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Emotion Controlled Health Monitoring System based on IoT Design

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Abstract: *In this paper, IOT have been playing an immense importance in many fields all around the world. Its applications have contributed to the development of highly accelerated technology which has turned out to be the key component in the digital transformations in the health care industries. The proposed study was based on the development of an emotion response monitoring device on an android platform and also to monitor the data at online basis. The data were collected using three sensors: ECG sensor placed on the chest, EMG sensor placed on the upper trapezius muscle and IMU sensor to determine the head movement. These relevant sensors are connected to PIC microcontroller for the data acquisition and conversion to the digital format. The digital data are further directed to the serial port communicator on the PC. The signals are further processed using MATLAB to acquire the necessary features required for the classification of various emotions. The features are trained using SVM classifier and the classified emotions are displayed on the mobile device by an application. It has also been stored on to the cloud via Ethernet in order to access in online at an faster rate. This developed system could be applied in many application concerned with emotion monitoring systems in healthcare and also for future study analysis based on emotions.*

Keywords: *Health Monitoring, PIC microcontroller, signal processing, mobile application, emotion classifier, online display*

I. INTRODUCTION

IoT technology is used to support medical consultations among rural patients, health workers, and urban city specialists. With the use of IoT, M-health concept, which is defined as mobile computing, medical sensors, and communication technologies for healthcare, attracts more and more researchers applying fourth-generation (4G) mobile communication technology [1]. The above-mentioned uses of IoT technology bring both opportunity and challenges in ubiquitous data accessing medical services. More attentions have been paid in developing ubiquitous data accessing solutions to acquire and process data in decentralized data sources. [2]-[3]. Human emotions are hypothetical constructs based on psychological and physiological data. All emotions derive from a set of discrete basic emotions, common to human and animals. Basic emotions are thus considered as physiological processes based on specific neuronal circuits. Emotions require the global functioning of the brain, even if more specialized regions are involved. They play a fundamental role in the development of the child's psychological and social life. Emotional disturbances are major consequences of psychiatric or neurological disorders. The link between the results of neuropsychological studies of emotions based on the recognition of emotional facial expression according to the basic emotion theory, and the emotional disturbances experienced in daily life is highly questionable on account of the high complexity of human affective life. Emotions can be classified as primary and secondary. Primary emotions are those emotions arising due to the event that has occurred and secondary emotions are those emotions depending on the situation that the person is undergoing. Emotions may be positive or negative.. Positive emotions are those in which one feeling happy or positive about oneself. It includes happiness, optimism, passion and success. Negative emotions are those in which one consumes a lot of energy and mentally goes weak. It include fear, anxiety, stress, fatigue, shock, anger and many more which affect the normal functioning of heart, brain and muscles. The features like heart rate, respiration rate, pulse rate, abnormalities in heart signals, muscular activities are being altered as a result of above mentioned negative emotions. The emotions classified can be displayed on mobile device using android application. The study emphasizes on developing a wearable device compatible with three sensors placed on different positions of the body. The system helps to measure the stress and fatigue induced in different patients at various situations. This helps to perform various studies on mentally disordered patients, to develop emotion-aware solutions for Autistic children and also used for safety alert based applications. This include driving based situations, in which the driver undergoes many kind of emotions during the travel. Due to these emotions they can be cases where there is a chance of a road accident. To prevent such situations, depending on the threshold values of each emotion, an alarm system or an emergency alert can be designed. This system can be further modified by developing it as an IOT based strategy. IoT offer greater promise in the field of healthcare, where its principles are already being applied to

improve access to care, increase the quality of care and most importantly reduce the cost of care. As per the study, the classified emotions at different situation could be viewed online and also stored in the cloud for future references.

II. LITERATURE SURVEY

EEG signals provide enough information for the detection of human emotions with feature based classification methods. The proposed study was conducted on an offline computer aided emotion classifier. The EEG data was collected from nine participants using validated film clips in order to classify four emotions (amused, disgusted, sad and neutral). The method include feature extraction stage using STFT (Short Time Fourier Transform) followed by classification stage. The classification rate was evaluated using both unsupervised and supervised learning algorithms. It was found that SVM classifier showed the highest accuracy rate among all other classifiers. However, Stefano Valenzi designed an approach to considerably improve the classification accuracy of human emotions. Results suggested that it was possible to classify some selective human emotions using EEG in a reliable way and can be made feasible by an online technique. [8]

Studies have presented that the driver vigilance level has serious implication in the causation of road accidents. The study focused on integrating the vehicle-based control behavior and physiological state to predict the driver vigilance index which is evaluated by using a smart watch. The vehicle control behavior was observed from the steering wheel movement whereas physiological state of driver was reflected on the driver's capability of safety alert driving which was estimated by photo-plethysmogram (PPG) and respiration signals. The PPG sensor is integrated in a sport wristband with a Bluetooth low energy module, which was transmitted using PPG signals to smart watch in real time. The steering angle was derived from smart watch built-in accelerometer and gyroscope sensors. On the other hand, the respiration was derived using the PPG peak baseline method. The extracted descriptive features served as parameters to the classifier to determine the driver aptitude status. The features were analyzed for their correlation with the subjective Koralinska sleepiness scale and through recorded video observations.[9] Boon-Giin Lee, made an approach to develop a embedded device to estimate the vigilance state of driver by using PPG sensor built into a smart watch.

A nonintrusive prototype computer vision system was designed on real time basis to estimate the driver's vigilance state. It was based on a hardware system for a real-time acquisition of driver's images using an active IR illuminator and the implementation of software algorithms for the realtime monitoring of six parameters that characterized the fatigue level of the person. A fuzzy classifier was implemented to merge all the parameters into a single DIL. The monitoring of other inattention categories was possible using this method. The system was fully autonomous. It was tested using different sequences recorded in real driving conditions with different users during several hours. The system worked robustly at night and for those users not wearing glasses, yielded an accuracy percentage close to 100%. The performance of the system decreased during daytime, especially during bright days, and at the moment, the system remained non-functional. Luis M. Bergasa provided an approach to detect problems related to drowsiness and hence would be completed with actual drowsiness data. [10]

III. PROPOSED TRANSFORMATIONS

A. Design Model

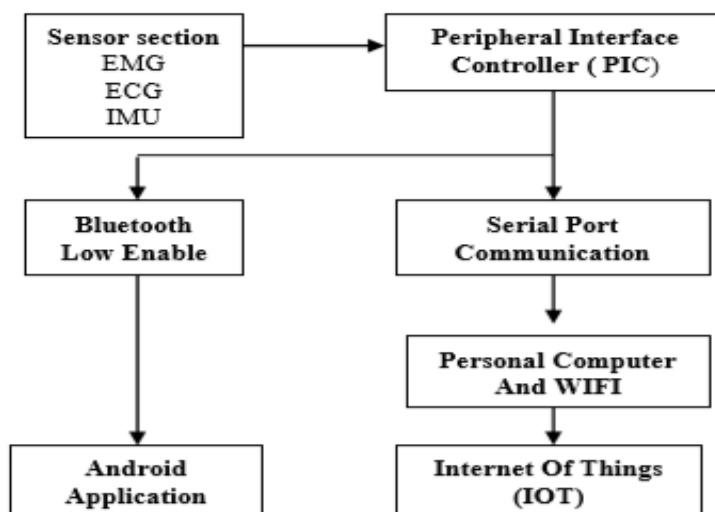


Fig 1. Block Diagram of system design

B. Hardware System

The system consists of three sensors: ECG Sensor consisting of three probes located at different regions, EMG sensor placed on the upper trapezius muscles and IMU sensor placed for positioning. ECG and EMG sensors have built in filters to remove the unwanted noise present in it and also to produce an amplified signal. The following sensors help to determine the features: heart rate, muscle activation and different angles of head rotation. The sensors are then connected to the PIC 16F877A for data acquisition and in built ADC converts it to digital format. The processed digital data are directed to serial port communicator to process for signal processing section. The signals are displayed on MATLAB platform for acquiring the above mentioned features. ECG and EMG signals are further processed for filtration. ECG data determines the R peak followed by other peaks such as P, T and QRS complex. These peaks and filtered EMG data are further decomposed to acquire the coefficients necessary for the classification. SVM classifier was used to classify the features according to real time basis. The classified results were displayed on a mobile phone using an android application. The alert module will be triggered if the predicted emotional responses are classified as negative ten consecutive times. It is also stored on the cloud server and accessed on website easily.

C. Software System

ECG and EMG data after which are displayed on the MATLAB need to be further processed to acquire more significant features. The EMG signals are filtered to remove the unwanted noise present in the data. These noises arise due to many factors like: motion artifacts, interference signals and electrode displacement. Filters used are Extended Kalman Filter and Butterworth Filter. The filtered signal is rectified and normalised to get a good frequency content. Further the neural and muscle activation of the signals are plotted. Features like measurement angle, angle spectrum, energy spectrum, Welch power spectral density estimation was determined. FFT of these signals were determined. The first Fourier transform (FFT) is most common method for determining the frequency spectrum of the EMG signal. The frequency spectrum of EMG is used to detect muscle fatigue force production, and muscle fiber signal conduction velocity. Wavelet decomposition using eight level decomposition were performed to determine the RMS values of the signals. Whereas in the case of ECG signals, the input signals was decomposed using four level decomposition to get smoothed signal. R peak was detected followed by the other peaks such as, p wave, T wave, QRS complex along with their amplitudes. Statistical values like standard deviation, RMS values were determined along with that, morphological features like, heart rate, PR segment and ST segment was determined.

The features obtained after the processing stage was given to the SVM classifier. SVM classifier is a machine learning algorithm used in pattern recognition. It is a supervised learning technique. The core idea behind the SVMs is building an optimal hyper plane in order to use in classification of linearly separable patterns. The decision function of the SVM classifier is defined by a hyper plane separated by a line, also known as the decision boundary, among the support vectors, that is, points that are positioned around the hyper plane line, as described elsewhere. The usual logistic regression model can only derive classes with a straight-line decision boundary. In contrast, the boundary line in the SVM does not necessarily have to be linear, as its function is nonparametric and locally operated.

D. Developing Android Application

The input features from the PIC microcontroller are transferred to the mobile device using blue-tooth module further processed in the device. As the sensors placed on different location, these data need to be displayed at real time. The aim of designing such a system to create awareness to the persons undergoing different emotion strategy. When they go beyond threshold value at the specified time, an alert module detects and hence can take preventive measures to control the adverse situation in actions. The input data from the sensors are separated based on morphological features. They include heart rate variability, pulse rate, muscle activity, head motion. Depending on these features, it is converted into vector format in order to classify then using SVM classifier. They are classified based on trained data sets. After classification, the alert message activates depending on threshold condition and also the simultaneous emotion is being classified.

E. Developing IoT

Internet of Things (IoT), devices gather and share information directly with each other and the cloud, making it possible to collect, record and analyze new data streams faster and more accurately. Its relation to healthcare systems are based on the essential definition of the IoT as a network of devices that connect directly with each other to capture and share vital data through a secure service layer (SSL) that connects to a central command and control server in the cloud. The main aim of this platform is to gather information in order to take preventive measures at early diagnosis in case of any acute complications and also for analysis which can help in future diagnosis. It also helps to gather data to remove the limitations of human-entered data by automatically obtaining

the data doctors need, at the time and in the way they need it. The automation helps to reduce the risk of error. Fewer errors can mean to increase efficiency, lower costs and improvements in quality.

The classified results are documented to the cloud storage and displayed on online website. The real time based results gets updated timely. This helps to keep a watch on the health parameters of various patients. The data were transferred using wifi module incorporated in the Personal Computer. It can be spread to any type of devices for easy accessibility.

IV.RESULTS AND DISCUSSIONS

Signals were acquired using specified sensors and then programmed using PIC. The data was converted into digital format and was sent for further processing stages.

A. EMG Processing Section

EMG signals were displayed on MATLAB software for processing section. Fig 2 shows the ‘input EMG signal’, acquired from the sensors by placing the electrodes on different positions of arm. The input EMG signal after acquisition was further filtered to remove the unwanted noise.

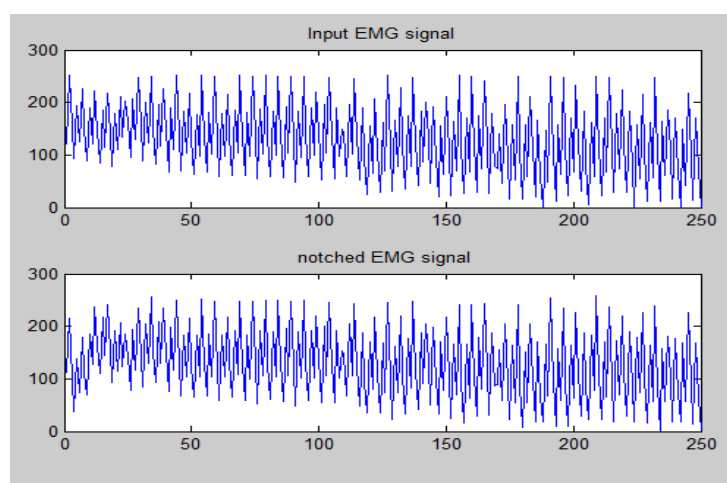


Fig 2. Input EMG Signal and notched EMG signal

Noise arises due to certain factors like motion artifacts, electrode displacement and interference signals. In order to remove these noise signals, various types of filters were used. Fig 2 also showed the results of notched EMG signal. Common type of noise contains 50 Hz frequency, which can be notched by placing a filter. The signals were then filtered using low pass butter worth filter, of frequency 700 Hz of 1000 samples and also rectified the filtered signals to remove the DC offset. Normalising an EMG signal gives a positive peaks that exist in that signal. Fig 3 shows the low pass filtered EMG signal , rectified signal and normalized signal.

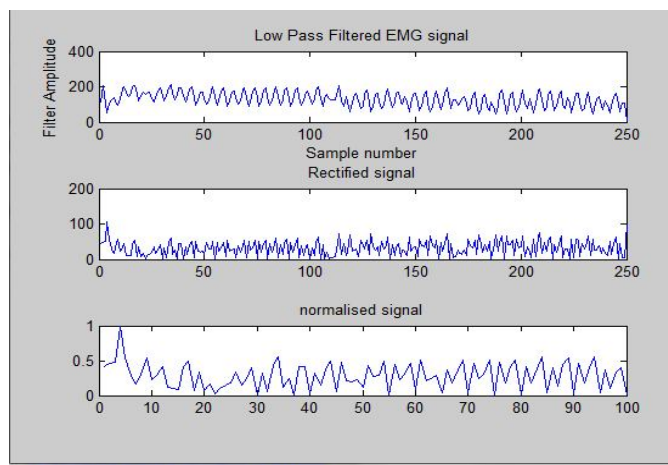


Fig 3. Low pass, rectified and normalised EMG signal

Fig 4.explains the various activities taking place in muscle. The graph depicts alpha, beta, gamma, theta, delta which shows the muscular activations. These are the muscular contraction and relaxation taking place inside, during various muscular movements. After the moment of muscle was plotted. FFT of EMG signal was found in order to determine the energy and power spectra. Depending on the statistical features , the classification could be performed. RMS value of muscle also determined to find the muscle tension. Fig 4 shows the statistical features like angle, energy and power spectra.

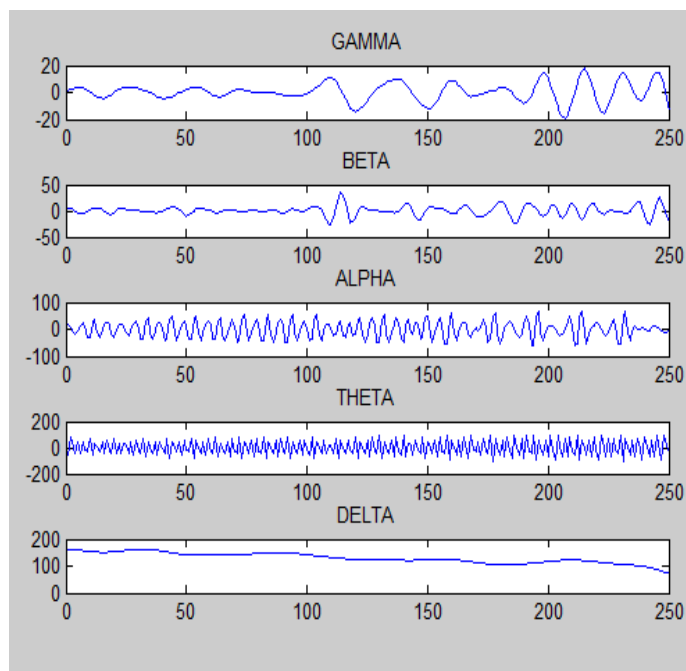


Fig 4. Moment of muscular activations

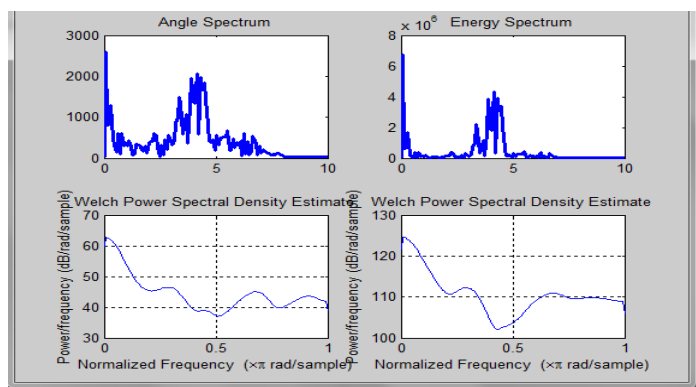


Fig 5. Angle, Energy and Power spectrum of EMG signals

B. ECG processing Section

ECG signals were acquired from the sensors using three electrodes placed at right arm, left arm and right leg. At real time the data were acquired and was displayed on 'MATLAB' for further processing sections. Fig 6.shows the input or the acquired ECG signal along with the filtered section. The next stage is to find the locations of peaks in the signal. There are five peaks followed by their amplitudes. The peaks were P wave, QRS complex and T wave. Detection of R peak is primary followed but the remains peaks. R peak detection was performed by Pan-Tompkins Algorithm. According to this, the input signal was band passed in the range of (5-15) Hz frequency. Placing a derivative filter, derivation was plotted. The signal were squared to detect the positive peaks and integrated by summing up all the signals. Further by setting two threshold the R Peak was located for sample of eight intervals and so on for the sample. As per the method, THRESH-SIG denotes the threshold for the signal amplitude (0.25 of the max ECG signal) and THRESH-NOISE denotes the threshold for noise amplitude (0.25 of the THRESH-SIG). Based on this principle, the R peak was located with their amplitude. Following the heart rate was calculated

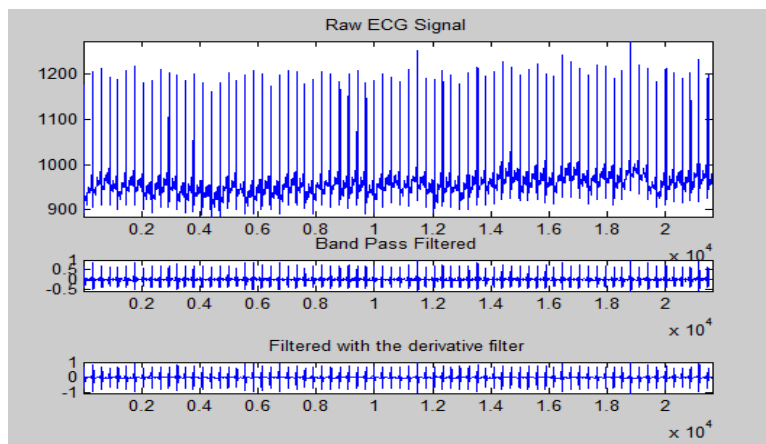


Fig 6. Raw ECG signal, band pass filtered and derivative filtered output signal

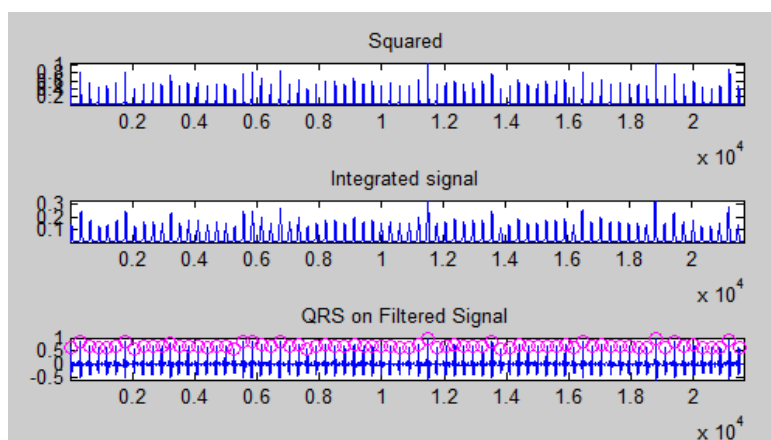


Fig 7. Squared, integrated and detected R peak ECG signal

The raw ecg signal was plotted for detection of P and T wave. As the normal PR interval lies between (0.12-0.22) seconds, hence the P location and amplitude was determined. Firstly, R peak was baselined by placing zeroes. According to thresholding technique, P wave should lie between (0.09 to 0.18) seconds where the sampling frequency was taken as 3600 samples per sec. Normal QRS width lies between (0.08- 0.12) seconds. Depending on those Q and S locations were determined. Finally, is the detection of T wave. Normal QT interval lies between (0.37- 0.43) seconds. Hence, T wave location was thresholded between (0.32 to 0.44) seconds. Fig 8. Displays the raw ECG signal, along with QRS replaced with zeroes, followed by P and T wave locations.

Table i. Features extracted for ecg and emg signals

| Ecg signal | Heart rate | P-P int | P-P mean | P-R int | PR mean | R-R Int | R-R mean | ST segment |
|------------|------------|----------------|----------|----------------|---------|-------------|----------|------------|
| Ecg data 1 | 73.62 | 0.814 | 293.33 | 0.1901 | 68.43 | 0.81 | 294.5 | -5.28 |
| ECG data2 | 101.5 | 0.600 | 216.21 | 0.0710 | 25.577 | 0.599 | 215.86 | -0.004 |
| ECG data3 | 124 | 0.481 | 173.3 | 0.14 | 50.52 | 0.482 | 173.65 | -0.0153 |
| ECG data4 | 66.8 | 0.8993 | 323.76 | 0.0104 | 3.75 | 0.8979 | 323.2273 | 0.0107 |
| EMG Signal | Max EMG | Angle spectra | | Energy Spectra | | Neural mean | | RMS value |
| EMG data1 | 163 | -11.50 + 0.04i | | 2.15e+04 | | 163 | | 6.796 |
| EMG data2 | 251 | -13.50 + 0.24i | | 2.45e+04 | | 135.54 | | 630.57 |

The table I. shows the various features extracted from the real time ECG and EMG signals acquired from sensor section. From the ECG sensor, R-R interval, RR-mean PR interval P-R mean, P-P interval P-P mean was calculated, whereas from the EMG signal, Maximum of EMG, Angle spectrum, energy spectrum and power spectrum was plotted. RMS value of EMG signals was also calculated to diagnose muscle dysfunction. From these extracted features, the wavelet decomposition was carried out. Hence, the coefficients were given to the SVM classifier to classify different emotions. Stress, shock, muscle tension, drowsy, anxiety and normal are the six classes of emotions to be classified.

Based on the features, the classified results were displayed on mobile application and on online site for easy diagnosis. In the case of mobile application, it was developed as an application such that the emotions could directly been displayed on to the screen. In case of any emergency situations, such as crossing the threshold value, the alert message will be sent to the health care centre or to their family members assigned in the mobile contacts. This can greatly decrease the chances of any adverse conditions.

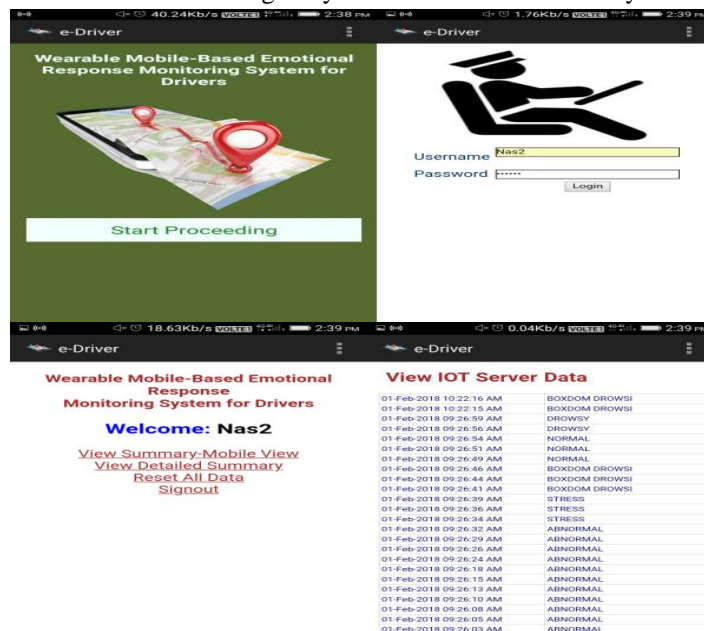


Fig 9. Results of mobile application and their classified emotions

Iot based emotional results were displayed on the site after logging in personal id. These can be globalized without any login to access it anywhere around the world. Figure10. shows the final classified emotions of various persons from their acquired signals. From the results, different emotions could be analyzed and studied for future studies and access in order to apply in various applications. These emotions can be basically taken into account in road based applications in order to prevent road accidents by controlling the stressed and drowsy situations.

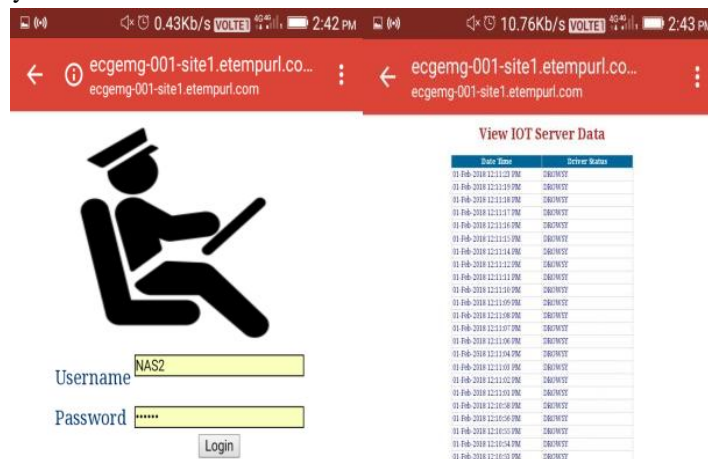


Fig 10. Iot based emotion classifier in online site

V. CONCLUSIONS

In this paper, IoT have been playing an immense role in modern technology especially in field of healthcare. It helps in easy portable, and highly efficient systems. The proposed system consists of sensor section, programming module and processing stages to acquire the required features. ECG, EMG and IMU sensors were used for signal acquisition and hence programmed using PIC16F877A, and then processed further in MATLAB, for signal development. The processing stages consist of filteraton, wavelet decomposition and finally the classification section. SVM classifier was used to classify the six classes of emotions. The classified emotions were displayed on mobile device by developing an application and also on the online site by developing an IoT platform. These emotions can further been developed and analyzed for future studies also be used in some application based systems.

VI.ACKNOWLEDGEMENT

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REFERENCES

- [1] K. Natarajan , “Smart Health Care System Using Internet of Things” , Journal of Network Communications and Emerging Technologies (JNCET)
- [2] R. Kyusakov, J. Eliasson, J. Delsing, J. V. Deventer, and J. Gustafsson, “Integration of wireless sensor and actuator nodes with IT infrastructure using service-oriented architecture,” IEEE Trans. Ind. Informat., vol. 9, no. 1, pp. 43–51, Feb. 2013.
- [3] N. Pereira, B. Andersson, and E. Tovar, “WiDom:Adominance protocol for wireless medium access,” IEEE Trans. Ind. Informat., vol. 3, no. 2, pp. 120–130, May 2007
- [4] Boon Giin Lee, Member, IEEE, Teak Wei Chong, Boon Leng Lee, Hee Joon Park, Yoon Nyun Kim, “Wearable Mobile-Based Emotional Response-Monitoring System for Drivers
- [5] M. M. Parker and R. H. Ettinger, “Emotion and stress,” in Understanding Psychology, 3rd ed. 2010.
- [6] R. S. Lazarus, “From psychological stress to the emotions: A history of changing outlooks,” Annu. Rev. Psychol., vol. 44, no. 1, pp. 1–21, 1993. [Online]. Available: <http://www.annualreviews.org/doi/pdf/10.1146/annurev.ps.44.020193.000245>
- [7] Boon Giin Lee , Jae-Hee Park , “Smart watch-Based Driver Vigilance Indicator With Kernel-Fuzzy-C-Means-Wavelet Method” IEEE Sensors Journal 2016
- [8] Boon-Leng Lee, “Smart-watch-Based Wearable EEG System for Driver Drowsiness Detection Gang Li” IEEE Sensors Journal, Vol. 15, No. 12, December 2015
- [9] Boon-Giin Lee, “Wristband-Type Driver Vigilance Monitoring System using Smart watch” IEEE Sensors Journal 2015 [10] Luis M. Bergasa, “Real-Time System for Monitoring Driver Vigilance” IEEE Transactions On Intelligent Transportation Systems, Vol. 7, No. 1, March 2006



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