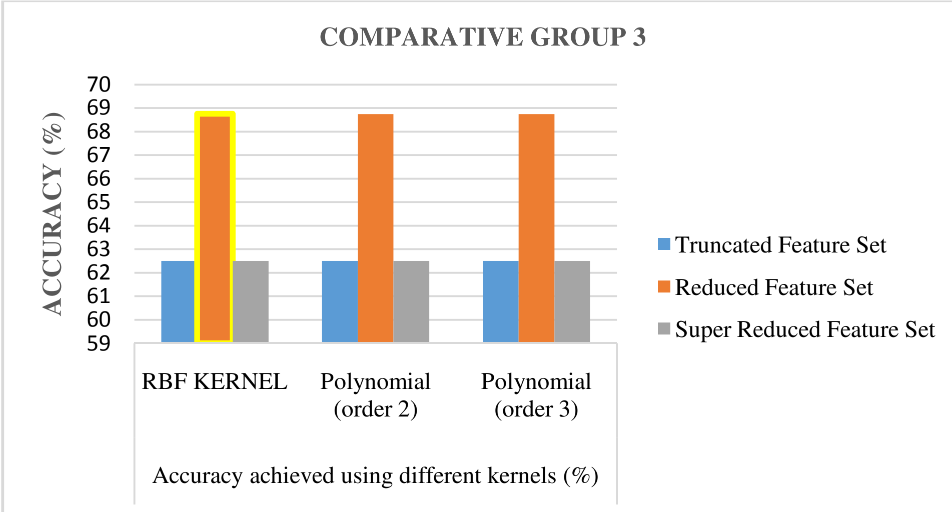



Figure 6: Graphical representation of accuracies achieved while classifying Comparative Group 3

The highlighted bar describes the best accuracy achieved. It has been observed that the best accuracies is achieved when Radial Basis function kernel is used.An accuracy of 75% is attained while classifying Comparative Group 1, an accuracy of 75% is attained while classifying Comparative Group 2 and an accuracy of 68.75% is attained while classifying Comparative Group 3.Also **"Reduced Feature Set"**is giving us the consistent results for the enhanced Pitta detection. The confusion matrix for the best accuracies obtained is formed and further sensitivity and specificity are calculated.

**CONFUSION MATRIX**

The Confusion Matrix showing best results attained while classifying Reduced Feature Set of the three Comparative Groups is formulated.The information about the actual and predicted class is contained in the confusion matrix. TP (true positive) here depicts the number of samples correctly classified as high Pitta. TN (true negative) signifies the number of samples correctly classified as low Pitta. FN (false negative) and FP (false positive) signifies the number of samples incorrectly classified as low Pitta and high Pitta respectively.

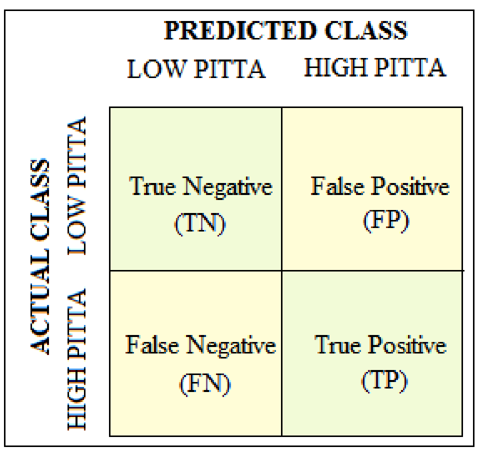



Figure 7: Formulation of Confusion Matrix

The confusion matrix of the best trained network for the three Comparative Groups is illustrated in Figure 8. The values of accuracy, sensitivity and specificity achieved are listed below in Table 4.

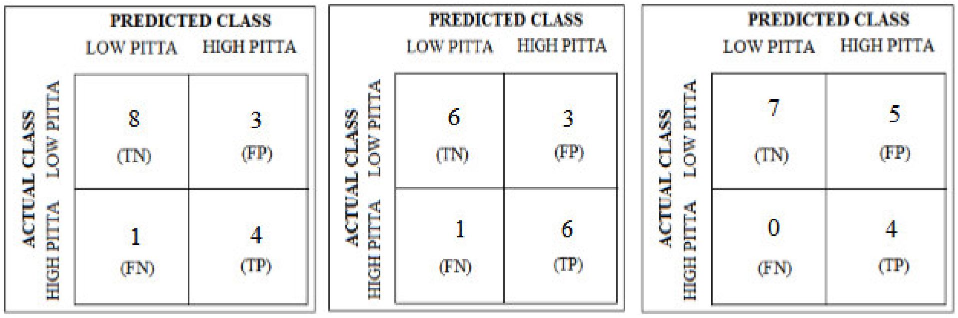



Figure 8: (a) Confusion Matrix (Comparative Group 1) (b) Confusion Matrix (Comparative Group 2) (c) Confusion Matrix (Comparative Group 3)

Table 4: Obtained values of Parameters

| Parameters | Comparative Group 1 | Comparative Group 2 | Comparative Group 3 |
|---|---|---|---|
| Accuracy (%) | 75 | 75 | 68.75 |
| Sensitivity (%) | 80 | 85.71 | 80 |
| Specificity (%) | 72.72 | 66.66 | 60 |

## 6. CONCLUSION

It has been observed that Comparative Group 1 and Comparative Group 2 are classified effectively with an accuracy of 75% whereas Comparative Group 3 achieved an accuracy of 68.75%. Also reduced feature set is giving us the consistent results for the enhanced Pitta detection. These results though encouraging need to be improved further by exploring some alternative classification techniques like Artificial Neural Networks (ANN).

## REFERENCES

[1]The Three Doshas: The keys to your individual nature, *available at*http://www.eattasteheal.com/ ayurveda101/eth_bodytypes.htm

[2] A. E.Kalange, B. P. Mahale, S. T. Aghav, and S. A. Gangal. "Nadiparikshanyantra and analysis of radial pulse." Physics and Technology of Sensors (ISPTS), 1st International Symposium on, pp. 165-168. IEEE, 2012.

[3]Mandeep Singh and SpitiGupta, “Correlation studies of finger pulse profiles for detecting ayurvedicdoshas”, International Journal of Computer Science and Communication, vol. 2, No. 2, pp. 373-375, July-December 2011.

[4]Mandeep Singh and SpitiGupta, “PPG profile investigations for different fingers in a subject”, International Journal of Computer Science and Communication, vol. 2, No. 2, pp. 377-379, July-December 2011.

[5]Mandeep Singh and TanushreeSharma, “Feature extraction from finger pulse plethysmography for determining pitta level in human body”, International Journal of Computer Science and Communication, vol. 3, No. 1, pp. 81-82, January-June 2012.

[6]Mandeep Singh and TanushreeSharma, “Finger pulse plethysmography feature selection for pitta detection in human body , “International Journal of Computer Science and Communication, vol. 3, No. 1, pp. 83-84, January-June 2012.

[7]Mandeep Singh and TanushreeSharma, “Proposal for exploring possibilities for finger photoplethysmography as a substitute for pulse diagnosis in Ayurveda”, International Journal of Computer Science and Communication, vol. 3, No. 1, pp. 77-79, January-June 2012.

[8]Mohamed Elgendi, M.Jonkman, and F.Boer. "Applying the APG to measure heart rate variability" Computer and Automation Engineering (ICCAE), The 2nd International Conference on, vol. 3, pp. 514-517, IEEE, 2010.

[9]Accelerated Plethysmography waveform, *available at*http://www.nature.com/hr/journal/v35/n2/fig_tab/hr2011152f2.html

[10]Mandeep Singh and SakshiBansal, “Automatic feature extraction in acceleration plethysmography”,International Journal of Computer Science and Communication, vol. 5, No. 2, pp. 1-9, Sep 2014.

[11]Mandeep Singh, Mooninder Singh, SachpreetKaur,”Optimal feature selection for APG based enhanced pitta classification”,International Journal of Computer Science and Communication, vol. 6, No. 2, Sept 2015.

12)Chang, Chih-Chung; Lin, Chih-Jen (2011). "LIBSVM: A library for support vector machines", *available at* http://www.csie.ntu.edu.tw/~cjlin/libsvm/

13)Cortes, Corinna, and Vladimir Vapnik, "Support-vector networks." Machine learning 20, no. 3, 273-297, 1995.