BIOFEEDBACK: ANALYSING IMPACT OF ENERGY UTILIZATION & ENERGY RECOVERY STATES ON WELLBEING

Major Project Report

Submitted in Partial Fulfillment of the Requirements for the Degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER ENGINEERING

By

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May 2020

CERTIFICATE

This is to certify that the Major Project Report entitled "Biofeedback: Analysing the Impact of Energy Utilization & Energy Recovery States" submitted by Ms. Shah Himani Shitalkumar(16BCE057) towards the partial fulfilment of the requirements for the award of degree in Bachelor of Technology in the field of Computer Engineering of Nirma University is the record of work carried out by her under our supervision and guidance. The work submitted has in our opinion reached a level required for being accepted for examination. The results embodied in this major project work to the best of our knowledge have not been submitted to any other University or Institution for award of any degree or diploma.

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TO WHOMSOEVER IT MAY CONCERN

This is to certify that Shah Himani Shitalkumar (16BCE057) a student of B.Tech in Bachelor of Technology from Institute of Technology, Nirma University worked in Wellness Space LLP as a Healthcare Data Analytics Intern during. During this period Jan 2 to May 15 she was found regular and had done her project on Evaluation of " Biofeedback Analysing the Impact of Energy Utilization & Energy Recovery States for Wellbeing " under my supervision.

She has worked with utmost dedication and high level of engineering and analytical competence.We wish her all the best for her future endeavors.

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Undertaking for Originality of the Work

I, Shah Himani Shitalkumar Roll No. 16BCE057, give undertaking that the Major Project entitled " Biofeedback Analysing the Impact of Energy Utilization & Energy Recovery States for wellbeing" submitted by me, towards the partial fulfilment of the requirements for the degree of Bachelor of Technology in Computer Engineering of Nirma University, Ahmedabad, is the original work carried out by me and I give assurance that no attempt of plagiarism has been made. I understand that in the event of any similarity found subsequently with any other published work or any project report elsewhere; it will result in severe disciplinary action.

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First and foremost, I would like to thank our Mentor Gunjan Trivedi, Co-Founder at Society of Energy and Emotions (SEE)-Wellness Space for his tremendous support and constructive suggestions throughout the making of this project. I would also like to give my special appreciation to Rajan bhai, Dhwani Ma'am, Friends, Family and the LD team for volunteering to be part of the data collection.

Further, I would also acknowledge the support of our internal guide Preksha Pareek, Assistant Professor at Nirma University for being kind enough to add her suggestions. All the combined efforts and results resulted in the success of this project.

ABSTRACT

This project revolves around understanding how stress and physical activity impact energy balance in daily life. How do humans recover from these energy consuming activities? Stress has a huge impact in causing mental or physical imbalance. And therefore, it is of utmost importance to determine what percentage of our daily activities fall into energy expenditure state or energy recovery state. Here, we would analyse the effect of stress in the Autonomic Nervous System (ANS) by closely working on 41 HRV parameters and 3 tri-axial Accelerometer parameters.

The main goal is to determine the time duration to which the user is exposed to stressful activity. Including visualization of the most contributing parameters of the ANS (i.e. Parasympathetic Nervous System or PNS and Sympathetic Nervous System or SNS).

24 hours ECG Data recording of 40 individuals, using Bittium Faros 180 sensor is analysed using Machine Learning and Deep Learning approaches to accurately differentiate ES (Emotional Stress) from PA (Physical Activity). Combining above activities causes consumption of energy. Synthetic Minority Oversampling Technique or SMOTE has been used to solve the problem of overfitting due to imbalance in instances of each class. The above approach delivers us an accuracy of 98.44 %. Using ClassA Framework, the analysis provided the percentage distribution of both energy recovery and stress inducing states in a pie-chart form and case studies.

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

ECG:	Electrocardiogram
HRV:	Heart Rate Variability
PNS:	Parasympathetic Nervous System
SNS:	Sympathetic Nervous System
EE:	Energy Expenditure (kcal/min)

CONTENTS

Chapter 1: Introduction

1.1 About the Company

1.1.1 Introduction of the Company

Wellness Space centers around relapse treatment, internal identity treatment, instructing, sound mending, official training, neuro etymological programming (NLP), hypnotherapy and previous existence relapse through individual and group change.

Society of Engineering (SEE) at Wellness Space chips away at undertakings and research considers and teams up with rumored foundations and has the chance to be available in many contextual analyses. As of late, Wellness Space has worked with Indian Institute of Public Health, Gandhinagar to offer an elective to the Masters Students on Quality of life and Chronic sickness.

Figure 1.1 Wellness Space Logo

1.1.2 Quality Policy

Common challenges Wellness Space help with include anxiety, depression, fear, phobia, stress, goal setting, identifying life purpose and any situations mainly driven by emotions and energy. Their publications, case studies related to quality of life and chronic disease and the global experience enables us to provide meaningful solutions to our clients based on scientific evidence.

1.1.3 Resources

Wellbeing Space has decided to advance and investigate approaches to quantify the viability of their business related to human vitality and feelings. This is overseen by comprehension and estimating human physiology, vitality and feelings by means of the estimation of Heart Rate Variability, human bio-field and built up reviews. A few advancements and overviews incorporate pulse fluctuation (HRV) and ECG gadgets, Bio-Well GDV (Gas Discharge Visualization) gadget for estimating bio-field, passionate weight and human vitality, reviews, for example, WHO-5 prosperity, etc. Such apparatuses give us where to test as well as distinguish what's working and how the customer is reacting to the mediations.

1.2 Research Project Profile

1.2.1 Title

The project title is providing Biofeedback Analysing the Impact of Energy Utilization & Energy Recovery States for wellbeing. Their daily activities like sleep, Meditation, Physical Activity and Emotional stress can be monitored.

1.2.2 Defining the System

This main aim of the proposed work is to enhance the lifestyle of people: improve their knowledge about the impact of stress on them so that future chronic diseases can be avoided. Prevention is always better than cure, this will allow users to take charge of their own body.

Following are major steps:

- ➢ Choose the labelled data file generated from Kubios in .csv file as input
- ➢ Classification into 4 Major categories using SPSS
- ➢ Output with percentage of stressful activities

Kubios Software:

The most important HRV parameters are the parasympathetic nervous system (PNS) and sympathetic nervous system (SNS) indexes. This has proven to be a huge advantage for our scientific research project for detection of percentage stress and recovery.

SPSS:

It is a software platform offering advanced statistical Analysis, vast library for Machine Learning and transparent use in deployment of applications. It mainly does Hypothesis Testing, finds hidden patterns in data and improves efficiency.

1.2.3 Objectives and Purpose

To give away every individual an opportunity to monitor their own wellbeing. They shall use this platform for following purpose:

- Self-Monitoring

The outcome can help clients to monitor their daily recovery in order to live a healthy life based on the reliable statistics of physiological recovery. This is useful for professional athletes and sports players to optimize their training duration. This can also be used by common people who are enthusiastic to know about the level of stress in daily bases. Students, fireworkers, Houseworkers, workaholic people can measure the percentage of overall bodily stress and recovery.

- For Research purpose:

  This live data can be used for anomaly detection in individuals via monitoring the RR interval. This can provide a huge scope for the research domain whether it is the finding fraction of REM and NREM sleep in the recorded sleep pattern.

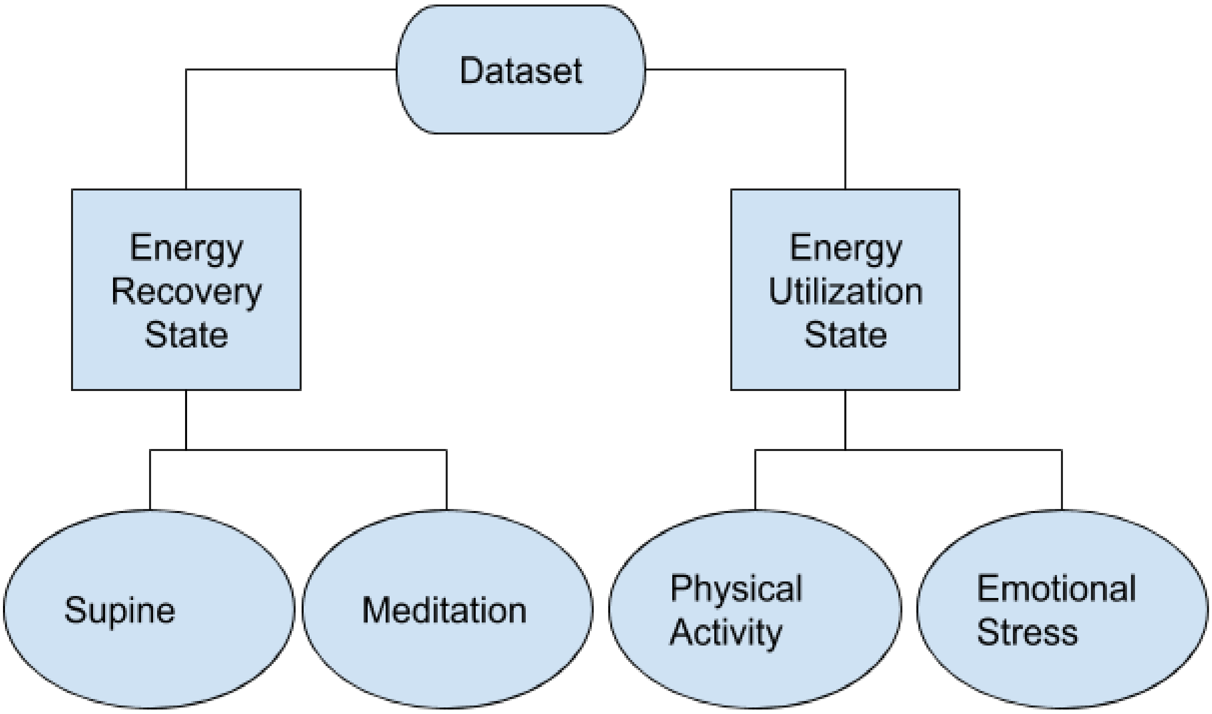

Figure 1.2 Represents the possible classification and subclassification of dataset.

1.2.4 Hardware and Software Requirements

Following are system requirements:

- ➢ Hardware Specifications
  - Processor: Intel core i3 processor
  - RAM: minimum 8 GB
- ➢ Software Specifications
  - OS can be Windows or Linux
  - Brower: Chrome

Chapter 2:   System Design

2.1   Flow Diagram

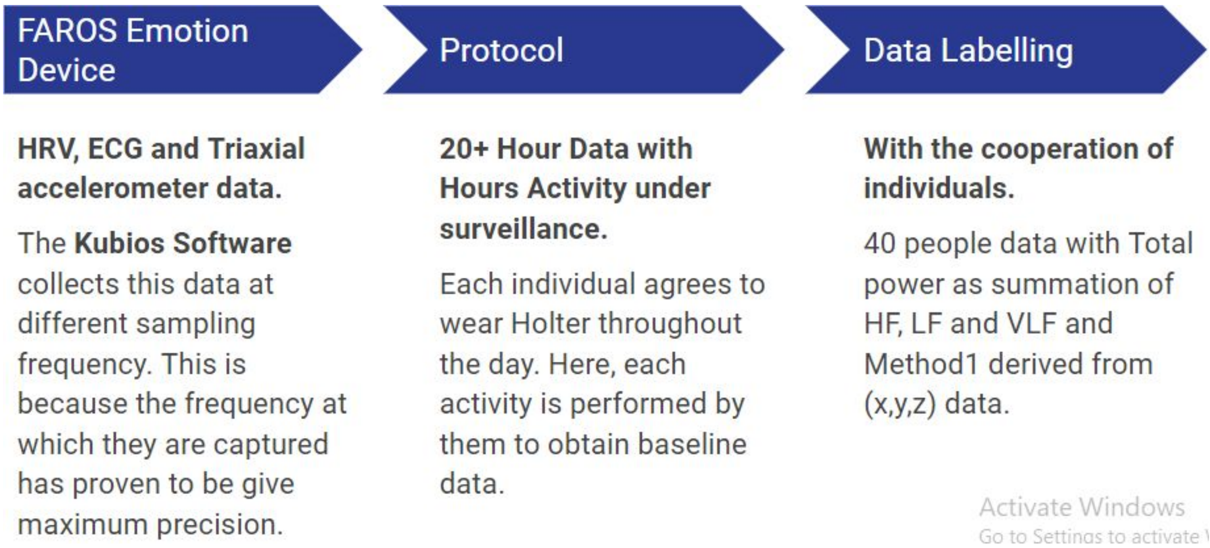

Figure 2.1 Data Acquisition

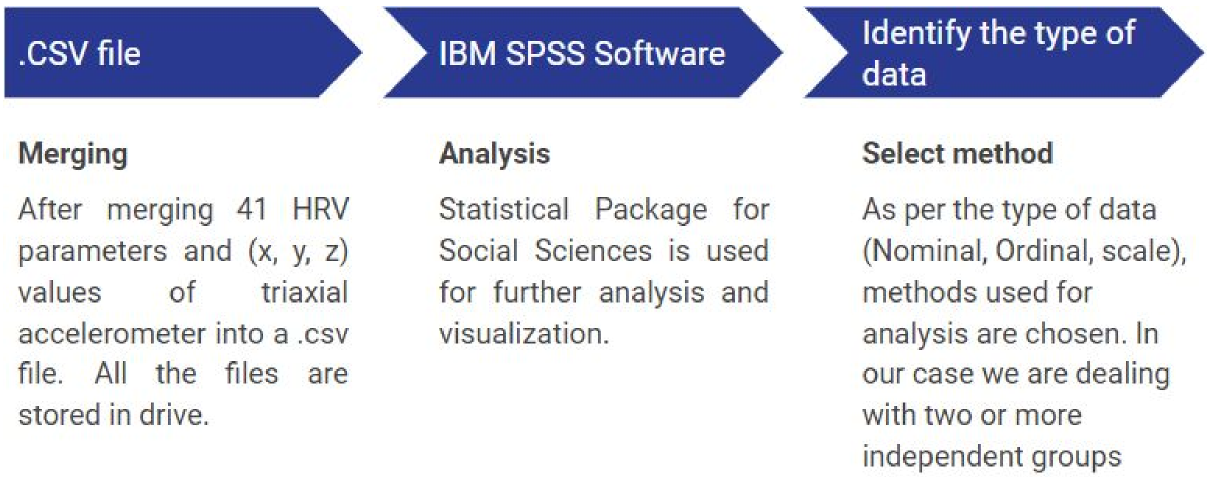

Figure 2.2 Procedure

Chapter 3: User Manual

3.1 Classification

3.1.1 Description

In this project, 40 participants with each having 20 hour data has been classified into following categories:

Activity	Label	Time
Emotional Stress (ES)	1	63 hours 22 mins
Meditation	2	71 hours 2 mins
Physical Activity (PA)	3	29 hours
Supine	4	270 hours 2 mins

Table 3.1 Listing details of each activity

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	4093	15.6	15.6	15.6
	2	4268	16.2	16.2	31.8
	3	1739	6.6	6.6	38.4
	4	16210	61.6	61.6	100.0
	Total	26310	100.0	100.0	

Figure 3.1 Represents the number of data points for each class

3.1.2 Requirement

Software Requirement:

- ➢ Kubios Software Premium Version
- ➢ EDF viewer
- ➢ Google Colab

Hardware Requirement:

- ➢ Bittium Faros 180 sensor
- ➢ Three Electrodes and 2 wires

3.1.3 Methodology Adopted and Data Extraction

Dataset has been recorded using a Bittium Faros 180 sensor. The minimum length of the data procured has been set to 20 hours of ECG data. The data consisted of 40 recordings of each volunteer.

The data collected through Bittium Faros Sensor had the following parameters:

- ECG signal values digitized at 25 Hz
- R-R interval (in milliseconds)
- Acceleration in X, Y and Z directions.

Then, the data is reduced after removing the noise. This is done with the help of a software EDF viewer which is used to reduce signals. Two more preprocessing were done using Kubios.

1. Artefact Correction

2. The values of parameters were calculated for a window of 60 seconds. ie. 1 minutes.

The 24-hour signal is recorded in edf format. First, the edf format is converted into a comma-separated file (csv) which is then preprocessed to be used in the desired form.All these 42 parameters were calculated from the ECG signal and R-R interval data.

For the accelerometer data to be useful, we needed to calculate the average acceleration over that 1 minute period. As the sampling was of 25 Hz, we had values from the Bittium faros sensor every 0.04 seconds. So, we needed to run a moving average over the entire accelerometer data. After performing the moving average we integrated the respective accelerometer data to obtain the entire dataset.

The entire database is built by labelled according to the activities that the subjects carry out during that period of wearing the device.

The convention used for labelling is as shown below-

State	Activity	Assigned Number
Energy Utilization	Emotional Stress	1
Energy Recovery	Meditation	2
Energy Utilization	Physical Activity	3
Energy Recovery	Supine	4

Table 3. 2 Shows Mapping with the assigned numbers for each class

This prepares the data for training using ML. The dataset is then divided into training and testing tests. The training dataset is processed using CNN Model for the classification. The testing dataset is used to evaluate the performance of the machine learning model in accomplishing that particular task. Accuracy is used as a metric to determine the efficiency of the classification model. The trained model can now be used to classify any unknown instance.

Overall Process:

- Collect data using Bittium Faros 180 sensor
- Analyze our collected data in Kubios and remove any noise using edf viewer
- Convert edf file into csv using Kubios after artefact correction
- Extract accelerometer data using edf viewer using edf viewer and integrate the dataset
- Label the dataset using the convention as described
- Process it using Various Machine Learning Methods

Chapter 4: Proposed Method

4.1 Statistical Analysis

4.1.1 Condition Tests

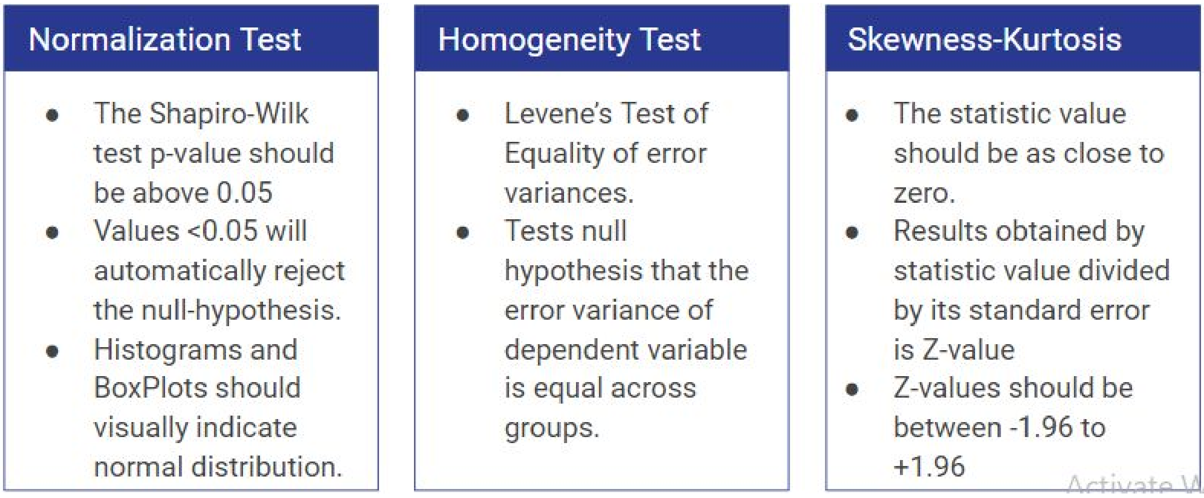

Figure 4.1 Kruskal Wallis Test or One-way ANOVA

Objective: These tests are conducted to find out appropriate methods for analysing the strength of each of the 44 parameters. Kruskal Wallis or One-way ANOVA?

Following were the results of above conducted tests:

- A Shapiro-Wilk's test (p>0.05) and visual inspection of their histograms, normal Q-Q plots and box-plots show that the HRV parameters are approximately normally distributed.
- The Skewness and Kurtosis are in range -1.96 to +1.96
- But, Leven's p = (value is <0.05) thereby rejecting the null hypothesis of Homogeneity Test.
- If any one of the tests fail then ANOVA cannot be applied. Instead Kruskal-Wallis Test is used for non-parametric data.

Therefore, we used Kruskal Wallis Method for analysing.

4.1.2 Kruskal-Wallis Test

Kruskal Wallis Test: This is a one-way analysis of variance used to determine whether there is any statistically significant difference between two or more independent groups of equal or different sample sizes. This is a non-parametric test, where there is a pair-wise comparison between Supine, Mental Arithmetic, Meditation, and Physical Activity.

Platform used for Analysis : SPSS

Description of input data: Input is Labelled .CSV file

Objective: To know the collected data and it's behavior so that appropriate ML methods can be used.

To perform analysis using the Kruskal-Wallis test our data should satisfy the assumptions. As per the results shown above, our data satisfies all the criterias mentioned in figure 4.1.

Carried by following steps:

Step 1: Generate Z Scores to scale up all the values using descriptives

Z Score: describes the position of the actual score in terms of its distance from the calculated mean, measured in SD units. It makes easier to compare scores of different variables by generating a standard distribution (Normalization).

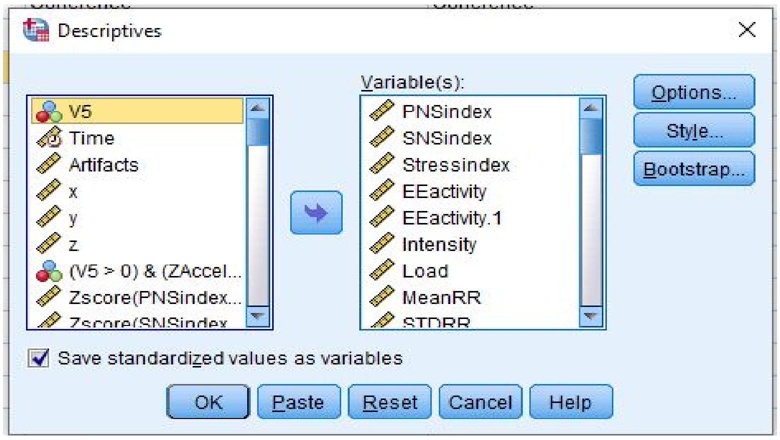

Figure 4.2

Step 2: Open Non parametric tests ----> independent samples

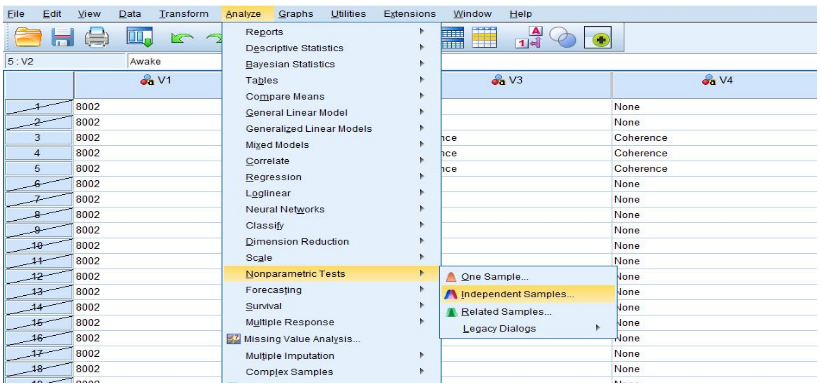

Figure 4.3

Step 3: Select all 44 parameters in Z Score values as test files and group them by Label.

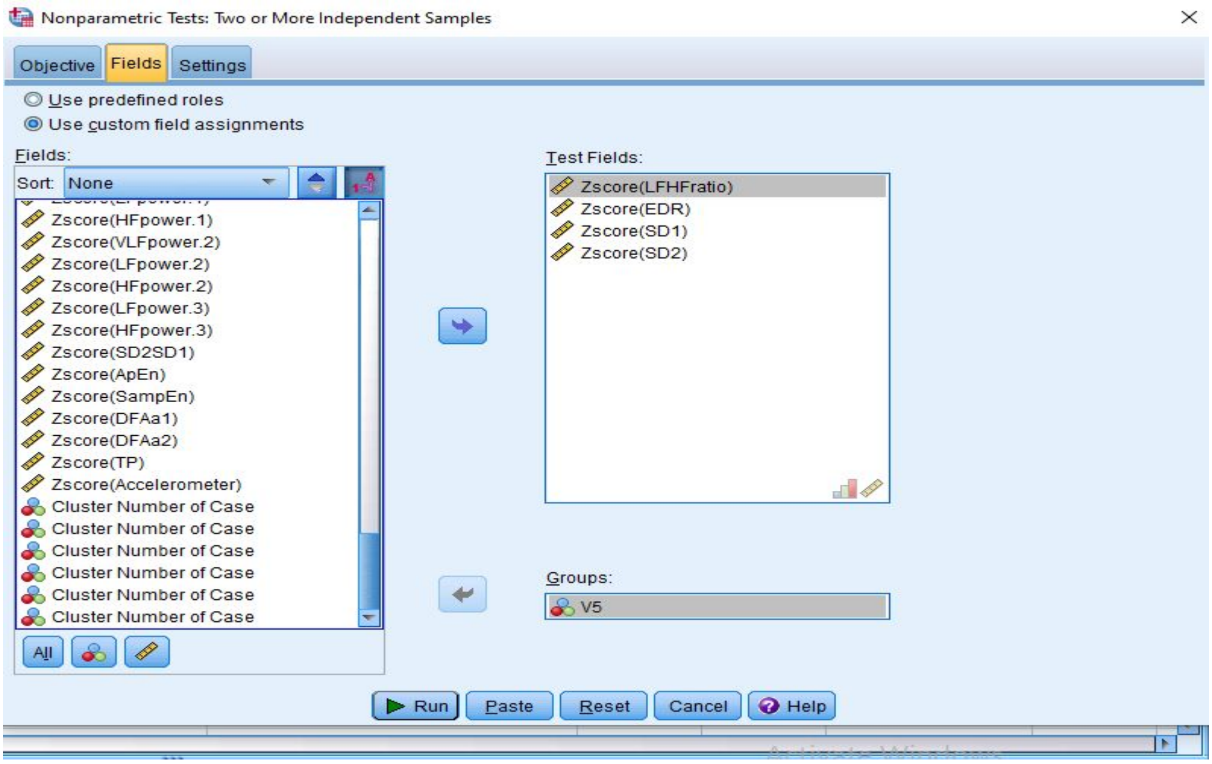

Figure 4.4

Step 4: Choose Kruskal Wallis 1 way ANOVA for pairwise comparisons

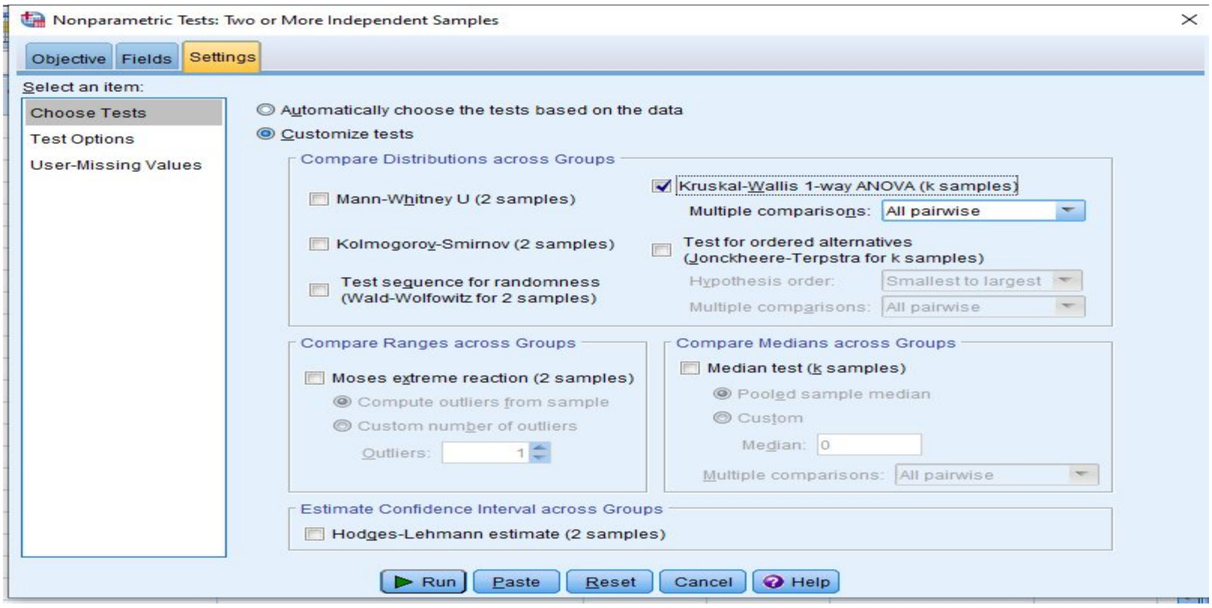

Figure 4.5

vDescription And Advantages: This table is displaying the outcome of the above conducted test. Thus, we obtain the 14 significant parameters to reduce complexity of ANN, K-Means, CHAID, CRT and Random Forest. These are used for Machine Learning and Deep Learning Methods. The significance level during the test is 0.05 generally, here we have adjusted significance values by Bonferroni correction for multiple tests (for ties).

PARAMETER	TEST	P-Value	DIFFERENCE as per Bonferroni correction (Pairwise Comparison)	SIGNIFICANCE
PNS index TINN pNNxx Mean RR STDRR Mean HR Min HR Max HR NNxx EE Activity SD2/SD1 EDR DFA1 DFA2 Load	Kruskal-Wallis Test	<0.0001	All have p -value <0.05	Best for differentiating all the mentioned activities
Intensity	Kruskal-Wallis Test	<0.0001	4-2 p-value(1>0.05) Rest have p -vaue<0.05	Problem differentiating between two recovery activities (Sleep & Meditation)
SNS index	Kruskal-Wallis Test	<0.0001	4-2 p-value(0.083>0.05) Rest have p -value<0.05	Problem differentiating between two recovery activities (Sleep & Meditation)
Stress Index	Kruskal-Wallis Test	<0.0001	1-3 p-value (0.057>0.5) Rest have p-value<0.05	Problem differentiating between two stress inducing activities (Stress & Physical Activity)

PARAMETER	TEST	P-Value	DIFFERENCE as per Bonferroni correction (Pairwise Comparison)	SIGNIFICANCE
LF/HF	Kruskal-Wallis Test	<0.0001	1-3 p-value (1>0.5) Rest have p-value<0.05	Problem differentiating between two stress inducing activities (Stress & Physical Activity)
Total Power	Kruskal-Wallis Test	<0.0001	1-3 p-value (0.089>0.05) Rest have p -value<0.05	Problem differentiating between two stress inducing activities (Stress & Physical Activity)
HRVTi	Kruskal-Wallis Test	<0.0001	1-3 p-value (0.567>0.05) Rest have p -value<0.05	Problem differentiating between two stress inducing activities (Stress & Physical Activity)
RMSSD	Kruskal-Wallis Test	<0.0001	1-3 p-value (0.018>0.05) Rest have p -value<0.05	Problem differentiating between two stress inducing activities (Stress & Physical Activity)
SD1	Kruskal-Wallis Test	<0.0001	1-3 p-value (0.018>0.05) Rest have p -value<0.05	Problem differentiating between two stress inducing activities (Stress & Physical Activity)

Table 4.1 Representing the significance of each parameter as per the Kruskal Wallis Test

4.1.3 PNS, SNS And EE Activity

PNS Index Parasympathetic nervous system activity is known to decrease heart rate and increase heart rate variability.

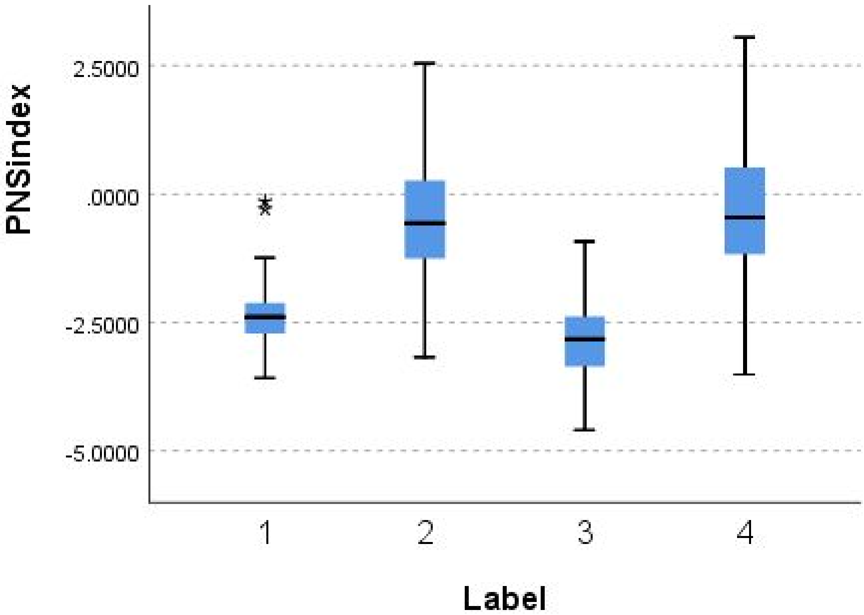

Figure 4.6 PNS tends to amount close to zero during Energy Recovery states (Meditation and Sleep)

A PNS or SNS index value of zero means that the parameters reflecting parasympathetic or sympathetic activity are on average equal to the normal population average. Correspondingly, non-zero PNS index values describe how many SDs below i.e. negative values or above i.e. positive values the normal population average the parameter values.

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
PNSindex	26310	9.4384	-4.5951	4.8433	-.767711	.0092374	1.4983338	2.245
Valid N (listwise)	26310							

Figure 4.7 Detailed description of PNS index

SNS Index the sympathetic nervous system activity having the opposite effect on heart rate and heart rate variability, i.e. it increases HR and decreases HRV.

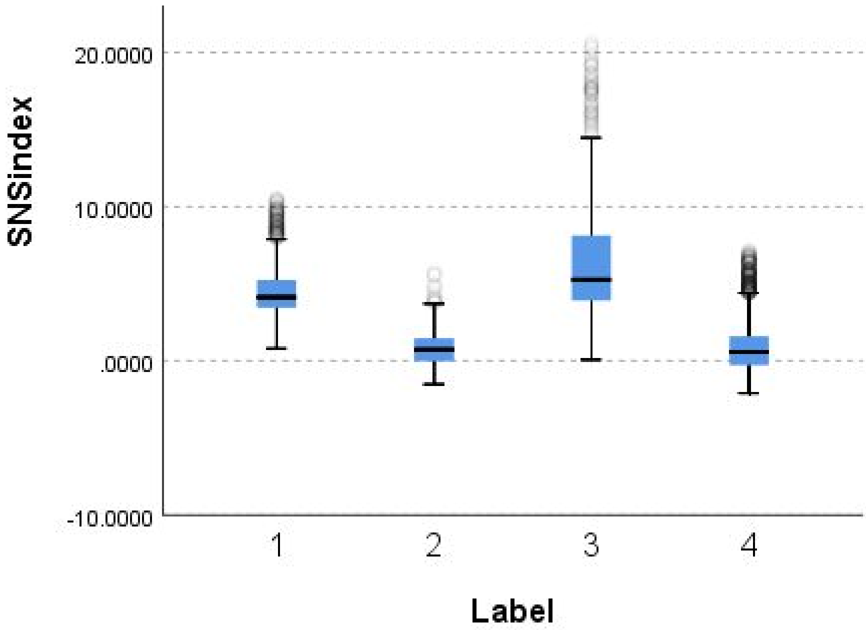

Figure 4.8. SNS tends to amount close to zero during sleep and Meditation.

Instantaneous EE(kcal/min) is computed using heart rate, body weight, height, and age. It provides the distribution of energy throughout the day. HRV Kubios calculated this using Keytel's formula.

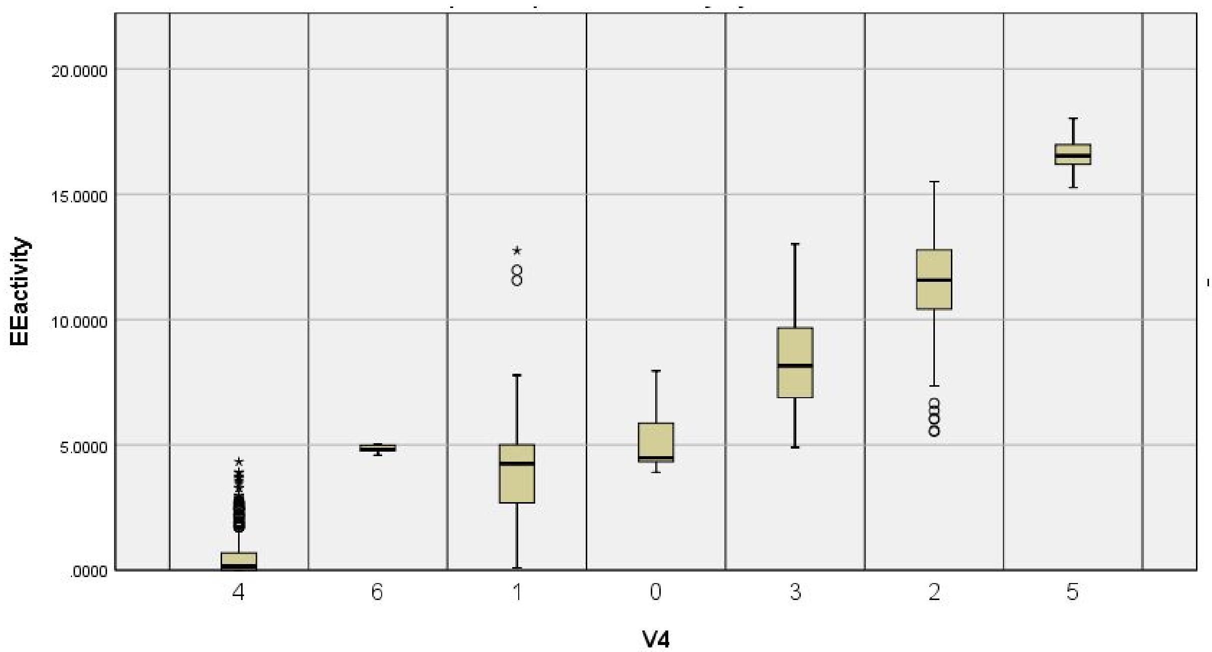

Figure 4.9. EE Activity for static and dynamic activities refer table 4.6

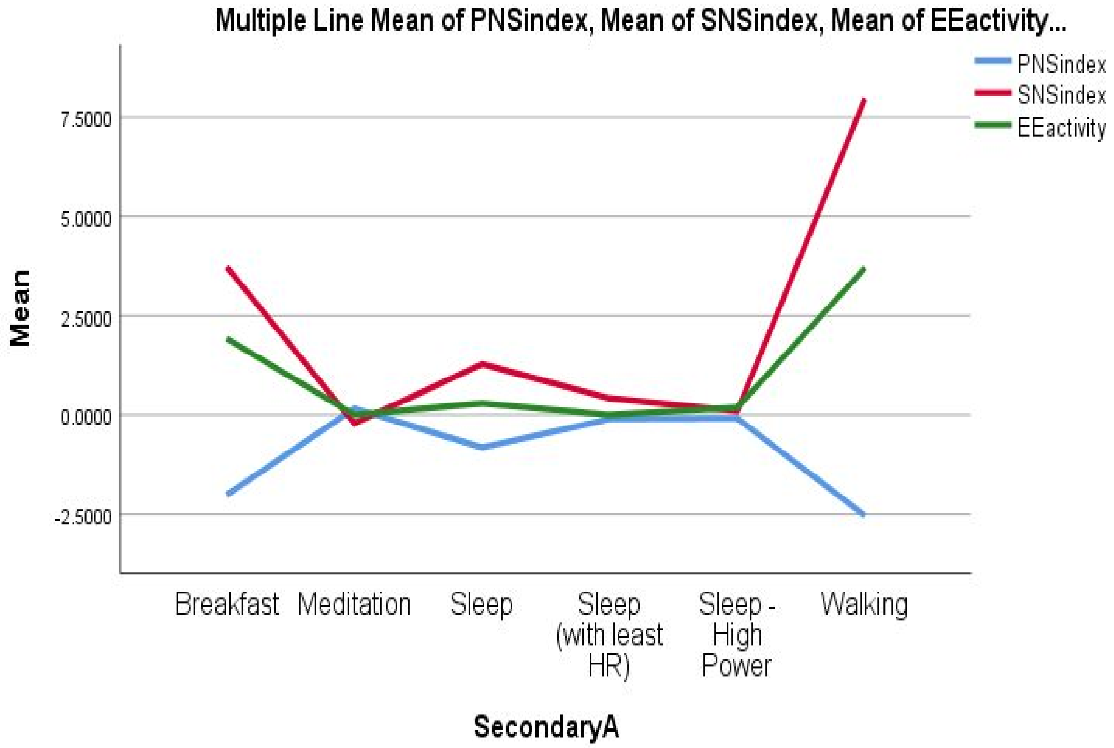

Figure 4.10 During Meditation and sleep PNS, SNS and EE Activity tends to zero.

4.1.4 Stress Index And Intensity

Stress Index (The Baevsky's stress index)

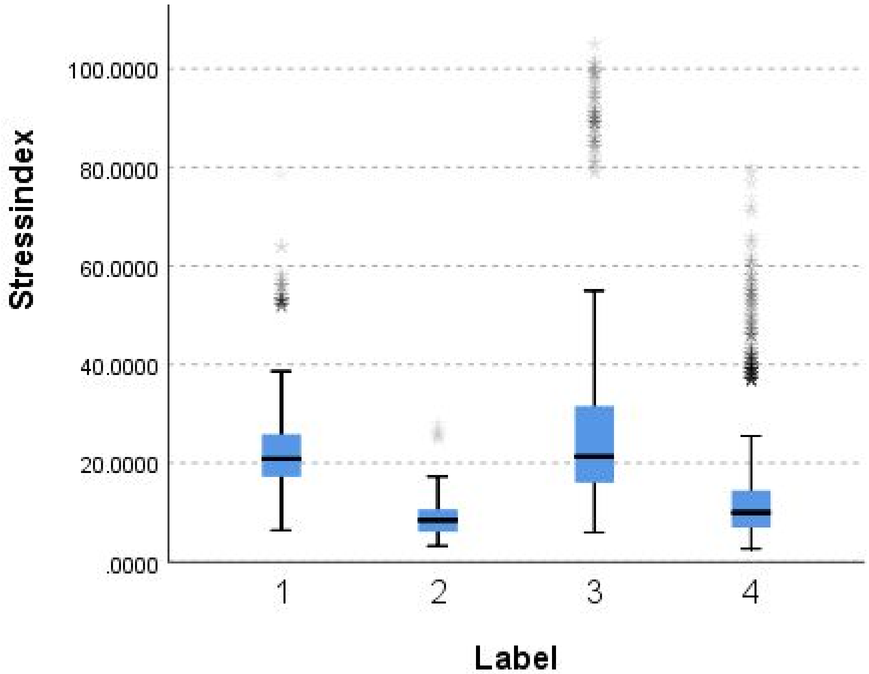

Figure 4.11. Stress index is close to Zero while sleeping and Meditation.

TRIMP is computed in Kubios by using beat-to-beat HR values computed according to Banister's model separate for both Male and Female. This is directly linked to the training intensity.

$TRIMP = T * \Delta HR * 0.64e^{1.92*\Delta HR}$ (Male) - Equation 4.1

$TRIMP = T * \Delta HR * 0.86e^{1.67*\Delta HR}$ (Female) - Equation 4.2

Where T is the duration of exercise and ΔHR is the heart rate reserve ratio.

Figure 4.12 The value increases with the increase exponentially as a function of exercise intensity.

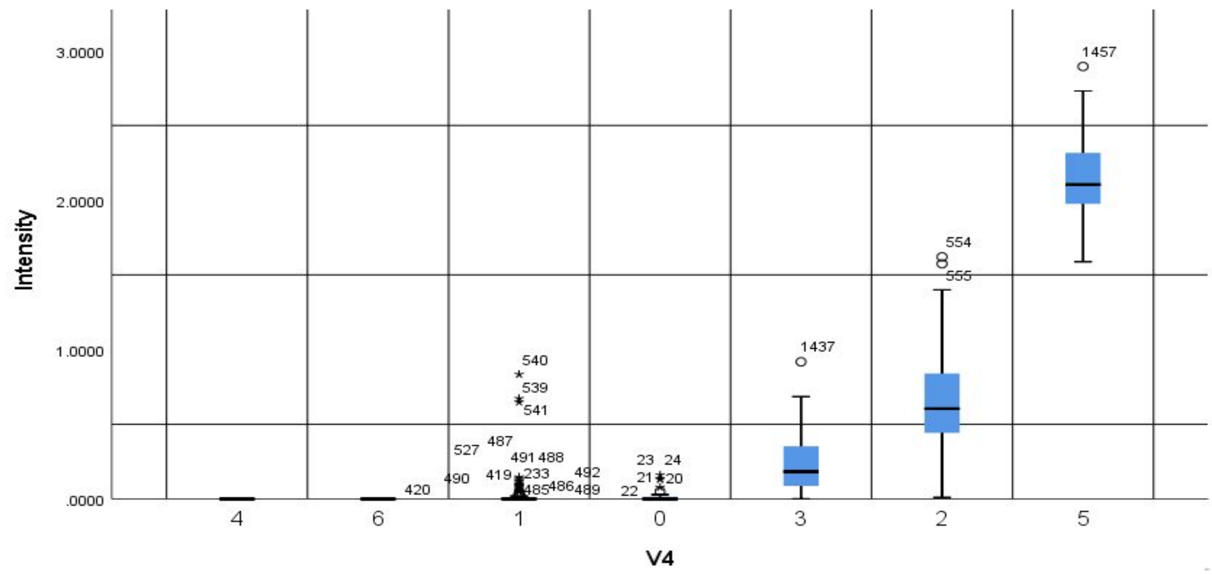

Figure 4.13 Intensity values for static and dynamic activities

V4	0	1	2	3	4	5	6
Activity	Standing	Sitting	Cycling	Walking	Sleep	Running	Humming

Table 4.6

As we saw in above figure and figure 4.9, both EE Activity and Intensity shows relatively increase in values for activities like sleep, Humming, sitting, standing, walking, cycling and running. Thus, we can easily differential PA with other activities by these two parameters.

4.1.5 Frequency Domain Analysis

EDR is ECG derived respiration

Seconds	0-1080	1140-2280	2340-4020	4080-5040
Activity	Supine	Emotional Stress	Meditation	Physical Activity

Table 4.2 Supporting information for following image

Here, we can observe a sudden rise in EDR, SNS index during Physical Activity and fall during Meditation.

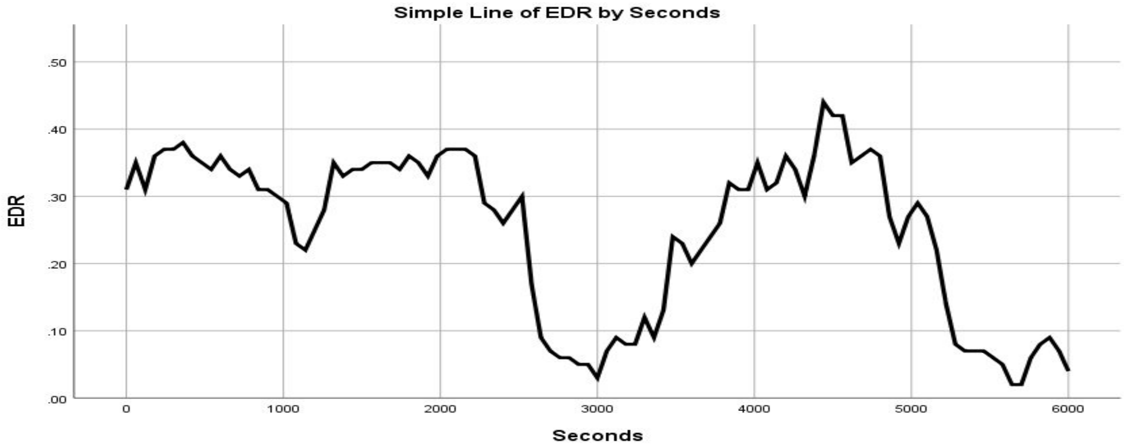

Figure 4.15

<u>Need to separate PA from ES:</u> From the box-plots of Intensity,Stress Index, EE Activity, PNS Index, SNS Index, and EDR we could clearly differentiate Energy Consuming states (ES and PA) from Energy Recovery States (Meditation and supine). Now, we need to further know exactly where we are losing energy.(Emotionally stressful activity or Physically challenging activity?)

4.2 With and without Accelerometer data

Effective formula used for three tri-axial parameters :

$$\sqrt{((x2-x1)^2 + (y2-y1)^2 + (z2-z1)^2)} \qquad \text{Equation 4.3}$$

Where, x(n), y(n) and z(n) represents magnitude of acceleration in that direction at nth instance.Each of the following methods K-Means Clustering, CHAID, CRT and ANN are used to obtain significant improvement in accuracy with introduction of acceleration data within three coordinate directions.

Method	With Accelerometer	Without Accelerometer	Highest Contributing Parameter
K - Means	75%	70%	MeanHR
CHAID	89.8%	84.3%	-
CRT	83.3%	83.3%	-
ANN	88.9%	85.8%	EDR

Table 4.3 Used for classification of all four classes

Especially While differentiating ES (Emotional Stress) from PA (Physical Activity). Yet, due to inequality between the number of cases in each class the model has been observed to overfit.

Method	With Accelerometer	Without Accelerometer	Highest Contributing Parameter
K - Means	91.5%	85%	Mean HR
CHAID	83.5%	83.3%	-
CRT	85%	85%	-
ANN	87.8%	88%	STD RR

Table 4.4 Used for classification of Physical Activity (PA) and Emotional Stress (ES)

4.3 SMOTE for imbalanced data

4.3.1 Implementation and Drawbacks

Oversampling the majority class to make its count equal to the minority class by Synthetic Minority Oversampling Technique (SMOTE).

Class	Count
PA (Physical Activity)	4088
ES (Emotional Stress)	1648

Table 4.5 Shows statistical difference between PA and ES

<u>Method:</u>

Firstly, SMOTE takes a random instance and searches for its k nearest neighbors. Then, a synthetic instance is generated by choosing one of the k nearest neighbors x at random and connecting x and y to form a line segment in the feature space. The synthetic instances are generated as a convex combination of the two selected instances x and y.

<u>Drawbacks faced by using SMOTE :</u>

As the samples are generated without taking in account of characteristics shown by the majority class, can result in ambiguous states.

4.3.2 Random Forest

Random Forest algorithm has been used for the classification of PA and ES after balancing the count to obtain 98.44% accuracy.

```
Correlation coefficient          0.9844
Mean absolute error              0.0494
Root mean squared error          0.177
Relative absolute error          4.9356 %
Root relative squared error     17.698  %
```

Figure 4.20

Following Figure shows Random Forest Classifiers Errors:

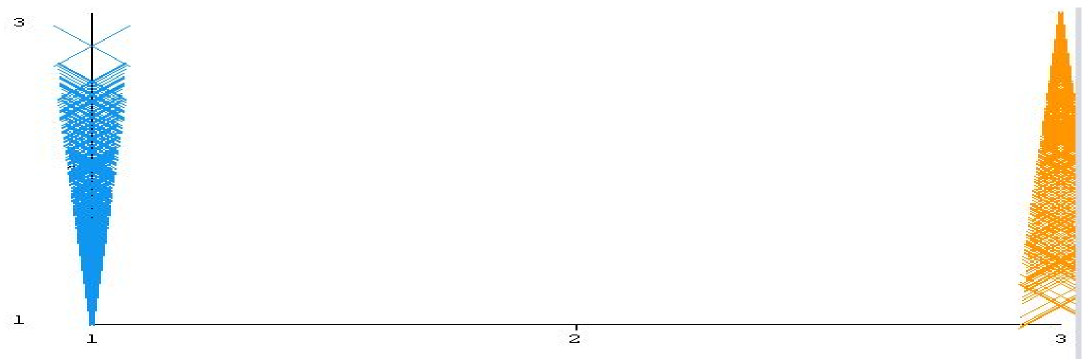

Figure 4.21

X- Axis Labeled data Y- Axis Predicted Label

1 - ES (Emotional Stress) 3- PA (Physical Activity)

Therefore, we have been able to improve the classification accuracy from 88% by ANN method to 98.44 % by Random Forest Method.

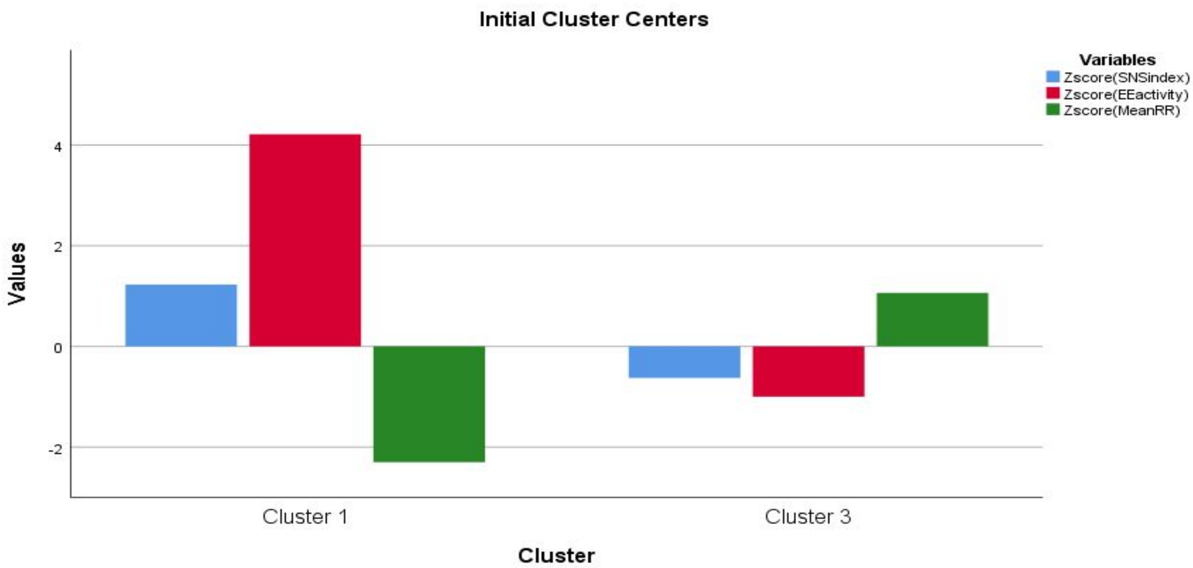

Figure 4.22

The above figure shows the centers of cluster 1(Emotional Stress) and Cluster 3 (Physical Activity) with Z scores of first three parameters (i.e. SNS Index, EE Activity and Mean RR) obtained using Kruskal Wallis Test. We can now clearly differential between PS and ES. Thus, providing accurate and precise feedback to the users.

Chapter 5: Conclusion

Beginning with the classification of daily activities into Energy Utilizing (Physical Activity or PA & Emotional Stress or ES) and Energy Recovery States (Meditation & Sleep). For this we collected and labelled data from 40 subjects, processed the data and made it usable for our defined Model. And we are successfully able to showcase the percentage distribution of the same via pie-chart for easy layman interpretation.

We also targeted to further classify Energy Consuming states into PA and ES with cann accuracy of 88% using ANN. Later, used Synthetic minority oversampling technique to obtain 98.44% accuracy.

Chapter 6: Limitations & Future work

6.1 Limitations

The following are major Limitation of this system:

- If a client fails to follow the guidelines to make use of the Holter device, then there are high chances of trash data generation which will misguide the results.
- Input to the system has to be a .csv file and it also requires manual efforts for the merger of HRV and Triaxial-accelerometer data.

6.2 Future Work

Following are few approaches that could be done keeping in mind the collected dataset:

- We have 270 hours of supine data, which can be divided into subcategories of REM (Rapid Eye Movement) and NREM (Non Rapid Eye Movement).
- PA (Physical Activity) can be further classified into Static (Standing, sitting) and Non-static or Dynamic (Running, Ascending, walking) activities by calculating θ from a vertical axis: $sin^{-1}(x1/\ (\sqrt{((x2-x1)^2 + (y2-y1)^2 + (z2-z1)^2}))$.
- A Mobile App Development for easy communication between client and company.
- ANN and CRT best used in Anomaly Detection for T1 Diabetes Patients.
- Classify the stress into one of the four levels as no stress, low stress, medium stress and high stress.

Chapter 7: APPENDIX

7.1 ANN Model

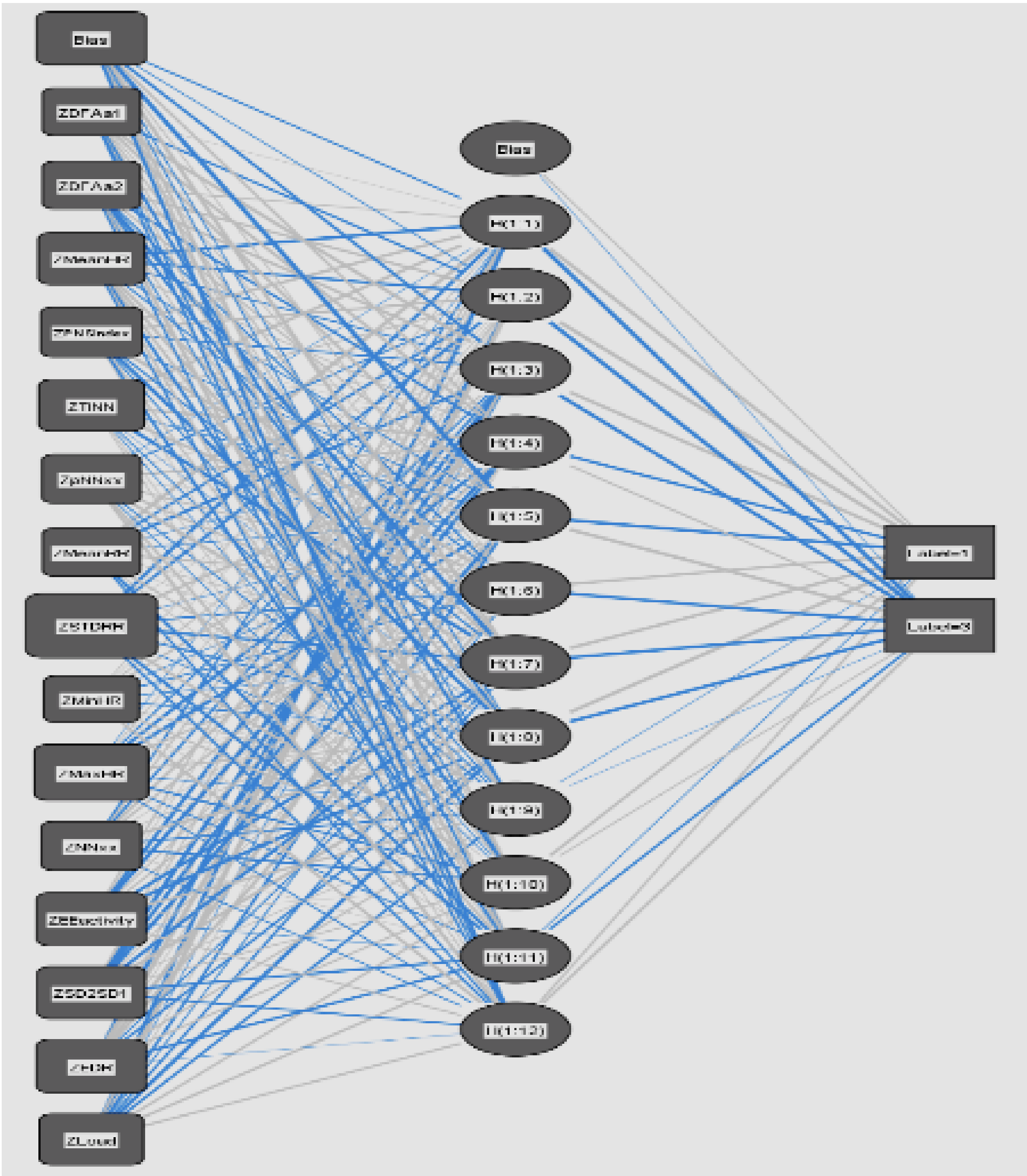

Figure 6.1 Depicts the Model Layers with Activation Function- Hyperbolic Tangent and Output Layer activation Function- Softmax. (Grey- Synaptic weight >0 and Blue- Synaptic weight<0)

7.1.1 Architecture and Working

Artificial Neural Network (ANN) is a tool for nonlinear statistical modelling, which results in complex relationships between input and output. It is also called the MultiLayer Perceptron Model.

7.1.2 ROC Analysis

Sensitivity means True Positive Rate and Specificity means False Positive Rate.

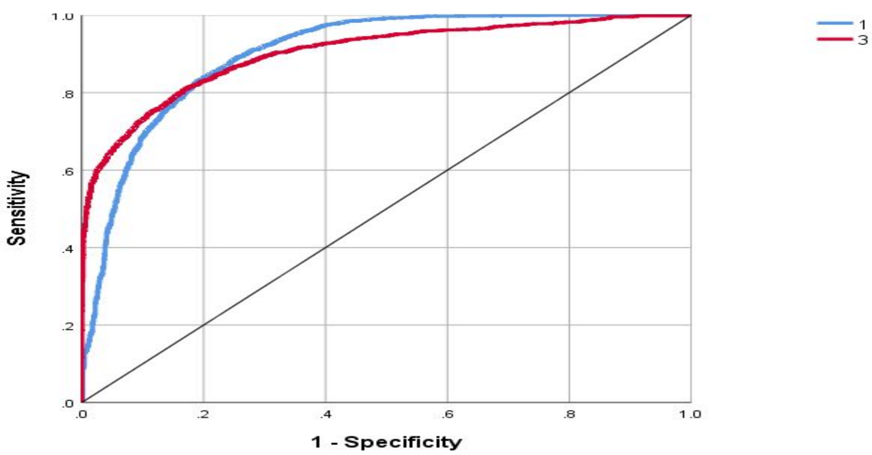

Figure 6.2. ROC curve

Receiver Operating Characteristics (ROC) :

Area under the curve represents the degree to two which model can distinguish between PA and ES. If the area under the curve is 0.7 then there is 70 percent accuracy in separating two classes. ROC represents the probabilistic curve. If we decrease the threshold sensitivity increases with decrease in specificity.

		Predicted		
Sample	Observed	1	3	Percent Correct
Training	1	2402	88	96.5%
	3	304	494	61.9%
	Overall Percent	82.3%	17.7%	88.1%
Testing	1	1015	45	95.8%
	3	121	206	63.0%
	Overall Percent	81.9%	18.1%	88.0%

Figure 6.3 Results

7.2 K- Nearest Neighbor Algorithm(KNN)

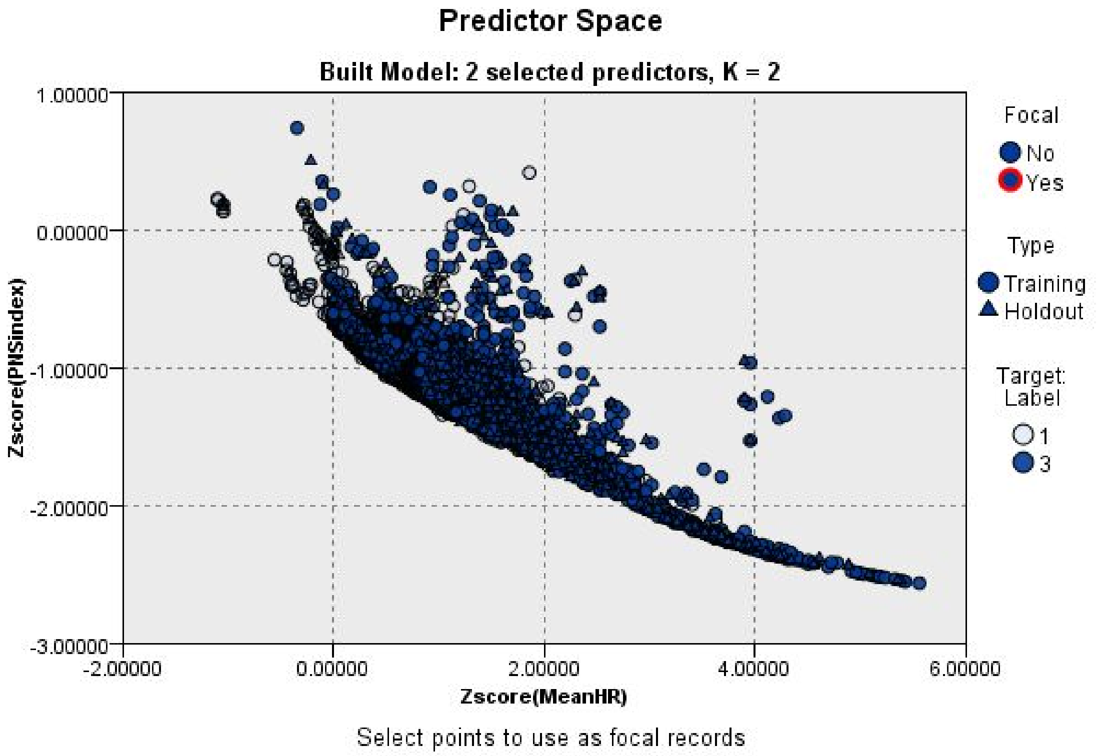

Figure 6.4 KNN

Steps taken after Loading the data for classification of PA and ES:

- Assign A value to choose number of neighbors
- For each example in the data obtain the distance between the test example and the current example from the data and save these distances in ascending order into a table format.
- Choose first K from the selected batch
- Obtain the label for selected K entries

7.3 CRT (Classification and Regression Trees)

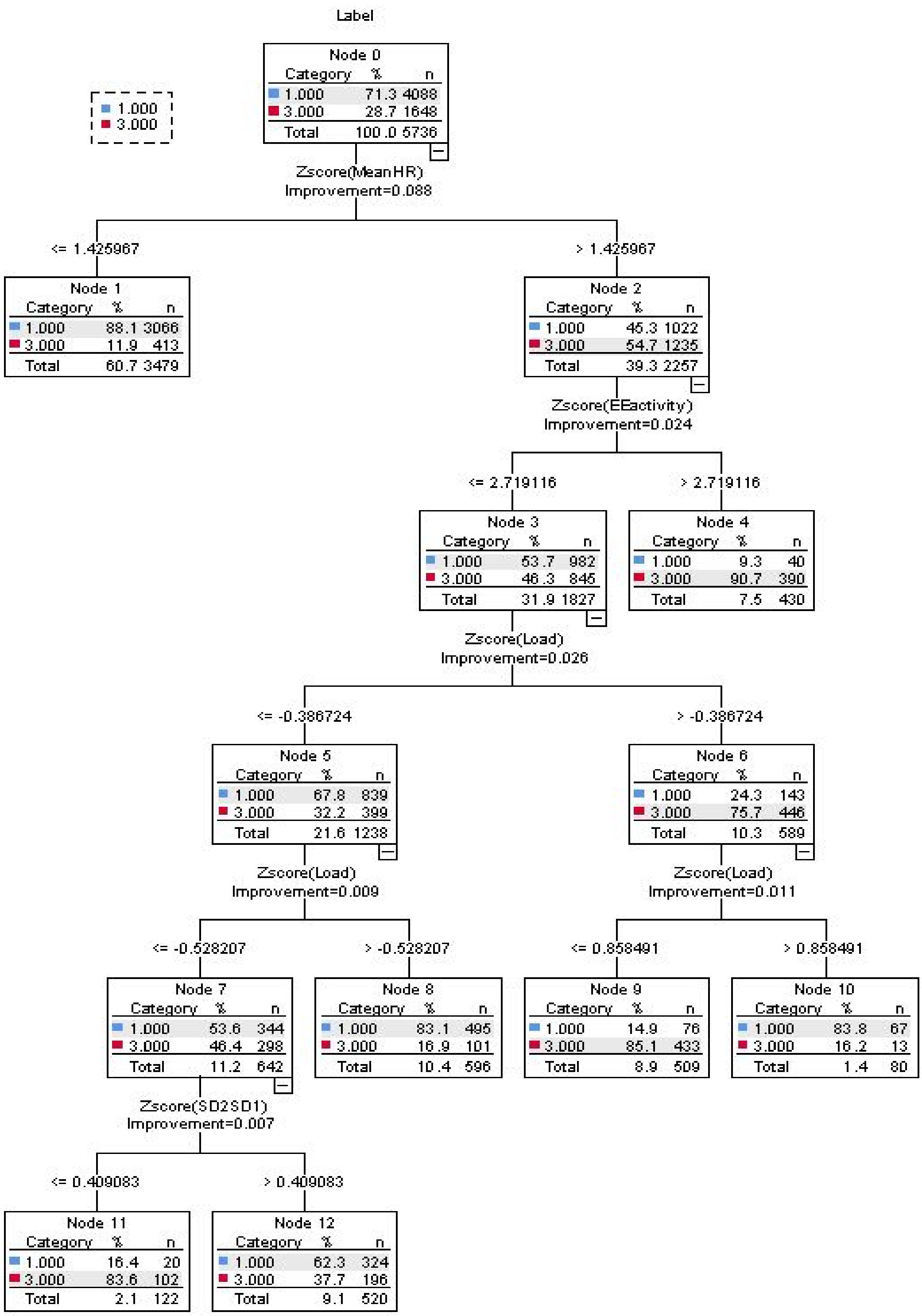

Figure 6.5 Depicts the Classification of 5832 instances into PA nad ES

Working of CRT and few key Advantages:

- It is a non Model based classification and therefore it uses automatic selection at each stage.
- Minimum number of cases in the parent node are 10% of the provided instance.
- Stopping rule for node termination is 5% of the provided data.
- Tenfold cross-validation to validate the tree.
- Tree pruning to avoid overfitting with a maximum acceptable difference in risk between the pruned and the subtree of one standard error(1SE).
- Missing data are handled by surrogate splits by not discarding the data and choosing a variable which best matches the pattern of output variable. Thus, allowing the complete utilization of a given dataset.

	Predicted		
Observed	1	3	Percent Correct
1	3952	136	96.7%
3	723	925	56.1%
Overall Percentage	81.5%	18.5%	85.0%

Figure 6.6. Classification Results for PA and ES

Chapter 8: Bibliography

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