EFFECT OF HORROR CLIPS ON THE PHYSIOLOGY OF ANS & HEART

A thesis submitted in partial fulfilment of the requirements for the degree of

Bachelor of Technology

In

Biomedical Engineering

Submitted

By

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CERTIFICATE

This is to certify that the thesis entitled "**EFFECT OF HORROR CLIPS ON THE PHYSIOLOGY OF ANS & HEART"** submitted by **MR. SIDDHARTH NAYAK** in partial fulfilment of the requirements for the degree of **Bachelor of Technology** in **Biomedical Engineering** embodies the bonafide work done by him in the final year of his degree under the supervision of the undersigned. The thesis or any part of it has not been submitted earlier to any other University / Institute for the award of any Degree or Diploma.

(Dr. KUNAL PAL)

Assistant Professor

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ACKNOWLEDGEMENT

I would like to extend my warm regards to my thesis supervisor, Dr. Kunal Pal, Assistant Professor, Department of Biotechnology and Medical Engineering, National Institute of Technology, Rourkela, without whose constant guidance and, endearing support the successful completion of my B.Tech. thesis won't have been made possible. His presence and, deep instilled patience were crucial for a guy like me who often needs a pathway to follow. All the steps were explained to me step by step. The presence of Biswajeet Champaty (Ph.D.) had a calming effect as ever on my experimental proceedings. I was fortunate to have Saikat Sahoo (M.Tech.) around me who was kind enough to lend his laptop for ECG data acquisition using DAQ and, gave a clue also on how to analyse the results.

I'm thankful to NIT Rourkela for helping me in utilization of its laboratory facilities and, to provide a conducive environment for carrying out my B.Tech. project.

Last but, not the least, I would like to thank my friends for their constant help and, support in during the length of my experiments and, to gracefully accept in being a subject to my ECG experimental readings. It was kind of them to share their medical history and, other personal information without a fuss and, help me all along the way.

Siddharth Nayak
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ABSTRACT

The current study deals with the ECG and, HRV parameter analysis to study the physiology of ANS and, the heart by taking data from 20 volunteers under the effect of horror clips. The volunteers had their ECG reading recorded under normal and, horror situations by showing them the same video clips and, at relatively the same time of the day(after dinner hours) to keep uniformity in the readings and, reduce any ambiguity that might be present. Our results showed us that the effect of HRV parameters on the physiology of heart was significant. The time series data and, the time series data using wavelet (db-06 wavelet) didn't affect the ECG readings of horror much more than that of normal readings of the same subjects. This was also verified by t-test grouping. The results clearly show that HRV parameters affect the horror ECG readings.

Keywords: ECG, HRV, ANS, horror clips, db-06, t-test grouping

1. INTRODUCTION

ECG readings are a measure of heart rate variability (HRV) and, the latter is a measure of the physiology of the Autonomous Nervous System (ANS) and, the heart [1]. The precision and, the physical conditions in which ECG data is acquired goes in a long way to determine the final results of the experiments. The standards of measurement of HRV are well documented and, these are followed during ECG signal measurement. The ECG signal analysis can be broadly classified into two classifications. viz., HRV parameters and, time domain parameters. The time domain parameters are further classified into time domain features and, wavelet based time domain features [2]. The ECG signal extracted for HRV parameter features were to be of 5 minutes duration and, that for time domain features and, wavelet based time domain features were to be of 5 seconds duration. Any irregularity in the ECG readings can be associated with heart rate variability. [3].

Over the last decade, with rapid advancements in the field of signal processing and, medical instrumentation, it has been found that this HRV can be quite effectively measured and, linked to changes in emotional level including that with horror affected ECG signals. [4] The cardiac muscles respond to influence of ANS. ANS helps in maintenance of heart beat fluctuations and, that in turn affects the HRV. HRV is nothing but, the beat to beat heart rate variations. HRV There is a marked change in the ANS activity with changes in various emotions. The various changes associated with emotions can be studied non-invasively by analysis of HRV parameters [5]. Thus, it can be used as an indicator for the analysis of ECG signals.

In the current study attempts were made to study the effects of emotional changes due to HRV parameters on the physiology of ANS and, the heart [6]. The HRV parameters were used to calculate time domain features, FFT based frequency domain features, Poincare plot, AR spectrum (PSD versus frequency feature) and, subsequently these were used for classification via linear and, non-linear classifiers. The linear classifier used was t-test grouping while the non-linear classifiers used were- General Classification/Regression tree models (CART), Boosted Tree (BT), Random Forest [7]. The classifiers' results were compared with Artificial Neural Network's (ANN) results to find any similar patterns present in the physiology of ANS during emotional changes associated with the heart [8]. CART, BT and, Random Forest were used to find the important features to be used as inputs for the ANN classifier. Multilayer perceptron (MLP) and, Radial basis functions (RBF) were used for network architecture in ANN classifiers [9]. A conscious effort was made to study the changes in the patterns of the physiology of ANS and, the heart due to the HRV parameters measured during post stimulus of ECG signals. (Post- stimulus used was horror video clip).

2. LITERATURE REVIEW

Heart Rate Variability (HRV) is a measurement of identical activity in cardiac time cycles across a stipulated time interval. It's in fact the measurement of the variations that occur along cardiac cycles as we move along in time. It gives us information on RR and, HR intervals; together they make up HRV [10].

HRV is used as a non-invasive electrocardiographic method to measure the autonomic nervous system. HRV has been shown to be a parameter for acting as a marker for sympathetic nervous system and, the sinus [11].

Emotion recognition with the use of ECG and, HRV parameters is a growing field and, a lot of current research is going on in this field. Emotion to be recognised may be comedy, horror, thriller, fear, sadness or, anxiety. All of these emotions affect the physiology of the ANS. The physiological changes to each emotion may be different [12].

Frequency versus time domain analysis of ECG has been done already using the signal averaged electrocardiograms with variations in probability ($p < 0.05$). A study was done on the reproducibility of the results and, spectral methods were found to be giving better results than others [13].

HRV has been also documented to be a measure of the cardiac activity and, in turn regulate the stress and, welfare in humans by evaluating their stress and, emotional state levels by analysis of neurophysiological processes of the stress levels [14].

Artificial Neural Networks using Data mining software's have been used extensively for ECG signal analysis and, its further classification. P-QRS-T waves or, segments is what ECG is basically made up of. Its analysis gives us crucial information required in the diagnosis of cardiovascular diseases. Some basic methods for classification of ECG signals and, their extraction have been proposed in this paper [15] .

It has been proved that ECG readings fluctuate with the difference in interest of subjects to various movie scenes that is, various emotions. The emotional changes are clearly thus reflected on the physiological analysis of ECG readings. In this paper a feature extraction method has been proposed to help in ECG signal's physiological analysis of emotional changes [16] .

ECG studies on smokers and, non-smokers using HRV have been documented before. Use of wavelets is a new approach in these studies. Comparison of original ECG signal with the wavelet reconstructed signal obtained from ECG of smokers and, non-smokers has been as the classification criteria of the various HRV parameters and, their physiological influence on the ANS and, heart [17] .

Study of cardiac physiology and, its effect when viewing horror films have been shown here. The different physiological changes have been observed with care and, documented in this paper. It serves as a guide to future work on horror film viewing and, its physiology [18].

3. HEART RATE VARIABILITY (HRV)

Heart rate variability (HRV) is the variations of beat to beat rhythmic change of heart beats. It becomes a critical factor in study of cardio vascular physiology and, analysis of cardiac arrhythmias and, other coronary heart diseases. It's a non-invasive method for analysis of QRS peaks and, report its results for use in cardiac physiology. The various parameters of HRV imply a lot of meanings in the modulation necessary for the diagnosis of heart diseases [19]. Different components of QRS peaks suggest different meanings. All have their own physiological interpretations. HRV is dependent on heart rate (HR). Based on post- or, pre- stimulus HR changes effectively and, so does HRV for a particular person. HRV is thought to reflect changes in Autonomous Nervous System (ANS) of an individual and, thereby acts as an indicator for cardiac activity [20].

Time domain factors including calculation of R-R intervals are becoming popular in physiological interpretations of various diseases. Heart rate variability (HRV) is also thought to become popular as HR for acting as a measuring stick for future calibrations with respect to most cardiac diseases in future. HRV is already used to describe variations in R-R intervals and, Heart Rate (HR).

In order to monitor R-R intervals effectively, RR mean and, RR standard deviation parameters are important. This helps in analysis of consecutive RR beats and, not just the Heart Rate (HR) per second. Even in rest state which we call normal state, the physiology of the heart doesn't remain constant so, the HR fluctuates with minute.

There are various methods to measure heart rate namely- ECG, pulse wave, blood pressure, and etcetera. However, ECG is considered the best among these conventional techniques of heart rate measurement because it originates in the Sino-Atrial Node (SA Node) of the heart and, SA node is closely related to Autonomous Nervous System (ANS) [21]. These days, NN are taken instead of RR for Heart Rate (HR) readings. NN stands for normal ECG reading instead of RR (rate to rate reading). Most of these readings are taken for a short time interval because a small time interval in enough to reflect the changes in the HRV readings. These HRV parameters suggest changes in sympathetic or, parasympathetic nervous system (ANS is sub-divided into these two) [22].

3.1 Clinical significance of HRV

1. From earlier research, it is known that ECG readings are affected by time of day, food habits, age, sex, creed, etc. Also, it's a widely established fact that sudden death due to cardiac arrest or, other sudden coagulations in the pulmonary artery lead to changes in HRV and, may cause death of an individual [23].
2. More research on HRV has demonstrated that under extreme emotional stress, HR readings can vary significantly and, they have a marked effect on the sympathetic and, parasympathetic nervous system of an individual [24].

   Many other patterns such as breathing habits, food habits, sleeping habits, climatic conditions, and hormonal changes also effect HRV in a significant way [25].

3.2 Disadvantages with measuring HRV

Measuring HRV requires documentation of a large volume of ECG data to be acquired for subsequent analysis. These devices measure ECG over long time intervals, generally over 24 hours. This large data can't be expected to be free of physical parameters whose changes creep up in a few weeks. These can vastly influence the final HRV reading and, can thereby affect the final results. Quality of the signal acquired and, its subsequent noise removal is thus critical for ECG data analysis. For patients suffering from irregular heartbeats that is, ventricular or, atrial arrhythmias, measuring HRV and, its later interpretation becomes all the more difficult. Small physical movements can cause a large amount of noise in the time and, frequency domain readings and, thus need to be effectively filtered so as to ensure its proper analysis.

3.3 Effect of HRV on ANS

The autonomous nervous system (ANS) links all the functional activities and, organs of the human body as a whole. It is involuntary in nature so, it functions even when we take rest or, sleep. Effect of physical exercise tends to increase HRV values. ANS is divided into sympathetic and, parasympathetic nervous systems. Sympathetic nervous system is responsible for systemic vasoconstriction, increase in Heart Rate (HR) value and, volume of blood flow in a single stroke. The HRV response to sympathetic nervous system is relatively slower than that of parasympathetic nervous system. It takes the former 5 seconds to start and, about 30 seconds to fully reach its peak value while the latter functions almost instantaneously [26] . Sympathetic nervous system influences in the proper functioning of several organs. On the other hand, parasympathetic nervous system restricts the activity of the same organs.

3.4 Influence of horror as an emotion on the cardiovascular system

In both male and, female cardiovascular system, effect of horror as an emotion is different. Emotion affects HRV readings significantly. In general emotions cause reduction in HRV parameters. Lower HRV and, hence vagal activity has been reported thus due to horror affected ECG signals [27] . Generally, low frequency short time readings are taken for ECG as they effectively give the result of changes in HRV parameters. LF, HF and, LF/HF are in the important parameters as found to be influenced by horror movie clip [28].

3.5 Different methods for measurement of HRV analysis

ECG readings were taken and, the methods used were:

- Analysis of HRV parameters

- Analysis of time domain features
- Time domain features

  - Wavelet domain features

  The analysis of HRV parameters were done when ECG signal affected by horror movie were extracted for 5 minutes. While, the time domain features were analysed for ECG readings of 5 seconds each.

3.6 ECG and, HRV parameter analysis

The various HRV parameters were tested to observe their changes on the ANS and, the heart. The time domain features of HRV (NN 50, pNN50, RRM, RRS, RMSSD, RRI, and TINN) were short term recordings. There are features such as LF, HF and, LF/HF which are particularly important for this kind of study. Poincare plot is also effective in determining short term or, long term variability of data.

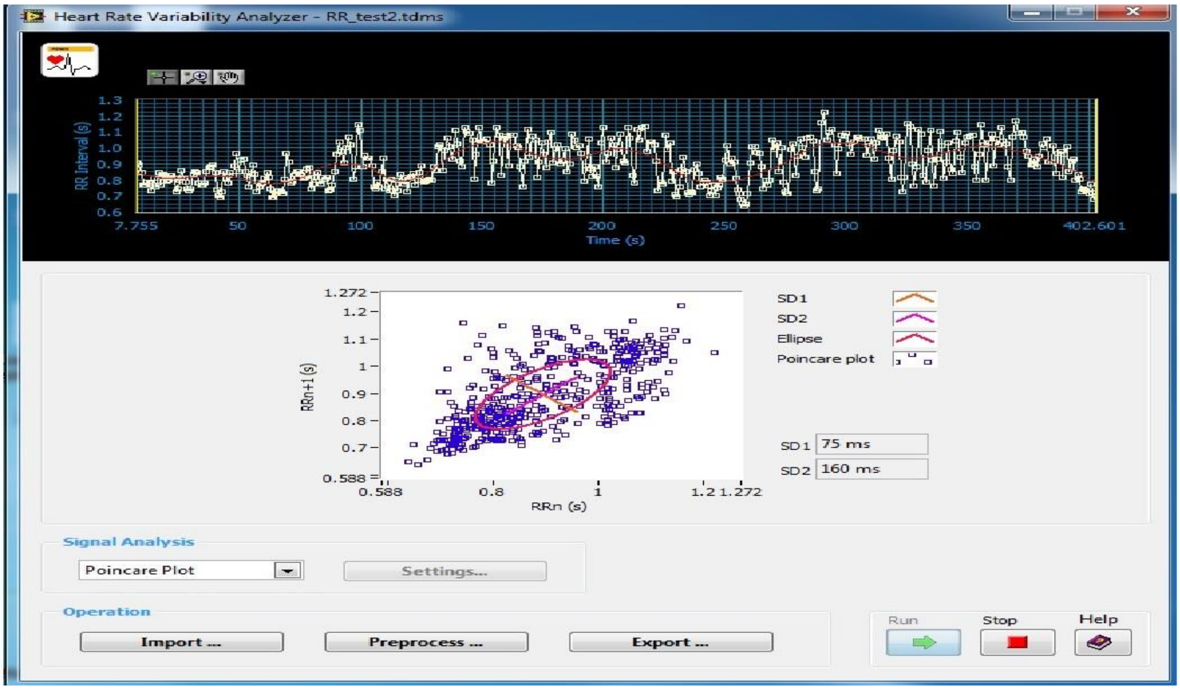

Figure 1: - A Poincare plot showing the values of SD1 (Short term variability) and, SD2 (long term variability)

3.7 ECG and, Time domain analysis

The Time domain analysis mainly deals with the following ECG parameters: - Arithmetic Mean, Standard Deviation, Skewness, Variance, Mode, Median, Kurtosis, Summation, ED (Energy Density), SE (Shannon Entropy), LE (Log Energy).

Arithmetic mean: The mean reading across various QRS peaks of ECG signal.

Standard deviation: It's the deviation from the mean QRS reading of an ECG signal. **Skewness:** A measure of asymmetry across the mean reading.

Variance: Measures of the spread of ECG signal across the time domain.

Mode: The most frequently occurring QRS peak along the time domain of the ECG reading.

Median: The mid value QRS peak of the ECG reading.

Kurtosis: It gives a measure of the peakedness of the ECG reading implying its shape of the QRS peaks.

Summation: It stands for the sum of the QRS peak readings along the time domain of the ECG signal.

ED (Energy Density): It represents the instantaneous energy in the time domain spectrum.

SE (Shannon Entropy): It measures the average unpredictability of the QRS peaks equivalent to its RR intervals (that is, its information content)

LE (Log Energy): It measures the log values of the energy over the time domain of ECG signal.

4. MATERIALS AND METHODS

In this present study, the ECG signals of young healthy males within the age group of 21 to 23 was recorded by using Electrode and Data acquisition System (DAQ) based device with clamp electrodes and, electrolyte gel to ensure proper skin conductance. The ECG signals were taken from 9-11 pm. (an hour after dinner) so as to maintain the uniformity in the readings. After acquiring the ECG signals the Biomedical Workbench software was used to extract the different time and frequency domain features of HRV (e.g. Mean heart rate (HR), Mean RR, Sd1 and Sd2 of Poincare plot, Mean NN, standard deviation of RR intervals (SDNN), root mean square of successive difference (RMSSD), NN50, pNN50). The LABVIEW software was used here to calculate the different statistical parameters of the each ECG signal. The HRV features and ECG signal statistical features were combined and then these sets of features were analysed by non-linear statistical analysis (CART, Boosted tree (BT) and, Random Forest classification) to determine the significant features.

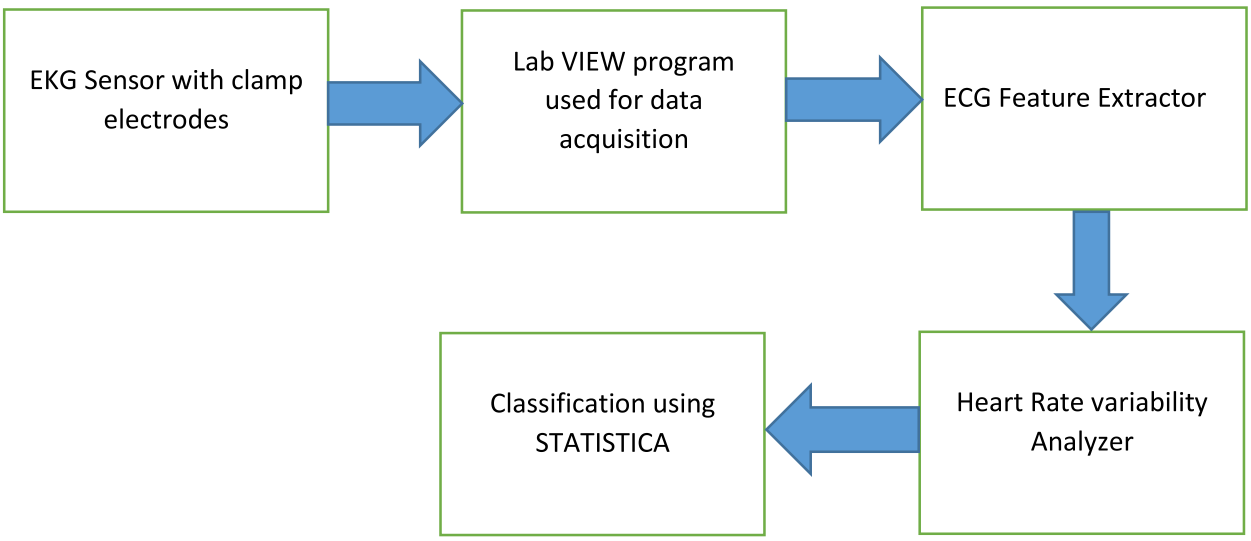

Figure 2:- Complete block diagram of ECG signal acquisition Procedure

Figure 3:- ECG Feature Extractor (Biomedical Workbench)

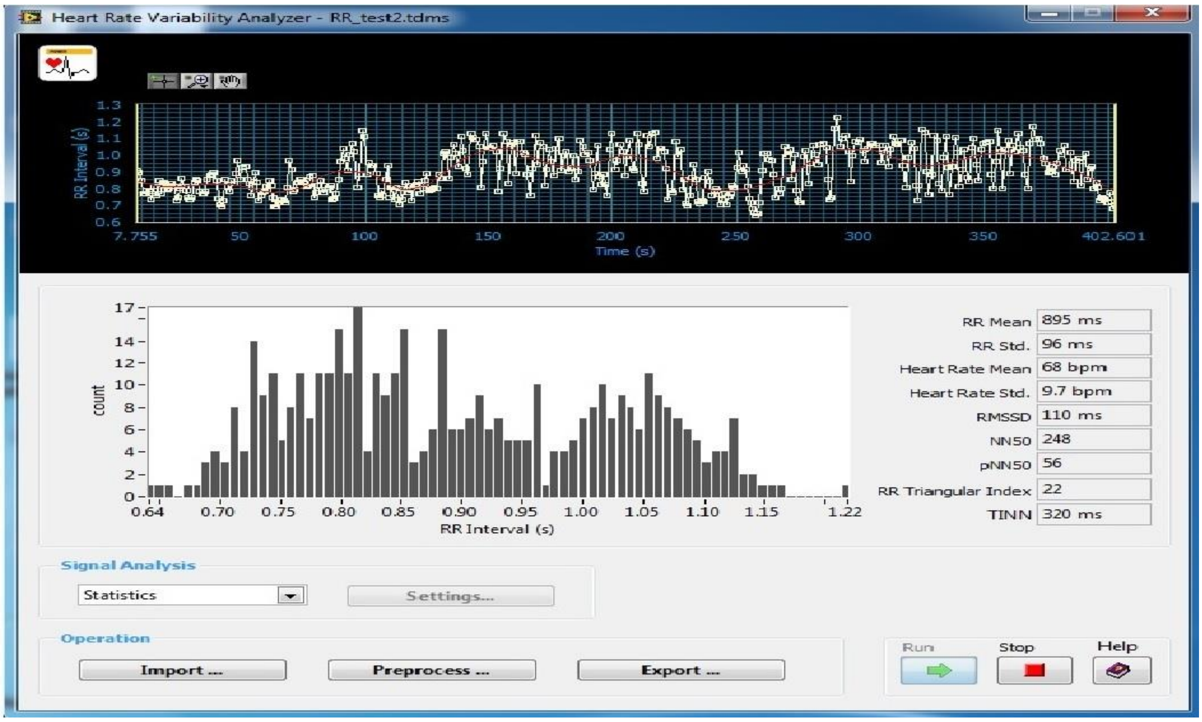

Figure 4: - Heart Rate variability Analyser depicting Statistical (time domain) features.

The HRV features were as follows:

- Statistical Measures (RRM, RRS, HRM, HRS, RMSSD, NN 50, p NN 50)
- Histogram Measures (RRI (RR Triangular Index), TINN), Poincare Plot (Sd1, Sd2)
- FFT Spectrum (VLFPe, LFPe, HFPe, VLFPo, LFPo, HFPo, VLF, LF, HF, LF n.u, HF n.u, LF/HF)

- AR Spectrum (VLFPe_1, LFPe_1, HFPe_1, VLFPo_1, LFPo_1, HFPo_1, VLF_1, LF_1, HF_1, LF n.u_1, HF n.u_1, LF/HF_1). Here 'Po' is abbreviated as Power and, 'Pe' is abbreviated as Peak. RRM stands for RR Mean whereas, RRS stands for RR Std. and, so on [8] [9].

The following ECG signal statistical features were found in time series data and, time series data using wavelets:

- Arithmetic Mean
- Standard Deviation
- Skewness
- Variance
- Mode
- Median
- Kurtosis
- Summation
- ED(Energy Density)
- SE(Shannon Entropy)
- LE (Log Energy).

With the help of Lab VIEW codes, data sheets were prepared for HRV parameters, time series data and, time series data using wavelets. Then, STATISTICA 9.1 software was used to highlight the higher predictor importance of the parameters of HRV and, ECG statistical features. The data were properly classified using ANN (Automated Neural Networks). STATISTICA software uses a random network types comprising of MLP (Multi-Layer Perceptron) and, RBF (Radial Basis Function) having their specific hidden neurons and, weight matrix specification. A confusion matrix is obtained from this having training and, test samples. The MLP 2-4-2 signifies that there are two input neurons followed by 4 hidden neurons and, two output neurons. A sample RBF 3-4-2 is as shown below:-

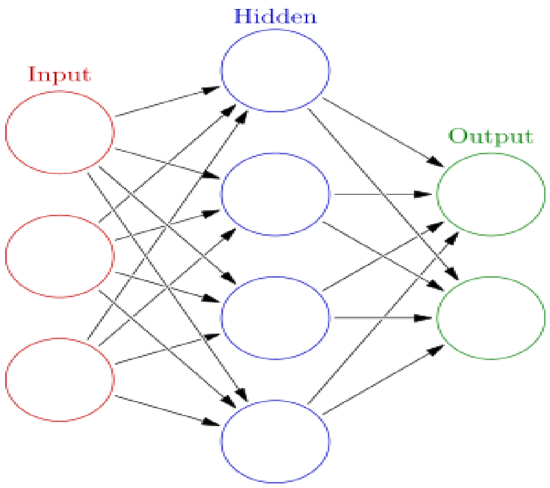

Figure 5: - An architecture of RBF.

Similarly, other MLPs can be constructed.

The error functions used are- SOS (Sum of Squares) and, CE (Cross Entropy). The activation functions used are – identity, logistic, tanh, exponential for both the hidden neurons as well as the output neurons. In addition to these, hidden neurons used Gaussian as their activation function and, output neurons used Softmax function. The algorithm used for MLP is BFGS while for RBS is RBFT. By merely manipulating the maximum and, minimum number of hidden neurons in the network types of RBS and, MLP, we can obtain different training and, testing results.

A description of the activation functions:-

1. **Identity:** This activation function gives the same value in output as the input unit. It is only used for output layers.
2. **Logistic:** This activation function gives linear results to non-linear inputs. It is therefore used to remove non linearity in neural networks applications.

3. **Tanh:** This activation function gives a curve similar to sigmoid function. It however has advantage in the range (-1 to +1) than the conventional sigmoid function (0 to +1). Since, hyperbolic tangent activation function covers a greater range, it is used often in neural network applications.
4. **Exponential:** This activation function gives values from 0 to infinity. It has the largest range among all neural network activation functions.
5. **Softmax:** This activation function is generally employed at output layer of classifications. It gives values in the range of (0, +1).
6. **Gaussian:** This activation function is derived from the exponential function. It gives a bell shaped curve at its centre. Its values can cover a variable range.

   T-tests grouping was also carried out on all the three data sets to classify which parameters were less than 5% probability distribution. These parameters were taken as being significant with respect to the others.

5. RESULTS

5.1 HRV parameter analysis

The important parameters in the predictor importance chart for CART analysis- HFPe and, LF were noted down and, their plot was obtained using STATISTICA 9.1 software.

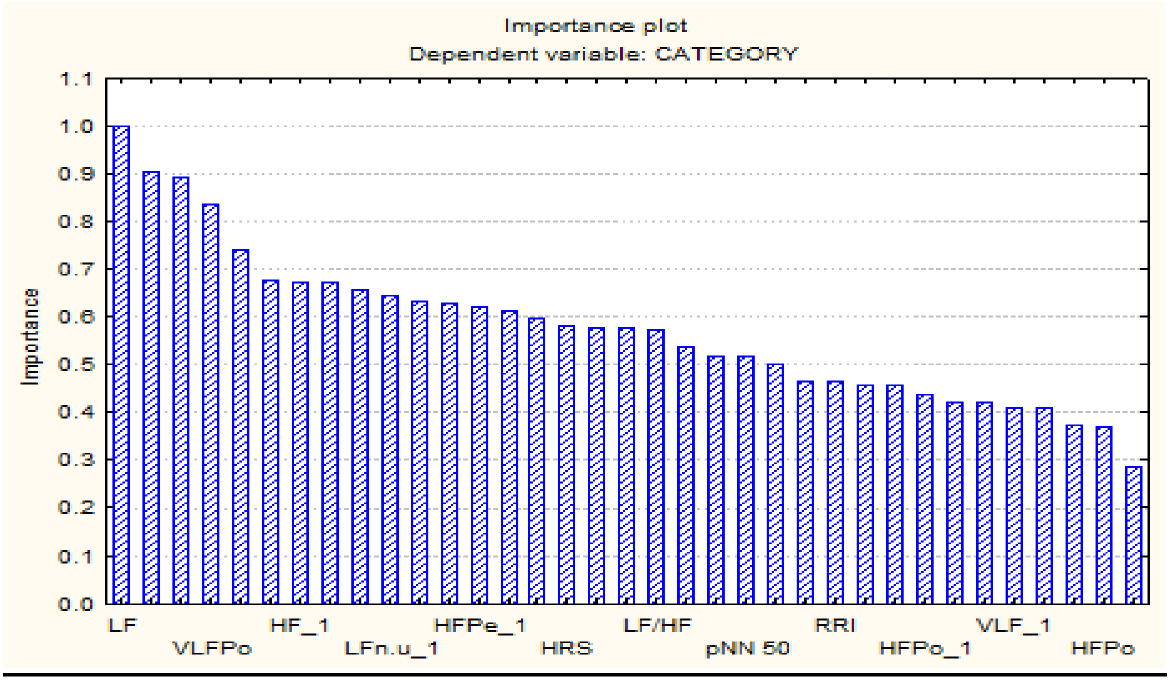

Figure 6: - A predictor importance plot showing the important features obtained through CART analysis.

Similarly, the important parameters in the predictor importance chart for BT analysis were noted down and, their plot was obtained using STATISTICA 9.1 software.

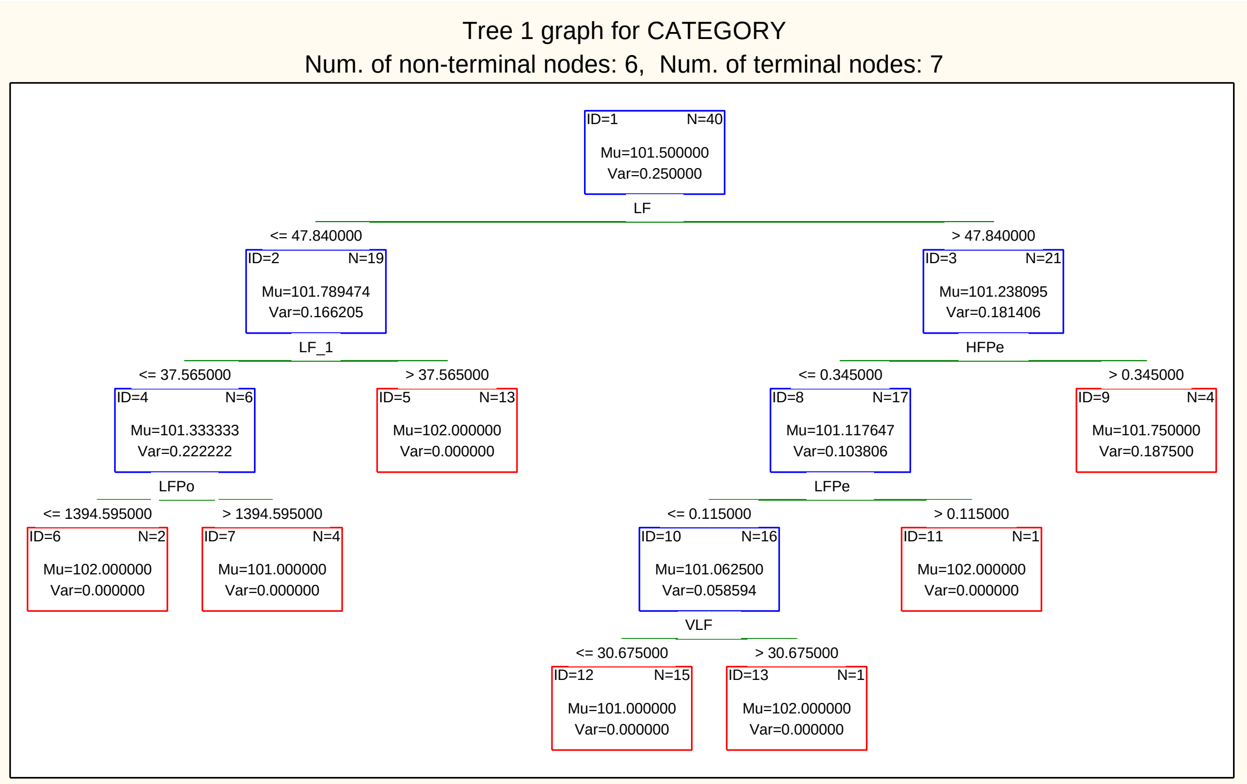

Figure 7:- Tree Graph of CART analysis showing important predictor features.

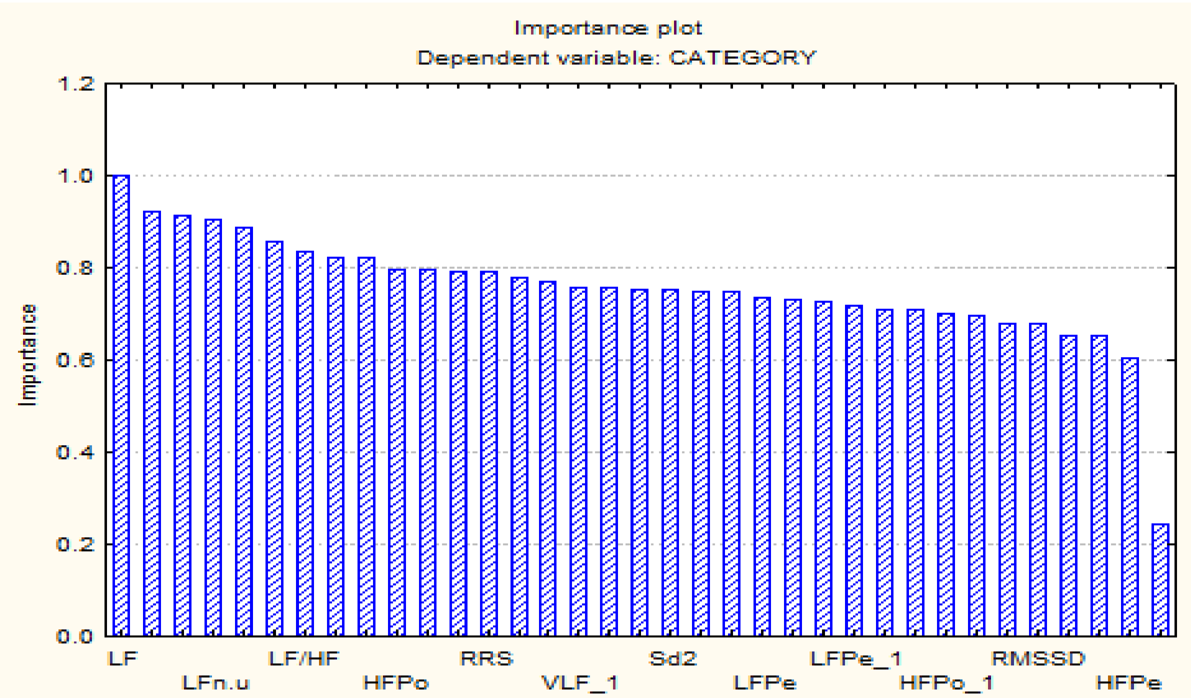

Figure 8:- A predictor importance plot showing the important features obtained through BT analysis.

The important HRV features obtained from Boosted Tree (BT) were- TINN, VLFPo, LF and, LF n.u.

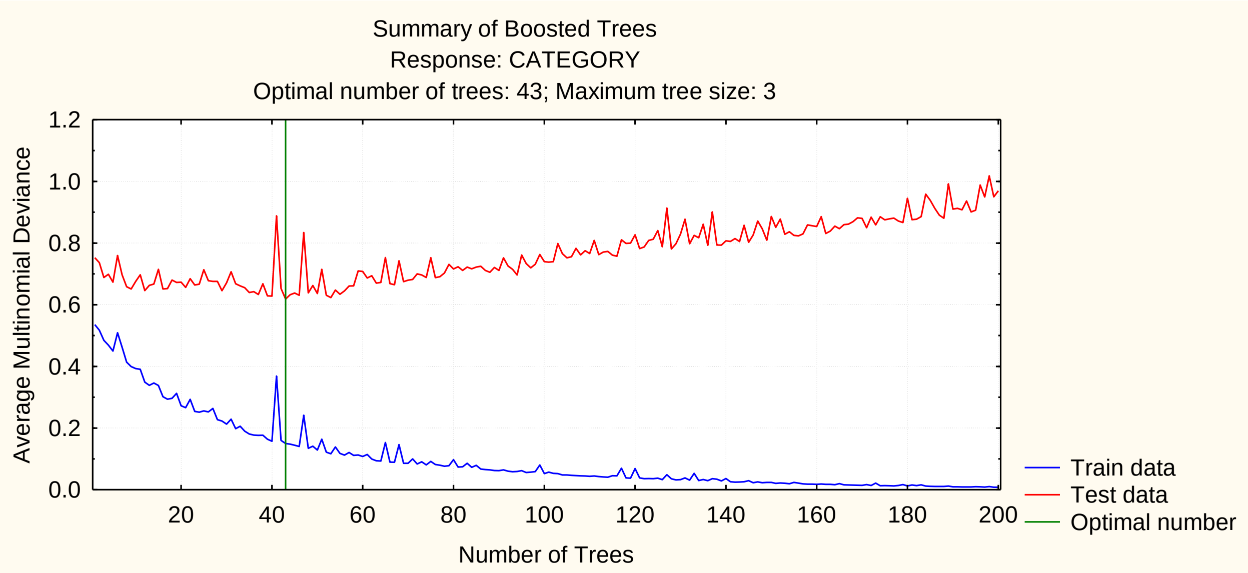

Figure 9: - Summary of the Boosted Tree analysis showing training and, testing data along with the optimal number of trees.

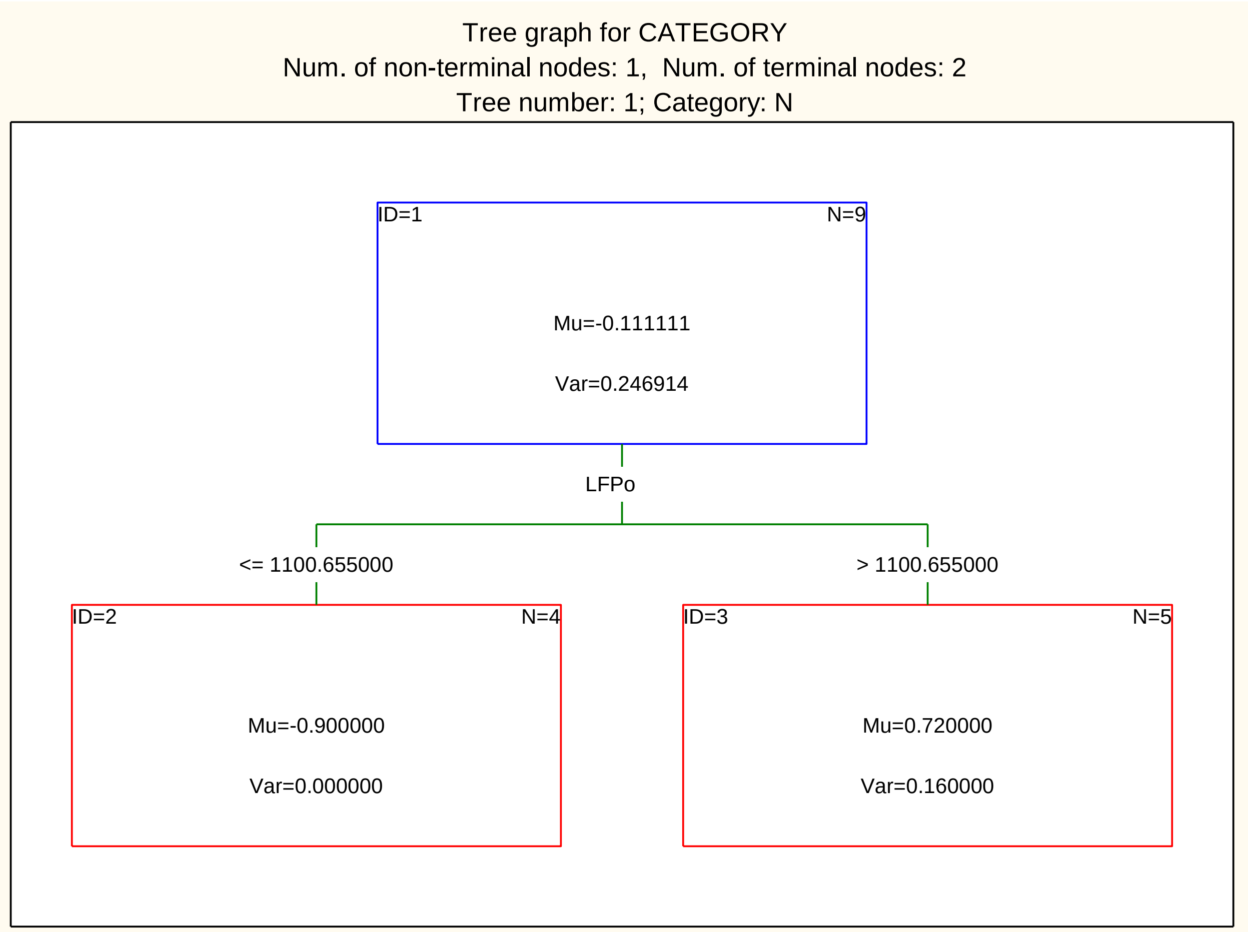

Figure 10: - Tree Graph of BT analysis showing important predictor features

Similarly, the important parameters in the predictor importance chart for Random Forest were noted down and, their plot was obtained using STATISTICA 9.1 software.

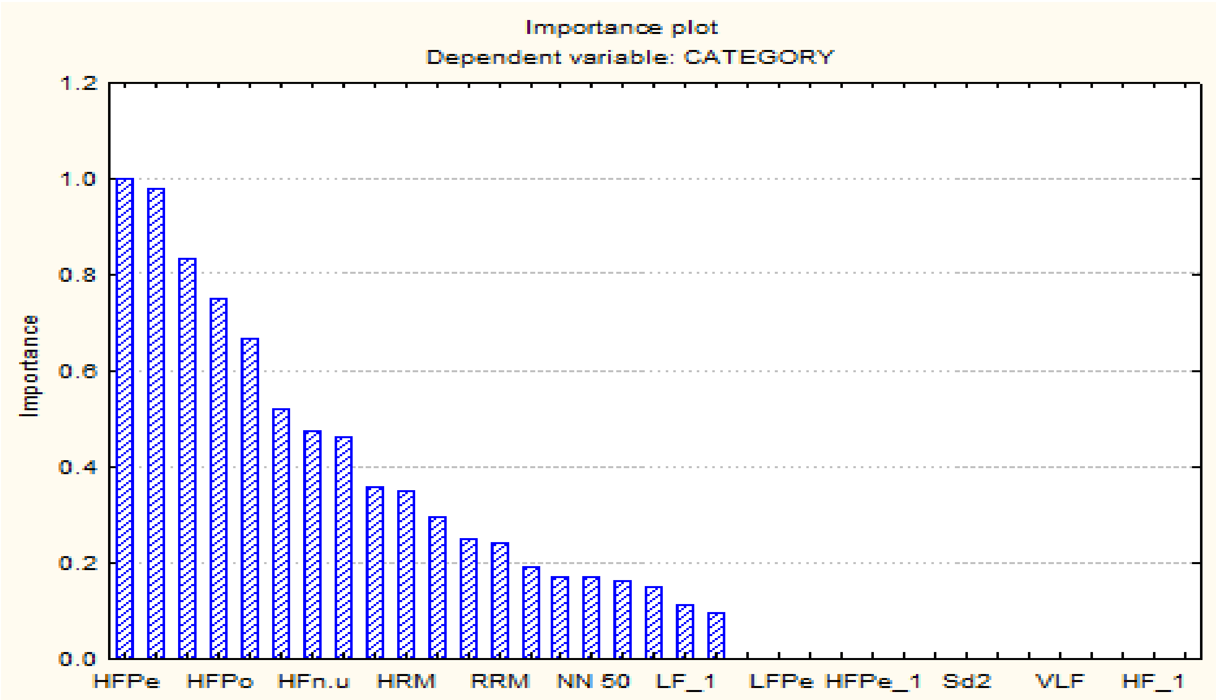

Figure 11:- A predictor importance plot showing the important features obtained through Random Forest

The important HRV features obtained from Random Forest were- Sd1 and, HFPe.

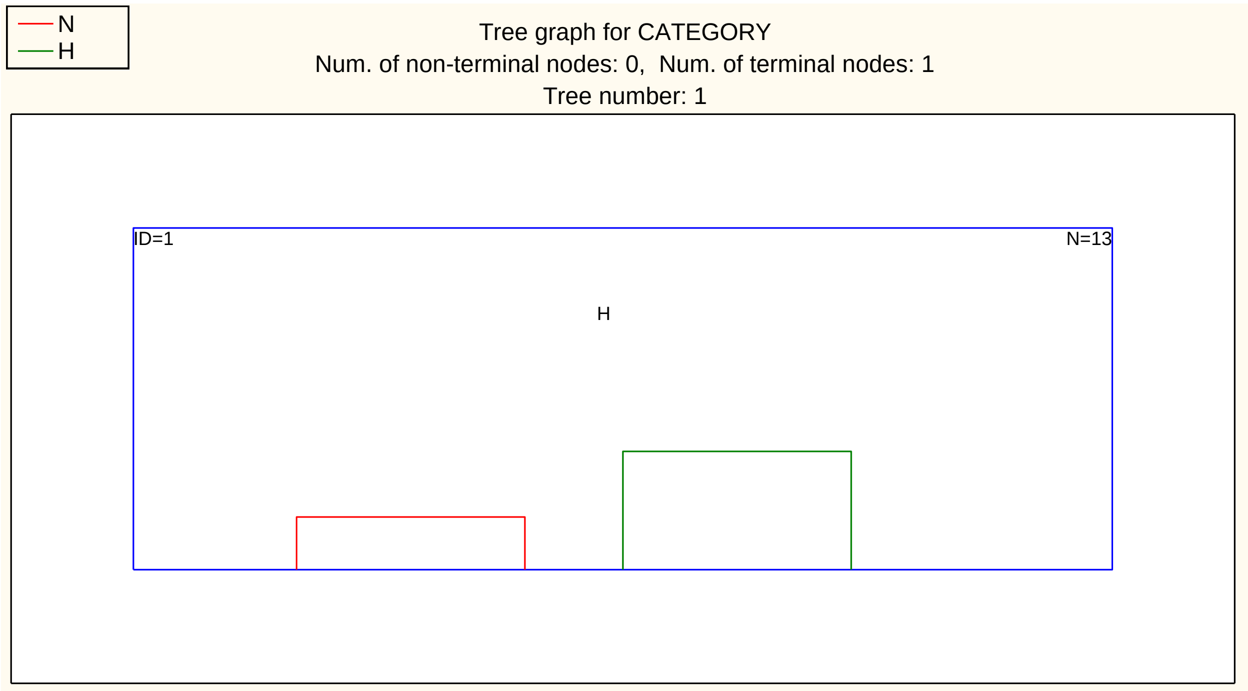

Figure 12:- Tree Graph of Random Forest classification

The important RR intervals for the HRV features such as RRM and, RRS as obtained from t-test are given below in Box and, Whisker plots.

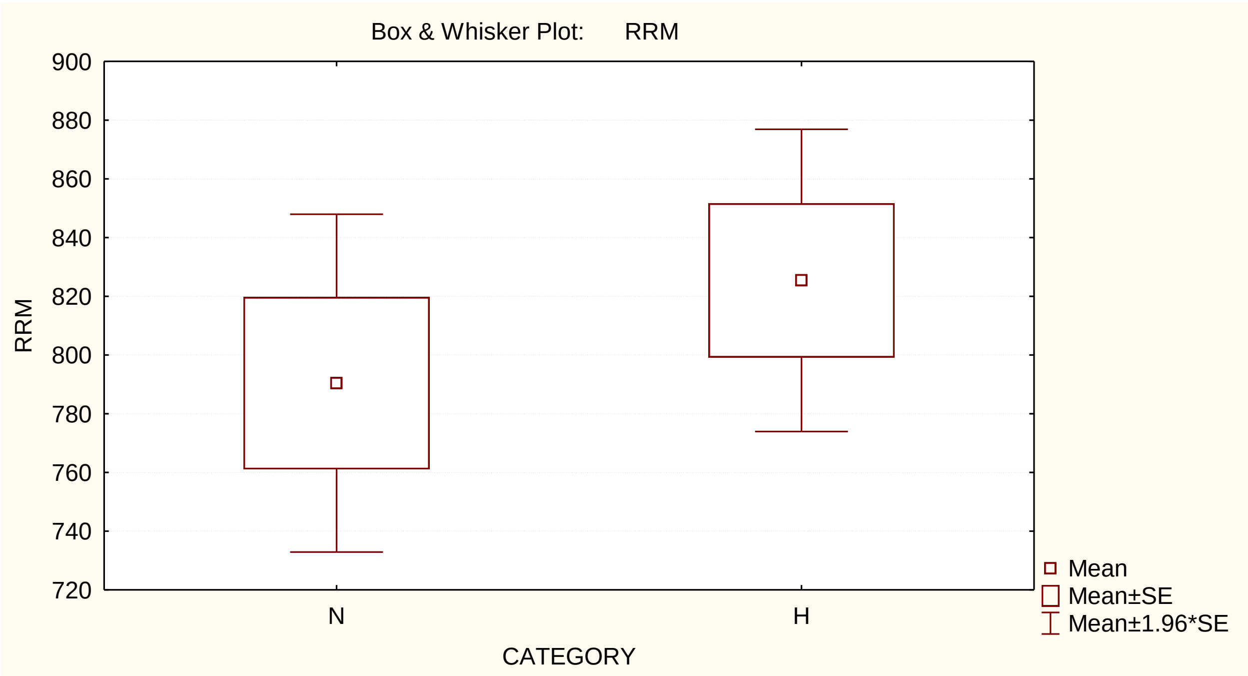

Figure 13: - Box & Whisker Plot of RR Mean showing category of normal and, horror.

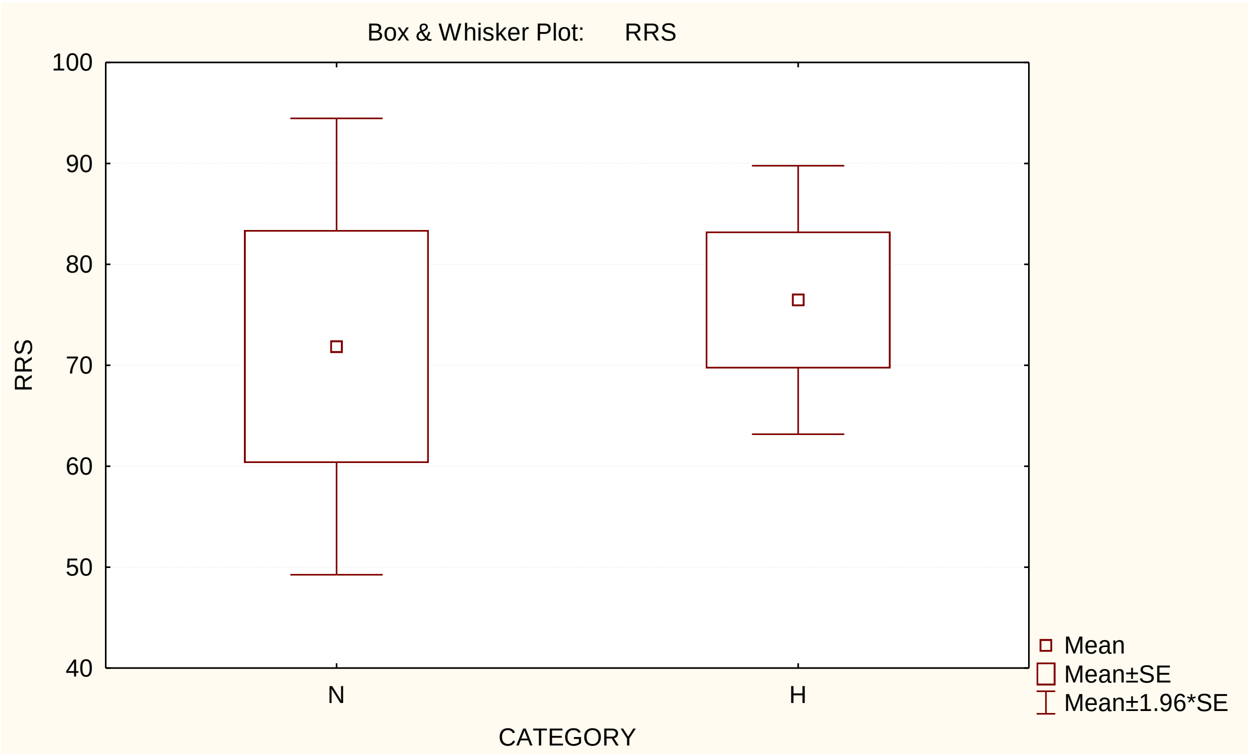

Figure 14:- Box & Whisker Plot of RR Standard Deviation showing category of normal and horror.

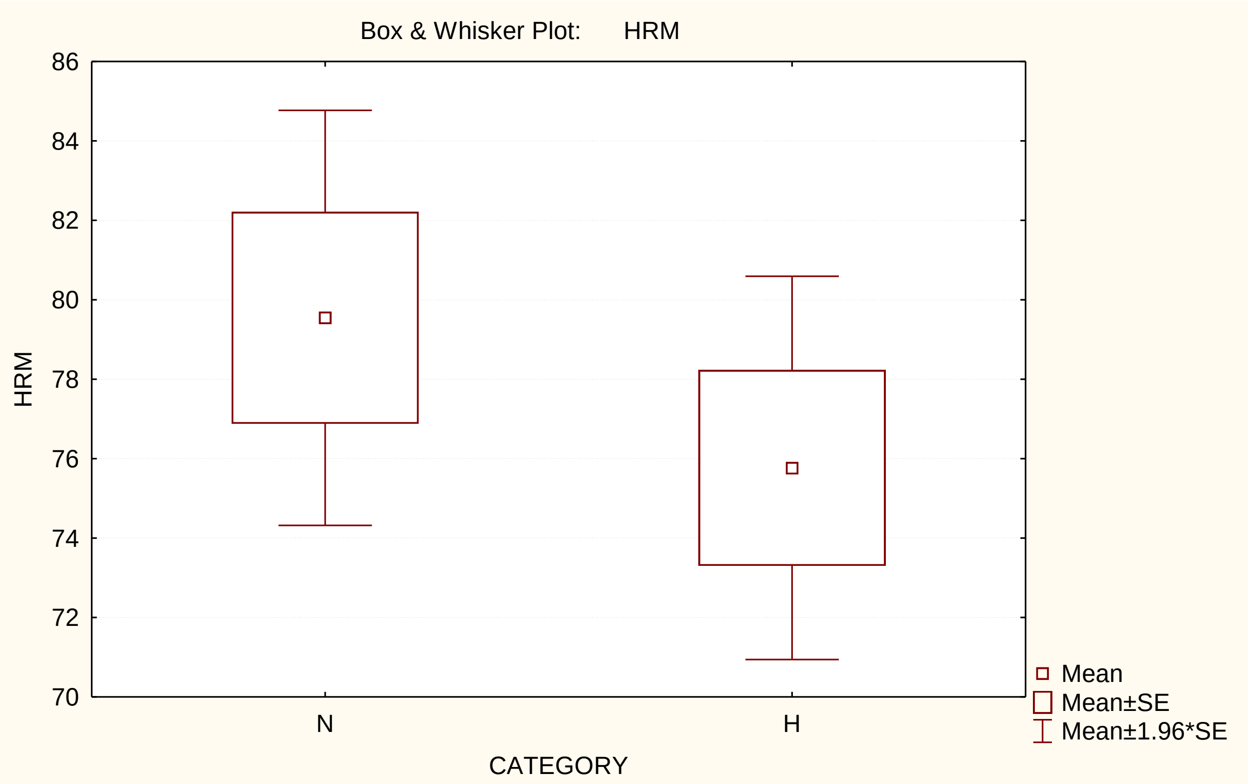

Figure 15:- Box & Whisker Plot of Heart Rate Mean showing category of normal and, horror.

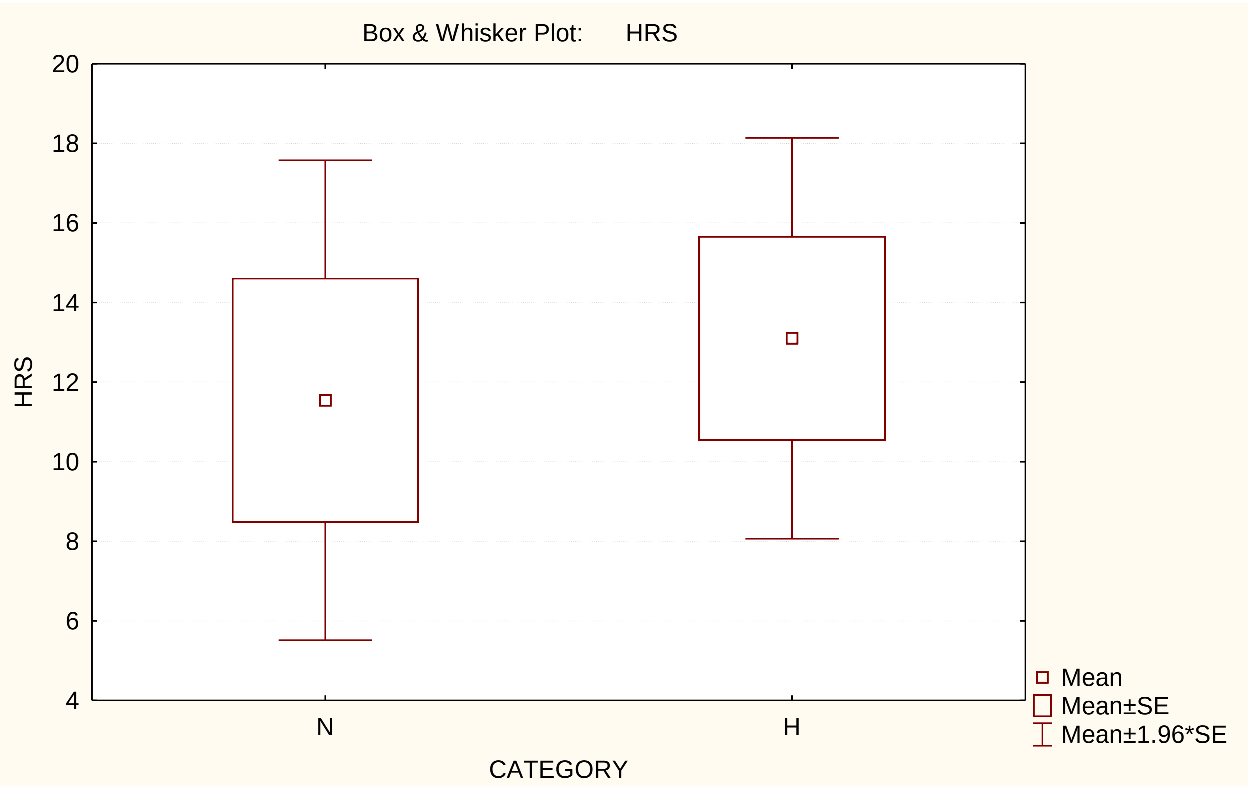

Figure 16:- Box & Whisker Plot of Heart Rate Standard Deviation showing category of normal and, horror.

The important parameters obtained using these linear and, non-linear classifiers were used in various combinations to act as input layers for ANN classification. The confusion matrix tables obtained from CART analysis for RBF and, MLP using LF and, HFPe as parameters are as shown below. (Table 1 and, Table 2). The corresponding ANN tabulation is given in table 3.

Table 1:- Confusion Matrix for MLP network

	CATEGORY –H	CATEGORY-N	Total
TOTAL	20.00	20.00	40.00
CORRECT	18.00	17.00	35.00
INCORRECT	2.00	3.00	5.00
CORRECT (%)	90.00	85.00	87.50
INCORRECT (%)	10.00	15.00	12.50

Table 2:- Confusion Matrix for RBF network

	CATEGORY –H	CATEGORY-N	Total
TOTAL	20.00	20.00	40.00
CORRECT	17.00	17.00	34.00
INCORRECT	3.00	3.00	6.00
CORRECT (%)	85.00	85.00	85.00
INCORRECT (%)	15.00	15.00	15.00

Table 3:- Parameters of the RBF and MLP networks

Network	Features used	Classification efficiency	Algorithm	Error function	Hidden Act.	Output Act
RBF 2-11-2	LF and, HFPe (FFT)	87.50%	RBFT	CE	Gaussian	Softmax
MLP 2-13-2	LF and, HFPe (FFT)	85%	BFGS 31	CE	Exponential	Softmax

The confusion matrix tables obtained from BT analysis and, Random Forest classification for RBF and, MLP using TINN and, LF and, Sd1 and, HFPe as parameters are as shown below. (Table 4 and, Table 5). The corresponding ANN tabulation is given in table 6.

Table 4:- Confusion Matrix for MLP network

	CATEGORY –H	CATEGORY-N	Total
TOTAL	20.00	20.00	40.00
CORRECT	16.00	17.00	33.00
INCORRECT	4.00	3.00	7.00
CORRECT (%)	80.00	85.00	82.50
INCORRECT (%)	20.00	15.00	17.50

Table 5:- Confusion Matrix for RBF network

	CATEGORY –H	CATEGORY-N	Total
TOTAL	20.00	20.00	40.00
CORRECT	18.00	17.00	35.00
INCORRECT	2.00	3.00	5.00
CORRECT (%)	90.00	85.00	87.50
INCORRECT (%)	10.00	15.00	12.50

Table 6. Parameters of the RBF and MLP networks

Network	Features used	Classification efficiency	Algorithm	Error function	Hidden Act.	Output Act
RBF 2-25-2	Sd1 and, HFPe (FFT)	87.50%	RBFT	CE	Gaussian	Softmax
MLP 2-17-2	TINN and, LF	85%	BFGS 5	SOS	Exponential	Identity

5.2 Time domain analysis

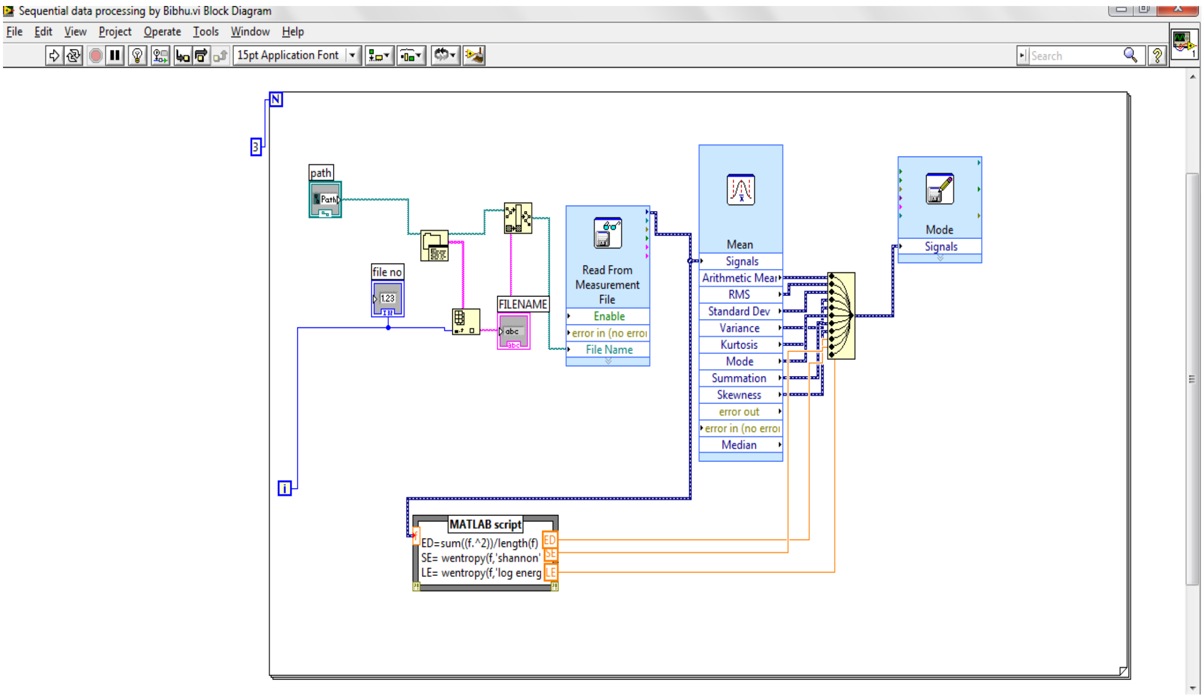

Figure 17: - A block diagram of Lab VIEW code depicting time domain ECG analysis

The important parameters in the predictor importance chart from CART analysis were noted down and, their plot was obtained using STATISTICA 9.1 software. AM, SUM and, ED were the important parameters.

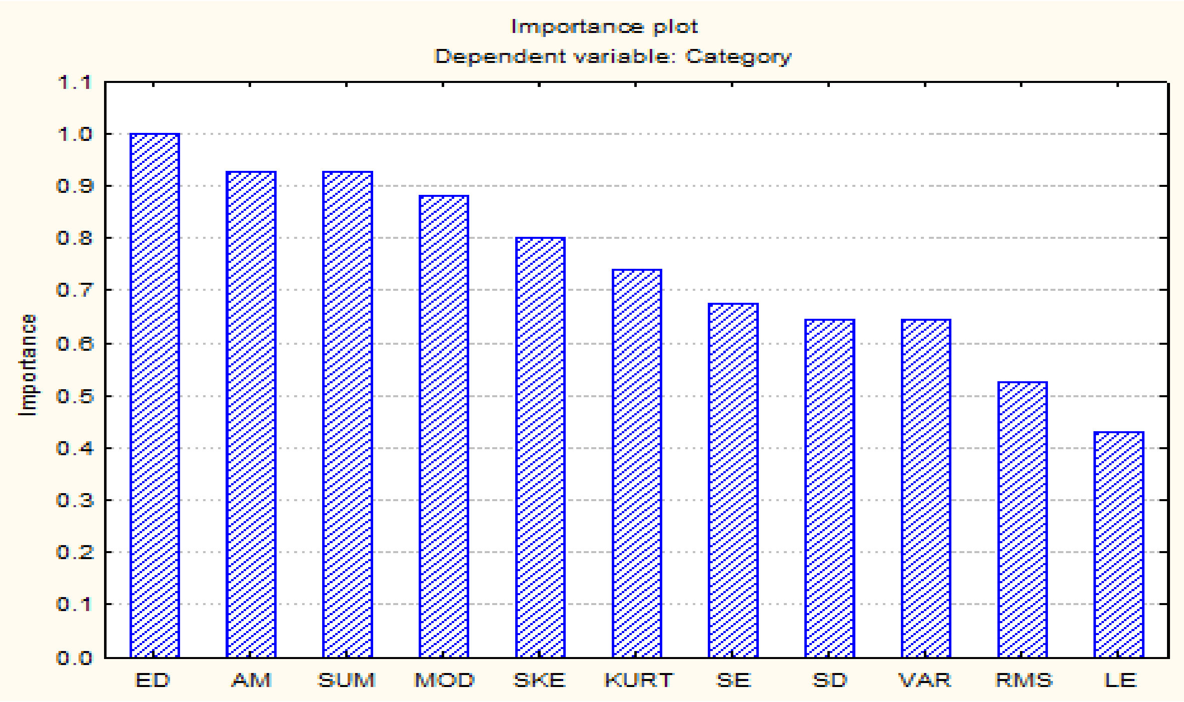

Figure 18:- A predictor importance plot showing the important features obtained through CART analysis.

Similarly, the important parameters in the predictor importance chart from BT analysis were noted down and, their plot was obtained using STATISTICA 9.1 software. SE was the importance parameter obtained.

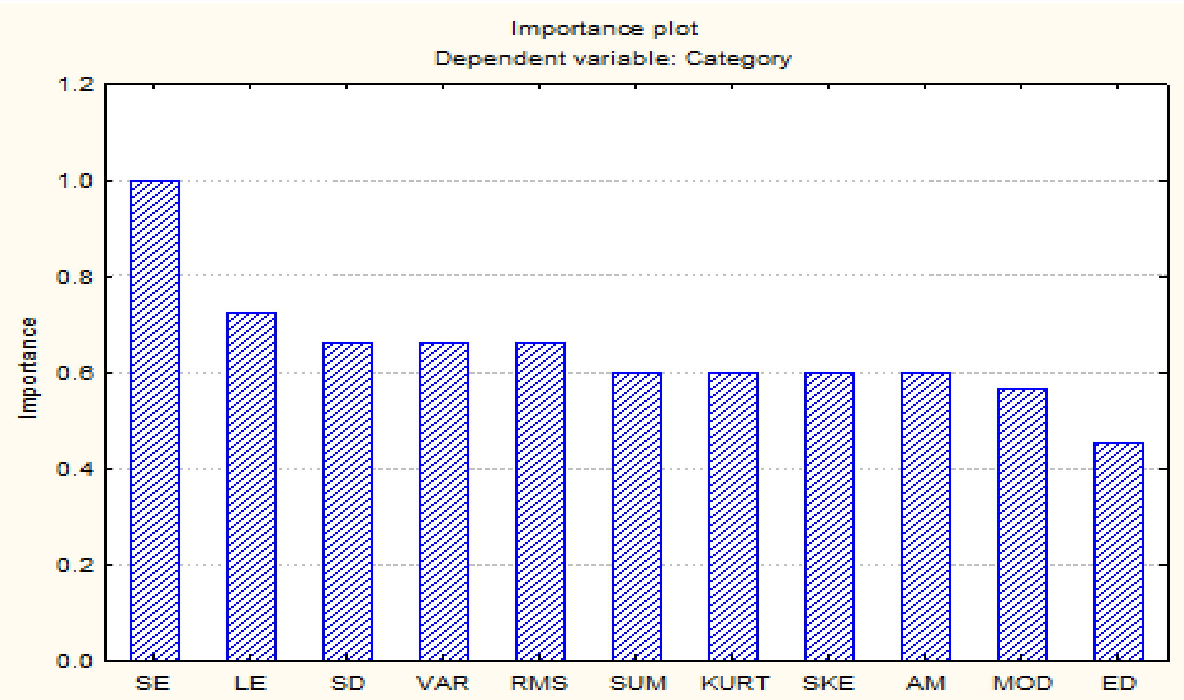

Figure 19:- A predictor importance plot showing the important features obtained through BT analysis

RMS, SUM and, LE were the importance parameter obtained from Random Forest in the importance plot.

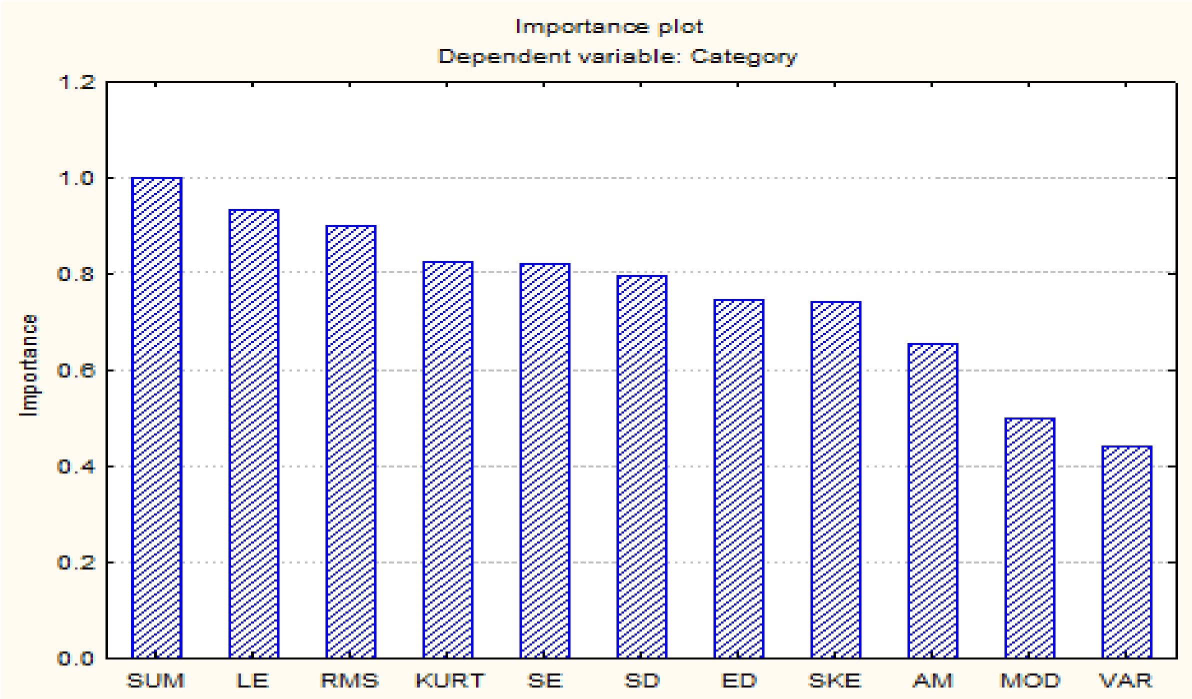

Figure 20:- A predictor importance plot showing the important features obtained through Random Forest classification

The confusion matrix tables obtained from CART analysis for RBF and, MLP using AM and, SUM as parameters are as shown below. (Table 7 and, Table 8). The corresponding ANN tabulation is given in table 9.

Table 7:- Confusion Matrix for RBF network

	CATEGORY –H	CATEGORY-N	Total
TOTAL	20.00	20.00	40.00
CORRECT	18.00	15.00	33.00
INCORRECT	2.00	5.00	7.00
CORRECT (%)	90.00	75.00	82.50
INCORRECT (%)	10.00	25.00	12.50

Table 8:- Confusion Matrix for MLP network

	CATEGORY –H	CATEGORY-N	Total
TOTAL	20.00	20.00	40.00
CORRECT	17.00	11.00	28.00
INCORRECT	3.00	9.00	12.00
CORRECT (%)	85.00	55.00	70.00
INCORRECT (%)	15.00	45.00	30.00

Table 9. Parameters of the RBF and MLP networks

Network	Features used	Classification efficiency	Algorithm	Error function	Hidden Act.	Output Act
RBF 2-12-2	AM, SUM	82.50%	RBFT	CE	Gaussian	Softmax
MLP 2-9-2	AM, SUM	70%	BFGS 5	SOS	Exponential	Exponential

5.3 Wavelet based time domain analysis

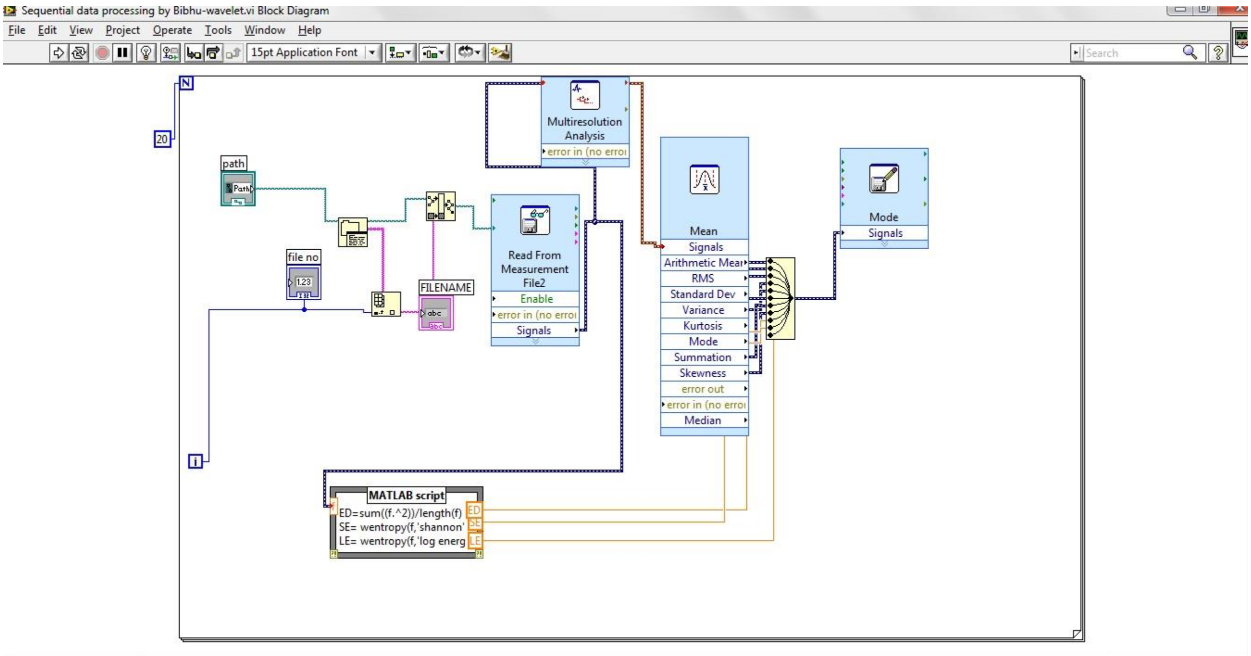

Figure 21: A block diagram of Lab VIEW code depicting time domain wavelet based ECG analysis

The important parameters in the predictor importance chart from CART analysis were noted down and, their plot was obtained using STATISTICA 9.1 software. Skewness (SKE) was the important parameter.

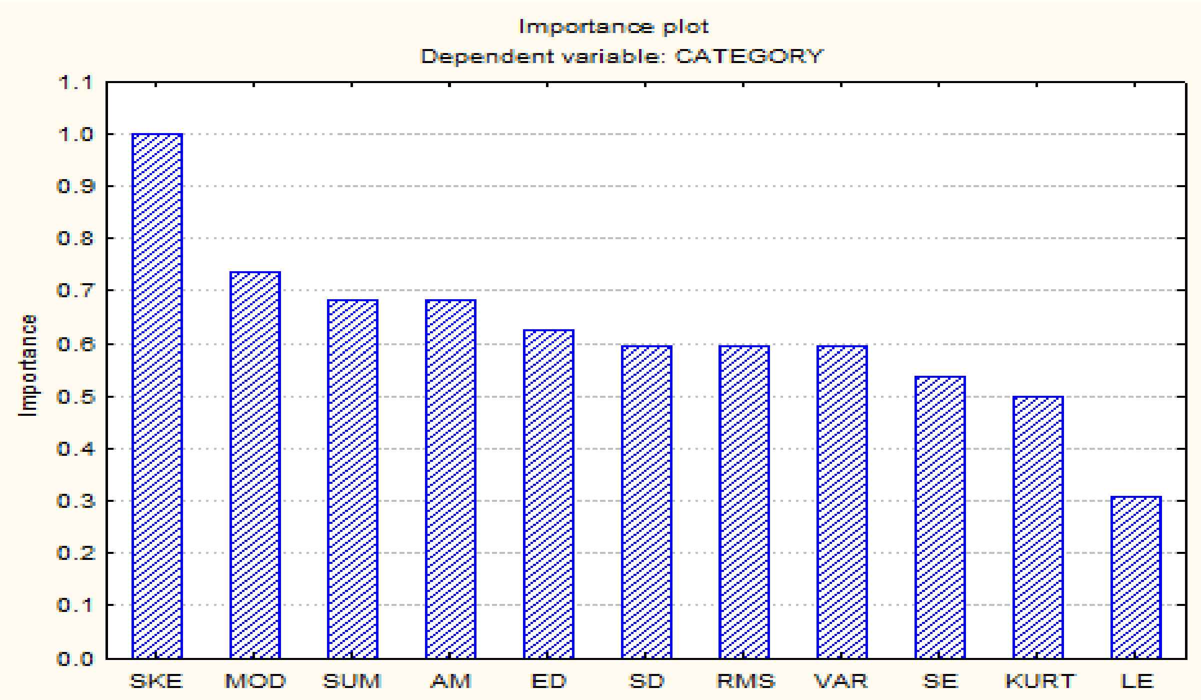

Figure 22:- A predictor importance plot showing the important features obtained through CART

The important parameters in the predictor importance chart from BT analysis were noted down and, their plot was obtained using STATISTICA 9.1 software. RMS, SD, Variance (Var), Kurtosis (KURT) and, Mode (MOD) were the important parameters.

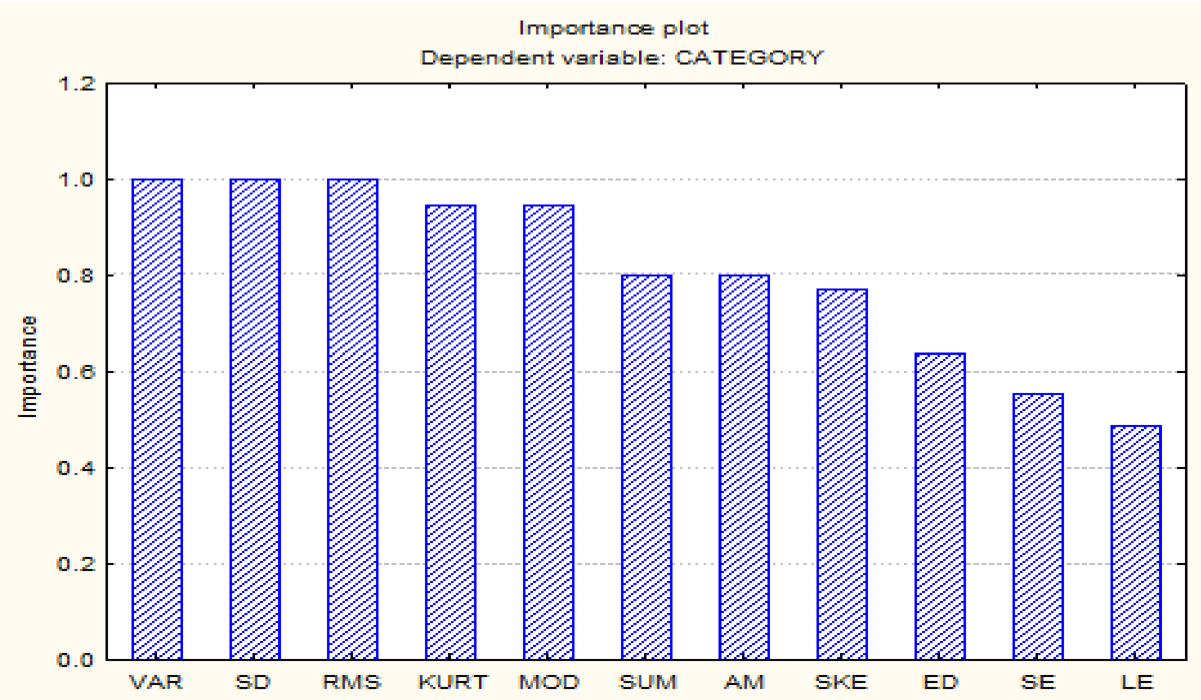

Figure 23:- A predictor importance plot showing the important features obtained through BT.

ED was the important parameter obtained through Random Forest.

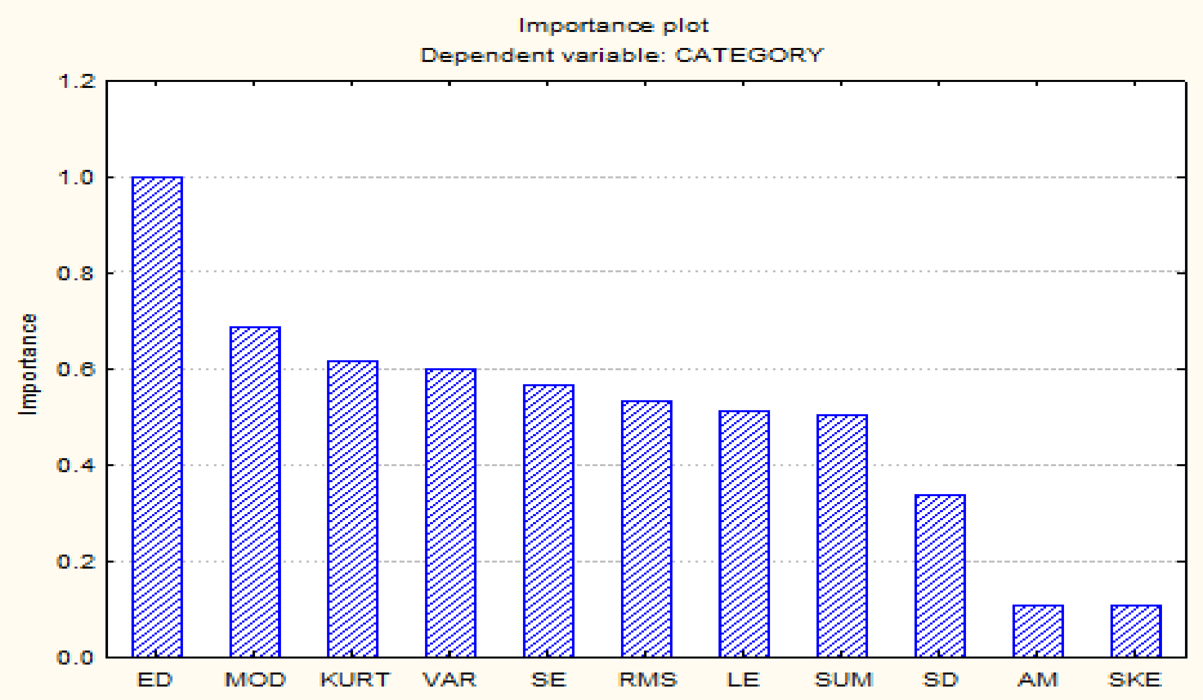

Figure 24:- A predictor importance plot showing the important features obtained through Random Forest.

The confusion matrix tables obtained from BT analysis for RBF and, MLP using RMS and, SD as parameters are as shown below. (Table 10 and, Table 11). The corresponding ANN tabulation is given in table 12.

Table 10:- Confusion Matrix for RBF network

	CATEGORY –H	CATEGORY-N	Total
TOTAL	20.00	20.00	40.00
CORRECT	13.00	15.00	28.00
INCORRECT	7.00	5.00	12.00
CORRECT (%)	65.00	75.00	70.00
INCORRECT (%)	35.00	25.00	30.00

Table 11:- Confusion Matrix for MLP network

	CATEGORY –H	CATEGORY-N	Total
TOTAL	20.00	20.00	40.00
CORRECT	13.00	12.00	28.00
INCORRECT	7.00	8.00	12.00
CORRECT (%)	65.00	60.00	62.50
INCORRECT (%)	35.00	40.00	37.50

Table 12. Parameters of the RBF and MLP networks

Network	Features used	Classification efficiency	Algorithm	Error function	Hidden Act.	Output Act
RBF 2-12-2	RMS, SD	82.50%	RBFT	CE	Gaussian	Softmax
MLP 2-9-2	RMS, SD	70%	BFGS 5	SOS	Exponential	Exponential

The various classification efficiency using various HRV parameters were measured and, noted down neatly. In general a classification efficiency of greater 80% is observed which is considered quite good for ANN classification [29].

6. DISCUSSIONS

The different non-linear classifiers gave different results. CART, BT and, Random Forest all have been employed to obtain different classification results using ANN. There weren't many significant features as obtained from the t-test linear classifier. But, it was as expected too because HRV is not a linear phenomenon. The experimental setup wasn't ideal and, there were a few other crucial factors which could not be controlled. However, the similarity in a few parameters of HRV and, time domain with that of ANN confirms us that the presence of horror clips does affect the ECG and, thereby the HRV and, ANS of an individual. More sophisticated set-up was avoided due to privacy reasons. The tree structures obtained from CART, BT and, Random Forest go in a long way to tell us about the arrangement of terminal and, non-terminal nodes [30]. The mean and, the variance values in the tree graph help us get a rough estimate of whether a value will go to LF or, HF or, LF/HF box and, so on.

HRV affects the ANS directly. This was proved by the impact of HRV parameters on both linear and, non-linear classifiers for ANN classification whereas, time domain features and, wavelet based features weren't so effective in giving difference in classification values. A few parameters have been well documented earlier and, these were significant from our experiment also. (LF, HF, LF/HF and, LFn.u.).

7. CONCLUSION

The high classification values obtained from the importance predictor when tested in ANN as inputs suggests that HRV has a deep effect on ANS. The effect of horror on HRV parameters could also be established from the above results. The effect of HRV parameters on ANS and, the heart were not as prominent with the linear t-test classifier as expected due to variability in the heart rate caused by heart rate variability (HRV) parameters. The ECG signal extraction serves as a crucial step in HRV parameter analysis and, its effect on the physiology of ANS and, heart. The impact of noise is also significant. The subtle effect of the clamp electrodes and, the application of electrolytic gel on the different hand positions as given by the EKG sensor is influential in the final HRV readings.

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APPENDIX – I

NITRKL/IEC/FORM 2

NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA
INSTITUTIONAL ETHICS COMMITEE

Date:

ACCEPTANCE FORM FOR PURPOSED RESEARCH WORK

As a member of committee we have reviewed and here by approve the purposed research work plane which would be reviewed from time to time for the safeguard of Institutional Ethics Guidelines.

Name of Research Project: Development of biosignal (EOG, EMG, ECG and EEG) Acquisition hardware, signal acquisition, signal processing and use of the developed hardware in controlling human-computer interface devices

Name of Principal Investigator: Dr. Kunal Pal

Name of Researcher:

Institutional Ethical Committee Members:

1. CHAIRMAN: Dr. Saroj K Mishra
2. MEMBER SECRETARY: Dr. K. Pramanik 13/12/2013
3. MEMBER: DR. D. R. Mishra 13/12/13
4. MEMBER: MR. BIJOY B. MATHUR 13/12/2013
5. MEMBER: Dr. Madhusmita Mishra 13/12/13
6. MEMBER: 13/12/2013 Mohan Roy
7. MEMBER: Prasanjeet Sarkar 13/12/13
8. LEGAL EXPERT: Ashok Kurup 13/12/13

APPENDIX – II

DEPARTMENT OF BIOTECHNOLOGY & MEDICAL ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

EFFECT OF COMEDY & HORROR CLIPS ON THE PHYSIOLOGY OF ANS & HEART

Volunteers History &Consent Form

NUMBER: **Date:**

1. General Information

1. Name (Mr./Ms/Mrs.)______________________________
2. Date Of Birth ________________________Age______
3. Address____________________________________
4. Contact No ____________E-Mail __________________
5. Body Weight (kg)______Height (mt)______BMI (kg/m^2)________

2. Medical information

1. **Medical History**
   *a) None*________________
   *b) Specify If Any*____________
2. **Surgical History**
   *a) None*________________
   *b) Specify If Any*____________
3. **Gynecological Problem**
   a) None ________________
   b) Specify If Any ____________
4. **Drug History**
   a) None ________________
   *b) Specify If Any*____________
5. **Sleeping Disorder**
   a) None ________________
   *b) Specify If Any*____________
6. **Appetite**
   *a) None*________________
   *b) Specify If Any*____________
7. **Diet Habit**
   a) Vegetarian ______________
   *b) Non-Vegetarian*____________
   *c) Eggetarian*______________

DEPARTMENT OF BIOTECHNOLOGY & MEDICAL ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

3. Habitual information

1. Exercise

a) Yes _____________

b) No _____________

c) If Yes, What Type____

d) Frequency And Activity

i) Regularly____

ii) Weekly ____

iii) Rarely ____

2. Smoking

a) Yes _____________

b) No _____________

c) If Yes, Frequency of Smoking

i) Regularly____

ii) Weekly ____

iii) Occasionally ____

Any other comments you may want to make:_________________________________

____

Declaration:

I Mr. /Miss. _______________________ hereby declare that I have been verbally made aware about the details of the study and the risk involved in it. I give my consent to the below-mentioned researchers to acquire and analyze the ECG signal. I understand that the results obtained from the analysis of the ECG signals acquired will be used to compile a report which will lead to the B.Tech thesis dissertation of Mr Siddharth Nayak. I also give my consent to them to use the results for writing scientific manuscripts and dissemination to the scientific world either digitally or in print-form.

....
Signature of the participant with date

Researchers involved in the study

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