ABSTRACT

Title of Document : Classification of Psycho-physiological signals to different affective states using Machine Learning

Pritesh Sankhe, B.Tech. EE, 2009-13

Research Advisor : Prof. Uttama Lahiri

Recognizing affective feedback from the user is important for intelligent human-computer interaction (HCI). Software agents with ability to sense and respond appropriately to user affective feedback are of growing importance. This projects aims at developing a machine learning model that recognizes human affective states based on different physiological signals. The objective is to evaluate affective states recognition in typically developing (TD) individuals as well as those with Autism Spectral disorder (ASD). The project presents and compares accuracy of the learning model based on Support Vector Machines with different sets of physiological data which primarily consists of Electrocardiogram (ECG), Photoplethysmography (PPG), Skin Temperature (SKT), Galvanic Skin Response (GSR) and Electrodermal activity. The final model achieved classification accuracy of over 80% for the TD participants on a single class of affective state namely Anxiety. The future goal is to achieve similar accuracy on other classes of affective states and analyze the differences of physiological patterns for the ASD individuals.

Classification of Psycho-physiological signals to different affective states using Machine Learning

By

Pritesh Sankhe

Thesis submitted to the Faculty of Engineering,
Indian Institute of Technology Gandhinagar, in partial fulfillment
Of the requirements for the degree of
Bachelor of Technology in
Electrical Engineering with
Minors
[2012]

Advisory Committee:
Professor Uttama Lahiri, Chair
Professor K V V Murthy
Professor Rajendran

Acknowledgements

I would like to thank Dr. Uttama Lahiri for her valuable mentorship. I am really grateful that she helped me to explore my interests in Machine Learning and its application in Human-Computer Interaction. Her guidance has been very much appreciable and the physiological data-sets provided by her has been the basis for my research.

I would also like to thank Selvia Kuriakose for her help in different parts of the project.

Table of Contents

Earlier Developments

Introduction and Literature Review:

Emotions play a vital role in rational thinking and intelligent behavior. They play an important role in understanding of messages in different forms like the visual or speech. Sometimes the importance of the message is conveyed on not what the message contains but more importantly the way it is conveyed. Negative emotions may hamper the thinking process which forms an essential part for our very survival. [2]

Could these emotions be realized or recognized through physiological changes? There is a vast amount of literature [2] that presents the findings about how physiological signals can be correlated to the emotional changes. Many studies on emotion have reported that there is a correlation between basic emotions like anger, happiness, sadness, etc. and physiological responses. To give an example; A stranger shaking your hand can feels its clamminess which relates to the skin conductivity.

Many studies have further extended these analyses to develop a learning model to classify the physiological data into different emotional states. Some important observations are:

1. The accuracy of the model strongly depends on the data sets which were obtained in laboratory conditions. It becomes difficult to label emotion classes for physiological signals without uncertainty. [1]
2. Accuracy of emotion classification was seen to be largest for the Support Vector Machines (99.04%) which was found to be highest amongst different algorithms that consisted of Fischer linear discriminant analysis (FLD), Classification and Regression Tree (CART), Self-organizing Map Algorithm (SOM), Naïve Bayes and Support Vector Machine (SVM). [1]
3. The same literature suggests that Skin Temperature variance reflects the nervous system activity and is effective indicator of emotional status. [1]
4. To improve the accuracy of the model, some article suggested technique of Analysis of Variance for feature extraction. The popular methods include Principal Component Analysis as well as Fischer projection. [4]
5. The major problem of training a learning machine to perform supervised classification is to find a function – kernel function that can not only capture the essential properties of the data distribution but also prevent the over-fitting problem. [3]

Steps involved for Physiological Feature Processing

The data set obtained from performing the experiment on different participant forms the basis for training the Support Vector Machine. The entire process is based on three major steps

1. Data Cleaning
2. Feature Reduction
3. Classification using Machine Learning

The first two steps are implemented completely and as a step ahead the learning model would be analyzed to improve its accuracy as well as its performance measure.

Data Cleaning

The raw data is essentially the values of 51 different attributes relating to the various physiological measures like ECG, PPG, Skin Temperature, Galvanic Skin Resistance and EMG. The data is available for 26 different participants out of which 13 participants are typically developing while the other 13 are those suffering from Autism Spectrum Disorder (ASD). Other than the physiological data for all the participants, the Therapist Self report on different emotional states mainly anxiety, like/dislike and engagement for every participant is available which would be necessary to train the learning machine.

Each of the participants is tested on for 24 different cases or scenarios over a period of two days. Also, each participant has a different baseline or different physiological parameters when he or she is not exposed to any test condition. The baseline for all the participants for each of the two days is also available.

Different parameters have different units and these needs to be normalized before feeding it to the Machine. Also every participant has a different baseline and moreover each participant himself has different baselines for different days overcoming the inter-day variability. So, relative deviation from normal behavior or baseline for each story on each day needs to be considered. Else the learning model may not be able to interpret the data set. So the data cleaning process involves the following steps:

1. Obtaining a modified dataset with values for all the physiological signal attributes relative to the baseline for every participant. This is essentially the difference of all the parameters during test condition relative to the ones obtained during baseline condition.
2. This dataset is then normalized to obtain all the values between -1 and 1.

The steps above are implemented in Matlab and the required clean data is obtained. [Please refere Appendix I for the Matlab code]

Feature Extraction:

Overall, for each participant, the dataset is in the form of 51 by 24 matrix, 51 different feature values for 24 different cases. All features may not be of primary importance in classification of different emotional states and this could be different for different parameters depending on how each participant would react to any given situation. In a nutshell, the emotions and the physiological behavior are totally subjective.

For e.g., when a participant A is highly anxious his heart rate may rise but he may not show any muscular reaction like frowning or it might not be reflected on his facial expressions while for participant B both of the aspects may be seen in times of anxiousness. Similarly, different people engage in a given activity differently, psychologically as well as physiologically.

So, in order to train the learning model, we first try to look at only the statistically important parameters. To do so, the P-value test is implemented using Matlab and R.

P-value is defined as the probability of obtaining a test statistic at least as extreme as the one that was actually observed assuming that the null hypothesis is true. [6] The calculation basically involves looking at the distribution of the feature data in terms of mean and standard deviation.

These P-values were calculated for each of the features and then the features were marked to be statistically significant if the p-value was less than 0.05. All the data corresponding to these highlighted features are then selected to form the training data set to be fed to the machine used for classification.

When this method was carried out to find the statistically significant features for the first participant, 19 features were highlighted and were then used as a training data set for the learning algorithm.

Classification using Machine Learning

The data set that was obtained from the previous step is used to train a learning model. This is called as supervised learning in Machine Learning. More specifically the training set consists of the input as well as the desired output. In this case, the input data consists of all the features obtained from the above step whereas the output is the scale from 1 to 2 based on the therapist's report. E.g.1 for Low Anxiety and 2 for High Anxiety.

As a powerful supervised learning model, we use support vector machines that analyze data and recognize patterns and are mainly used for regression and classification. [5] A support vector machine (SVM) essentially constructs a hyperplane in a high dimensional space that can be used for classification, regression.

Let's account for the first participant. As said earlier, 19 different features were obtained after performing the P-value test. So, a data point in this case would be viewed as a 19-dimensional vector, a list of 19 numbers. This comprises the input data in the training data set. The output is the class (1 or 2) based on the therapist report. Each training data point is associated with this class and we want to find if all these data points can be classified. This could be achieved by using an 18 dimensional hyperplane. The job of the Support Vector Machine is to identify one such hyperplane that best classifies the training data. The term "best" means that the hyperplane that represents the largest separation or margin between the two classes is more useful.

Once the Learning machine identifies this hyperplane, it could be used to test by providing a test dataset and find out the output class to see if it matches with the therapist report (class: 1 or 2).

The support vector machine was trained with the data set relating to the first participant. The training data set comprised of 23x19 matrix meaning 23 different cases with 19 statistically significant features. Here we use the 24^{th} data point as a test data to check the accuracy of the learning model. Matlab provides powerful functions for support vector machines which were used to train and classify the dataset. Different kernel functions like the radial basis, polynomial, linear and quadratic were used to observe which classification gave the desired output.

Observations and Result:

The physiological dataset was segregated based on Anxiety (Low Anxiety - LA and High Anxiety - HA) for the first participant into training data and the test data. The selected test data for the first participant was correctly classified by the support vector machine when used with the linear function. The P-value test could prove to be a good feature reduction method. [Refer Appendix II for the code]

Development ahead:

1. Apply SVM for each of the 26 participants for Low (LA) and High Anxiety (HA).
2. Repeat for Low Engagement (LE) and High Engagement (HE) as well as Low Likeness (LL) and High Likeness (HL)
3. Apply different Kernel functions for the Support Vector Machine as well as feature reduction techniques to improve the accuracy of the learning model.

More on P-value Test:

As mentioned earlier, in statistical hypothesis testing, the ***p*-value** is the probability of obtaining a test statistic at least as extreme as the one that was actually observed, assuming that the null hypothesis is true. [9]One often "rejects the null hypothesis" when the *p*-value is less than the significance level α (Greek alpha), which is often 0.05 or 0.01. Null hypothesis can be viewed as a status quo. [5] Essentially, null hypothesis implies that you assume that whatever you are researching has no effect. In this project, that would mean that a particular physiological feature or attribute has no influence in determination of the affective states and that it can be discarded from including in the training set for the learning model. Then we check if the null hypothesis was indeed true, what is the probability that we would have got the desired results – accurate classification of the signals to the affective state class. And if this probability is really small then the null hypothesis is probably not true. We could reject the null hypothesis and assume that the other hypothesis that the physiological signal influences the classification is true. The probability of the null hypothesis being true is related to the P-value. Low P-value for a physiological signal or attribute would mean that it is highly statistically significant and should be used in training and testing the model.

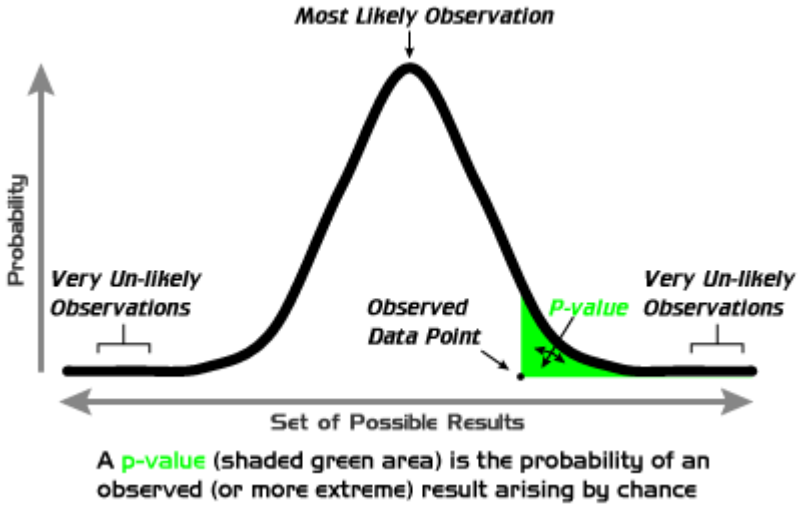

Figure 1 : P-value test http://en.wikipedia.org/wiki/P-value

The P-value test is a good feature extraction method and is used in different approaches throughout the project.

Results:

The data-set was cleaned appropriately as described earlier in the Data Cleaning section. The model was developed, tested and analyzed for a single class of affective state of Anxiety on a 1-2 level where 1 corresponds to Low Anxiety and 2 corresponds to High Anxiety.

A P-value test was carried out for every participant to extract statistically significant physiological features. Every participant might behave differently to a given emotional stimulus and correspondingly the physiological signals may vary. For the given data-set, conducting P-value test on individual participant does not give a good number of statistically significant physiological attributes. This was true for data-sets corresponding to both the TD as well as the ASD participants. Only two sets of participants gave good number of attributes to train the machine. The SVM based learning model with linear kernel function provided an accuracy of about 75% for these participants.

In many research studies, the attributes relating to the physiological signals ECG, PPG, GSR and SKT have been shown to have a profound influence for affective states like anxiety, fear, surprise because these signals reflect the activity of the autonomic nervous system which plays a major role in maintaining the internal equilibrium of the body. For each participant both belonging to TD and ASD, the attributes relating to these four physiological signals, 20 in all were used to train the SVM. The SVM was trained with four different kernel functions: Linear, Quadratic, Polynomial and Radial Basis function. The results are as below:

- For typically developing participants; 13 such participants:

Participant No	Linear	Quadratic	Polynomial	Radial basis Function
1	58.333	50	62.5	70.833
2	79.167	70.833	79.167	87.5
3	50	83.333	70.833	58.333
4	41.667	50	33.333	62.5
5	70.833	66.667	62.5	62.5
6	62.5	58.333	58.333	58.333
7	54.167	75	58.333	75
8	54.167	70.833	66.667	79.167
9	37.5	58.333	45.833	54.167
10	87.5	75	83.333	83.333
11	95.833	95.833	95.833	95.833
12	87.5	87.5	83.333	87.5
13	75	87.5	91.667	87.5

Table 1 : Accuracy of SVM using ECG, PPG, GSR and SKT for TD participants

- For ASD participants; 13 such participants:

Participant No	Linear	Quadratic	Polynomial	Radial basis Function
1	58.333	62.5	58.333	62.5
2	45.833	58.333	58.333	58.333
3	62.5	62.5	66.667	58.333
4	37.5	25	33.333	62.5
5	58.333	45.833	54.167	54.167
6	41.667	25	33.333	41.667
7	37.5	54.167	50	50
8	58.333	37.5	29.167	58.333
9	66.667	50	58.333	58.333
10	45.833	54.167	41.667	58.333
11	33.333	54.167	41.667	50
12	58.333	41.667	45.833	62.5
13	62.5	45.833	41.667	0

Table 2: Accuracy of SVM using ECG, PPG, GSR and SKT for ASD participants

For the typically developing participants, SVM provided an accuracy of over 80% for six different participants with the radial basis kernel function. The maximum accuracy achieved using this model is over 95% (participant 11). This shows that physiological parameters relating to the ECG, PPG, GSR and SKT have a significant influence in affective states classification.

In the case of ASD participants, the accuracy is quite low mostly ranging from 50% to 60% for the radial basis function. Atypical behaviors such as averting the gaze from faces, looking out of the corner of the eyes are well known symptoms of this developmental disorder. [7] Since the experimental setup is a virtual setting, the ASD participants might have difficulties engaging in non-social stimuli; a possible explanation for the irregularities of the physiological signal data.

This method primarily studies the significance of the four major physiological signals and how they are influenced by the affective states.

Next approach was to develop a more generic model by extracting significant features taking all the participants' physiological data into consideration for the P-value test. The physiological data relating to the motion artefacts and the heart sound were excluded since these signals tend to be noisy and inaccurate. The P-value test was carried for both the TD and the ASD participants separately. For each participant, the extracted features were used to train the SVM unlike the earlier case where features extracted for individual participants could be different. The following observations were made:

- For the ASD participants, the features extracted are less. Only 3 features out of 45 were found to be statistically significant based on the P-value test.
- For the TD participants, 10 different features were found to be statistically significant. These extracted features were related to ECG, PPG, SKT as well as EMG.

  Using these 10 features, the SVM was trained and the accuracy of the model was found to be as follows:

%efficiency		P-value approach		
Participant No	Linear	Quadratic	Polynomial	Radial basis Function
1	66.667	54.167	62.5	70.833
2	70.833	70.833	79.167	87.5
3	45.833	37.5	41.667	45.833
4	50	62.5	50	62.5
5	75	75	62.5	54.167
6	50	70.833	54.167	54.167
7	70.833	66.667	50	75
8	66.667	66.667	79.167	79.167
9	58.333	66.667	70.833	37.5
10	75	83.333	79.167	83.333
11	83.333	87.5	87.5	95.833
12	70.833	62.5	66.667	87.5
13	75	79.167	62.5	87.5

Table 3: Accuracy of SVM using P-value test for TD participants

The accuracy of the model is slightly better than the earlier one which considered the ECG, PPG, GSR and SKT physiological signals. The Radial basis kernel function is found to yield better results as compared to the linear, quadratic and the polynomial functions. The data set for the TD participants is also found to be consistent.

Children with ASD often react outwardly in ways unlike developmentally typical children [6]. Using the EMG signals for the ASD participants to train the SVM helps to evaluate how effective the muscle movements are in determining affective states. The accuracy of the model for the EMG signals is shown below:

%efficiency		EMG		
Participant No	Linear	Quadratic	Polynomial	Radial basis Function
1	79.167	83.333	83.333	66.667
2	45.833	50	50	58.333
3	58.333	37.5	50	50
4	58.333	58.333	50	62.5
5	75	62.5	58.33	50
6	41.667	37.5	37.5	50
7	58.333	33.333	54.167	50
8	66.667	50	41.667	58.333
9	37.5	41.667	50	58.333
10	33.333	58.333	58.333	58.333
11	54.167	62.5	58.33	54.167
12	62.5	62.5	75	62.5
13	41.667	54.167	37.5	0

Table 4: Accuracy of SVM using P-value test for ASD participants

With the focus on improving the accuracy of the model for recognizing affective states for the ASD participants, different combinations of physiological signals were used to train the SVM. This study could also show which of the physiological signals have more impact for a given emotional stimulus. In most research literature, SKT has been found to be an effective indicator of the emotional status. The following results were obtained with SKT signal attributes as a training set for the ASD participants.

%efficiency		SKT		
Participant No	Linear	Quadratic	Polynomial	Radial Basis Function
1	50	66.667	58.333	62.5
2	25	58.333	54.167	62.5
3	54.167	37.5	41.667	50
4	50	79.167	62.5	66.667
5	50	79.167	62.5	66.667
6	12.5	50	45.833	33.333
7	41.667	37.5	37.5	50
8	58.333	20.833	41.667	41.667
9	75	75	70.833	62.5
10	20.833	54.167	41.667	50
11	50	50	50	41.667
12	58.333	58.333	58.333	62.5
13	25	29.167	41.667	25

Table 5: Accuracy of SVM using SKT for TD participants

In the case of a couple of participants the model classifies as accurately as 75%. There is some improvement in the accuracy of the model as a whole considering only the SKT data which is in agreement to the observations found in different research literature.

The rest of the study tries to evaluate the accuracy of the classification by the model considering different combinations of the physiological signals. Two major combinations of physiological signals namely ECG-PPG and GSR-SKT have been considered and the accuracy for the respective models can be seen as below:

ECG-PPG:

- For ASD participants:

%efficiency	ECG - PPG			
Participant No	Linear	Quadratic	Polynomial	Radial Basis Function
1	66.667	66.667	54.167	58.333
2	50	45.833	50	50
3	50	62.5	70.833	50
4	50	29.167	37.5	54.167
5	66.667	54.167	58.333	45.833
6	41.667	37.5	45.833	33.333
7	33.333	50	33.333	45.833
8	37.5	33.333	33.333	45.833
9	50	50	41.667	54.167
10	41.667	54.167	54.167	50
11	16.667	37.5	33.333	33.333
12	58.333	41.667	45.833	62.5
13	33.333	45.833	50	16.667

Table 6: Accuracy of SVM using ECG, PPG for ASD participants

- For TD participants:

%efficiency	ECG-PPG			
Participant No	linear	quadratic	polynomial	Radial Basis Function
1	58.333	58.333	66.667	70.833
2	79.167	79.167	87.5	87.5
3	54.167	54.167	45.833	41.667
4	54.167	66.667	62.5	62.5
5	75	70.833	62.5	54.167
6	58.333	50	58.333	54.167
7	54.167	50	41.667	75
8	62.5	58.333	70.833	79.167
9	33.333	54.167	58.333	50
10	91.667	79.167	87.5	83.333
11	91.667	91.667	91.667	95.833
12	66.667	70.833	70.833	87.5
13	83.333	83.333	83.333	87.5

Table 7: Accuracy of SVM using ECG, PPG for TD participants

GSR-SKT:

- For ASD participants:

%efficiency	GSR+SKT			
Participant No	Linear	Quadratic	Polynomial	Radial Basis Function
1	58.333	62.5	62.5	62.5
2	41.667	41.667	37.5	45.833
3	54.167	58.333	54.167	58.333
4	58.333	33.333	41.667	45.833
5	54.167	75	62.5	45.833
6	8.3333	54.167	41.667	33.333
7	58.333	41.667	45.833	50
8	66.667	58.333	58.333	50
9	70.833	54.167	58.333	50
10	54.167	45.833	41.667	50
11	50	54.167	50	50
12	41.667	45.833	45.833	54.167
13	75	41.667	70.833	12.5

Table 8: Accuracy of SVM using GSR and SKT for ASD participants

- For TD participants:

%efficiency	GSR+SKT			
Participant No	Linear	Quadratic	Polynomial	Radial Basis Function
21	58.333	50	62.5	70.833
22	83.333	83.333	79.167	87.5
23	70.833	79.167	66.667	62.5
24	54.167	37.5	33.333	41.667
25	70.833	45.833	45.833	54.167
26	50	50	45.833	54.167
27	70.833	75	66.667	75
28	70.833	70.833	70.833	79.167
29	29.167	37.5	45.833	37.5
30	75	62.5	70.833	83.333
31	91.667	87.5	91.667	95.833
32	83.333	83.333	83.333	87.5
33	83.333	79.167	87.5	87.5

Table 9: Accuracy of SVM using GSR and SKT for TD participants

Conclusion and Future Work:

The study was to evaluate affective states recognition for typically developing individuals as well as those with Autism Spectral Disorder and develop an efficient learning model based on SVM. The results showed that the P-value test on the combined data-sets for the typically developing participants is efficient in extracting features which helps to design the SVM for two class classification achieving over 80% accuracy. Also, the algorithm showed lower accuracy of affective states classification for the ASD participants. This study is based on a unique experimental setup that relies on virtual reality for providing the emotional stimulus.

Though a desirable amount of accuracy is achieved using the SVM model for the typically developing participants, it would be more efficient and purposeful to develop a model with similar accuracy for the recognition of affective states for the ASD participants. Also, the aim of this research would be to extend the model to different affective states like Engagement and Likeness.

Appendix I: Matlab code

```
[num,txt,raw] = xlsread('raw.xls','B3:AZ12');           %reads the
data for the participant on the first day with a different baseline
num = num(setdiff(1:size(num,1),[2]),:);                %this
removes the second column which is the audio only -- this is not
required
outMat = bsxfun(@minus,num(:,:),num(1,:));              %bsxfun
applies element by element binary operation to two arrays --
subtracts each elements by baseline
outMat = outMat(setdiff(1:size(outMat,1),[1]),:);       %remove the
baseline row from the matrix since it is not useful now
[num1,txt1,raw1] = xlsread('raw.xls','B13:AZ30');       %repeat the
above process for the second day with a different baseline
num1 = num1(setdiff(1:size(num1,1),[2]),:);
outMat1 = bsxfun(@minus,num1(:,:),num1(1,:));
outMat1 = outMat1(setdiff(1:size(outMat1,1),[1]),:);
A = [outMat;outMat1];                                   % A is the
matrix obtained by joining the above two matrix - relative
amplitudes
%A = bsxfun(@rdivide, outMat , max(abs(outMat(:,:))));
data = bsxfun(@rdivide, A , max(abs(A(:,:))));          %element by
element binary operation of dividing with the maximum value
%data = [A;A1] ;
c1 = data(24,:);                                        %this is the
test data i.e the 24th sample
A1 = data(setdiff(1:size(data,1),[24]),:);              %this
removes the 24th sample from the matrix -- will serve as the
training data
theclass1 = xlsread('raw.xls', 'BD5:BD12');             %output
values
theclass2 = xlsread('raw.xls', 'BD15:BD30');
theclass = [theclass1;theclass2];
theclass3 = theclass(1:23,1);
c4 = svmtrain(A1, theclass3, 'Kernel_Function','rbf');
%group = svmclassify(c4,c1);


j = 1; k = 1;
[nrows,ncol] = size(theclass);
[row_size,col_size] = size(data);
class1 = zeros(1,col_size);
class2 = zeros(1,col_size);

%classification
for i = 1:nrows
    if theclass(i) == 1
        class1obj = data(i,:);
        class1  = [class1;class1obj];
        j=j+1;
    else
        class2obj = data(i,:);
        class2 = [class2;class2obj];
        k=k+1;
```

```
    end
end

class1 = class1(setdiff(1:size(class1,1),[1]),:);
class2 = class2(setdiff(1:size(class2,1),[1]),:);
                                                    %Tvalue calc
for i = 1 : col_size
    [T,df] = Ttest_Modular(class1(:,i),class2(:,i));
    T_Value(1,i) = T;
    df_Value(1,i) = df;
end

csvwrite('TValueParticipant1.csv',T_Value);
csvwrite('DFValuePartic ipant1.csv',df_Value);

%[h,p,c1] = ttest2(class1(:,5),class2(:,5));

[num2,txt2,raw2] = xlsread('indicesParticipant1.xlsx','B2:B52');
[nrows1,ncol1] = size(num2);
dataset = zeros(24,1);
for i = 1:nrows1
    if num2(i) == 1
        datacol = A(:,i);
        dataset = horzcat(dataset,datacol);
    end
end
dataset(:,1) = [];
trainingdata = dataset(1:23,:);
testdata = dataset(24,:);
trainoutput = theclass(1:23,1);

c2 = svmtrain(trainingdata, trainoutput,
'Kernel_Function','quadratic');
group = svmclassify(c2,testdata);
```

Appendix II: Code in R

```
data <- read.table(file =
"D:/academics/BTechProject/Project
files/TValueParticipant1.csv",sep = ",")
pvalue = 0
index = 0
j = 1
for (i in 1:51){
     pvalue[i] = (2*pt(-abs(as.numeric(data[i])),df =
22))
     print(pvalue[i])
     if(pvalue[i] < 0.05)
     {
          index[j] = 1
     }
     else
     {
          index [j] = 0
     }
     j = j+1
}
write.table(pvalue,"D:/academics/BTechProject/Project
files/pvaluesPaticipant1.csv",sep = ",")
write.table(index,"D:/academics/BTechProject/Project
files/indicesParticipant1.csv",sep = ",")
```

References:

1. Identification of the Optimal Emotion Recognition Algorithm using Physiological Signals. E. Jang, B. Park, S. Kim, Y.Eum, J.Sohn
2. Toward Machine Emotional Intelligence: Analysis of Affective Physiological State, Richard W. Picard, Senior Member, IEEE, Elias Vyzas, and Jennifer Healey
3. C. J. C. Burges, "A Tutorial on support vector machines for pattern recognition," Data Mining and Knowledge Discovery, vol. 2, pp. 121-167, 1998
4. From Physiological Signals to Emotions: Implementing and comparing selected methods for feature extraction and classification; Johannes Wagner, Jonghwa Kim, Elisabeth Andre, Institute of Computer Science, University of Augsburg, Germany
5. Hypothesis Testing and P-values http://www.khanacademy.org/math/statistics/v/hypothesis-testing-and-p-values
6. Physiological Signals of Autistic Children Can be Useful; Karla Conn Welch http://lifesciences.ieee.org/articles/feature-articles/98-physiological-signals-of-autistic-children-can-be-useful
7. Machine Vision-Based analysis of gaze and visual context: an application to visual behavior of children with autism spectrum disorders; Basilo Noris http://lasa.epfl.ch/publications/uploadedFiles/Noris11-Thesis.pdf
8. SupportVectorMachine http://en.wikipedia.org/wiki/Support_vector_machine
9. P-value test. http://en.wikipedia.org/wiki/P-value