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From Physiological data to Emotional States: Conducting a User Study and Comparing Machine Learning Classifiers

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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) and k-Nearest Neighbors (IBK) classifiers. 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: Physiological devices, International Affective Picture System, Machine learning classifier, User studies.

1. 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 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.

2. Related Work

Recognizing emotional states by using automated systems have increased in recent years. Researchers developed systems for recognizing emotional states using speech [23-25], facial expressions [26, 27, and 28] and physiological devices [20-22, 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 [20-22, 30], joy/happy [20-22, 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]. Previously, we used only J48 classifier [46] but in this paper we also want to evaluate IBK classifier in order to have a comparison with both classifiers. In this paper, we used four physiological sensors in order to recognize few emotional states.

Table 1 gathers a summary on the physiological devices involved in emotional states detection within the literature. In our work; we used four physiological sensors (i.e. BVP, GSR, EMG and Temperature) in order recognize emotional states (i.e. Stress, Joy/Happy, sad, normal/Neutral, dislike and no idea). The above mentioned researchers used different parts of body but in our research we used only left arm for the sensor placement.

Table 1. Literature review on Physiological signals involved in Emotional states detection

Physiological devices	Emotional States	Accuracy	Ref
GSR, HR	Stress	99.5 %	[47]
EEG (Forehead), GSR (fingers -> mouse), pulse sensor (earlobe)	Joy, Anger, Sad, Fearness, Relax	41.7 %	[20]
ECG, EMG, Skin conductance, Respiration sensor	Joy, anger, Sadness, Pleasure	97 %	[22]
GSR, BVP, Pupil diameter (PD), Skin temperature	Stress and relaxed	90 %	[48]
Electrocardiogram (EKG), Electromyogram, skin conductance and respiration	Stress	97 %	[49]
EMG, ECG, SC and respiration rate	Joy, Anger, pleasure and happiness	80 %	[50]
EMG, ECG, SC and respiration rate	Joy, Anger, sadness and pleasure	75 to 85 %	[51]
EMG, BVP, GSR and Skin temperature	Stress, Joy/Happy, Sad, Normal/neutral, Dislike, No-idea, Positive and Negative	98 %	Our proposed method

3. 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 classifiers (i.e. J48 and IBK).

4. Experimental Methodology

We developed the following systems for the user study.

4.1. eHealth Platform and Application

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

Fig. 1. eHealth platform.

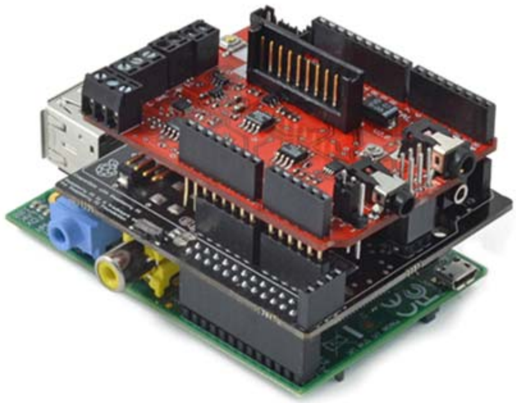


Fig. 2. Raspberri pi with eHealth platform.

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 Fig. 3.

“The e-Health Sensor Platform has been designed by Cooking Hacks (the open hardware division of Libelium) in order to help researchers, developers and artists to measure biometric sensor data for experimentation, fun and test purposes. Cooking Hacks provides a cheap and open alternative compared with the proprietary and price prohibitive medical market solutions. However, as the platform does not have medical certifications it cannot be used to monitor critical patients who need accurate medical monitoring or those whose conditions must be accurately measured for an ulterior professional diagnosis" [1]. We connected 'GSR, 'EMG', 'BVP' and 'skin 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 in the following structure.

emg (raw_volt) , bvp (raw_volt), gsr (raw_volt), temp,(raw_volt).

Fig. 3. Pulse sensor.

4.2. Blood Volume Pulse

Blood volume pulse (BVP) is the amount of blood running though the vessels. BVP is measured by photoplethysmograph (PPG), with the help of photo sensor and light source [45].

4.3. Electromyogram

Electromyography (EMG) records electric tendency produced by muscle membranes due to neurological or electrical triggering. In other words, a high muscle tension produces frustration or stress. EMG is measured by using bio sensors over face or hands [45].

4.4. Galvanic Skin Response (GSR)

Galvanic skin response sensor, Electrodermal response (EDR) or skin conductivity (SC) measures the conductivity of the skin. It increases if the skin is sweaty and indicates stress. It also differentiates between conflicts and peace situations or anger and fear. External factors like outside temperature can influence GSR, which is its biggest disadvantage [45].

4.5. Skin Temperature

Skin temperature is determined by the temperature of skin surface. This implies under strain, the muscles get tensed causing contraction in the blood vessels which in turn cause a decrease in temperature like EDR. Research states that skin temperature also depends on external factors [45].

4.6. 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

4.7. 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 [33-39]. 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 (Fig. 4 (b)) approach. We chose 100 IAPS images from different categories and presented them in the order shown in Fig. 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

Fig. 4(a). Chosen IAPS images.

Fig. 4(b). Questionnaire form.

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.

4.8. Experimental 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 (Fig. 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.

Fig. 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.

4.9. 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.

4.10. 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.

5. Results and Analysis

Our experimental setup was able to change participants' emotional states; following are the results.

Table 2. Chosen Emotional states

Emotional States	Correct response/Total Stimuli	Comments
Sad	21/24	'Sad' was ignored by 3 participants
Dislike	24/24	'Dislike' was chosen by all participants
Joy	24/24	'Joy' was chosen by all participants
Stress	20/24	'Stress was ignored by 10 participants
Normal	14/24	'Normal was ignored by 10 participants
No-Idea	10/24	No-Idea was ignored by 14 participants

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 shown in Table 2. "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}

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 3); 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 1. Groups.

Group (s)	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 Skin temperature where the sample rate was around 650Hz. We applied following formula on EMG, BVP and GSR.

[code]
//Convert the read value to voltage.
*float voltage = (VALUE * 5.0) / 1023;*
[/code]

We took a window of five seconds and normalized the data.

Normalized: xn = (x-min)/(max-min)

We analyzed both types (i.e. Type 1 and Type 2) in the following three different ways:

5.1. Individuals

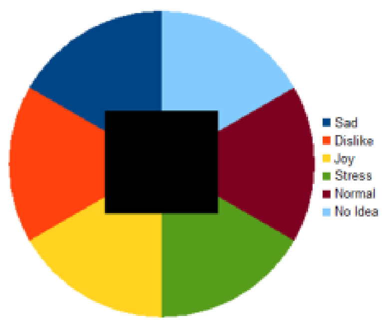
We applied J48 and IBK classifiers [43] on the dataset of each participant.

5.2. Group-wise

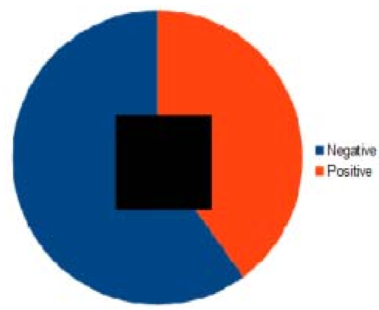
We divided the participants in 6 groups (as shown in Table 3) and applied J48 and IBK classifiers on the dataset of each group.

5.3. 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 Fig. 6(a) and Fig. 6(b) below.



(a)



(b)

Fig. 6 (a). Type 1, (b). Type 2.

5.4. Analysis Structure

We got two types of data i.e. "Two-Class (Type2)" and "Six-class (Type1)"; each type was analyzed on "Individual", "Group" and "Portioned" basis. We applied J48 and IBK classifiers with 10-fold cross validation.

5.5. Two-Class

Individuals (J48): 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.

Individuals (IBK): The outcome from the IBK classifier represents the average data of 24 participants where it correctly classified the instances with the accuracy of 98.03 %; Min: 95.04 %; Max: 99.34 % and SD: 0.9.

a b <-- classified as
2140403 70319 | a = Positive
71817 4752044 | 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 96.82 % and 98.51 % by IBK classifier respectively.

Group-wise (J48): 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
194474 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.

Group-wise (IBK): 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 97.56 %; Min: 96.8 %; Max: 98.47 %; SD: 0.46.

a b <-- classified as
2126046 84676 | a = Positive
87113 4736748 | 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 96.17 % and 98.19 % by IBK classifier respectively.

Portioned data (J48)*:* 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

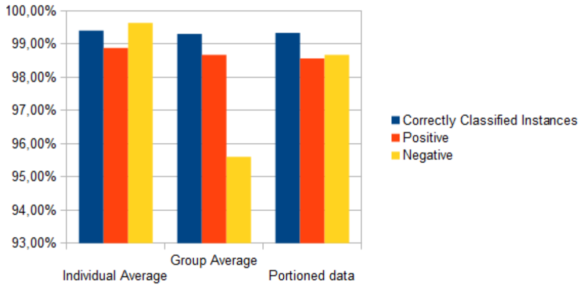


Fig. 7(a). Comparison (J48).

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

Portioned data (IBK)*:* Our results show that IBK was able to correctly classify the instances with the accuracy of 97.56 % and it was also able to predict positive and Negative emotional states with the accuracy of 96.19 % and 98.16 % respectively.

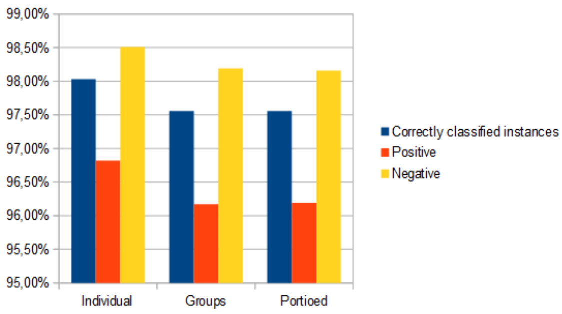


Fig. 7(b). Comparison (IBK).

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

5.5. Six-Class

Individuals (J48): 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.

Individuals (IBK): The outcome from the IBK classifier represents the average data of 24 participants where it correctly classified the instances with the accuracy of 96.27 %; Min: 90.75 %; Max: 98.87 % and SD: 1.81.

a b c d e f <-- classified as
1257943 26122 15282 8612 3408 1639 | a = Sad
25771 2087741 25097 20615 8460 3634 | b = Dislike
14895 23109 1410973 14190 4874 2194| c = Joy
8262 17459 13238 1293719 5031 1828 | d = Stress
3328 8366 4696 5038 717661 1398 | e = Normal
1601 3269 1921 1743 1519 334961 | 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 95.81 %, 96.15 %, 95.97 %, 96.58 %, 96.92 % and 97.09 % by IBK classifier respectively.

Group-wise (J48): 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.

Group-wise (IBK): 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 95.49 %; Min: 94.58 %; Max: 96.47 %; SD: 0.62.

a b c d e f <-- classified as
1246491 30108 17228 12272 4825 2082 | a = Sad
29813 2074139 28534 22867 11572 4393 | b = Dislike
17782 27141 1399881 16288 6737 2406 | c = Joy
11082 21197 15794 1282046 7106 2312 | d = Stress
4325 10152 6061 7008 710992 1949 | e = Normal
2039 4107 2370 2418 1857 332223 | 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 94.93 %, 95.52 %, 95.21 %, 95.71 %, 96.02 % and 96.29 % by IBK classifier respectively.

Portioned data (J48): 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

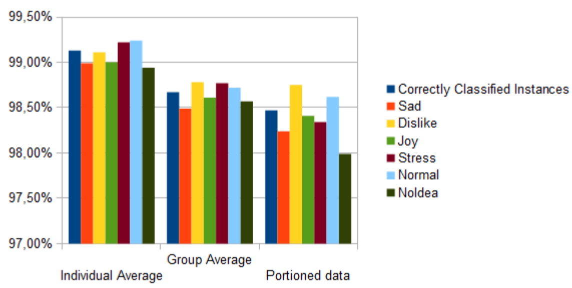


Fig. 8(a). Comparison (J48).

We also compared the accuracy between the categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Fig 8(a) which shows that there is not much difference in results among them.

Portioned data (IBK): Our results show that IBK was able to correctly classify the instances with the accuracy of 95.46 % and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 94.9 %, 95.77 %, 95.22 %, 95.36 %, 96.1 % and 95.54 % respectively.

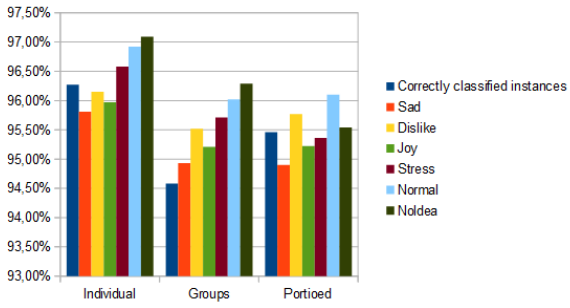


Fig. 8(b). Comparison (J48).

We also compared the accuracy between the categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Fig 8 (b) which shows that there is not much difference in results among them.

6. Conclusions and Future Work

We used the following approaches for analyzing the data.

1) We took data of each participant and applied J48 and IBK classifiers and then took an average of ‘Individual’ data.

2) We took integrated data from six participants, applied J48 and IBK classifiers and then took an average of ‘Group’ data.

3) We took a small portion of data randomly from each participant and applied J48 and IBK classifiers 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 machine learning classifiers (i.e. J48 and IBK) with high accuracies. Results have shown that few physiological devices are enough for recognizing required emotional states (‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’, ‘No-Idea’, ‘Positive’ and ‘Negative’). Our results show that J48 classifier was the better algorithm for identifying aforementioned emotional states. 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.

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