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Performance Analysis of Machine Learning Classifiers in Estimating the Driver's Fatigue using Physiological Signals

M G Srinivasa[1], P S Pandian[2]

Department of Electronics & Communication Engineering, Maharaja Institute of Technology, Thandavapura[1]

Defence Research & Development Organization (DRDO), LRDE Campus, C V Raman Nagar, Bangalore[2]

Abstract: Driving fatigue is one of the significant factors that cause road accidents and often result in a huge socio-economic loss to the country. The accurate and reliable driver fatigue state assessment system can reduce the accident rate. In this proposed work, Heart Rate Variability (HRV) derived from Electrocardiography (ECG) is used as input to measure driver fatigue state. Machine learning classifiers like Support Vector Machine (SVM) classifier, Decision Tree, K-Nearest Neighbour (KNN) algorithm, Ensemble bagged tree classifier, Quadratic discriminant method and Deep Auto encoder techniques are used to estimate the driver fatigue state and their performance is also analysed. These machine learning classification systems use HRV features measured in time domain, frequency domain and also nonlinear HRV features. This study was conducted on 10 healthy individuals in simulator driving environment. The results have shown that deep auto encoder technique achieves highest accuracy of 97% in determining the fatigue level of drivers.

Keywords: ECG, HRV**,** Fatigue, SVM, KNN, Deep Auto Encoder

Objectives of the proposed work are to show that:

- Heart Rate Variability (HRV) is one of the strong parameter to indicate the Fatigue Level
- To acquire the ECG data from the subject using wearable ECG electrode and to calculate the heart rate using RR-Interval
- To make use of the machine learning classifiers for estimating the fatigue level and also make the performance analysis of the classifiers used in the test.

I. INTRODUCTION

Fatigue is defined as the transient interval between wakeful state and sleep and if uninterrupted, may lead to sleep [1]. It indicates the psychophysiological effect that a person experience at the time of continuous activity [2]. Fatigue may reduce attention and response readiness of an individual [3].
The driver drowsiness and fatigue detection techniques proposed in the past few decades can be mainly categorized into three a) vehicle-based measures, b) driver behavioural measures, and c) Physiological measures [4]. Vehicle-based measures give driving performance evaluation by assessing the capabilities of driver to control the vehicle. This method includes monitoring of small movements of the steering wheel, deviations in lane position of the vehicle, and applied pressure on the acceleration pedal [5]. The driver behavioural measures, evaluate the driver's performance, through behavioural parameters such as driver's head position, eye closing and movements, over a period of time and Average Eye Closure Speed (AECS), yawning, and facial expression [6-7]

In fatigue detection method using physiological signals, unlike vehicle-based and behavioural based methods, the changes in the physiological signal will be evident in the earlier stages of fatigue [4]. Therefore, physiological based fatigue detection methods are more acceptable in real time driver fatigue detection studies. Different physiological parameters such as Electroencephalography (EEG) [8-12] Electrocardiography (ECG) [13-14], Electrooculogram (EOG) [15-16] and Electromyography (EMG) [17] has been used to calculate the levels of fatigue in drivers.

Many researchers have suggested that Heart Rate Variability (HRV), extracted from ECG can be used to detect driver fatigueness. A decrease in HRV is an indication of fatigue, which can occur followed by a prolonged monotonous driving activity [18]. The lower HRV may associate with reduced alertness, which can negatively influence the performance of the driver. With the latest technology non-contact capacitive type ECG sensors are being used for long term recording [19-20] with minimum discomfort [21-23]. However, appropriate filtering of physiological signals is

required for the appropriate fatigue classification as the signals are susceptible to movement artefacts and noise involved while driving.
Various Machine Learning techniques have been widely employed for driver drowsiness detection and fatigue level classification [24-30]. Few of the machine learning techniques frequently used for fatigue classification studies are a) Support Vector Machine (SVM) b) Decision Trees c) K-Nearest Neighbour Classification (KNN) d) Ensemble Classifier e)Linear Discriminant analysis. In the proposed work auto encoder method based on deep learning is used for the detection of fatigue level. The output is compared with the various machine level classifiers explained above to get the overall performance of the system.

II. MATERIALS AND METHODS

Participants:
The ECG signals were collected from ten healthy volunteers, about 25 years of age, who did not have any known diseases and had normal vision. The participants were advised to have minimum 6 hours sleep at night before the study to avoid the effects of sleep deprivation on the experiment. The written consent was obtained from all the volunteers before the experiment for the physiological signals recording during the drive. The experiment was performed using a static driving simulator in a controlled laboratory environment.

About the Participants:
- The subjects participated in the experiment are in the age group of 25 to 35 years.
- In the experiment **8 males and two females** participated.
- All the participants are healthy subjects having valid driving license.
- All the subjects were informed to have minimum **6 hours sleep** before the experiment.
- We have taken the **written consent** from all the subjects.

Experiment Design:
Driving simulator used in this study consists of the steering wheel, gear shift lever, leg brake, accelerator and a driving environment for visual feedback as shown in Fig 1. A monotonous driving environment with low traffic density was selected for this study as the drivers are more susceptible to fatigue in a simulator with a monotonous setting [31]. Just before the actual driving task, subjects were instructed to rate their sleepiness on the Karolinska Sleepiness Scale (KSS) [32].The driving task for fatigue study last for 120 minutes. For marking the fatigue levels we had given the subjects a key pad with the keys marked from 1 to 9. The key pad was connected to a seven segment display. When the subject presses a particular key we use to get a display. Based on this output the external observer used to mark the fatigue levels. The KSS score was recorded for every five minutes. The schematic to mark KSS value is as shown in Fig 1a.

Data Acquisition and analysis of ECG:
Fig. 2 illustrates the block diagram used to acquire ECG signal in the Lead-I configuration. It consists of instrumentation amplifier [33] for conditioning the weak ECG signal. Further it consists of 8 bit ATMEGA microcontroller used for digitizing the raw inputs and wireless communication module for transmitting data to the remote station. The instrumentation amplifier is constructed using the INA128 OP-AMP which has high Slew rate and high CMRR of the order of 120dB. The first stage of the ECG amplifier has a gain of 10 followed by 2nd order Butterworth Bandpass filter circuit with the frequency range of 0.5-100Hz. The 2nd stage amplifier has a gain of 100 followed by a notch Filter stage used to remove the 50Hz power line frequency. The power supply circuitry consists of 7.4V, 1.2AH Lithium battery followed by a 5V and 3.3V regulator. The analog section works on 5V and the digital section works on 3.3V. A battery charging circuit is provided for charging the battery.
The signal acquired by the hardware consists of baseline wandering and 50 Hz powerline interference. These are removed from the recorded ECG data in MATLAB. Power line interference of 50Hz is removed using a 50 Hz notch filter [34]. Baseline wandering is removed [35-36] using wavelet decomposition technique as follows. Wavelet decomposition is performed at level 10 using db6 wavelet and the approximation and decomposition coefficients extracted. Using the approximate coefficients, the signal is reconstructed at level 8 using the same db6 wavelet. From this processed ECG signal, the RR interval is calculated. The HRV parameters are derived from the RR intervals for every 5 minutes.

Classification of Fatigue based on KSS Score:
To determine the ground truth labels for fatigue detection, the experimental protocol was followed and fatigue and KSS scores were used. The recorded signals were segmented into 5-minute segments and assigned to no-fatigue, low, medium and high labels based on the increase in the fatigue levels as shown in **Table 1**. The no-fatigue, low, medium and high fatigue was given labels of 4, 3, 2 and 1 respectively [37]. The KSS, assessing subjective fatigue levels of

each driver spans nine levels as shown in **Table 2**. During the driving task in every 15 minutes, the external observer was asked to give the number that closely indicates their fatigue level at that instant.
The KSS values from 1 to 3 were considered to be 'non-fatigue' state, 4 and 5 as low fatigue, 6 and 7 as 'medium fatigue' and 8 and 9 were considered as 'high fatigue' state. These levels of fatigue were marked based on the HRV variations of the driver calculated from the ECG RR-interval. For every stage of fatigue level threshold value is fixed based on the HRV. The threshold value is displayed to the external observer in the hand held instrument using seven segment displays as shown in Fig 1a. For computing the threshold value for each stage of fatigue an algorithm is developed in MATLAB using the RR-interval variations of the subject's ECG as input along with the different HRV parameters.
If the threshold value crosses some then the external observer gives the corresponding number from the range 1 to 4 which maps to the nine levels of KSS scale. The threshold values were derived from HRV parameters measured from different methods.

HRV parameters for fatigue detection:
There are several methods available for the assessment of HRV such as time domain, frequency domain, geometrical and non-linear methods. This work is utilizing the time domain, frequency domain and nonlinear analysis methods of HRV for driver fatigue estimation.

Time domain methods:
The time-domain features are computed using mean and the standard deviation of the RR interval series [38]. Following are the time domain parameters computed in this study for fatigue classification.
Average Heart Rate: It is the number of heart beats per minute and it is defined as

$$\boldsymbol{Average\ HR = \frac{Number\ of\ RR\ Intervals}{Duration\ in\ Minute}}$$

SDNN: The standard deviation of NN intervals (SDNN) for the given segment of data is described as the square root of the variance of the NN intervals. Since the variance in the time domain is equal to the total power in the frequency domain, SDNN describes the cyclic components accountable for variability [39]. Mathematically, SDNN is defined as:

$$\mathbf{SDNN} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{RR_i} - \mathrm{RR_{mean}})^2}{\mathrm{N}-1}}$$

Where

$$\mathrm{RR_{mean}} = \frac{\sum_{i=1}^{n}\mathrm{RR_i}}{\mathrm{N}}$$

SDSD: The standard deviation of the successive differences of the NN intervals describes the short-term variation in RR interval series. It can be described as:

$$SDSD = \sqrt{\frac{\sum_{i=1}^{n}\left(|RR_i - RR_{i+1}| - RR_{diff}\right)^2}{N-1}}$$

Where $RR_{diff} = \frac{\sum_{i=1}^{n}|RR_i - RR_{i+1}|}{N-1}$

RMSSD: Root-mean-square of successive differences of adjacent NN intervals. Similar to SDSD, RMSSD also shows the short-term variability of the RR interval series. It can equivalent to the high frequency variation in the spectral analysis [40]. Mathematically RMSSD can defined as

$$\mathbf{RMSSD} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{RR_{i+1}} - \mathrm{RR_i})^2}{\mathrm{N}-1}}$$

NN50 and pNN50: NN50 is the number of consecutive RR intervals that differ more than 50ms and pNN50 is the fraction obtained by dividing NN50 by the total number of RR intervals in the given segment [41] pNN50 is utilized for the estimation of the high-frequency variation in RR interval series. Unlike RMSSD, pNN50 is much less susceptible to the presence of noise and artifact in the recording [42]. Mathematically, it is defined as:

$$\mathbf{NN50} = \sum_{i=1}^{n}\{|\mathrm{RR_{i+1}} - \mathrm{RR_i}| > 50ms\}$$

$$\mathbf{pNN50} = \frac{NN50}{N} \times 100\%$$

Frequency domain Analysis:
The frequency domain parameters give the accurate and effective feature evaluation of HRV compared to time domain [43]. In this analysis the power spectral density (PSD) of HRV is calculated. The output gives the information about power distribution of spectral components obtained from RR intervals. The high frequency (HF) is characterised by the

parasympathetic activity of the autonomous nervous system whereas the low frequency (LF) is a good indicator of both parasympathetic and sympathetic activity. The LF, HF components and also the LF/HF ratio are used to indicate the stress or fatigue level of the subject under test. There is approximate correlation between time and frequency domain evaluation parameters [44]. The spectral features of HRV were calculated from RR interval data by power spectral density (PSD) using periodogram. The RR interval is sampled [45] at a frequency of 8 Hz. The RR interval samples were divided into overlapping segments with 50% overlap.

Nonlinear methods:
The nonlinear methods represent the correlation [46] between successive RR intervals. It also gives information about heart behaviour based on beat to beat RR interval repetitions. The Poincare plot is typically described by two descriptors SD1 and SD2 where SD1 represents the standard deviation of the points across the line of identity and SD2 represents the standard deviation of the points along the line of identity.SD1 describes the short term variability and the parasympathetic activity of the autonomous nervous system and SD2 describes the long term variability [47] and the sympathetic activity of the autonomous nervous system. The SD1 and SD2 are calculated using the following equations.

$$SD_1 = \sqrt{Variance(S_1)}$$
$$SD_2 = \sqrt{Variance(S_2)}$$

Where $S_1 = (RR_i - RR_{i+1})/2 \quad RR_i = (RR_1, RR_2 ------RR_{N-1})$

$$S_2 = (RR_i + R\,R_{i+1})/2$$
$$RR_{i+1} = \left(RR_{2,}RR_3 ------- RR_N\right)$$

Classification Fatigue:
The following section explains about the machine learning and deep learning classifier architectures used in this work for fatigue classification. The statistically relevant HRV features are used as the input dataset for the classifiers. Let us consider $D = \{(x_i\ , y_i)\}_{i=1}^{n}$ a training dataset consisting of n training samples, where $x_i \in R^D$ is HRV feature vector of size D and $y_i \in [1, K]$ is its corresponding fatigue class label. For a new HRV test data sample x_i , the aim is to classify the data correctly to its corresponding fatigue class.

Machine Learning Classifiers:
Machine learning is a field in computer science where future data is predicted or classified using existing data. It is extensively used in the fields of artificial intelligence, pattern recognition and computational statistics. Machine learning algorithm transforms the input data into features which can utilize for understanding forthcoming data [48]. Following are the machine learning classifiers used in this work.

Support Vector Machine (SVM)
Support Vector Machine (SVM), is a kernel-based supervised machine learning algorithm, which is commonly used for pattern recognition and data classification. It is based on the margin-maximization principle [49]. It utilizes machine learning principle to maximize the accuracy of prediction while eliminating the data over-fit. The type of SVM classifier used in this work is Fine Gaussian SVM.

Decision Trees
A decision tree is a prediction and classification method that enables decision making in sequential problems under uncertainty. A decision tree is a graphical model narrating decisions and their feasible results [50]. Decision trees have been widely used in disciplines such as machine learning, pattern recognition, statistics, and Data Mining. Fig 3 shows a decision tree structure.

K Nearest Neighbor Classification (KNN)
It is one of the simplest supervised machine learning classification method. It makes use of similarity between data samples for classification. The KNN algorithm classifies the unlabeled sample to the class where similar k-nearest neighbors in the training data sample are available. It utilizes Euclidean distances to determine the nearest neighbors in the data sample. KNN has been widely used for applications of cancer detection, Medical data mining, information retrieval and handwritten character classification [51].

Ensemble bagged tree Classifier
Ensemble methods are meta-algorithms which combine multiple machine learning algorithms to solve one problem. In contrast to other machine learning approaches which develop one classification model from training dataset, ensemble methods try to build multiple classification models and merge them as shown in the Fig 4.

Quadratic Discriminant Analysis

Discriminant analysis is a supervised machine learning technique used to determine a linear combination of the features in the dataset for classification. The main aim of discriminant model is to minimize computational cost by reducing the dimensions of data, after applying the discriminant analysis to a data samples, the new features maximizes the dispersion between samples of different classes and minimizes the dispersion between samples of the same class as shown in Fig 5.

Deep Auto encoder

An auto encoder is a symmetrical neural network work based on unsupervised feature learning. It is a dimensionality reduction algorithm which makes the output values to be equivalent to the inputs. The basic architecture of an auto encoder is given in the Fig 6. For the unlabeled training dataset $\{\boldsymbol{x_1}, \boldsymbol{x_2}, \boldsymbol{x_3}, \ldots\}\ \boldsymbol{where}\ \boldsymbol{x_i} \in \boldsymbol{R^n}$, the auto encoder tries to learn the approximation function $\boldsymbol{h_{W,b}}\,(\boldsymbol{x})$ in the output layer to identity function $\boldsymbol{x}$. This is accomplished by reducing the error between the input data at the encoding layer and its reconstruction at the decoding layer [52]. The deep auto encoder network can be developed by stacking auto encoders. This is done by feeding the output representation of preceding auto encoder layer to the current layer.

III. RESULTS

The results of the experiment on 10 subjects during 120 minutes simulator driving are presented in this section. The recorded ECG signals are divided into 24 segments of length 5 minutes and the HRV parameters are calculated for each these segments. Hence a total of 240 data samples were obtained. These were classified into 4 classes: No-fatigue, Low fatigue, Medium fatigue and High fatigue and used as the input for the machine learning classifiers. The split up of the 240 data points used for training and testing with the classifiers is as shown in Table 3. The analysis of the fatigue estimation is carried out in MATLAB software using the machine learning libraries.

The individual feature values registered corresponding to every 5-minute segment for all the 10 subjects were averaged. The trends in the calculated HRV parameters in time domain are shown in Fig 7 to Fig 13. The frequency domain parameters are shown in Fig 14 to Fig 16. The nonlinear parameters are shown in Fig 17. The error bars in the measurement block indicates the standard deviation from the mean.

The heart rate (HR) gradually decreased as the driver fatigue level increased as shown in Fig 7. In this study, SDNN, RMSSD, SDSD and NN50 measured have shown an incremental trend with increase in driver fatigue levels as shown in Fig 9 to Fig 12. The frequency domain parameters, low and high-frequency power showed an increasing trend from alert to fatigue transition as shown in Fig 14 and Fig 15. The LF/HF ratio graph as shown in Fig 16 show a strong trend in the fatigue level. The nonlinear HRV parameters, SD1 and SD2 showed an increasing trend as the fatigue level increased as shown in Fig 17. The SD1/SD2 ratio graph show appreciable trend in fatigue.

The extracted HRV parameters have been used as the input for the machine learning classifiers. The classifiers were trained and tested for four level fatigue classifications. The confusion matrix evaluates the performance of the classifiers. The confusion matrixes of machine learning classifiers for 4 fatigue levels are shown in Fig 18(a) to Fig 18(e). Fig 19 shows the performance evaluation of the machine learning classifiers used. It is seen that the KNN classifier has the highest accuracy of 95.5% compared the other machine learning classifiers in predicting the high fatigue state of the driver.

The deep auto encoder constructed by cascading two auto encoders and a softmax regression layer is used. The hidden neuron size of both layers in the cascaded structure is set as 15 and 10 respectively to obtain two different architectures to classify 4 fatigue levels. The confusion matrices for training and testing for hidden size 15 are shown in Fig 20(a) and Fig 20(b). The result shows training accuracy of 100% and testing accuracy of 97%. The confusion matrices for hidden size 10 are shown in Fig 21(a) and Fig 21(b). The result shows training accuracy of 100% and testing accuracy of 95.5%.

Fig 22 shows the overall performance accuracy of machine learning and deep learning classifiers. From the results, it shows that the deep learning encoder has the highest accuracy of 97% for four level fatigue classifications.

IV. CONCLUSION

In the proposed work, the experiment was carried out with 10 participants in a simulator-based monotonous driving environment. A set of statistical HRV parameters including time domain, frequency domain and nonlinear parameters were extracted for this purpose. The time domain measure, heart rate showed decreasing trend while SDNN, RMSSD, SDSD, NN50 and pNN50 showed an incrementing trend as fatigue levels increases. From the work, it suggests that HRV based systems could potentially be used to track drivers cognitive performance and fatigue levels. The statistically significant HRV features were used as the input for the classification algorithm. The performance of each

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model is captured in confusion matrix. Compared to machine learning techniques the study on deep auto encoder based on HRV analysis has achieved higher accuracy both two level and four level fatigue classification. In the available set of machine learning algorithms, KNN methods obtained maximum accuracy. In the proposed work the data size is limited for training of the classification network since we have taken the data from 10 subjects only. In the future experiments, ECG data recorded from a large population of participants with different physiology should be considered for training the deep learning networks.

In future work, different bio signal such as ECG, EEG and EMG can be integrated to develop multi- mode system with deep leaning classifiers for real-time fatigue detection.

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List of Figures:

Fig 1: Driving Simulator

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

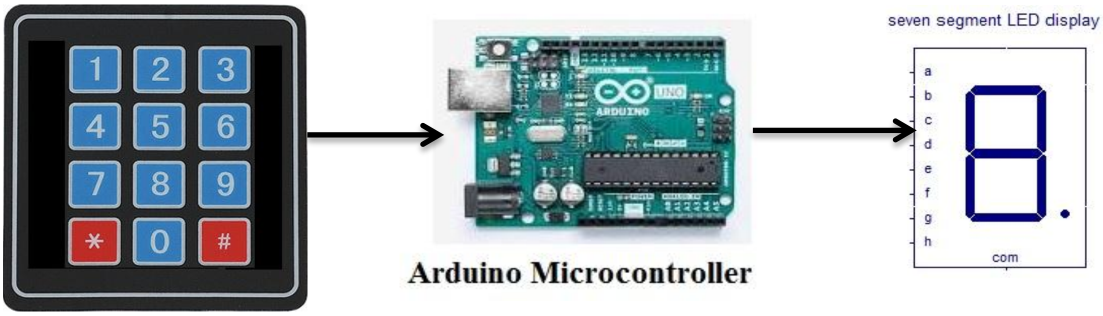

Fig 1a: Schematic to record Fatigue level using KSS

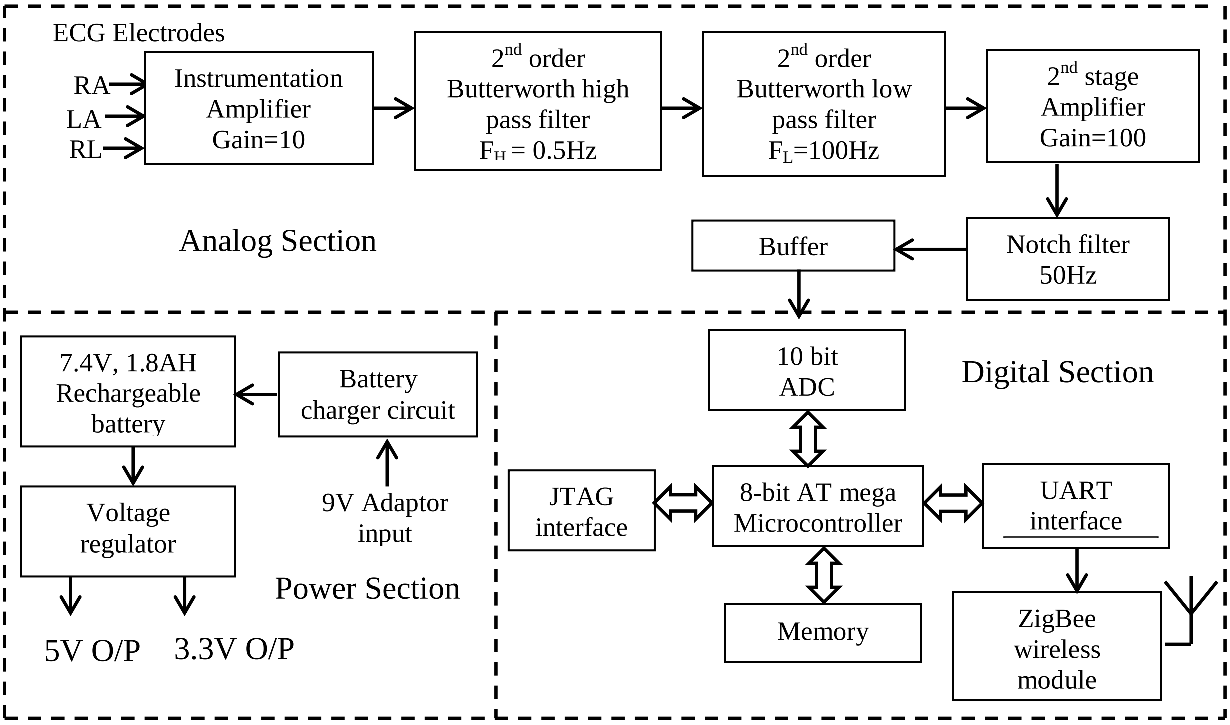

Fig 2: ECG Signal Acquisition Hardware

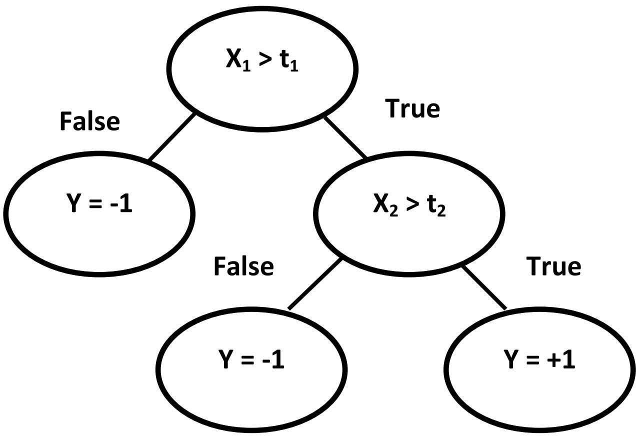

Fig 3: Decision Tree Architecture

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IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

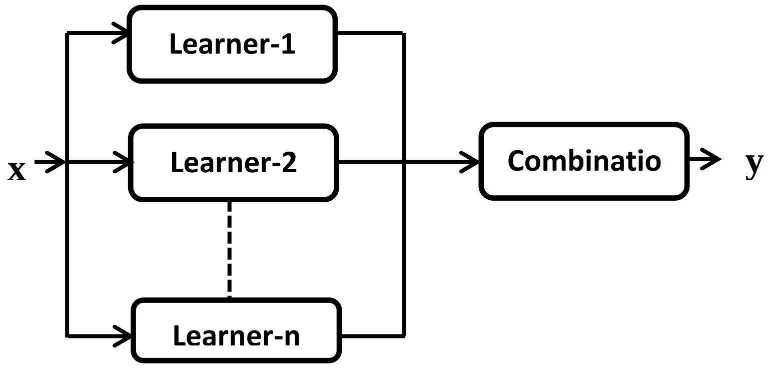


Fig 4: Basic ensemble architecture

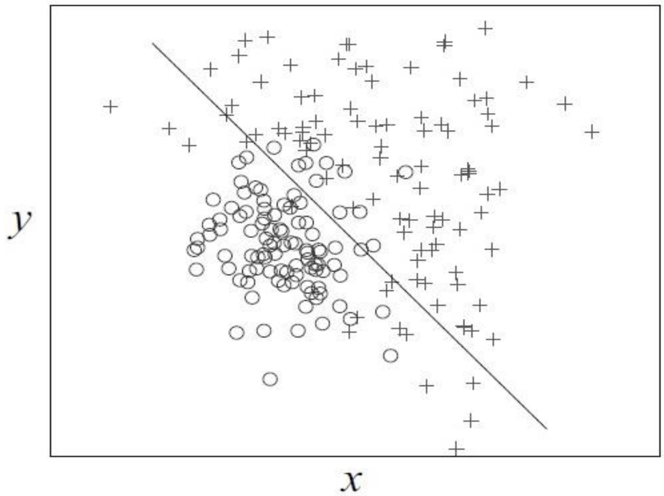


Fig 5: Boundary of Discriminant Analysis

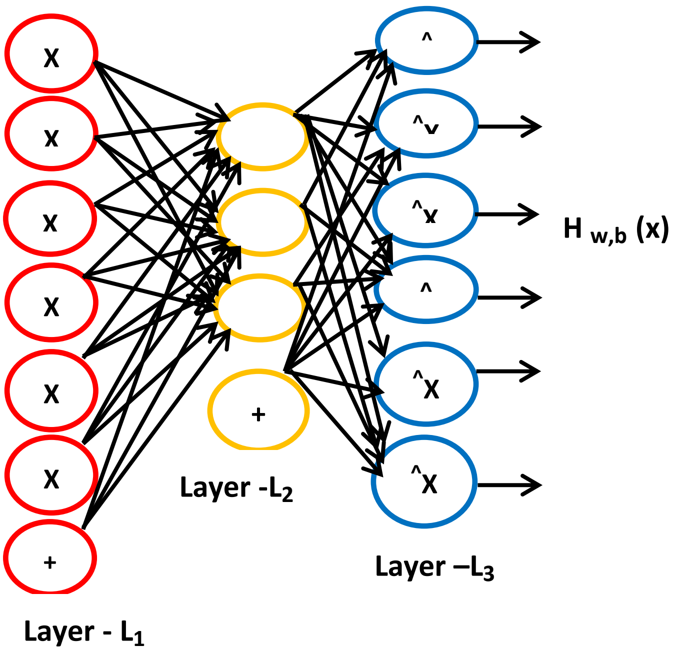


Fig 6: Deep auto encoder Structure

Vol. 7, Issue 12, December 2019

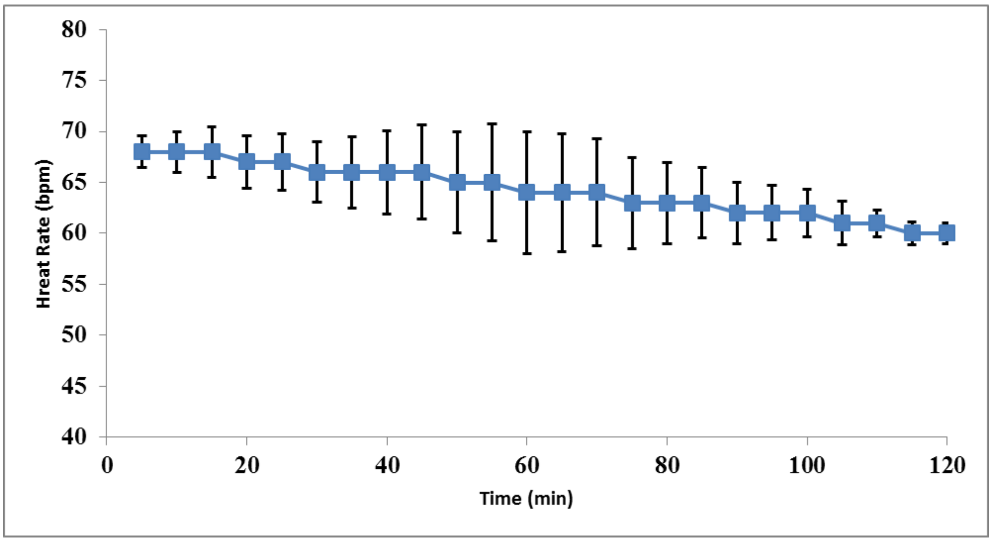


Fig 7: Heart Rate

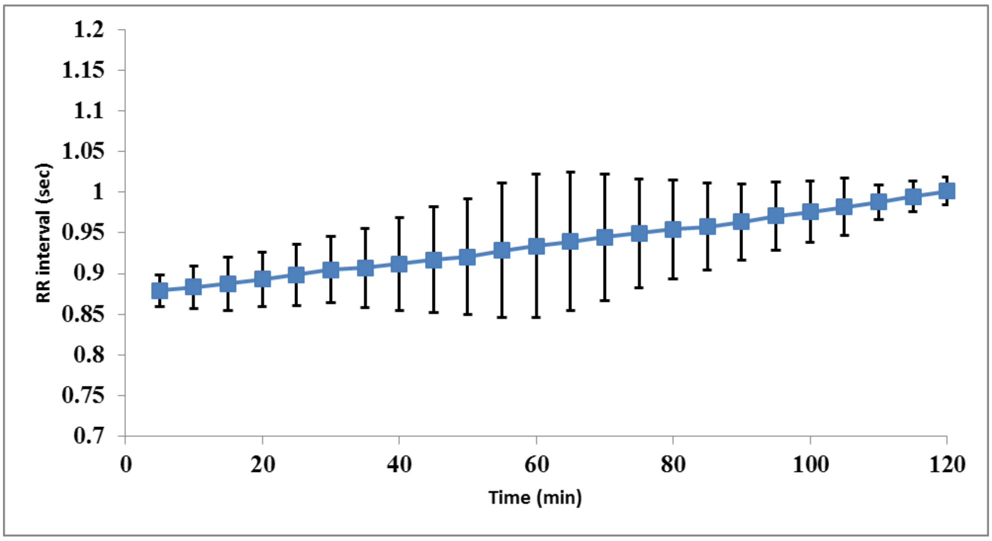


Fig 8: RR-Interval

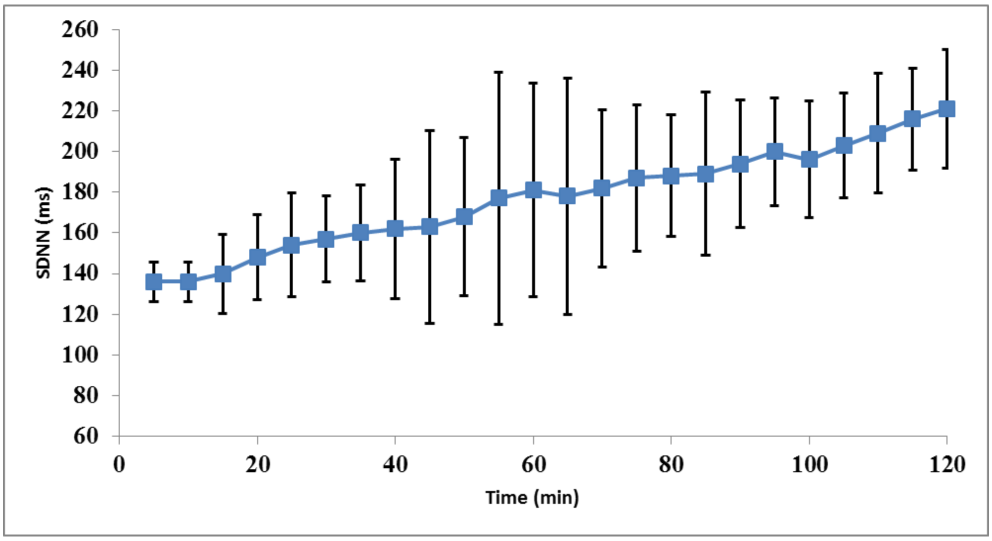


Fig 9: SDNN

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

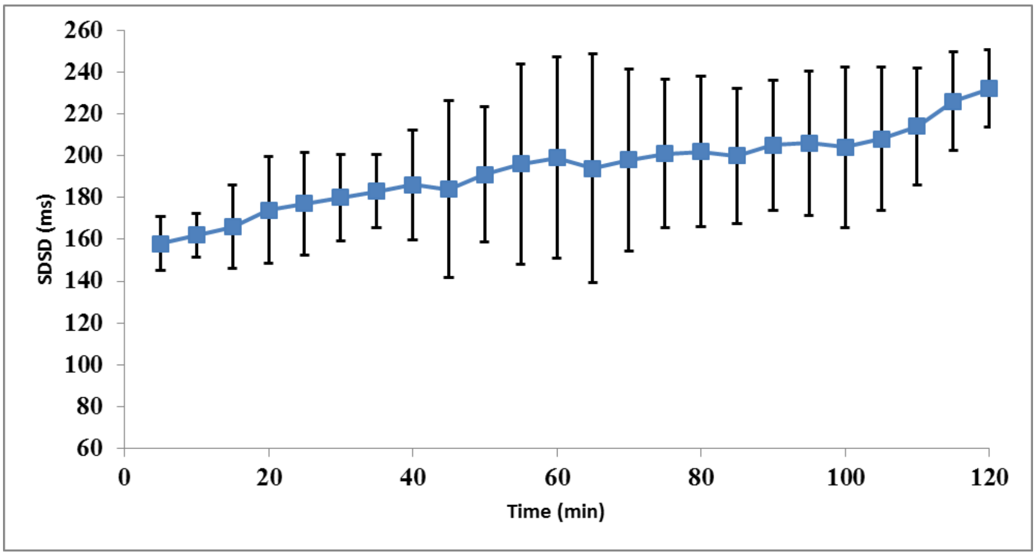


Fig 10: SDSD

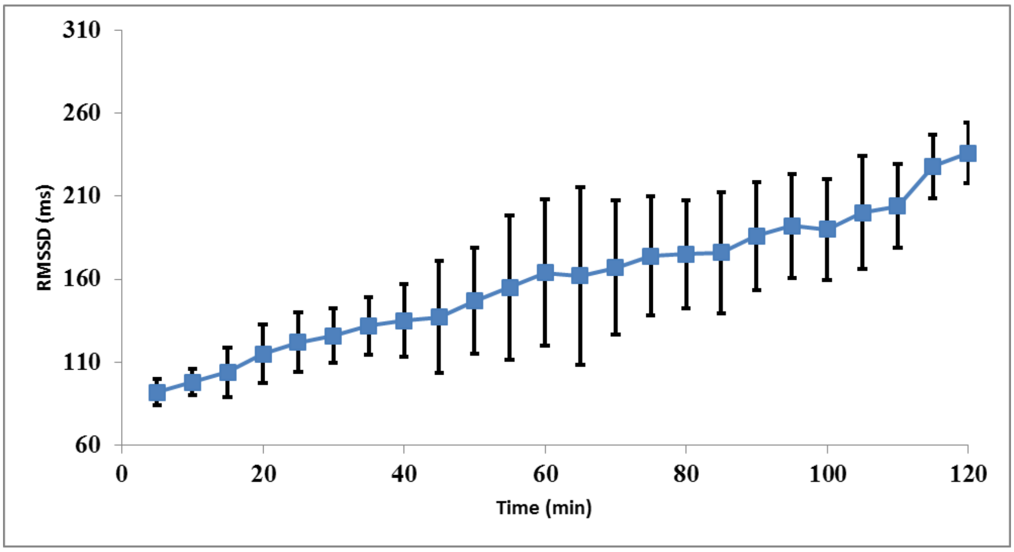


Fig 11: RMSSD

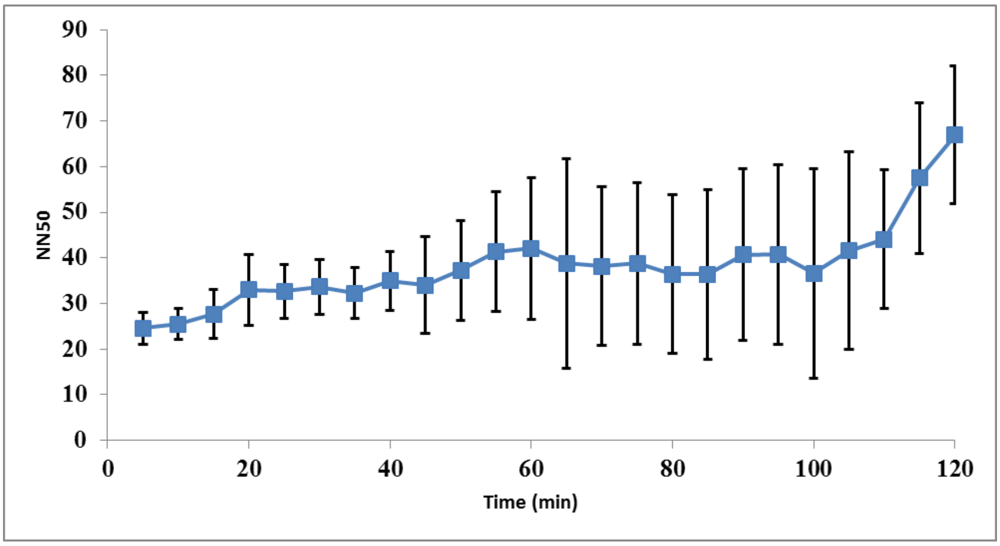


Fig 12: NN50

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

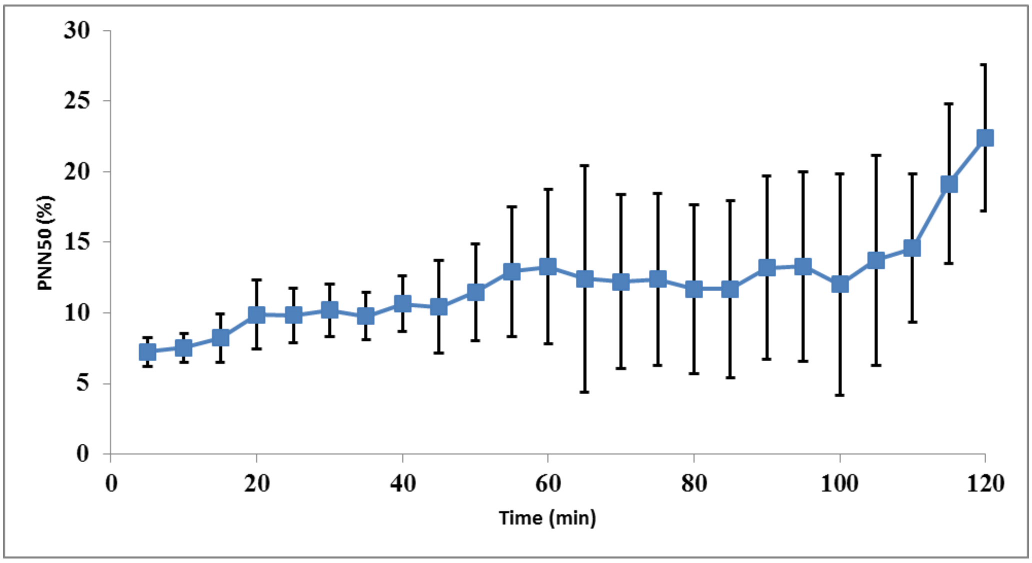


Fig 13: pNN50

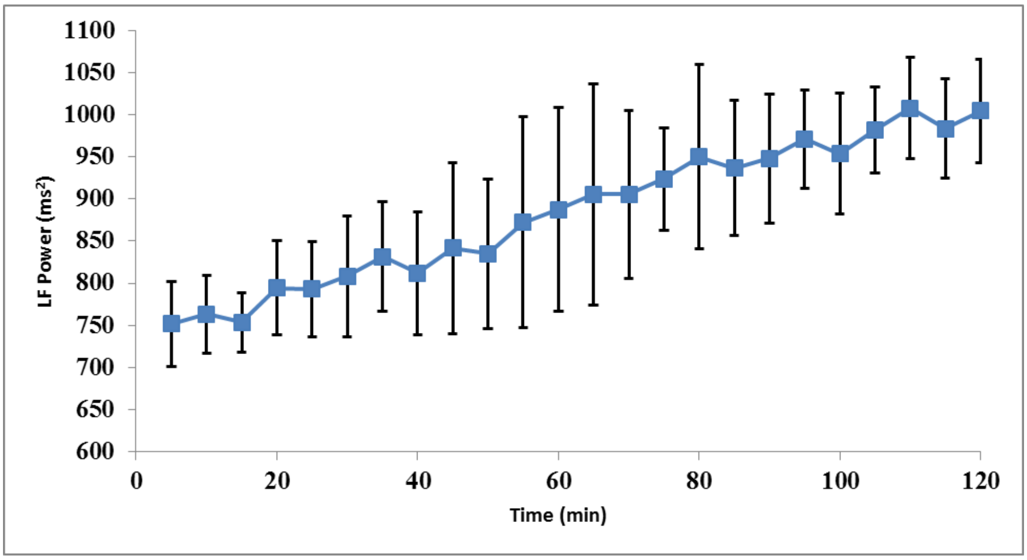


Fig 14: LF Power

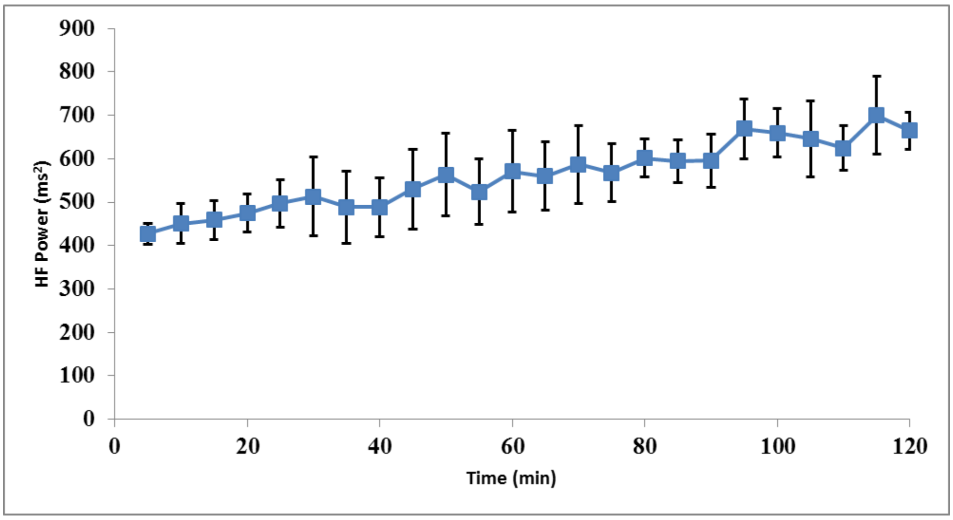


Fig 15: HF Power

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

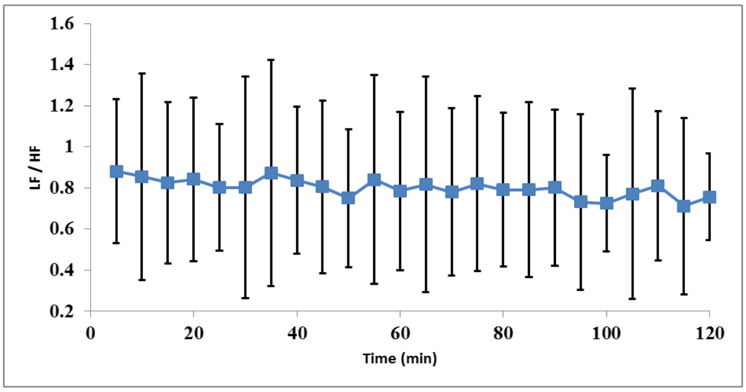


Fig 16: LF/HF Ratio

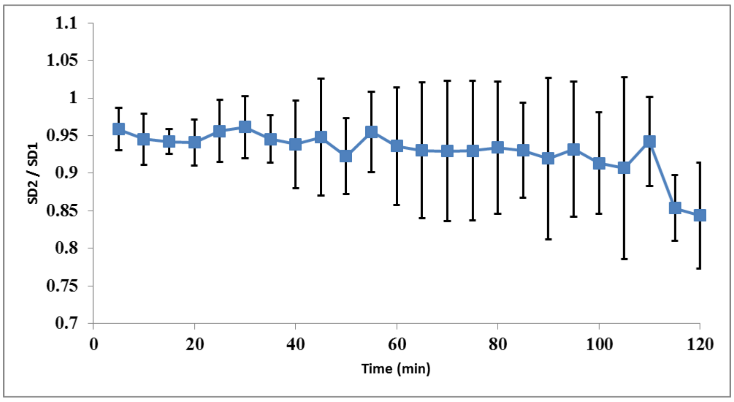


Fig 17: SD1/SD2 Ratio

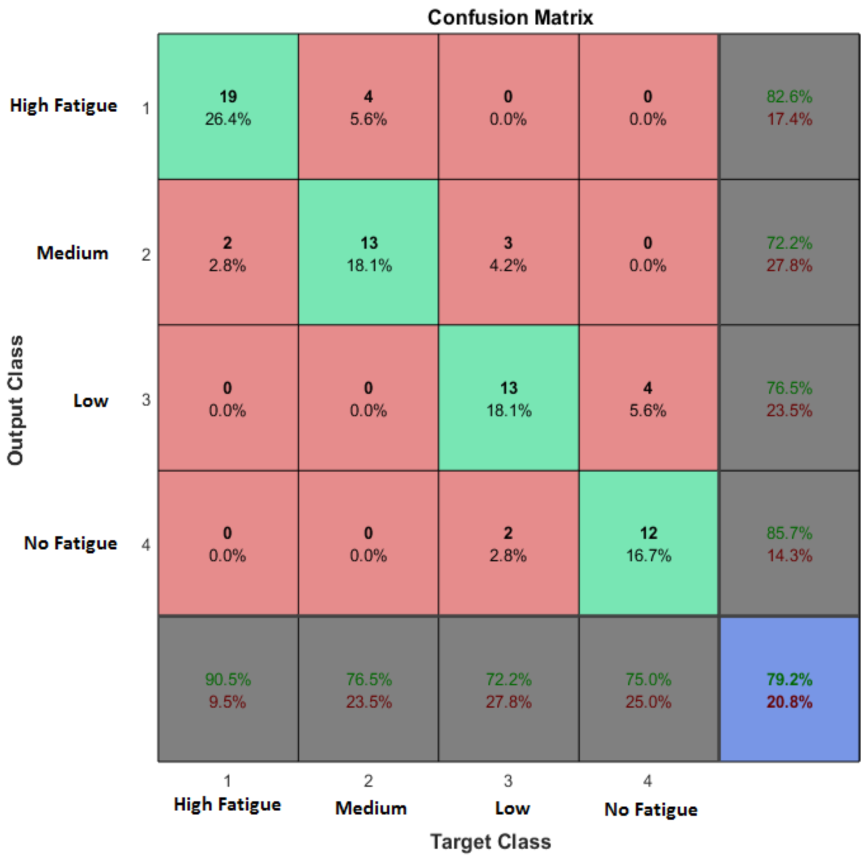


Fig 18(a): Fine Gaussian SVM Classifier

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

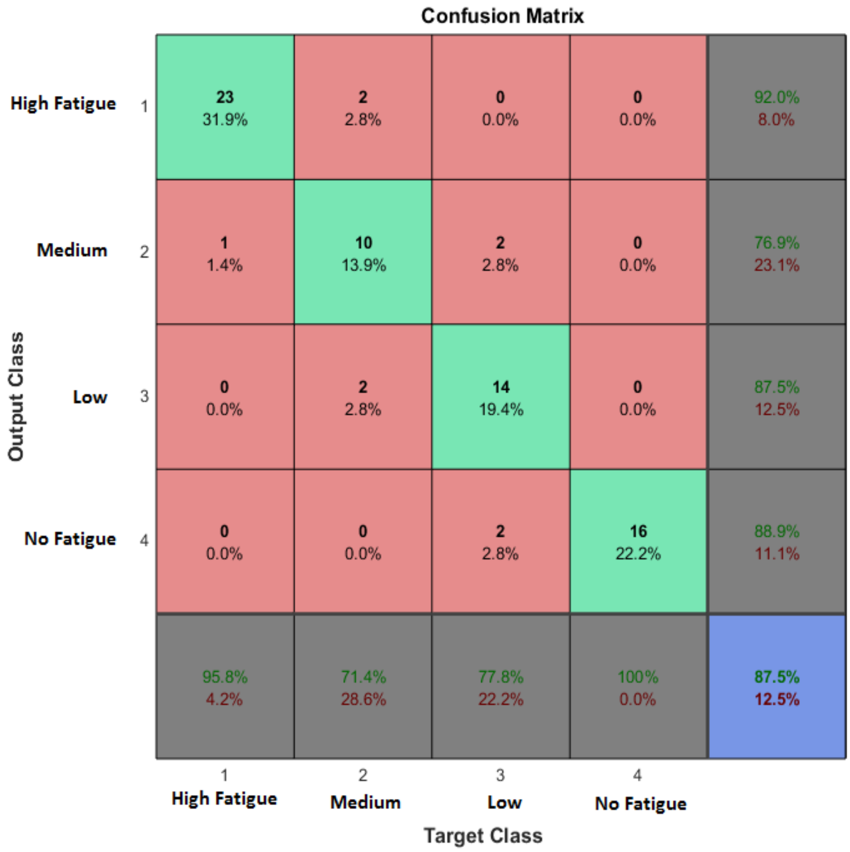


Fig 18(b): Complex Decision Tree Classifier

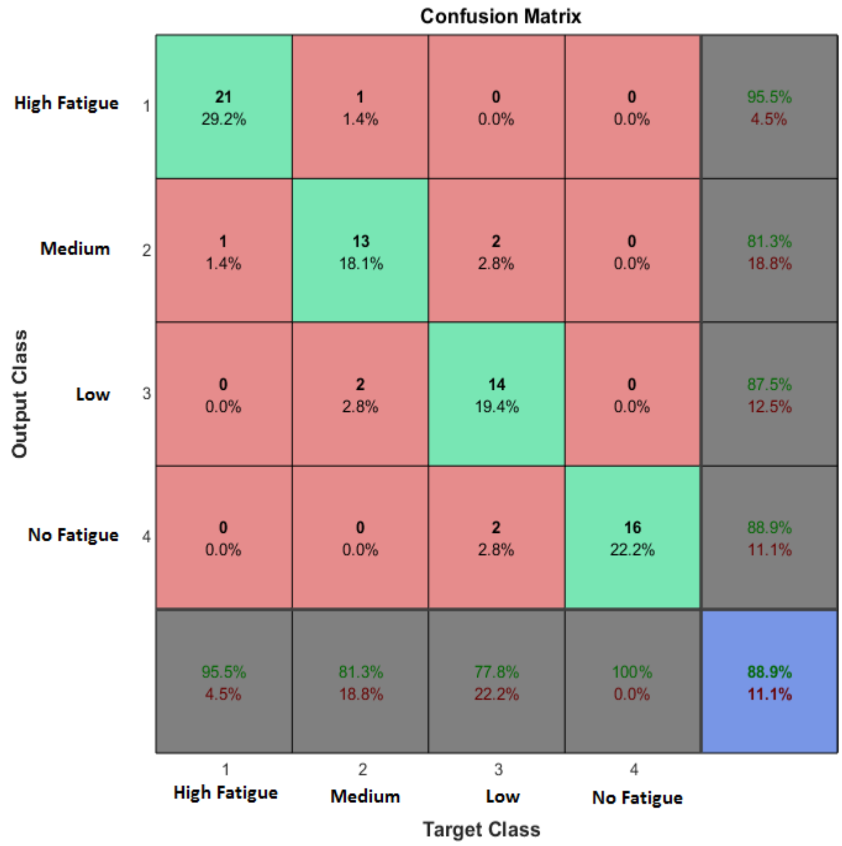


Fig 18(c): KNN Classifier

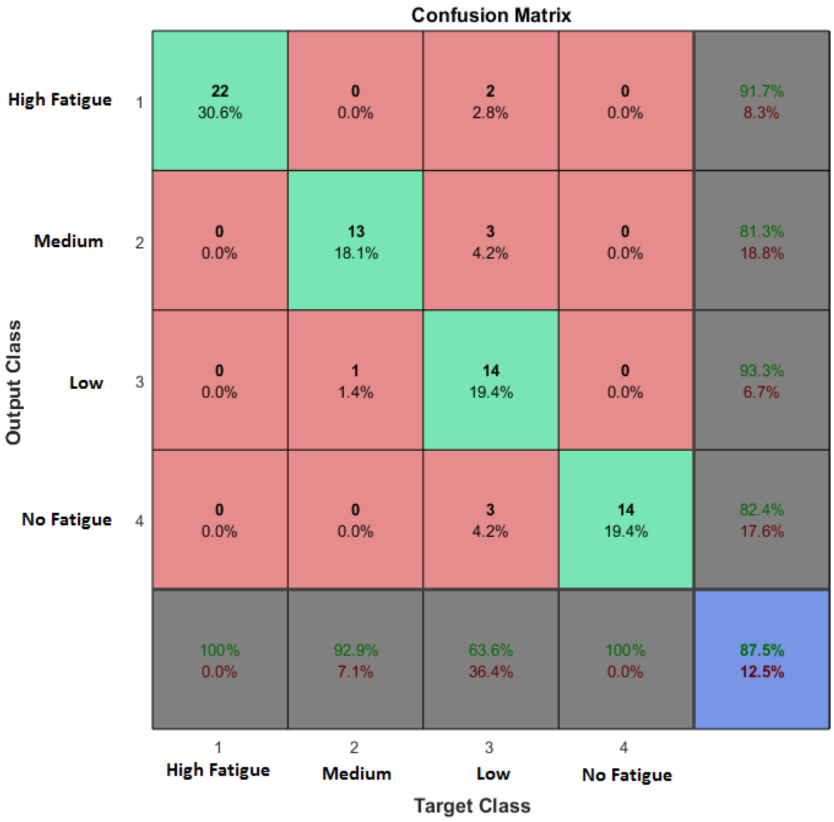


Fig 18(d): Ensemble Bagged Tree Classifier

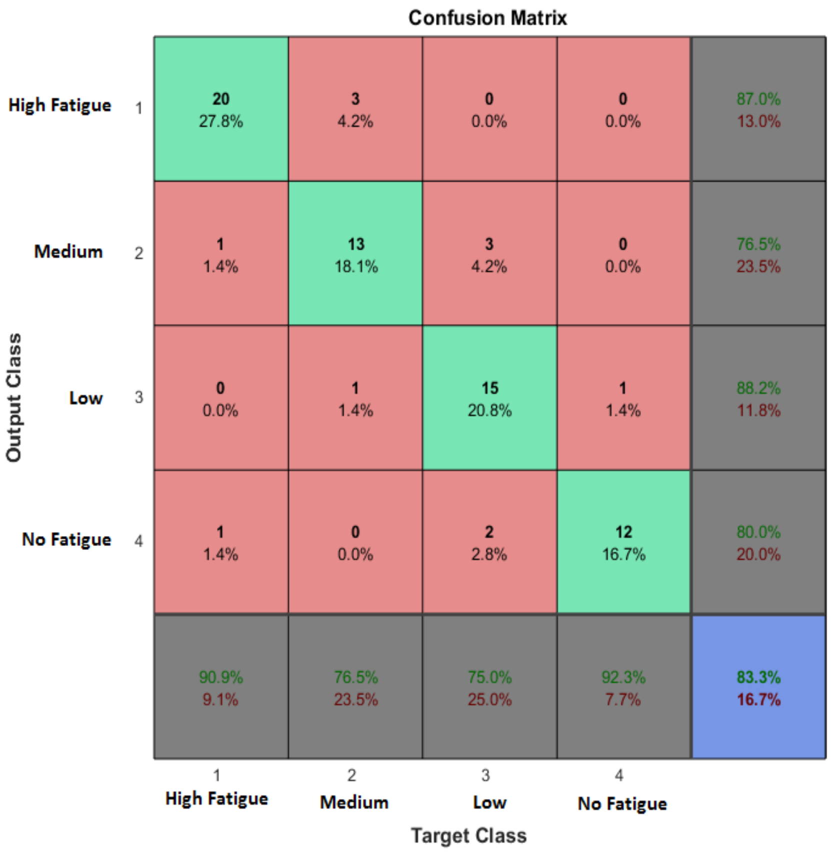
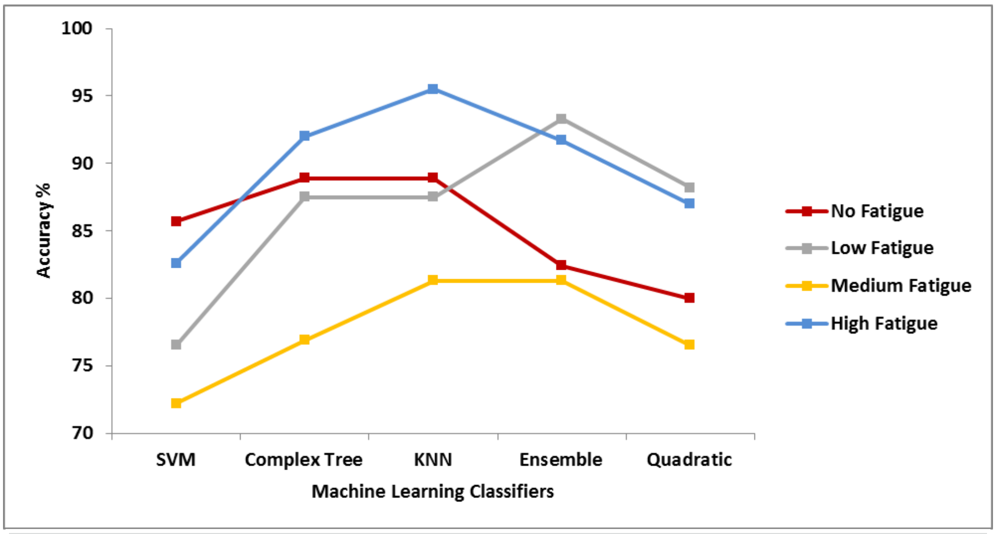


Fig 18(e): Quadratic Discriminant Classifier



	SVM	Complex Tree	KNN	Ensemble Bagged tree	Quadratic discriminant
No Fatigue	85.7	88.9	88.9	82.4	80
Low Fatigue	76.5	87.5	87.5	93.3	88.2
Medium Fatigue	72.2	76.9	81.3	81.3	76.5
High Fatigue	82.6	92	95.5	91.7	87

Fig 19: The performance comparison of various machine learning classifiers for No-fatigue, Low, Medium and High fatigue levels

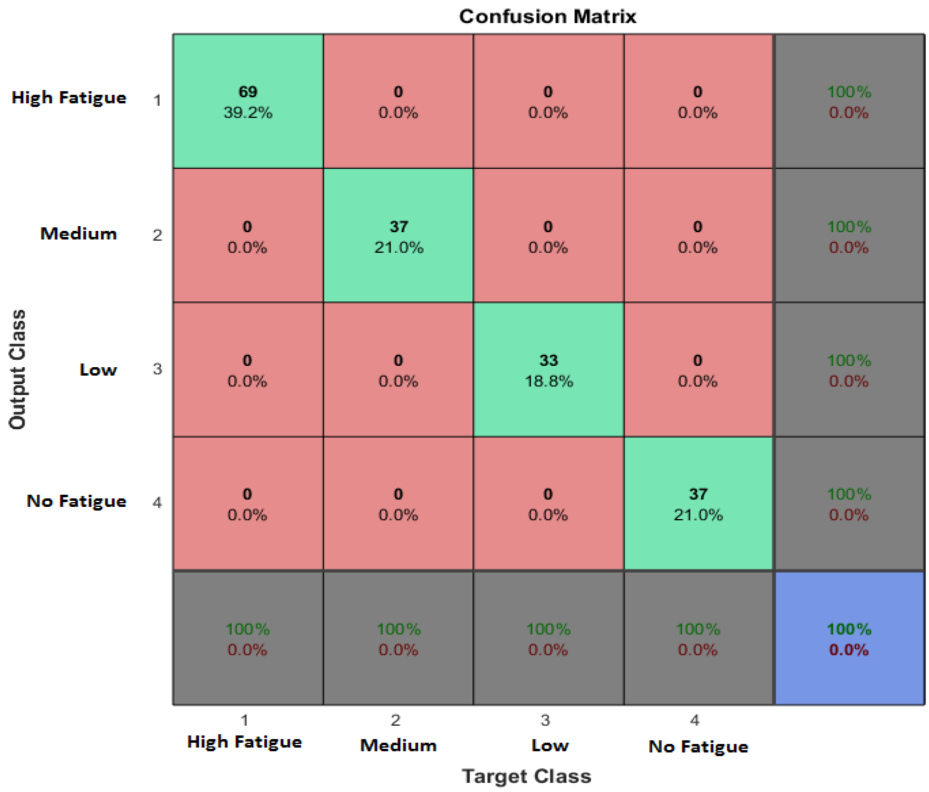


Fig 20(a): Confusion matrix of deep auto encoder with hidden size 15 for four level fatigue classification (Training)

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

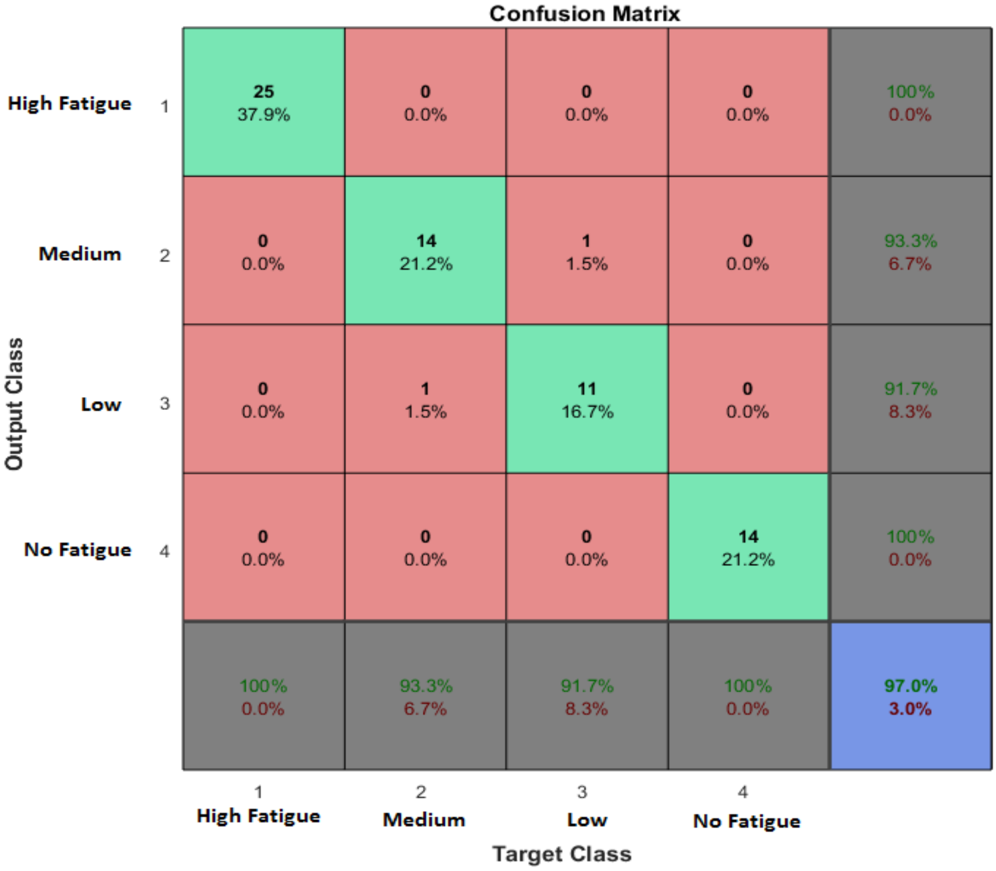


Fig 20(b): Confusion matrix of deep auto encoder with hidden size 15 for four level fatigue classification (Testing)

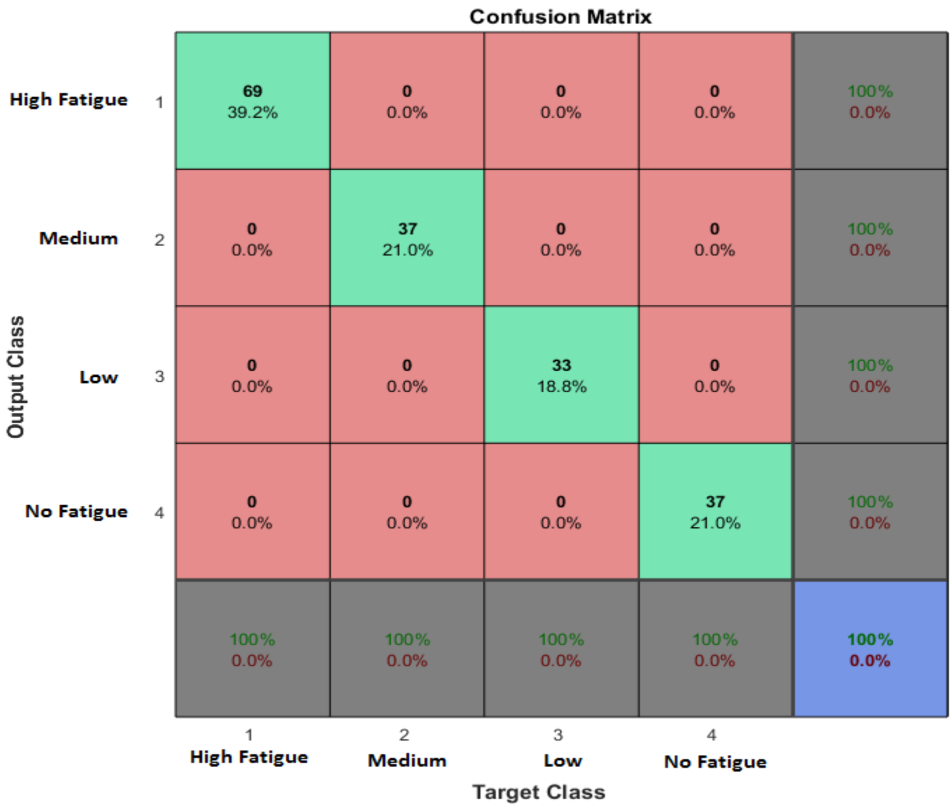


Fig 21(a): Confusion matrix of deep auto encoder with hidden size 10 for four level fatigue classification (Training)

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

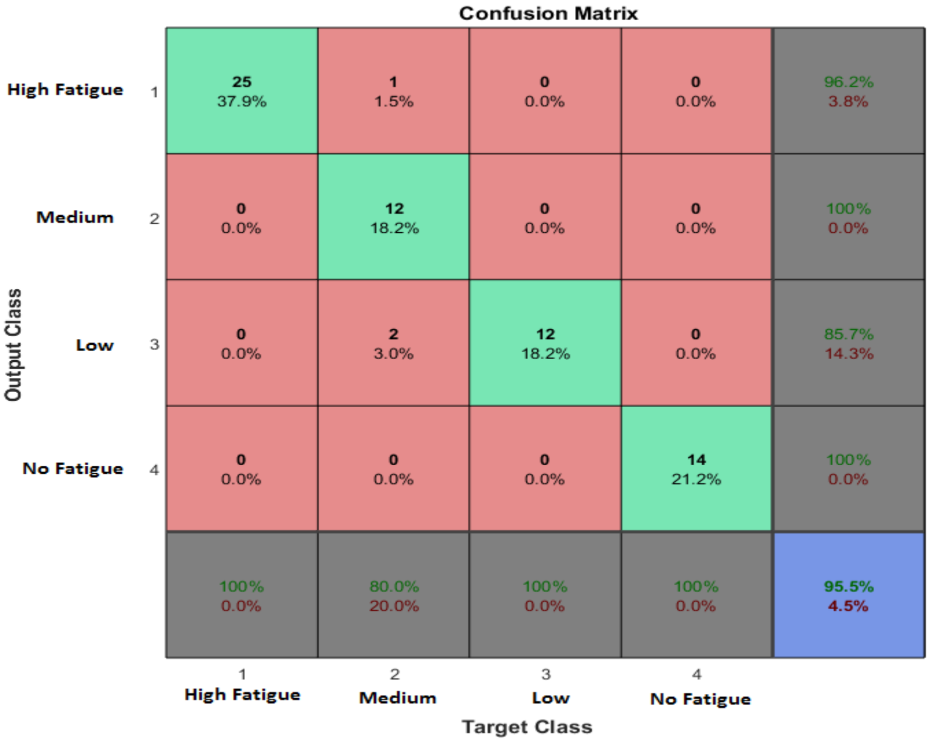
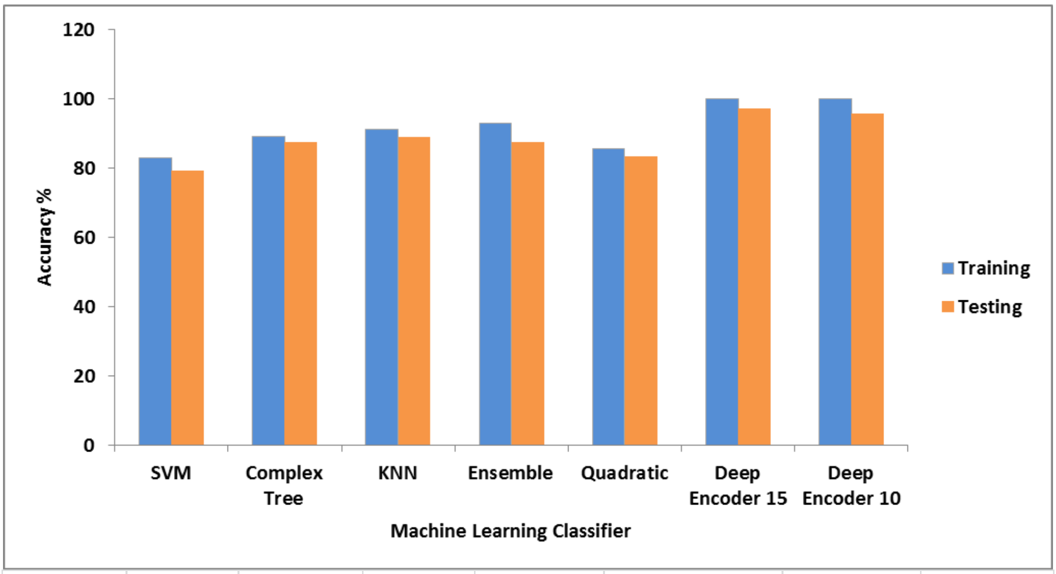


Fig 21(b): Confusion matrix of deep auto encoder with hidden size 10 for four level fatigue classification (Testing)



	SVM	Complex Tree	KNN	Ensemble	Quadratic Discriminant	Deep Encoder 15	Deep Encoder 10
Training Accuracy %	82.9	89.1	91.2	92.7	85.4	100	100
Testing Accuracy %	79.2	87.5	88.9	87.5	83.3	97	95.5

Fig 22: Performance accuracy of Machine Learning classifiers (4 level)

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 7, Issue 12, December 2019

List of Tables

Table 1. Fatigue scores

Score	Description
1	High Fatigue
2	Medium
3	Low
4	No Fatigue

Table 2. The Karolinska Sleepiness Scale (KSS)

Rating k	Description
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither
6	Some signs of sleepiness
7	Sleepy but no effort to stay awake
8	Sleepy but some effort to stay awake
9	Very sleepy, great effort to stay awake

Table 3: Split up of the data points for training and testing

SL. No	Classifiers	4 Level Fatigue detection	
		Training points	Testing points
1	SVM	168	72
2	KNN	168	72
3	Ensemble	168	72
4	Decision Tree	168	72
5	Quadratic	168	72
6	Deep Auto Encoder	168	72