# Wearable Recognition System for Emotional States Using Physiological Devices

Ali Mehmood Khan
TZi-AGKI, Universität Bremen
Bremen, Germany
e-mail: akhan@tzi.de

Michael Lawo
TZi-AGKI, Universität Bremen
Bremen, Germany
e-mail: mlawo@tzi.de

*Abstract*— **Recognizing emotional states is becoming a major part of a user's context for wearable computing applications. The system should be able to acquire a user's emotional states by using physiological sensors. We want to develop a personal emotional states recognition system that is practical, reliable, and can be used for health-care related applications. We propose to use the eHealth platform [1] which is a ready-made, light weight, small and easy to use device for recognizing a few emotional states like 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal', 'No-Idea', 'Positive' and 'Negative' using decision tree (J48) classifier. In this paper, we present an approach to build a system that exhibits this property and provides evidence based on data for 8 different emotional states collected from 24 different subjects. Our results indicate that the system has an accuracy rate of approximately 98%. In our work, we used four physiological sensors i.e. 'Blood Volume Pulse' (BVP), 'Electromyogram' (EMG), 'Galvanic Skin Response' (GSR), and 'Skin Temperature' in order to recognize emotional states (i.e. stress, joy/happy, sad, normal/neutral, dislike, no-idea, positive and negative).**

***Keywords- Emotional states; Physiological devices; International Affective Picture System; Machine learning classifier; User studies.***

## I. INTRODUCTION

It is hard to express your own emotions; no one can accurately measure the degree of his/her emotional state. According to Darwin, "....the young and the old of widely different races, both with man and animals, express the same state of mind by the same movement" [16]. According to Paul Ekman, there are seven basic emotions which are fear, surprise, sad, dislike, disgrace, disgust and joy [14]. The concept behind emotional states (also known as affective computing) was first introduced by Rosalind Picard in 1995 [2]. Since then the affective computing group have produced novel and innovative projects in that domain [3]. Emotional states recognition has received attention in recent years and is able to support the health care industry. Emotions and physical health have a strong link in influencing the immune system too [15]. Due to untreated, chronic stress; occurrence of an emotional disorder is more than 50% [6]. According to Richmond Hypnosis Center, due to stress; 110 million people die every year. That means, every 2 seconds, 7 people die [4]. According to American Psychological Association, in 2011 about 53 percent of Americans claimed stress as a reason behind personal health problems [5]. According to WebMD, intense and long term anger causes mental health problems including anxiety, depression, self-harm, high blood pressure, coronary heart disease, colds and flu, stroke, gastro-intestinal problems, and cancer [6]. The Occupational Safety and Health Administration (OSHA) reported that stress is a threat for the workplace. Stress costs American industry more than $300 billion annually [6]. According to Dr. Alexander G. Justicz, in the 21st century, stress is a huge problem for men [9]. Stress affects our health negatively, causing headaches, stomach problems, sleep problems, and migraines. Stress can cause many mouth problems, the painful TMJ (temporomandibular joint) syndrome, and tooth loss [7]. "Stress has an immediate effect on your body. In the short term, that's not necessarily a bad thing, but chronic stress puts your health at risk" [8]. Long term and intense anger can be caused of mental health problems including depression, anxiety and self-harm. It can also be caused of "high blood pressure", "cold and flu", "coronary heart disease", "stroke", "cancer" and "gastro-intestinal problems"[13]. "If you have a destructive reaction to anger, you are more likely to have heart attacks" [12] whereas "an upward-spiral dynamic continually reinforces the tie between positive emotions and physical health"[17].

Modern day lifestyle has led to various physical and mental diseases such as diabetes, depression and heart diseases as well. Although the negative effects of stress are known to people, they choose (deliberately or otherwise) to ignore it. They need to be forcefully notified, that they must shrug off negative emotions; either by sending them calls or some video clips/text messages/games [10]. Emotions are the feelings which influence the human organs. According to number of studies, negative thinking or depression can adversely affect your health [19]. Probably automatic and personal applications can be very helpful if it can monitor one's emotional states and persuade people to come out of negative emotional states. According to William Atkinson; "*The best way to overcome undesirable or negative thoughts and feelings is to cultivate the positive ones*" [18]. Emotional recognition technology can tackle this problem as it is able to monitor an individual's emotional states. This kind of system can also send an alarming call to a person when he is in a negative emotional state for long time or notify the caregivers or family members. The system can also log an individual's emotional states for later analysis. In some cases, especially in heart diseases, emotional states are also required along with the physical activities and physiological information for doctors in order to examine their patient's conditions when he is away from the doctor's clinic [11].

Emotional computing is a field of human computer interaction where a system has the ability to recognize emotions and react accordingly. We want to develop a

 ISBN: 978-1-61208-470-1

system for recognizing emotional states using physiological sensors which should be able to identify a few emotional states like sad, dislike, joy, stress, normal, no-idea, positive and negative. In our research we want to prove that it is possible to recognize the aforementioned emotional states by using physiological sensors.

## II. Related Work

Recognizing emotional states by using automated systems have increased in recent years. Researchers developed systems for recognizing emotional states using speech [23, 24, and 25], facial expressions [26, 27, and 28] and physiological devices [20, 21, 22, 29, and 30]. In this research, we want to recognize different emotional states using body worn physiological devices (EMG, BVP, GSR and temperature). Researchers used physiological devices in order to recognize for different emotional states like sad [20, 21, 22, 30], joy/happy [20, 21, 22, 30, 31], normal/neutral [21, 30, 31], negative [29] etc. However, the aforementioned researches have used different physiological devices in their work. For example; some researchers recognized emotional states using EEG (Electroencephalogram), GSR and pulse sensor and they recognized joy, anger, sad, fear and relax. Audio and visual clips were used as a stimulus for eliciting the emotions [20]. Some researchers recognized emotional states using ECG (Electrocardiography) and they recognized 'Happiness', 'Sad', 'Fear', 'Surprise', 'Disgust' and 'Neutral'. Audio and visual clips were used as a stimulus for eliciting the emotions [21]. Some researchers recognized emotional states using ECG, EMG, skin conductance, respiration sensor and they recognized Joy, anger, Sadness and Pleasure. Music songs were used as a stimulus for eliciting the emotions [22]. In another case, researchers gathered the data from the “blood volume pulse”, “electromyogram”, “respiration” and the “skin conductance sensor”. They conducted 20 experiments in 20 consecutive days, testing around 25 minutes per day on each individual. They figured out neutral, anger, hate, grief, love, romantic, joy and reverence emotion states from the data. They got 81% classification accuracy among the eight states [31]. Different techniques can be used as a stimulus for eliciting the emotions i.e. pictures, video clips, audio clips, games etc. In our work, we used International Affective Picture System (IAPS) for stimulation. IAPS is widely used in experiments studying emotion and attention. The International Affective Picture System (IAPS) provides normative emotional stimuli for emotion and attention under experimental investigations. The IAPS (pronounced eye-aps) is being produced and distributed by the Center for Emotion and Attention (CSEA) at the University of Florida [32]. In our previous work, we took two physiological sensors (i.e. BVP and GSR) for the analysis, IAPS were used as a stimulus and our system was able to recognize few emotional states with good accuracy [44]. In this paper, we used four physiological sensors in order recognize few emotional states. The above mentioned researchers used different parts of the body but in our research we used only left arm for the sensor placement.

## III. Hypothesis

The physiological data measured by wearable devices (EMG, blood volume pulse, temperature and skin conductance sensor) indicate a person’s emotional state (‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’, ‘No-Idea’, ‘Positive’ and ‘Negative’) using a machine learning classifier.

## IV. Experimental Methodology

We developed the following systems for the user study.

### A. *eHealth platform and application*

We used eHealth platform [1] in order to recognize emotional states (Figure 1) and connected Raspberry Pi [41] to eHealth platform as shown in Figure 2.

Figure 1. eHealth platform

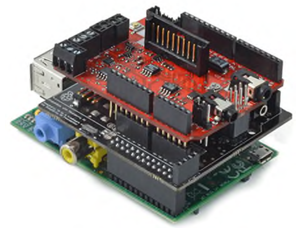

Figure 2. Raspberri pi with eHealth platform

The eHealth sensor comes with few sensors like 2D Accelerometer sensor, Blood pressure sensor (Breathing), Pulse and oxygen in blood sensor, body temperature sensor, airflow sensor, Electrocardiogram sensor (ECG), Electromyography sensor (EMG) and Galvanic skin response sensor. We used Galvanic skin response sensor, body temperature sensor, Electromyography sensor (EMG) and we used another blood volume pulse sensor [40] as shown in Figure 3.

Figure 3. Pulse sensor

We connected ‘GSR, ‘EMG’, ‘BVP’ and ‘body temperature sensor’ to the board. We wrote a piece of code which reads the values from the aforementioned sensors and writes it to a network port.

 ISBN: 978-1-61208-470-1

### *B. Application for reading sensors from eHealth platform*

We wrote an application in Java which reads the sensed data from a network port and stores it to a text file with a timestamp in the following structure for post analysis.

Time_stamp|emg, bvp, gsr, temperature

### *C. IAPS and its application (Application for Stimulus)*

We got access to IAPS [32] images and these images are already used by several researchers for emotional computing [33,34,35,36,37,38,39]. We implemented an application in C#.net that shows participants' IAPS images in a sequence in order to change participants' emotional states and also states the starting and ending time for each IAPS image during experiments. After showing participants five different images from each group, our application used to ask participants about their current emotional state by using the Likert scale (Figure 4 (b)) approach. We chose 100 IAPS images from different categories and presented them in the order shown in Figure 4(a).

Sad (5 images) Questionnaire Dislike (5 images) Questionnaire Joy (5 images Questionnaire Stress (5 images) Questionnaire

Dislike (5 images) Questionnaire Joy (5 images Questionnaire Stress (5 images) Questionnaire Sad (5 images) Questionnaire

Joy (5 images Questionnaire Stress (5 images) Questionnaire Sad (5 images) Questionnaire Dislike (5 images) Questionnaire

Stress (5 images) Questionnaire Sad (5 images) Questionnaire Dislike (5 images) Questionnaire Joy (5 images Questionnaire

Stress (5 images) Questionnaire Joy (5 images Questionnaire Dislike (5 images) Questionnaire Sad (5 images) Questionnaire

Figure 4(a). Chosen IAPS images

The images were shown as a slide show with a timer of 5 seconds for each image. For the questionnaire we used radio buttons and participants had to choose one emotional state. It also stores the participants' personal information i.e. age, gender, height and weight.

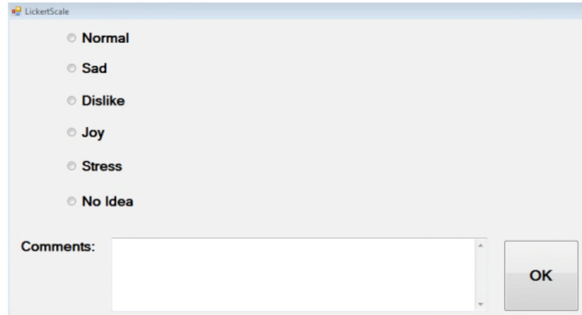


Figure 4(b). Questionnaire form

### *D. Experiment setup*

Experiments were conducted in a calm room with normal temperature; there was no noise or distraction. To make sure the readings from GSR were accurate we asked the participants to dry their hands with a dryer before beginning with the experiment. Since GSR measures sweat glands as well, moist hands would result in an erroneous result. To ensure full concentration from the participants, the light in the room was kept very low and we also asked them to turn off their mobile phones during experiments. Participants were asked to wear sensors on their left arms, palms and fingers (Figure 5). They were also required to perform the experiments twice; the first experiment was useful in getting the participants to familiarize themselves with the setup, while the second attempt was actually used for analyzing their data.

Figure 5. Participant is wearing sensors

We recruited 26 participants (21 males, 5 females) for our experiment setup; two of them could not complete the experiments so we ended up with 24 participants (19 males, 5 females). The range of participants' age was from 20 to 44 (mean 26.17, SD 5.14) and ranged in BMI (body mass index) from 18.7 to 26.6 (mean 21.44, SD 2.17).Participants were required to do it twice in different days.

### *E.* First experiment

As described earlier, the intention behind the first experiment was only familiarization with the setup. This was done to accommodate all first time participants, as they were somewhat nervous due to physiological devices and long cables and this could adversely influence our data. For this reason, the results from the first experiment were never used for analysis.

 ISBN: 978-1-61208-470-1

### *F.* Second experiment

In the second experiment, all participants already knew about the setup and they were not hesitating with the sensors, they performed the task with confidence and their data was stored for later analysis. We used same settings for both experiments but IAPS images were different. We showed participants different images (IAPS) for changing their emotions to sad, dislike, joy and stress. After showing a set of images; our application used to show them the questionnaire forms for their emotional states. Physiological data was logged to a laptop with a time stamp and on the other hand image application was also logging the participants' feedback to the same laptop with timestamp. After that we merged both files to generate a single file for post analysis.

## V. RESULTS AND ANALYSIS

Our experimental setup was able to change participants' emotional states; only four of the participants chose all of the given emotional states. This was due to the fact that it was hard for the participants to distinguish between sad, dislike and stress. Also being asked to distinguish between joy and normal during experiments was not a straightforward task. That also explains why some emotional states were ignored by participants. "*As everyone knows, emotions seem to be interrelated in various but systematic ways: Excitement and depression seem to be opposites; excitement and surprise seem to be more similar to one another; and excitement and joy seem to be highly similar, often indistinguishable*" [42]. Therefore, we generated another dataset from our experimental data; we categorized emotional states into two collections:

- Positive {Joy, Normal}
- Negative {Sad, Dislike. Stress}; 'No-Idea' is excluded

Now, we have the following types of datasets:

- Type1: It contains {Normal, Sad, Dislike, Joy, Stress and No-Idea}
- Type2: It contains {Positive and Negative}

Due to the fact that it was a huge dataset, it was not possible for WEKA [43] application to process the data of all 24 participants together. Therefore, we divided our datasets into six groups, each group consisting the data of four participants (as shown in Table 2); we grouped the four participants who chose all emotional states together and put them in Group-1, others were assigned to remaining groups in alphabetic order.

TABLE I. GROUPS

| Groups | Age | Gender | Chosen Emotional states |
|---|---|---|---|
| Group 1 | 25, 24, 25, 26 | 3 Males, 1 Female | Normal(4), Sad(4), Dislike(4), Joy(4), Stress(4) and No-Idea(4) |
| Group 2 | 24,25,25, 38 | 4 Males | Normal(0), Sad(3), Dislike(4), Joy(4), Stress(4) and No-Idea(2) |
| Group 3 | 24,24,25, 44 | 3 Males, 1 Female | Normal(3), Sad(3), Dislike(4), Joy(4), Stress(4) and No-Idea(1) |
| Group 4 | 20,25,25, 33 | 2 Males, 2 Females | Normal(2), Sad(4), Dislike(4), Joy(4), Stress(2) and No-Idea(1) |
| Group 5 | 22,24,24, 25 | 3 Males, 1 Female | Normal(3), Sad(3), Dislike(4), Joy(4), Stress(3) and No-Idea(2) |
| Group 6 | 24,25,25, 27 | 4 Males | Normal(2), Sad(4), Dislike(4), Joy(4), Stress(3) and No-Idea(0) |

We received values from sensors i.e. EMG, BVP, GSR and Temperature where the sample rate was around 650Hz. We analyzed both types (i.e. Type 1 and Type 2) in the following three different ways:

### *A. Individuals*

We applied J48 classifier [43] on the dataset of each participant.

### *B. Group-wise*

We divided the participants in 6 groups (as shown in Table 2) and applied J48 classifier on the dataset of each group.

### *C. Portioned data*

As mentioned earlier due to the limitations of processing huge datasets in WEKA toolkit, we chose small portions of data randomly pertaining to each emotion from each participant in Figure 6(a) and Figure 6(b) below.

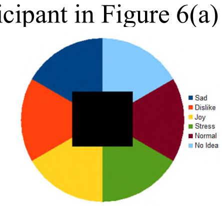


Figure 6(a). Type 1

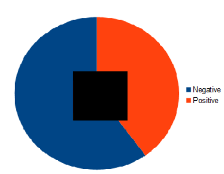


Figure 6(b). Type 2

### *D. Analysis structure*

We got two types of data i.e. "Two-Class" and "Six-class"; each type was analyzed on "Individual", "Group" and "Portioned" basis. We applied J48 classifier with 10-fold cross validation.

### E. *Two-Class*

*1) Individuals:* The outcome from the J48 classifier represents the average data of 24 participants where it correctly classified the instances with the accuracy of 99.4%; Min: 97.72%; Max: 99.67% and SD: 0.45.

| a | b | <-- classified as |
|---|---|---|
| 2169370 | 24518 \| | a = Positive |
| 18038 | 4896951 \| | b = Negative |

We took the confusion matrices from all participants and summed them all. Our results show the summation of all confusion matrices and accuracy of each emotional state where 'Positive' and 'Negative' emotional states were predicted with the accuracy of 98.88% and 99.63% by J48 classifier respectively.

*2) Group wise:* We took an average of correctly classified instances from all groups in order to figure out the variation amongst them. Our result shows that there is not a high variation among the groups and the average result was 99.3%; Min: 99.06%; Max: 99.45%; SD: 0.14.

| a | b | <-- classified as |
|---|---|---|
| 2181321 | 29401\| | a = Positive |
| 19447 4 | 804414\| | b = Negative |

We took confusion matrices from each group and summed them up. Our results show the summation of all confusion matrices from the groups and accuracies of emotional states where positive and Negative emotional states were predicted with the accuracy of 98.67% and 95.6% by J48 classifier respectively.

*3) Portioned data:* Our results show that J48 was able to correctly classify the instances with the accuracy of 99.33% and it was also able to predict positive and Negative emotional states with the accuracy of 98.56% and 99.67% respectively.

| a | b | <-- classified as |
|---|---|---|
| 409236 | 5982 \| | a = Positive |
| 3095 | 934177 \| | b = Negative |

We compared the accuracy between the categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 7 which shows that there is not much difference in results among them.

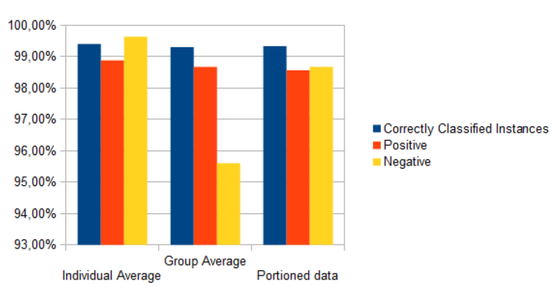


Figure 7. Comparison

### F. *Six-Class*

*1) Individuals:* The outcome from the J48 classifier represents the average data of 24 participants where it correctly classified the instances with the accuracy of 99.13%; Min: 98.39%; Max: 99.52% and SD: 0.25.

| a | b | c | d | e | f | <-- classified as |
|---|---|---|---|---|---|---|
| 1298734 | 7019 | 3629 | 2091 | 962 | 571 \| | a = Sad |
| 6760 | 2152047 | 5540 | 3829 | 2211 | 931 \| | b = Dislike |
| 4074 | 5775 | 1455566 | 3288 | 1008 | 524 \| | c = Joy |
| 2139 | 3890 | 2896 | 1329053 | 1092 | 467 \| | d = Stress |
| 915 | 2267 | 974 | 1120 | 734834 | 377 \| | e = Normal |
| 885 | 1214 | 602 | 502 | 450 | 341361 \| | f = NoIdea |

We took confusion matrices from all participants and summed them up. Our results show the summation of all confusion matrices and accuracy of each emotional state where 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea' emotional states were predicted with the accuracy of 98.99%, 99.11%, 99%, 99.22%, 99.24% and 98.94% by J48 classifier respectively.

*2) Group wise:* We took an average of correctly classified instances from all groups in order to figure out the variation amongst them. Our result shows that there is not a high variation among the groups and the average result was 98.67%; Min: 98.29%; Max: 99.04%; SD: 0.26.

| a | b | c | d | e | f | <-- classified as |
|---|---|---|---|---|---|---|
| 1293196 | 9506 | 4521 | 3550 | 1500 | 733 \| | a = Sad |
| 8791 | 2144771 | 7418 | 5817 | 3248 | 1273 \| | b = Dislike |
| 5020 | 8403 | 1449781 | 4449 | 1733 | 849 \| | c = Joy |
| 3484 | 6295 | 4432 | 1323013 | 1747 | 566 \| | d = Stress |
| 1619 | 3706 | 1749 | 1924 | 730989 | 500 \| | e = Normal |
| 1039 | 1708 | 897 | 684 | 609 | 340077 \| | f = NoIdea |

We took confusion matrices from each group and summed them up. Our results show the summation of all confusion matrices from the groups and accuracies of emotional states where 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea' emotional states were predicted with the accuracy of 98.49%, 98.78%, 98.61%, 98.76%, 98.72% and 98.57% by J48 classifier respectively.

*3) Portioned data:* Our results show that J48 was able to correctly classify the instances with the accuracy of 98.47% and it was also able to predict 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea' emotional states with the accuracy of 98.24%, 98.75%, 98.41%, 98.34%, 98.62% and 97.99% respectively.

| a | b | c | d | e | f | <-- classified as |
|---|---|---|---|---|---|---|
| 244303 | 2123 | 1016 | 800 | 278 | 168 \| | a = Sad |
| 1571 | 428263 | 1594 | 1481 | 507 | 288 \| | b = Dislike |
| 983 | 1977 | 275773 | 1020 | 303 | 162 \| | c = Joy |
| 913 | 1762 | 1142 | 250641 | 252 | 170 \| | d = Stress |
| 328 | 706 | 413 | 307 | 133139 | 107 \| | e = Normal |
| 210 | 509 | 241 | 199 | 130 | 62872 \| | f = NoIdea |

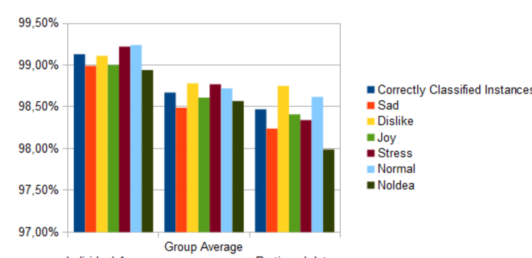


Figure 8. Comparison

We also compared the accuracy between the categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 8 which shows that there is not much difference in results among them.

## VI. Conclusions and Future Work

We used the following approaches for analyzing the data

1. We took data of each participant and applied J48 classifier and then took an average of 'Individual' data.
2. We took integrated data from six participants, applied J48 classifier and then took an average of 'Group' data.
3. We took a small portion of data randomly from each participant and applied J48 classifier on the data

We categorized data into the following collections:

- Six emotional states i.e. 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea'.
- Two emotional states i.e. 'Positive' and 'Negative'.

Our system was able to recognize the aforementioned emotional states by using physiological devices and J48 (decision tree) classifier with high accuracy. Results have shown that few physiological devices are enough for recognizing required emotional states ('Sad', 'Dislike', 'Joy', 'Stress', 'Normal', 'No-Idea', 'Positive' and 'Negative'). This prototype is only a "proof of concept" and our results show that our approach can identify the above mentioned emotional states independent of BMI (body mass index) and age group. The physiological sensor has to be fixed properly on the participants' skin in order to predict their emotional states successfully. We will conduct more user studies where we will use physiological data and facial expressions for recognizing these emotional states.

## References


[1] Cooking Hacks: e-Health Sensor Platform V2.0 for Arduino and Raspberry Pi [Biometric / Medical Applications]. http://www.cooking-hacks.com/documentation/tutorials/ehealth-biometric-sensor-platform-arduino-raspberry-pi-medical#step4_9. [Last Accessed 24th March, 2016 ].

[2] Professor Rosalind W. Picard. http://web.media.mit.edu/~picard/index.php. Last Accessed 24th March, 2016 ].

[3] Affective Computing: Publications. http://affect.media.mit.edu/publications.php .Last Accessed 24th March, 2016 ].

[4] Richmond Hypnosis Center. http://richmondhypnosiscenter.com/2013/04/12/sample-post-two/. Last Accessed 24th March, 2016 ].

[5] American Psychological Association: The Impact of Stress. http://www.apa.org/news/press/releases/stress/2011/impact.aspx . Last Accessed 24th March, 2016 ].

[6] WebMD: Stress Management Health Center. http://www.webmd.com/balance/stress-management/effects-of-stress-on-your-body.Last Accessed 24th March, 2016 ].

[7] Krifka, S., Spagnuolo, G., Schmalz, G., Schweikl, H. A review of adaptive mechanisms in cell responses towards oxidative stress caused by dental resin monomers. Biomaterials. 2013;34:4555–4563.

[8] Healthline : The Effects of stress on the Body. http://www.healthline.com/health/stress/effects-on-body. Last Accessed 24th March, 2016 ].

[9] Miamiherald: Chronic stress is linked to the six leading causes of death. http://www.miamiherald.com/living/article1961770.html. Last Accessed 24th March, 2016 ].

[10] Online Stress Reliever Games. *http://stress.lovetoknow.com/Online_Stress_Reliever_Games*. Last Accessed 24th March, 2016 ].

[11] Ali Mahmood Khan. (2011). Personal state and emotion monitoring by wearable computing and machine learning. BCS-HCI 2012, Newcastle, UK

[12] WebMD: Stress Management Health Center. http://www.webmd.com/balance/stress-management/features/how-anger-hurts-your-heart. Last Accessed 24th March, 2016 ].

[13] BetterHealth: Anger - how it affects people. http://www.betterhealth.vic.gov.au/bhcv2/bhcarticles.nsf/pages/Anger_how_it_affects_people. Last Accessed 24th March, 2016 ].

[14] Ekman, Paul (1999), "Basic Emotions", in Dalgleish, T; Power, M, Handbook of Cognition and Emotion (PDF), Sussex, UK: John Wiley & Sons.

[15] Health and Wellness: Are Happy People Healthier? New Reasons to Stay Positive. http://www.oprah.com/health/How-Your-Emotions-Affect-Your-Health-and-Immune-System.Last Accessed 24th March, 2016 ].

[16] Darwin, C. (1872). The expression of the emotions in man and animals. John Murray, London

[17] Kok, B.E., Coffey, K.A., Cohn, M.A., Catalino, L.I., Vacharkulksemsuk, T., Algoe, S., Brantley, M. & Fredrickson, B. L. (2013). How positive emotions build physical health: Perceived positive social connections account for the upward spiral between positive emotions and vagal tone. Psychological Science, 24(7), 1123-1132.

[18] Atkinson, William Walker (1908). Thought Vibration or the Law of Attraction in the Thought World.

[19] Rush, A. J., Beck, A. T., Kovacs, M. & Hollon, S. D. Comparative efficacy of cognitive therapy and pharmacotherapy in the treatment of depressed outpatients. Cognit. Ther. Res. 1, 17-38.

[20] Remarks on Emotion Recognition from Bio-Potential Signals: research paper (2004)

[21] Emotion Recognition from Electrocardiogram Signals using Hilbert Huang Transform (2012)

[22] Emotion Pattern Recognition Using Physiological Signals (2014)

[23] Walter Sendlmeier Felix Burkhardt, Verification of Acoustical Correlates of Emotional Speech using Formant-Synthesis, Technical University of Berlin, Germany.

[24] RECOGNIZING EMOTION IN SPEECH; Frank Dellaert, Thomas Polzin and Alex Waibel

[25] RECOGNIZING EMOTION IN SPEECH USING NEURAL NETWORKS; Keshi Dai, Harriet J. Fell and Joel MacAuslan

[26] Recognizing Emotion From Facial Expressions: Psychological and Neurological Mechanisms Ralph Adolphs, University of Iowa College of Medicine.

[27] Analysis of emotion recognition using facial expressions, speech and multimodal information. Proceedings of the 6th International Conference on Multimodal Interfaces, ICMI 2004, State College, PA, USA, October 13-15, 2004

[28] Recognizing Emotions from Facial Expressions Using Neural Network; Isidoros Perikos, Epaminondas Ziakopoulos, Ioannis Hatzilygeroudis.

[29] Emotions States Recognition Based on Physiological Parameters by Employing of Fuzzy-Adaptive Resonance Theory; Mahdis Monajati, Seyed Hamidreza Abbasi, Fereidoon Shabaninia, Sina Shamekhi.

[30] Classification of emotional states from electrocardiogram signals: a non-linear approach based on hurst; Jerritta Selvaraj, Murugappan Murugappan, Khairunizam Wan and Sazali Yaacob

[31] Jennifer Healey and Rosalind W. Picard (2002), Eight-emotion Sentics Data, MIT Affective Computing Group, http://affect.media.mit.edu."

[32] THE CENTER FOR THE STUDY OF EMOTION AND ATTENTION: http://csea.phhp.ufl.edu/Media.html#topmedia. Last Accessed 24th March, 2016 ].

[33] Cuthbert BN, Schupp HT, Bradley MM, Birbaumer N, Lang PJ.; Brain potentials in affective picture processing: covariation with autonomic arousal and affective report. Biol Psychol. 2000 Mar; 52(2): 95-111.

[34] Keil A, Bradley MM, Hauk O, Rockstroh B, Elbert T, Lang PJ.; Large-scale neural correlates of affective picture processing.;Psychophysiology. 2002 Sep; 39(5):641-9.

[35] Lang PJ, Bradley MM, Fitzsimmons JR, Cuthbert BN, Scott JD, Moulder B, Nangia V.; Emotional arousal and activation of the visual cortex: an fMRI analysis. Psychophysiology. 1998 Mar; 35(2):199-210.

[36] Bradley MM1, Sabatinelli D, Lang PJ, Fitzsimmons JR, King W, Desai P.; Activation of the visual cortex in motivated attention.; Behav Neurosci. 2003 Apr; 117(2):369-80.

[37] Sabatinelli D, Bradley MM, Fitzsimmons JR, Lang PJ.; Parallel amygdala and inferotemporal activation reflect emotional intensity and fear relevance.; Neuroimage. 2005 Feb 15;24 (4):1265-70. Epub 2005 Jan 7.

[38] Sabatinelli D, Lang PJ, Keil A, Bradley MM; Emotional perception: correlation of functional MRI and event-related potentials; Cereb Cortex. 2007 May; 17(5):1085-91. Epub 2006 Jun 12.

[39] Bradley MM, Codispoti M, Lang PJ.; A multi-process account of startle modulation during affective perception; Psychophysiology. 2006 Sep; 43(5):486-97.

[40] Maker Shed: Pulse Sensor AMPED for Arduino. http://www.makershed.com/products/pulse-sensor-amped-for-arduino .Last Accessed 24th March, 2016 ].

[41] Raspberry Pi. https://www.raspberrypi.org/ .Last Accessed 24th March, 2016 ].

[42] Russel and Bullock, Multidimensional scaling of emotional facial expressions, Journal of Personality and Social Psychology (1985), pp. 1290-1298

[43] Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Mining Software: An Update; SIGKDD Explorations, Volume 11, Issue 1

[44] Ali Mehmood Khan, Michael Lawo 2016, "Recognizing Emotion from Blood Volume Pulse and Skin Conductance Sensor Using Machine Learning Algorithms", MEDICON 2016, Paphos-Cyprus

 ISBN: 978-1-61208-470-1