

# Stress Detection of Automobile Drivers using Physiological Signals

Dikshita Sheth

M. Tech Scholar, Dept. of Electronics and Telecommunication Engineering, Dr. Babasaheb Aambedkar Technical University, Lonere, Maharashtra- India

\*\*\*

**Abstract** – Detection of the stress is very important, particularly in the automobile drivers as stress level forms a major factor for the accidents. This also provides information about how different roads and traffic conditions can affect the performance of the automobile drivers. This paper proposed a method to detect the stress levels using physiological signals such as ECG and EMG signals. The steps used involve data collection, renovation of noise, feature extraction and comparison. The data of physiological signals used in this paper were taken from Physionet Database. The results are obtained using MATLAB Simulation environment. Features extracted showed correlation with stress and also high accuracy of 78.57% for 60 seconds, 92.85% for 180 seconds and 92.85% for 360 seconds obtained for the detection.

**Key Words:** Drivers, stress, ECG, EMG, MATLAB, physiological signals.

## 1. INTRODUCTION

Stress can be defined as the body’s reaction to a change that requires a physical, mental or emotional response. Stress can alter our well-being life. Driving is one of the stressful activities in our day-to-day life [1]. According to survey conducted by Cigna TTK health insurance, about 89% of India’s population suffering from stress, as compared to the global average of 86%. All the drivers suffer from the stressful driving situation in their life even if they do not suffer daily.

Electrocardiograph (ECG) can be defined as the graphical representation of the electric activity of the heart [2]. The relationship of heart with the stress is clear to all of us. Heart rate can provide appropriate condition of the human stress. The connection between the heart rate variability [HRV] and the stress had been proven by the studies [3]. In this paper, we extract R-peaks and Average heart rate as the features for detection of the stress.

The Electromyography (EMG) signal is defined as a biomedical signal which measures electrical currents generated in muscles during its contraction and relaxation, representing neuromuscular activities. EMG is a random signal. In this paper, Zero Crossing Rate (ZCR) of the EMG signal is used as feature to detect the stress of drivers. When a driver suffers from high stress, the action potential propagates a chemical reaction that makes the contraction of muscle fibres. Hence the ZCR value is high and vice versa.

## 2. LITERATURE REVIEW

This paper describes the detection of stress level of different drivers under less and heavy traffic conditions. Different features used previously by the different researchers are video recordings of facial expressions and posture gesture changes [4], vocal inflection changes [5], blood-glucose levels, and other bodily changes [6], [7]. But video recordings have its own limitations. This also makes data acquisition expensive. In this paper, features are extracted only from the physiological signals so that they become more vigorous and reliable.

Many researchers had been doing work in detection of stress level. Notable ones are listed in the table 1. This table summarizes different approaches used by others.

**Table -1:** Various approaches used in different papers

| References                                       | Physiological signals used | Algorithm used                            | Populations used      | No. of Classes |
|--|----------------------------|---|-----------------------|----------------|
| Picard & Healey (2000) [8]                       | ECG, EMG, SC, Resp.        | Linear Discrimination Algorithm           | 3 experienced drivers | 3 stress class |
| Barreto & Zhai (2006) [9]                        | BVP, GSR, PD               | SVM (Support Vector Machines)             | 32 individuals        | 2 stress class |
| Singh R. R. & Banerjee R. (2013) [10]            | EDA, HRV, RSP signals      | LRNN                                      | 19 individuals        | 3 stress class |
| Karthik Soman, Sathiya A, Suganthi N (2014) [11] | ECG, EMG                   | SVM (Support Vector Machines)             | 14 individuals        | 2 stress class |
| Sowmya N, Shanmathi N, Menka R (2018) [12]       | EMG                        | Hebbian and perceptron learning algorithm | 2 individuals         | -              |

### 3. METHODOLOGY

Figure 1 represents the block diagram of the complete technology.

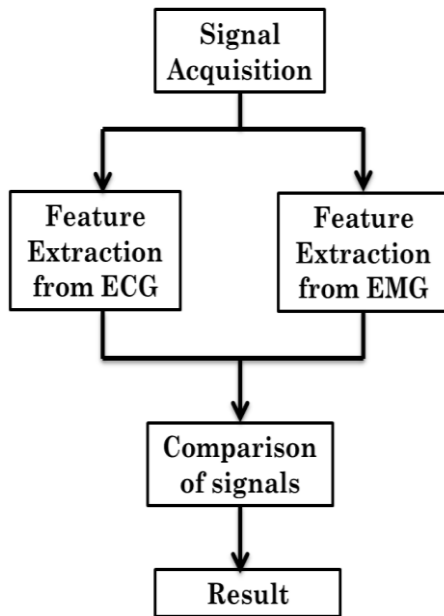


Fig -1: Block Diagram of Methodology

The first step is collecting ECG and EMG signal and removing noise from the signals. Next step is feature extraction. From the ECG signal data, R peaks of the signal are detected, heart rate is calculated and from EMG signal, Zero crossing rate is calculated. These features are then compared to detect the stress level of the signal and the result is stored.

#### 3.1 Signal Acquisition

The data of physiological signals used in this paper were taken from Physionet Database [8]. The data (ECG and EMG signals) were actually collected using electrodes connected to the drivers while they were driving. To acquire the ECG signal, Lead II electrode configuration was preferred in order to minimize the amplitude of the artifacts and maximize the amplitude of the R waves. While acquisition of EMG signals were done by placing the physiological sensors on the shoulder muscles. With the help of Flex comp A- D converter, ECG signal was sampled at 496Hz and EMG signal was sampled at 15.5Hz. These signals were acquired and processed by the embedded computer in the modified car. Data was collected for 14 drivers.

#### 3.2 Feature extraction of ECG signal

Extraction of the important information from the ECG signal, which contributes to an accurate driver stress level

detection model, is a challenging task. In this paper following steps are used to extract features from the ECG signal:

1. Pre-processing: In order to remove low frequency components following steps are used:

1.1 Find FFT of the ECG signal to shift signal into Frequency domain. The Fourier transform (FT) of the function  $x(j)$  is the function  $X(k)$  is calculated by

$$X(k) = \sum_{j=1}^N x(j)w_N^{(j-1)(k-1)}$$

1.2 Remove low frequency components by equating them to zero.

1.3 Again find IFFT of the signal to shift signal back to time domain. The Inverse Fourier transform (IFFT) of the function  $X(k)$  is the function  $x(j)$  is calculated by

$$x(j) = \frac{1}{N} \sum_{k=1}^N X(k)w_N^{-(j-1)(k-1)}$$

2. Window filter is used to find the maxima (R-peak). The cleaned raw ECG signals are divided into sequences of consecutive windows with a fixed size and a certain degree of overlap between the adjacent windows. In this paper, Peak and valley filter is used. Only use peak approach as only need to find local maxima. First we calculate the window size using sampling frequency. After that we compare amplitude of each sample with next sample to find the maximum value (R peak) within the window and then move the window to find next peak and so on.

3. Remove small values from the filtered signal and store significant ones.

4. Adjust the window size, and repeat steps 2 and 3.

Then Heartbeat rate in (beats/second) can be calculated by formula using detected R peaks:

$$\text{Rate} = 60 * \text{sampling rate} / (\text{R-R Interval})$$

#### 3.3 Feature extraction of EMG signal

For the noise removal, first find the FFT (Fast Fourier Transform) of the Raw EMG signal to shift the zero frequency components to the centre.

After this, Band-pass filter is generated with the cutoff frequencies -10hz to -5hz and 5hz to 10hz and with amplitude 1mv. Band-pass filtering is used to improve the S/N for the further attenuation of the noise relative to the signal. Now, find IFFT (Inverse Fourier transform) of the signal to shift signal back to the time domain.

In this paper, zero crossing rate of EMG signal is used as feature in order to detect the stress. The ZCR can be defined as the rate at which sign-changes along a signal, i.e., the rate of the signal changes from positive to zero to negative or from negative to zero to positive. ZCR for a signal's' of length T can be defined as:

$$ZCR = \frac{1}{T} \sum_{t=1}^T |s(t) - s(t - 1)|$$

### 3.4 Comparison between features of the signal

For the detection of the Stress level of automobile drivers, comparison is done between different features of ECG and EMG signal and threshold values. By making the use the comparison stress level of the driver is detected whether the driver is going through the high stress or low stress level. It is done using the algorithm described in the following flowchart:

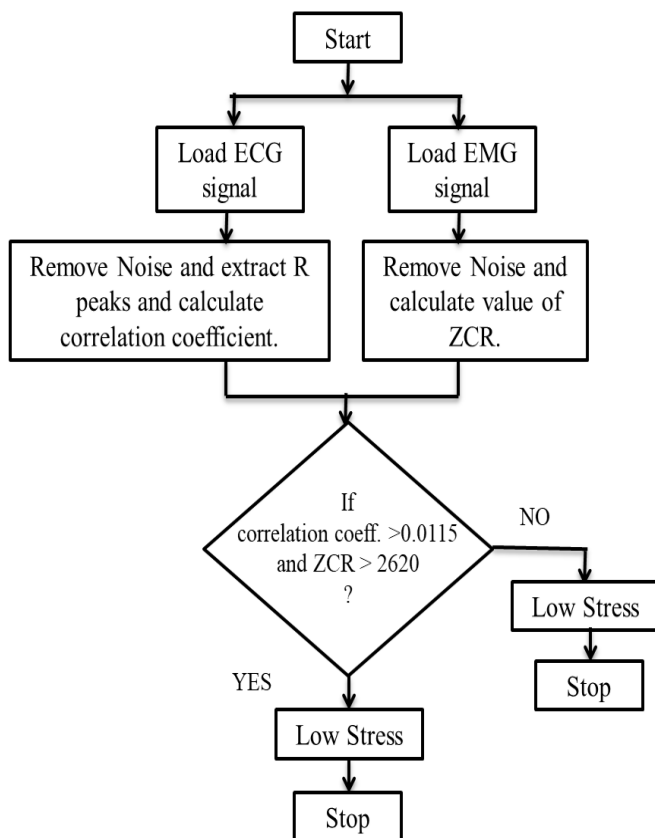


Fig -2: Algorithm for comparison

For the comparison, correlation between the features of ECG signals is performed and correlation coefficient is calculated; which will give similarity between signals and

then compare correlation coefficient with the threshold value.

Correlation coefficient is calculated using:

$$r = \frac{\sum_m \sum_n (A_{mm} - \bar{A})(B_{mm} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mm} - \bar{A})^2) (\sum_m \sum_n (B_{mm} - \bar{B})^2)}}$$

Where,  $\bar{A}$  = mean (A), and  $\bar{B}$  = mean (B)

For comparison between the features of the EMG signal Zero crossing rate of each signal is compared with the threshold value to determine the stress level.

### 4. OBSERVATIONS AND RESULTS

The entire experimentation was simulated using MATLAB. For obtaining the results using the proper approach, sets of ECG and EMG samples are taken from the Physionet database for detection of stress level. Total number of samples tested are 4, 55,700+.

Fig. 3, 4, 5 shows the detailed feature extraction of ECG signal for few samples. Fig. 6, 7, 8, 9 shows detailed waveforms for the feature extraction of EMG signals.

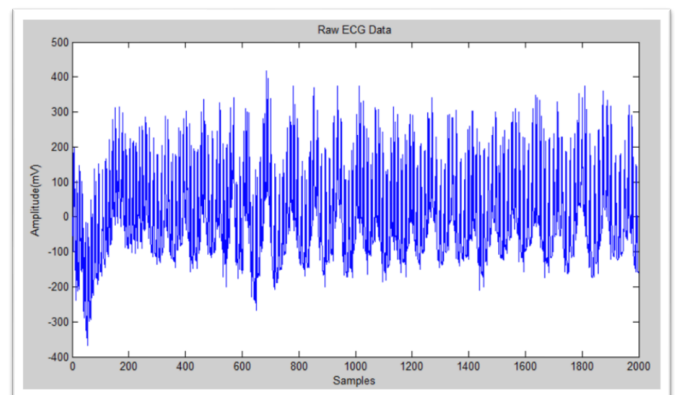


Fig.-3: Waveform of Raw ECG Data

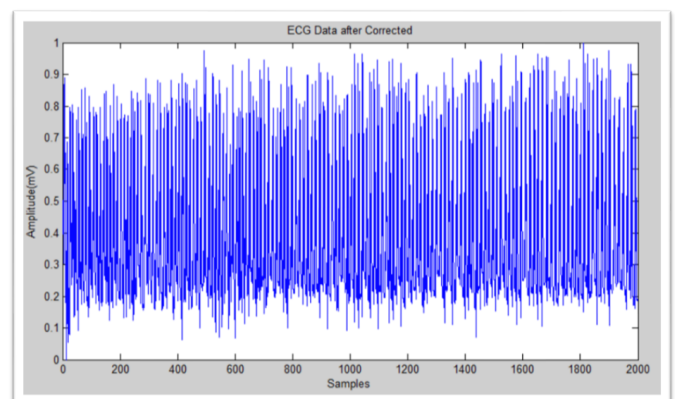


Fig.-4: Waveform of Corrected ECG Data

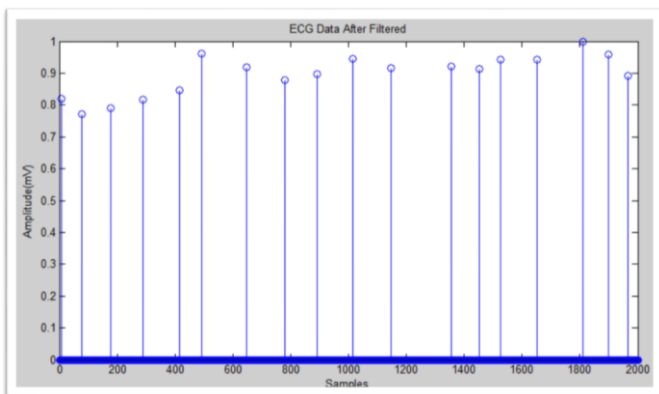


Fig-5: Waveform of ECG Data after filtered

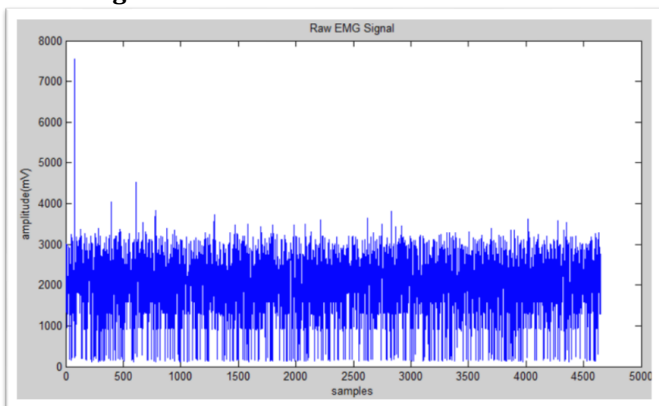


Fig-6: Waveform of Raw EMG signal (High Stress)

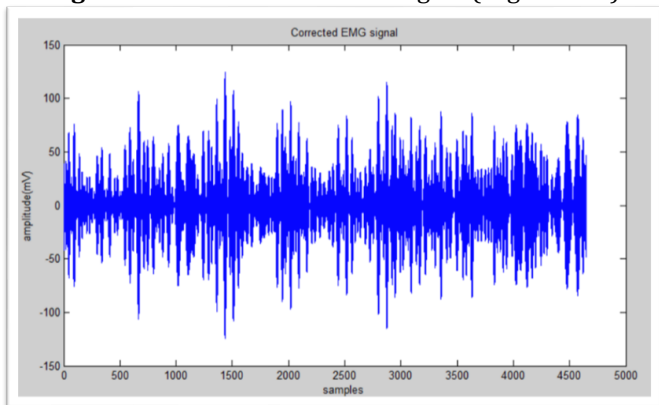


Fig-7: Waveform of Corrected EMG signal (High Stress)

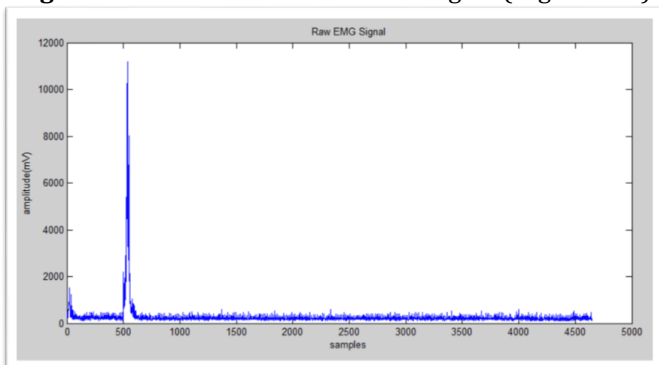


Fig-8: Waveform of Raw EMG signal (Low Stress)

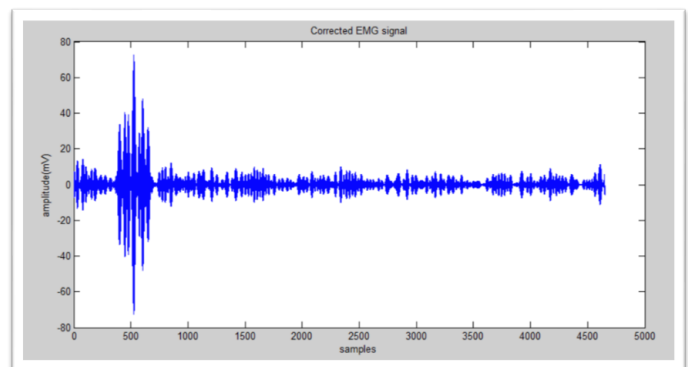


Fig-9: Waveform of Corrected EMG signal (Low Stress)

Fig. 10, 11 shows screenshots of the stress level detected in drivers using MATLAB software.

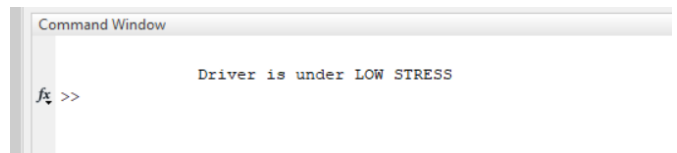


Fig-10: Screenshot of low stress signal detected

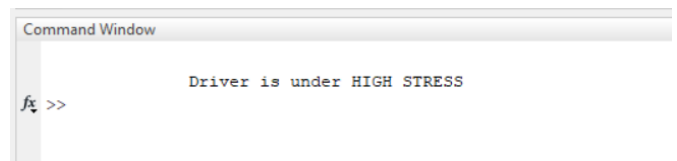


Fig-11: Screenshot of high stress signal detected

The features extracted from ECG signal are: R peaks, Average heart beat rate, Correlation coefficient and the features extracted from EMG signal are zero crossing rate, Absolute value, Variance. Table 2 shows results of 4 drivers for 2325 samples while table 3 shows the results for 4650 samples and table 4 shows results for 9300 samples.

Table -2: Result Table (for 60 seconds/2325 samples)

| Driver No. | Average Heart Beat Rate | Correlation Coefficient | ZCR  | Mean     | Variance   | Stress Level |
|------------|-------------------------|-------------------------|------|----------|------------|--------------|
| 02         | 117.7520                | 0.0815                  | 1373 | 32.2760  | 2400e+03   | HIGH         |
| 07         | 83.8794                 | -0.0081                 | 1330 | 307.5722 | 1.6514e+05 | LOW          |
| 12         | 85.8369                 | -0.0080                 | 1315 | 57.8332  | 3.9717e+04 | LOW          |
| 14         | 105.5409                | -0.0092                 | 1337 | 36.7833  | 3.7713e+03 | HIGH         |

Table -3: Result Table (for 180 seconds/4650 samples)

| Driver No. | Average Heart Beat Rate | Correlation Coefficient | ZCR  | Mean     | Variance    | Stress Level |
|------------|-------------------------|-------------------------|------|----------|-------------|--------------|
| 02         | 108.5613                | 0.0136                  | 2727 | 29.0341  | 1.7915 e+03 | HIGH         |
| 07         | 85.8816                 | -0.0088                 | 2600 | 333.4878 | 1.8384 e+05 | LOW          |
| 12         | 90.9682                 | -0.0091                 | 2635 | 44.1409  | 2.0580 e+04 | LOW          |
| 14         | 115.1581                | 0.0120                  | 2679 | 35.9631  | 4.3718e+03  | HIGH         |

**Table -4:** Result Table (for 360 seconds/9300 samples)

| Driver No. | Average Heart Beat Rate | Correlation Coefficient | ZCR  | Mean     | Variance   | Stress Level |
|------------|-------------------------|-------------------------|------|----------|------------|--------------|
| 02         | 106.8984                | 0.0169                  | 5434 | 44.7651  | 1.111e+03  | HIGH         |
| 07         | 81.9868                 | -0.0081                 | 5192 | 333.8309 | 1.8012e+05 | LOW          |
| 12         | 86.7688                 | -0.0084                 | 5269 | 48.1297  | 2.0405e+04 | LOW          |
| 14         | 113.3737                | 0.0024                  | 5313 | 40.5933  | 1.1732e+04 | HIGH         |

To evaluate the performance of the developed approach Accuracy parameter is used. The degree of closeness of measurements of a quantity to that of its actual (true) value is termed as Accuracy. Table 5 shows accuracy for detection of stress level of drivers for different number of samples and table 6 shows comparative results for different approaches.

**Table -5:** Accuracy for detection of stress level (for different no. of samples)

| Time (in seconds) | No. of Samples | Accuracy (%) |
|-------------------|----------------|--------------|
| 60                | 2325           | 78.57        |
| 120               | 4650           | 92.85        |
| 240               | 9300           | 92.85        |

**Table -6:** Comparative results for different approaches

| References                                       | Accuracy (%) |
|--|--------------|
| Picard & Healey (2000) [8]                       | 88.6         |
| Barreto & Zhai (2006) [9]                        | 91           |
| Singh R. R. & Banerjee R. (2013) [10]            | 94.92        |
| Karthik Soman, Sathiya A, Suganthi N (2014) [11] | 100          |
| Sowmya N, Shanmathi N, Menka R (2018) [12]       | -            |
| Proposed method                                  | 92.85        |

## 5. CONCLUSION AND FUTURE SCOPE

Stress level of a person was detected with high accuracy 78.57% for 60 seconds, 92.85% for 180 seconds and 92.85% for 360 seconds. This proposed method also proved the correlation between stress and features extracted from ECG

and EMG signal. This helps the technology to escalate automobile driver safety.

In the future, these can be used for developing machines which can respond intelligently to driver behaviour such as automatic management of in-vehicle information systems such as radios, cell phones, and on-board navigation aids. Some examples of this might include cell phone calls could be diverted to voice mail.

## ACKNOWLEDGEMENT

I like to acknowledge Dr. Jennifer A. Healey and Dr. Rosalind W. Picard for acquiring the signals which were used in this paper for the analysis.

## REFERENCES

- [1] Danx. Mc graw, "Driving can stress you out as much as skydiving", MIT studies, June 10, 2013.
- [2] Priton Adhikari, Titash Maity, Shalini Priy, Soham Biswas, Sutapa Ray, Lopamura Bhowmick and Adri Mukharjee, "A Novel Approach to find out QRS Complex for ECG signal", IEEE, 2016.
- [3] Pagani M, Malliani A. "Interpreting oscillations of muscle sympathetic nerve activity and heart rate variability". J Hypertens 2000; 18: pp. 1709–19.
- [4] I. Essa and A. Pentland, "A vision system for observing and extracting facial action parameters," in Proc. CVPR, 1994, pp. 76–83.
- [5] I. Essa and A. Gardner, "Prosody analysis for speaker affect determination," in Proc. Workshop Perceptual User Interfaces, 1997, pp. 45–46.
- [6] L. C. DeSilva, T. Miyasato, and R. Nakatsu, "Facial emotion recognition using multi-modal information," in Proc. IEEE Intell. Conf. Inf., Commun, Signal Process, 1997, pp. 397–401.
- [7] J. T. Cacioppo and L. G. Tassinary, "Inferring physiological significance from physiological signals," Amer. Psychol., vol. 45, no. 1, pp. 16–28, Jan. 1990.
- [8] Jennifer A. Healy, Rosalind W. Picard, "Detecting stress during real-world driving tasks using physiological sensors", IEEE Transactions on intelligent transportation system, vol.6, no.2, June 2005.
- [9] Barreto, A. & Zhai, J., "Stress detection in computer users based on digital signal processing of non-invasive physiological variables", 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. EMBS '06, pp. 1355–1358, 2006.
- [10] Singh, R. R., Conjeti S., & Banerjee, R., "A comparative evaluation of neural network classifiers for stress level analysis of automotive drivers using

physiological signals. "Biomedical Signal Processing and Control, 8(6), 740–754, 2013.

- [11] Karthik Soman, Sathiya A, Suganthi N, "Classification of stress of automobile driver using Radial Basis Function Kernel Support Vector Machine", ICICES, 2014.
- [12] Sowmya N, Shanmathi N, Shrivarshini S, Menka R, "Stress diagnosis using EMG signal", IEEE International conference, India, 2018.