Artificial Intelligence

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Personal State and Emotion Monitoring by Wearable Computing and Machine Learning

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Declaration

Thereby I declare that I have written this document exclusively by me. To my knowledge and understanding, I referenced all resources correctly, and not attempted for plagiarism.

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Acknowledgements

I cannot express enough thanks to my supervisor for his continued support and encouragement: Prof. Dr. Michael Lawo and Prof. Dongyi Chen. I offer my sincere appreciation for the learning opportunities provided by them.

My completion of this thesis could not have been accomplished without the support of my friends, Gero Mudersbach (late) and Bhavya Anand. Thanks to my immediate family members and especially to my mother, Mrs. Rehana Sarfraz for their moral supports.
Finally, to my caring, loving, and supportive wife, Sabah: my deepest gratitude. Your encouragement when the times got rough are much appreciated and duly noted. It was a great comfort and relief to know that you were willing to provide management of our household activities and taking care of our new born baby, Alisha while I completed my work. Many thanks; now you deserve a trip to your favorite location!
I dedicate my PhD thesis to my father; Sarfraz Mehmood Khan (late). The reason is to choose this topic was the sudden death of my father. His sudden death made me to think about the wearable solution for the heart patients so that they could utilize the technology in order to have more comfortable lives.

Lastly, I would like to justify the length of my thesis. Basically, it was a cumulative thesis; my work is already published which has been mentioned to the references and that is why my thesis consisting on limited pages.

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Abstract

One of the major scientific undertakings over the past few years has been exploring the interaction between humans and machines in mobile environments. Wearable computers, embedded in clothing or seamlessly integrated into everyday devices, have an incredible advantage to become the main gateway to personal health management. Current state of the art devices are capable in monitoring basic physical or physiological parameters. Traditional health systems procedures depend on the physical presence of the patient and a medical specialist that not only is a reason of overall costs but also reduces the quality of patients' lives, particularly elderly patients. Usually, patients have to go through the following steps for the traditional procedure:

Firstly, patients need to visit the clinic, get registered at reception, wait for the turn, go to the lab for the physiological measurement, wait for the medical expert's call, to finally receive feedback from the medical expert.

In this work, we examined how to utilize existing technology in order to develop an e-health monitoring system especially for heart patients. This system should support the interaction between the patient and the physician even when the patient is not in the clinic. The supporting wearable health monitoring system [WHMS] should recognize physical activities, emotional states and transmit this information to the physician along with relevant physiological data; in this way patients do not need to visit the clinic every time for the physician's feed-back.
After the discussion with medical experts, we identified relevant physical activities, emotional states and physiological data needed for the patients' examinations. A prototype of this concept for a health monitoring system of the proposed solution was implemented taking into account physical activities, emotional states and physiological data. The proposed solution was presented to health experts in the form of animated video accessible via YouTube [32] to get their opinions about the proposed solution.

The following studies cover the different aspects of this research:

1) ***Survey for feedback to the proposed system:***
A survey was first conducted for an opinion from the medical experts. We wanted to know about the needed physical activities, emotional states and physiological data are needed for the medical experts so that medical experts could assess their patients' health conditions while being away from their patients. The valuable feedback from the medical experts helped in collecting the requirements for the prototype. According to medical experts, it's worth to have this kind of system for the benefit of both the heart patients and the medical experts. This will be outlined in further detail in chapter 4.

2) ***Recognizing physical activities using a 3D accelerometer:***
Physical activities i.e. sitting, standing, running, walking, ascending/descending stairs, swimming, strength training etc. have an impact on health data while monitoring. Our research hypothesis was that one 3D accelerometer sensor is sufficient for recognizing the mentioned physical activities. On this research we firstly took usability issues into account. The system was able to recognize the physical activities with an accuracy of around 90% as outlined in detail in chapter 4.

3) ***Recognizing emotional states using physiological devices:***
   Emotional states i.e. happy, sad, stress, angry, normal etc. have a further impact on health data while monitoring. We used physiological devices (i.e. electromyogram, blood volume pulse, skin temperature and skin conductance sensor) and images [37] for stimulus. The system was able to recognize the mentioned emotional states with an accuracy of around 98%. This will be outlined in chapter 5.

This thesis uses a couple of peer review articles published already in recent years and two book chapters of which one book chapter is not yet published added as an appendix of this thesis. The two book chapters cover the following main aspects of this thesis.

1. ***Recognizing physical activities using wearable devices [34]***
   This chapter summarizes the user studies which were conducted during the presented research. The chapter explains the accuracy of mentioned physical activities; it also compares the accuracies of different machine learning algorithms and explains the body location with best fit for recognizing the physical activities of interest.

2. ***Recognizing emotional states using physiological devices***
   This chapter describes a user study conducted at Chengdu University [104] in China within this research. This chapter explains the setup of our study; how we conducted the study, how many physiological devices were used, how we collected the data, and analyzed it. This chapter also compares the importance of each physiological device and shows decreased accuracy when reducing the number of physiological sensors while measuring.

Keywords: *Physical activities; Emotional states; Physiological data; e-Health monitoring systems*

1. Introduction

Ideally, patients should be able to wear the devices comfortably for 24X7; devices should be able to collect the data and store for the analysis. We do have many definitions or explanations for Wearable Health Monitoring Systems (WHMS).

"*Wearable systems can be broadly defined as mobile electronic devices that can be unobtrusively embedded in the user's outfit as part of the clothing or an accessory. In particular, unlike conventional mobile systems, they can be operational and accessed without or with very little hindrance to user activity. To this end they are able to model and recognize user activity, state, and the surrounding situation: a property, referred to as context sensitivity*" [46].

"*A wearable health monitoring system consists of a set of intelligent physiological wearable sensors, a personal server (Internet enabled PDA or cell phone) and a network of remote health care servers and related services"* [47].

"*Wearable health monitoring systems can facilitate low-cost wearable unobtrusive solutions for continuous all-day and any-place health, mental and activity status monitoring*" [18].

Wearable Health Monitoring Systems (WHMS) using body worn sensors have received increasing attention in recent years. WHMS is an important and challenging field which can support many novel ubiquitous applications. Wearable Health Monitoring Systems are a multidisciplinary research area covering artificial intelligence, ubiquitous computing and human computer interaction aspects. Wearable Health Monitoring Systems incorporated into a tele-medical system are capable to early detect and probably prevent abnormal conditions e.g. [4, 5, 6, 7, 8] etc. The aim of Wearable Health Monitoring System is to recognize the actions or activities and physiological states of its users in an unobtrusive way observing the behavior of people and take necessary actions in response. Many patients can possibly benefit from continuous monitoring as a part of a diagnostic procedure, optimal maintenance of a chronic condition or during supervised recovery from an acute event or surgical procedure. Well-timed warnings issued to the patient, and a specialized medical response service can trigger action in the event of medical emergencies. Continuous monitoring along with early detection has the potential to provide patients with a higher level of confidence leading to a better quality of life. Wearable monitoring systems in health care support especially in elder care, long-term health/fitness monitoring, and assisting those with cognitive disorders [1, 2 and 3].

Health monitoring with body worn sensors is not a new research field and much research exists for this area. One can identify users' physical activities using wearable devices [20], recognize users' emotional states using wearable devices [21, 22, 23 and 24] and measure physiological data using off the shelf devices [25, 26, 27, 28 and 29].

Health telematics can play an important role in improving the quality of life for patients, particularly those disabled, elderly or chronically ill [9]. With some diseases like diabetes, heart problems, for mental disorders, patients are required to perform physical activities for keeping or increasing the personal fitness. In some cases patients need monitoring by nurses; this is very time consuming and cost intensive. The modern lifestyle increases in some cases the probability of diseases. According to the World Health Organization, at least 1.9 million people die annually because of physical inactivity [10, 11]. One can use wearable health monitoring technology to tackle this problem, as it is able to monitor an individual's physical activity and physiological data all the time. Giving feedback about daily activities or providing recommendations when failing to reach personal goals for the completion of enough exercises encourages people to conduct more activities [12, 13 and 14]. In some cases, as with heart diseases, physical activities are required along with the physiological information by doctors in order to examine the patient's conditions when being away from the doctor's clinic [15]. Mobile health-monitoring devices offer services for such patients without having the need of regular visits of the clinic. The treatment can focus on the patient using previously collected information; this helps chronically ill patients [9] by saving trips to their doctor; this is especially beneficial if patients reside in a remote location.

In the United States of America, overall health care expenditures reached $1.8 trillion in 2004, even though nearly 45 million Americans do not possess a health insurance [30]. The main factors for rising costs in patient healthcare are rising hospital expenses [17]. Increasing costs of healthcare liabilities have already affected many companies. In less than 10 years from now, the healthcare costs one expects to exceed almost 20% of the Gross Domestic Product (GDP) which is threatening for the wellbeing of the entire economy. The demographic trends are highlighting two main phenomena: life expectancy has increased from 49 years in 1901 to 77.6 years in 2003. The U.S. Bureau of the Census states that the number of elderly age 65 will rise from 35 million in 1990 to nearly 70 million by 2025 by the time the youngest Baby Boomers retire [31]. These statistics highlight the need for more affordable health care solutions. Other challenges are due to the current health care system trying to reduce health costs combined with universal and high quality of care. A mobile life style lets people wish more flexibility with the health care system; people wish to remain in touch with health care professionals around the clock [16]. This leads to the sheer need to monitor a patient’s health status in the personal environment instead of the hospital. A variety of products addresses this demand in recent years by providing accurate feedback about health condition, either to a medical center, the user or a supervising professional physician, while alerting the patient in case of health threatening conditions. To make healthcare system more affordable, wearable systems help by continuously monitoring patient’s vital signs providing feedback of the health status. Wearable computing gives more control to the patient. It decentralizes the healthcare system and alters the focus from treatment to prevention. Wearable computers can act like a personal health assistant. Current devices monitor basic physiological or physical parameters i.e. long-term heart monitoring, prediction of gait instability and falls.

Many patients suffering from non-life-threatening illnesses do not necessarily require hospitalizations – they basically need monitoring via a mobile system that includes intelligent capabilities to detect any abnormalities, provide temporary advice and if required, send urgent alerts to medical staff.

“*The majority of the currently developed WHMS research prototypes and products provide the basic functionality of continuously logging physiological data and possibly also that of alarm generation in case the sensed data exceed a predefined threshold value*” [18]. We also have WHMS research prototypes which recognize few physical activities e.g. [5, 8, 19] etc.

When focusing on heart patients, those have to visit their doctors for a routine medical check-up on a regular basis. Sometimes, they come from long distance and sometimes they miss some events because of their medical appointment. Question is that why patients always need to follow this old tradition. Can they not just send all needed information to the physician for assessment? What kind of information do physicians need for this purpose?

We do have wearable systems (products, prototypes, concepts etc.) which can measure physiological data and transmit it to the medical doctors [48, 49, 50, 51, 52, 53, 54 and 100]. But issue is that we cannot rely on these kinds of systems, How would the system figure out whether the user is in normal condition or not? For example, the user would have a different heart beat level, if he is running, sitting or standing. User also would have a different heart beat level, if he is frustrated or stressed and a different heart beat level, if he is happy or sad. Usually, existing wearable health monitoring systems do not take these factors into account [15].

We need to take contextual information into account while developing the wearable health monitoring system, meaning "*any information that can be used to characterize the situation of an entity*" [13]; who is the person, what he is doing, at which time, location and surroundings with environmental temperature etc.

The present research focuses on the patient's physical activities and emotional states. The general architecture for our proposed WHMS prototype is shown in Figure 1.

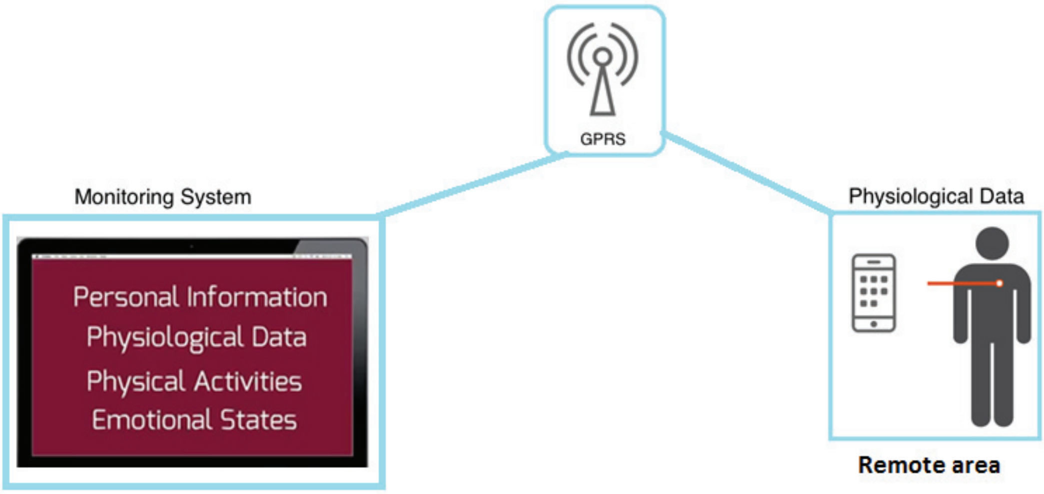

Figure 1: Overall architecture

According to the overall architecture, the patient is not in the hospital. The patient uses a medical system given by the medical doctor. The system connects to the patient's mobile phone via wireless technology i.e. Bluetooth/WiFi. All data (data from medical device and data from our proposed solution) goes to the mobile phone the patient is wearing. Our software system recognizes patient's physical activities using 3D accelerometer sensor and emotional states using physiological data. All information will be transmitted to the monitoring system. The monitoring system would already have personal information of the patient. The physiological data would be coming from the medical device given by the medical doctor based on the patient's medical condition. Physical activities and emotional states would be transmitted by the proposed system using GPRS technology for transmitting the data.

To design and evaluate such a system as outlined in figure 1, first the requirements need further elicitation. To discuss the research approach requires explanation, as it leads to a separation of recognizing the physical activities and emotional states.

Research approach: The research approach uses the assumption that wearable devices are sufficient to allow monitoring as well the physical activities as the emotional states of the patients and that wireless technologies support this approach sufficiently.

Recognizing physical activities: The requirements list the needed physical activities examined for diagnostic purposes; a number of studies for recognizing the physical activities using a 3D accelerometer sensor will be shown.

Recognizing emotional states: Based on the list of relevant emotional states from the "Requirement elicitation"; in a user study, we used physiological devices for recognizing the emotional states.

Conclusion and future work: We will explain our achievements going beyond the state of the art in computer science and the scientific contributions to computer sciences as outlined in the next chapter.

2. Requirement elicitation and research approach

As discussed in the 'Introduction', physical activities and emotional states are important for the usefulness of WHMS monitoring the medical state of patients.. In this chapter, we want to know which physical activity exactly is important, which emotional state is needed and what kind of physiological data is required. Last but not least, is it worth to develop this kind of system for heart patients? This chapter discusses how we elicited the requirements after conducting interviews with medical experts.

We followed the user centered design approach [55], starting by a discussion with two medical experts from USA and Pakistan in order to collect requirements. What is needed for medical doctors to assess patients' health conditions; if patients are not at their clinics?

After having a discussion with these medical experts we came up with an idea to develop an animated video accessible on YouTube [32] and shown as screen shot in Figure 2 which discusses the research approach; this video was shown to health experts and our system was later evaluated on the basis of health experts' feedback. A questionnaire as shown in Figure 3 was given to health experts along with the video. We used Likert scale approach [43] in order to evaluate the importance of each aspect.

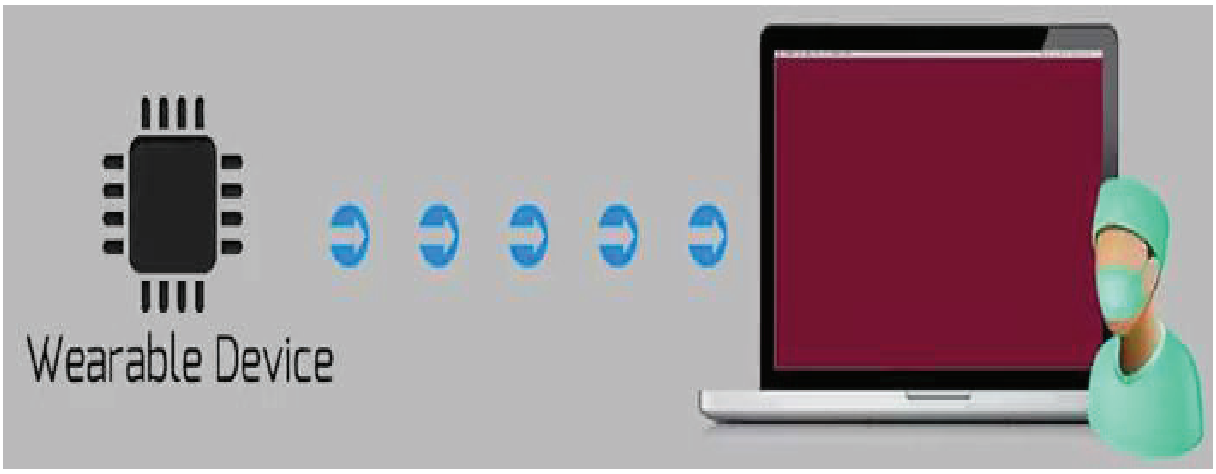

Figure 2: Animated video [32]

First name:	
Last name:	
Email:	
Phone:	
Affiliation:	
Experience years:	

How important it is for you to know the following information?
Not important: 1...5: very important

Physical activities	1	2	3	4	5
Lying					
Sitting					
Standing					
Walking					
Running					
Cycling					
Ascending stairs					
Descending stairs					

Comments	

How important it is for you to know the following information?
Not important: 1...5: very important

Emotional states	1	2	3	4	5
Sad					
Dislike					
Joy					
Stress					

Comments	

How important it is for you to know the following information?
Not important: 1...5: very important

Psyological data	1	2	3	4	5
Heart rate/ ECG					
Blood volume pulse					
Body temperature					
Respiratory rate					

Comments	

What do you think about this Project?

Extremely useless	**Useless**	**Slightly useless**	**Neither**	**Slightly useful**	**Useful**	**Extremely useful**

Comments about the project	

Figure 3: Questionnaire forms

2.1 Experts' feedback

We got feedback from five experienced health experts; they were from the USA and European countries. The range of health experts' experience was from 12 to 40 years (mean 26.2, SD 10.64). Health experts had different opinions about the needed physical activities and emotional states but most of them were convinced on the need of chosen physical activities, emotional states and physiological devices for focused heart patients as shown in Figure 4. Few activities like sitting, standing, cycling, ascending stairs and descending stairs were considered less important by some medical experts but others were strongly convinced about the need of also these physical activities.

Similarly, 'Dislike' as emotional state was considered less important for a medical expert but other medical experts were convinced to consider this emotional state.

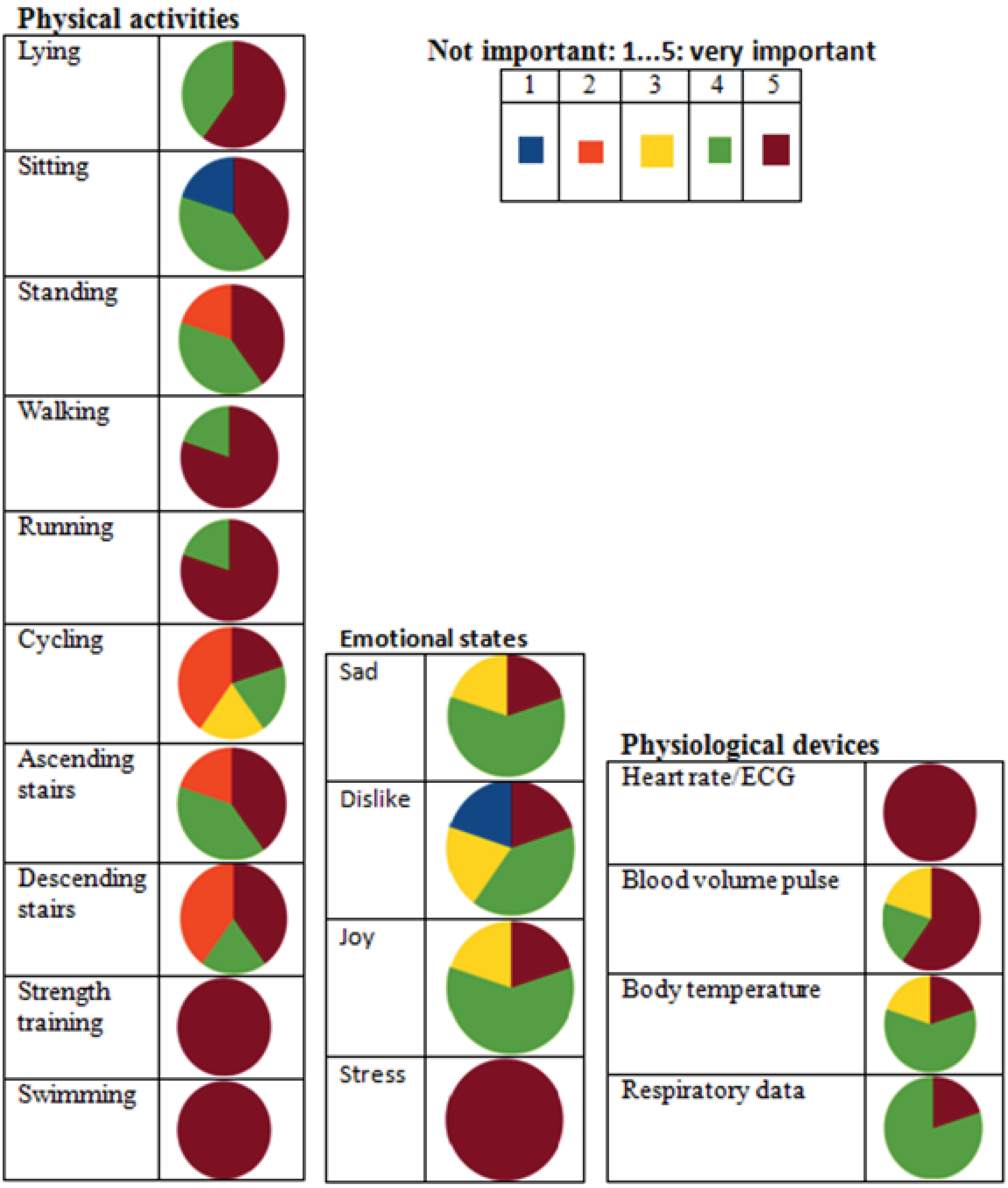

Figure 4: Experts' feedbacks for needed information

In general, four out of five medical experts think that the proposed solution would be able to detect all information listed in Figure 4 as 'Extremely Useful'. One medical expert thinks that it can be 'Useful' as a solution for both patients and medical experts.

Based on this survey, a wearable health monitoring system (WHMS) with a minimum amount of sensors has to have the following features:

- Recognize physical activities i.e. 'Lying', 'Sitting', 'Standing', 'Walking', 'Running', 'Cycling', 'Ascending stairs', 'Descending stairs', 'Strength-training' and 'Swimming'.
- Recognize emotional states i.e. 'Sad', 'Dislike', 'Joy' and 'Stress'.
- Measure needed physiological information i.e. 'Heart rate/ Electrocardiography', 'Blood Volume Pulse' and 'Respiratory data'.

Usually health monitoring systems do not take these factors into account i.e. physical activities and emotional states. Usually, patients are required to use health monitoring systems in stationary settings; not meant for mobile use [40]. According to our best knowledge, there is no system for heart patients taking emotional states into account while transmitting the physiological data to medical experts.

We can measure physiological information by simply using off the shelf devices given by medical experts to their patients. Our aim is to use minimum amount of sensors in order to recognize a specific physical activity, emotional state and physiological data to increase patients' comfort while wearing the devices. This usability aspect was taken into account while developing the concept.

2.2 Ethical reports and data security

We did not aim to conduct a medical study and did not store patients' physiological data at our place. We took accelerometer data for recognizing the physical activities, took physiological data for recognizing the emotional states and transmit it along with the physiological data from a medical device given by a medical doctor to the patient as soon as the research prototype is not used for clinical study, security standards like HL7 [44] need to be integrated.

2.3 Motivation

We use personas and scenarios as described by Nielsen [56] in order to explore the proposed solution. The following scenarios aim at saving time, resources and money both for the doctors and patients.

Personas:

Four personas; one medical doctor and three patients with different medical settings are part of the scenarios under investigation.

Dr. John, 52 years old, medical doctor; Bob, 46 year old, heart patient at risk; Julia, 80 year old, heart patient hating the clinic environment and Kathi, 80 years old, heart patient with previous heart problems.

The four chosen scenarios of individual perspective with their specifications result in different requirements of the solution needed.

a) **Scenario 'Time efficiency'**
   Dr. John always needs to welcome his patient by spending a few minutes in small talk. Afterwards, he measures the patients' physiological information (blood volume pulse, respiration rate, body temperature and Electrocardiography 'ECG') in order to examine them, which takes some time. On an average, he spends at least 20 minutes for each patient. On the other hand his patients also need to visit the clinic and have to wait for the personal examination; this usually seems to be a waste of time to the patients.

   Advantage of a wearable monitoring and measuring system: By using the system patients do not need to visit the hospital for regular check-ups every time, they can be examined by the doctor remotely.

b) Scenario 'User felt a problem in the past'

Kathi felt a heart problem at 12:00, it was a minor attack and she reached the hospital at 12:30.However by the time she was examined by the health physician, her heart was normal again and doctor could not work out the severity of the attack.

Advantage of a wearable system: By using the system, the doctor would have the possibility to ask the patient to wear the system 24 X 7 so to access the physiological data's recording, when checking the patient's health status at a later stage.

c) Scenario 'regular check-up'

Bob has to visit the clinic every alternative month, where the doctor asks him to perform physical activities (i.e. running on tread-mil, walking, standing etc.). Meanwhile the doctor examines his heart condition by using physiological information (blood volume pulse, respiration rate, body temperature and heart beat rate).

Advantage of a wearable system: By using the system the patient does not need to visit hospital every time, the checkup can also be performed remotely by just checking recorded data.

d) Scenario 'Different environment'

Julia does not feel comfortable at any clinic because it is a different environment. However due to her age, she has to visit the clinic every month for her regular check-up where she usually gets to know that everything is fine.

Advantage of a wearable system: By using this system the patient needs to visit hospital only in case of an urgent need for a face-to-face meeting.

2.4 Win-win situation

Basically, it is a win-win situation; doctors can save the time with their patients just for measuring purposes; they could much more focus on the treatment. By using wearable systems, doctors' expenses can be reduced which will in turn reduce the overall health costs.

2.5 Assumption

By a 3D accelerometer sensor for recognizing relevant physical activities and physiological devices for recognizing the emotional states, a continuous monitoring is sufficiently possible to provide the medical doctor with the relevant information. In our research, we are focusing on the two main aspects of physical activities and emotional states. Of course, specific medical devices would be given to patients by medical doctors. However, the patient specific medical device has nothing to do with our proposed solution; we will only transmit physiological data from the patient's specific medical device along with the physical activities and emotional states as a basis for interpretation by the medical doctor.

2.6 Research approach

Medical experts can simply give the wearable system to their patients for a specific time to recognize relevant physical activities using minimum amount of motion sensors and also recognizing relevant emotional states by a minimum amount of physiological devices.

2.7 Hypothesis

The thesis has the hypothesis that
The varying information of physical activities and emotion states can be recognized by a wearable system along with the physiological data like blood volume pulse, respiration rate, body temperature and heart rate pertaining to a patient and can be transmitted to a physician for examination with the same efficiency as if the patient was physically present. Furthermore, we hypotheses that

- The acceleration measured by a wearable 3D accelerometer reliably indicates, which activity of lying, sitting, walking and running, ascending/ descending stairs, cycling, swimming and strength-training a person performs.
- the physiological data measured by wearable devices as EMG, blood volume pulse, skin conductance sensor and skin temperature indicate the person's emotion state of sad, dislike, joy and stress with high reliability.

As a result of the presented research, it was found out that different activities can be distinguished by an accuracy of over 90% and the emotional states can be distinguished by an accuracy of over 95%.

2.8 Conclusion

In this chapter we identified with the help of medical experts the relevant physical activities and emotional states, necessary to know by a medical doctor when interpreting medical data collected by arbitrary medical devices to assess the patients' health status. Using the persona concept and scenarios we identified the need and benefit for doctors and patients. We set up two research hypothesis allowing to verify later based on extensive user studies the success of proposed approach.

With the above, we know which physical activity and which emotional state is needed by medical experts to assess the health condition of patients. The assessment of the presented research is that recognizing physical activities and emotional states using a minimal set of wearable devices is possible.

3. Recognizing physical activities

In the second chapter, we discussed the needed physical activities. In this chapter, we want to discuss how to recognize the physical activities medical doctors need to know when interpreting patient's data using minimum amount of sensors. This chapter presents the methodology and provides results of the research.

We want to develop a physical activity recognition system using a minimum amount of sensors which should be able to identify basic activities like lying, walking, running, sitting, standing, cycling, ascending and descending stairs. There are several ways to recognize person's daily activities. One way is using cameras to visually detect people's motion [63, 64]. The drawback of this solution is that a large number of cameras would be required in order to monitor a moving person. Such a system would also need to be designed to compute information from each camera and deal with other factors such as light, distance and angle, which make the system impractical. Using wearable sensors, researchers have identified various physical activities like sitting [57 ,60,61,62], standing [57,60,61 and 62], lying [60], walking [57,58,59,60,61,62], climbing stairs [57,58,60,61,62], running [59,61,62], cycling [59, 62], strength training [62] etc. However, they have always used more than one sensor. For example, some researchers [62] identified around 20 activities using 5 sensor boards; they identified walking, walking carrying items, sitting & relaxing, working on computer, standing still, eating or drinking, watching TV, reading, running, bicycling, stretching, strength-training, scrubbing, vacuuming, folding laundry, lying down & relaxing, brushing teeth, climbing stairs, riding elevator and riding escalator. They used Decision Table, IBL, C4.5 and Naive Bayes algorithms. They placed sensors on the limb positions and on the right hip. Similarly researchers [57] identified 12 activities using 3 sensor boards, they identified sitting, standing, walking, walking up stairs, walking down stairs, riding elevator down, riding elevator up and brushing teeth. In paper [58], three activities were identified; walking, climbing stairs and descending stairs using 9 tilt switches and K-means clustering and brute force algorithms. The sensors were worn just above the right knee.

We conducted four user studies and formulated six sub-hypotheses for using only one 3D accelerometer to predict the required physical activities. By classifiers one can recognize a high percentage of physical activities. The used prototype is only a "proof of concept". However, our results show that a single 3D accelerometer sensor can identify the above mentioned physical activities independent of BMI (body mass index), gender and age group. The output of any body-worn accelerometer depends on its location on the human body and can vary significantly for different locations on the body. The optimal position is the 'lower back-bone'. As a part of the thesis, this research has been published previously [34]. The accelerometer has to be fixed properly on the person's body in order to predict the participants' activities successfully.

Our results indicate good accuracy rate in order to prove our hypothesis; "*The acceleration measured by a wearable device (3D accelerometer) indicates which activity the person is performing (lying, sitting, walking and running, ascending/ descending stairs, cycling, swimming and strength-training)*".

We conducted four user studies using following devices for collecting data:

> We started with the WiiRemote [33] as it has a 3D accelerometer sensor and fixed it to a belt as shown in Figure 5. We were looking for water proof device to also recognize 'swimming'. The Wii remote is little bit bulky and not easy for the participants to wear it all the time so that we switched to the water proof Axivity device [1].

Figure 5: Wii remote

With the AX3 data logger containing 3-axis of accelerometer with flash memory and clock, this Axivity device is also water proof, small and easy to use. Its dimensions are 6x21.5x31.5 mm^3 and weight is only 9 grams. The device comes with pre-installed software and the possibility to configure its setting like sample rate, gravity etc. It continuously logs contextual information like time; hh:mm:ss and axis; X, Y, Z to its internal memory. One can also set the duration for logging this information with the possibility to export the logged data in CSV format.

3.1 User studies

We conducted four user studies with in total 53 participants using the Wii Remote and Axivity device for recognizing physical activities; we also investigated different body placements for the sensors with results as shown in Table 1.

Table 1: Recognizing physical activities

	Chosen device(s)	Number of participants	Body location (s)
a)	Wii remote	21	Low Back-bone
b)	Axivity	12	'Low backbone', 'Mid backbone', 'Upper backbone'
c)	Axivity	14	Right hands' upper arm
d)	Axivity	6	'Right hands upper arm', 'Low backbone' and 'Mid backbone'

a) Recognizing physical activities using Wii remote

Using J48 based decision tree classifier and the Wii remote placed at the low backbone, one can recognize the activities 'Lying down', 'Sitting', 'Walking' and 'Running' with an accuracy of around 96% as published in previous paper [65].

b) Recognizing physical activities using Axivity device

We conducted the same user study but using Axivity device and now collected the data from three body locations i.e. 'low part of backbone', 'middle part of the backbone' and the 'upper part of the backbone' as shown in Figure 6. We again used J48 based decision tree but also used IBk based kNN, Neural Network and Support Vector Machine classifiers. The system was able to recognize the activities 'Lying down', 'Walking', 'Running', 'Sitting', 'Standing', 'Cycling', 'Ascending stairs' and 'Descending stairs'. Our results show that IBk based kNN classifier correctly classified the instances with an accuracy of 94.19% and J48 based decision tree classifier correctly classified the instances an accuracy of 93.77%. 'Low backbone' was considered the best body location in terms of usability and accuracy, this research was previously published in [66].

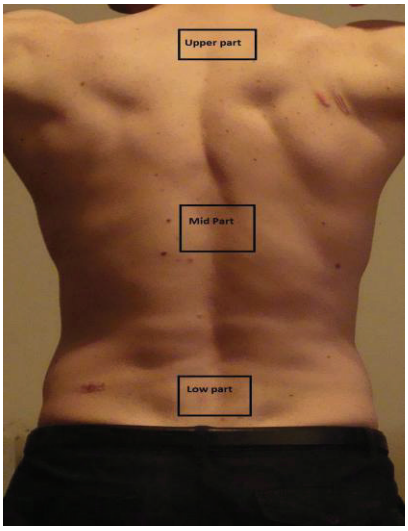

Figure 6: Backbone's location for the Axivity device

c) Recognizing strength-training techniques using Axivity device

To identify different strength-training techniques with the Axivity device i.e. 'Using Elliptical Trainer', 'Butterfly', 'Pull-down' and 'Bench-press, we chose 'upper-arm' to fix the device as shown in Figure 7. We again used and compared J48 based decision tree, IBk based kNN, Neural Network and Support Vector Machine algorithms [34]. The J48 based decision tree classifier correctly classified the instances with an accuracy of 93%, this was previously published in [67].

Figure 7: Body location for the Axivity device

d) Recognizing swimming techniques using Axivity device

In a further user study we used the Axivity device for recognizing different swimming techniques i.e. 'Dolphin', 'Back-stroke', 'Breast-stroke' and 'Free-style'. We chose 'upper-arm', 'mid part of the backbone' and the 'low part of the backbone' for the study. Our results showed that J48 based decision tree classifier correctly classify the instances with an accuracy of 68.67% as published in [68, 69]. 'Upper-arm' was considered the best location in terms of usability and accuracy [34].

3.2 Recognized physical activities

After the four user studies we had a system for recognizing physical activities using only one 3D accelerometer sensor placed at different locations on the body. Table 2 shows the recognition rate of each physical activity with respect to the body location. The 'lower backbone' is the optimal location for recognizing the required physical activities except for 'strength-training' and 'swimming' where ‘upper-arm’ was better suited. However, these activities were not as important to the medical doctors as shown in the requirements analysis. We further found that J48 decision based tree had best results.

Table 2: Recognized physical activities using Axivity device

S. No	Activity	Body location	Accuracy (J48 based decision tree classifier)
1	Sitting	Lower backbone	96.14%
2	Standing	Lower backbone	98.06%
3	Lying down	Lower backbone	95.14%
4	Walking	Lower backbone	100%
5	Running	Lower backbone	97.3%
6	Ascending stairs	Lower backbone	84.4%
7	Descending stairs	Lower backbone	82.15%
8	Cycling	Lower backbone	97%
9	Strength training	Upper arm	97.93%
10	Swimming	Upper arm	72.83%

The details of the user studies and evaluation with the different machine learning algorithms are given in [34], Recognizing Physical Activities using Wearable Devices.

3.3 Exploitation

The results show that one can recognize the above mentioned physical activities using only one 3D accelerometer; we used either the accelerometer of the Axivity device or the Wii-remote, which means that there is no dependency on particular hardware; any off-the shelf device or smart phone can be used for it. One can access the raw data of smart phone's accelerometer sensors by mobile apps [41]. There are also off-the shelf devices [42] which come with their software to retrieve acceleration data using smart phone application as shown in Figure 8.

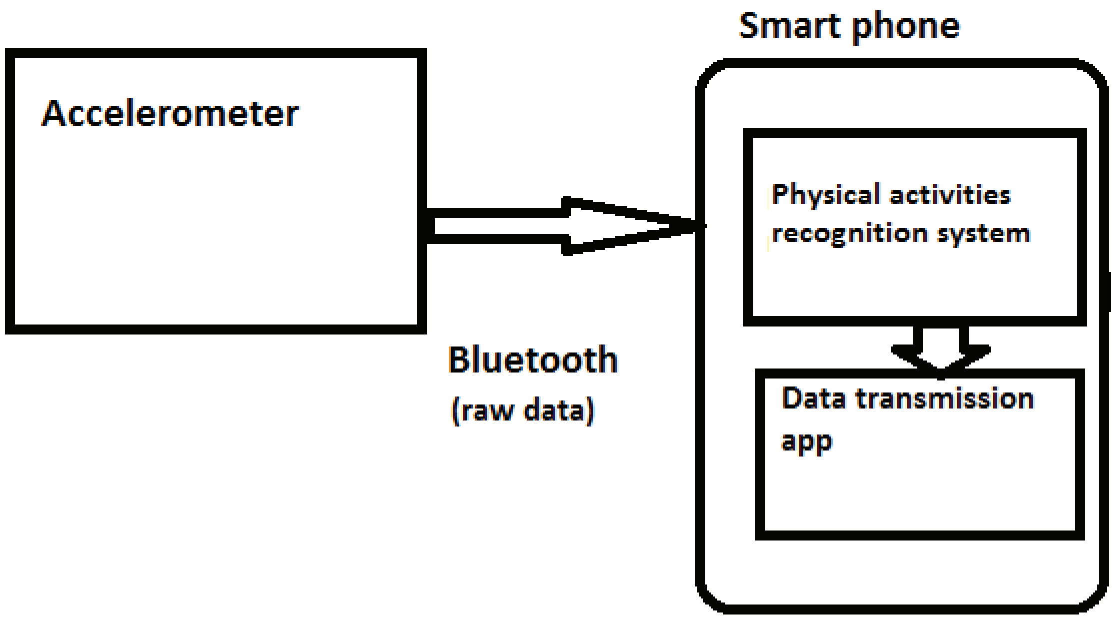

Figure 8: Standard solution for physical activities exploitation with an external accelerometer

In any case, the accelerometer has to be fixed properly on the backbone of the user in order to predict the user’s movements successfully. As a conclusion one can identify the aforementioned physical activities by using only one 3D wearable accelerometer placed at the lower part of the backbone.

4. Recognizing emotional states

The requirements indicate emotional states necessary to be recognized by physiological devices. This chapter presents the methodology and results of user study based research for recognizing the needed emotional states.

It is hard to express ones' own emotions; no one can accurately measure the own 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*" [99]. According to Paul Ekman, there are seven basic emotions which are fear, surprise, sad, dislike, disgrace, disgust and joy [73]. The concept behind emotional states, also known as affective computing was first introduced by Rosalind Picard in 1995 [71]. Since then the *affective computing* group has produced novel and innovative projects in that domain [72]. Recognizing emotional states is becoming a major part of user's context for wearable computing applications. Emotional state recognition has received attention in recent years and is able to support the health care industry. Emotions and physical health have a strong link influencing the immune system, too [74]. Emotional computing is a field of human computer interaction where a system has the ability to recognize emotions and react accordingly. Recognizing emotional states by using automated systems have increased in recent years. Researchers developed systems for recognizing emotional states analyzing speech [78, 79, and 80], facial expressions [80, 81, and 82] and physiological data [75, 76, 77, 84, and 85]. The wearable system in mind should be practical, reliable, and able for health-care related applications. The system should be able to acquire a user's emotional state by using physiological sensors. Here the eHealth platform [35] is a ready-made, light weight, small and easy to use device for recognizing the eight emotional states i.e. 'sad', 'dislike', 'joy', 'stress', 'normal', 'no-idea', 'positive' and 'negative' using decision tree classifier.

In the performed study we collected data from 24 different subjects. It was the intention to prove that "*The physiological data measured by wearable devices ('Electromyogram 'EMG', Blood volume pulse 'BVP', Skin temperature 'ST' and Skin conductance 'GSR' sensor) indicate which emotion state the person is in ('Sad', 'Dislike', 'Joy', 'Stress', 'Normal', 'No-Idea', 'Positive' and 'Negative')*" ; we used physiological devices and machine learning algorithms for this purpose. Different combinations as well as quantity of sensors we used to find the minimal number of sensors needed.

The body worn physiological device uses electromyogram 'EMG', blood volume pulse 'BVP', galvanic skin resistance 'GSR' and skin temperature. Physiological devices people used in the past to recognize different emotional states like sad [75, 76, 77, 85], joy/happy [75, 76, 77, 85, 86], normal/neutral [76, 85, 86], negative [84] etc. Table 3 gathers the literature on physiological devices involved in emotional state detection using different physiological devices. For example, some research [75] used EEG, GSR and pulse sensor to recognize joy, anger, sad, fear and relax. Audio and visual clips were used as a stimulus for eliciting the emotions. Other research [76] used ECG to recognize happiness, Sad, fear, surprise, disgust, and neutral using audio and visual clips as a stimulus for eliciting the emotions. Joy, anger, sadness and pleasure were recognized by using ECG, EMG, skin conductance and respiration sensor; music songs were used as a stimulus for eliciting the emotions [77]. The data of "blood volume pulse", "electromyogram", "respiration" and "skin conductance sensor" were used in 20 experiments in 20 consecutive days, testing around 25 minutes per day on each individual. The emotions detected were neutral, anger, hate, grief, love, romantic, joy and reverence emotion states with 81% classification accuracy for the eight states [86].

Literature indicates different techniques as a stimulus for eliciting the emotions i.e. pictures, video clips, audio clips, games etc. In our work, we used the International Affective Picture System (IAPS) for stimulation. The International Affective Picture System (IAPS) provides normative emotional stimuli for emotion and attention in experimental investigations. The target is to produce a large set of emotionally-evocative, standardized, color photographs, internationally-accessible including contents under semantic categories. The IAPS (pronounced eye-aps) is being produced and distributed by the Center for Emotion and Attention (CSEA) at the University of Florida [37]. The CSEA has a collection for different emotional states/categories: 'pleasant ', 'neutral', 'negative', 'un-pleasant', 'mutilations, 'attack'', 'household objects', 'families', 'erotica', 'non-threatening animals', 'neutral people',' neutral scenes', 'snakes'. The IAPS is widely used in research [87, 88, 89, 90, 91, 92 and 93] and here taken as a de facto standard.

Table 3: Physiological signals involved in Emotional states detection

Physiological Devices	Emotional States	Participants	Accuracy	Stimuli	References
GSR, HR	Stress	80 females (19 to 32)	99.5%		[94]
EEG (Forehead), GSR (fingers -> mouse), pulse sensor (earlobe)	Joy, anger, sad, fear, relax	12; age: 21-25; males; Native Japanese	41.7%	Audio, visual clips	[75]
ECG	Joy, sad, fear, surprise, disgust, neutral	7 males, 8 females; age: 21 to 24	comparison between low and high frequency	Audio, visual clips	[76]
ECG, EMG, Skin conductance, Respiration sensor	Joy, anger, sad		97%	Music songs	[77]
GSR, BVP, Pupil diameter (PD), Skin temperature	Stress and relax	32 (ages 21 -42)	90%	Stroop Effect; computer game'	[95]
Electrocardiogram (EKG), Electromyogram, skin conductance and respiration	Stress	24	97%	Car simulator	[96]
EMG, ECG, SC and respiration rate	Joy, anger		80%	Music	[97]
EMG, ECG, SC and respiration rate	Joy, anger, sadness	1	75 to 85%	Music	[98]
EMG, BVP, GSR and Skin temperature	Stress, joy, sad, normal/neutral, dislike, no-idea, positive and negative	24 (19 males and 5 females); Native Chinese	98%	IAPS images	Our proposed method

In our work; we used the IAPS [37] as stimulus and the four physiological sensors BVP, GSR, EMG and Temperature to recognize emotional states stress, joy/happy, sad, normal/neutral, dislike and no-idea. We also evaluated the collected data with different combinations as well as quantity of sensors. Above mentioned researchers used different parts of the body but in our research we only used the left arm for the sensor placement. We implemented the study by showing participants IAPS images in a sequence in order to change their emotional state. The starting and ending time for each IAPS image was fixed. After five different images from each group, the application asked participants about their current emotional state using the Likert scale [43] approach. Text files contain the participants' feedback for each emotional state and IAPS image with the timestamp. We used the eHealth platform [35] for collecting data connecting Raspberry Pi [36] to eHealth platform as shown in Figure 9.

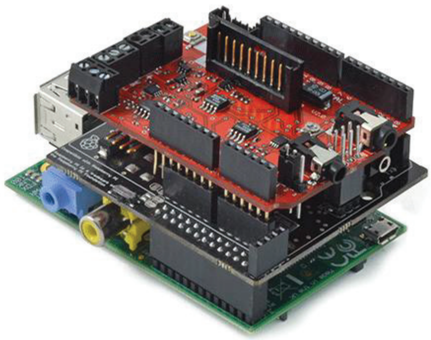

Figure 9: Raspberri pi with eHealth platform

The eHealth platform comes with few sensors like 2D accelerometer, 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. The system used few physiological devices i.e. 'blood volume pulse (BVP) ', 'electromyogram (EMG)', 'galvanic skin response (GSR)' and 'skin temperature (temperature)'. In Chengdu China, 24 participants were asked to wear the sensors as shown in Figure 10 using IAPS as a stimulus. The user study was conducted in the context of the collaboration project named HealthWear@AAL Sino-German collaboration.

4.1 User study

We faced following challenges while designing the user study:

- How to change participants' emotional states?
- What should be the settings?
- How to collect data?

The study was designed with the help of psychological department; Bremen University-Germany (i.e. Prof. Dr. Canan Basar-Eroglu and Dr. Timur Cetin). I was advised to use IAPS images as shown in Figure 10 because they are widely used in research. I was asked to conduct a study twice because participants have to be familiarized with the setup.

Figure 10: IAPS images

We got an access of 100 IAPS images, they were from different categories like 'Sad', 'Dislike', 'Joy' and 'Stress'. We used to show five images from each category and each image used to be shown to the participants for five seconds. After that they were asked to mention their emotional states which we took it as a ground truth. We did it in five iterations as shown in Figure 11.

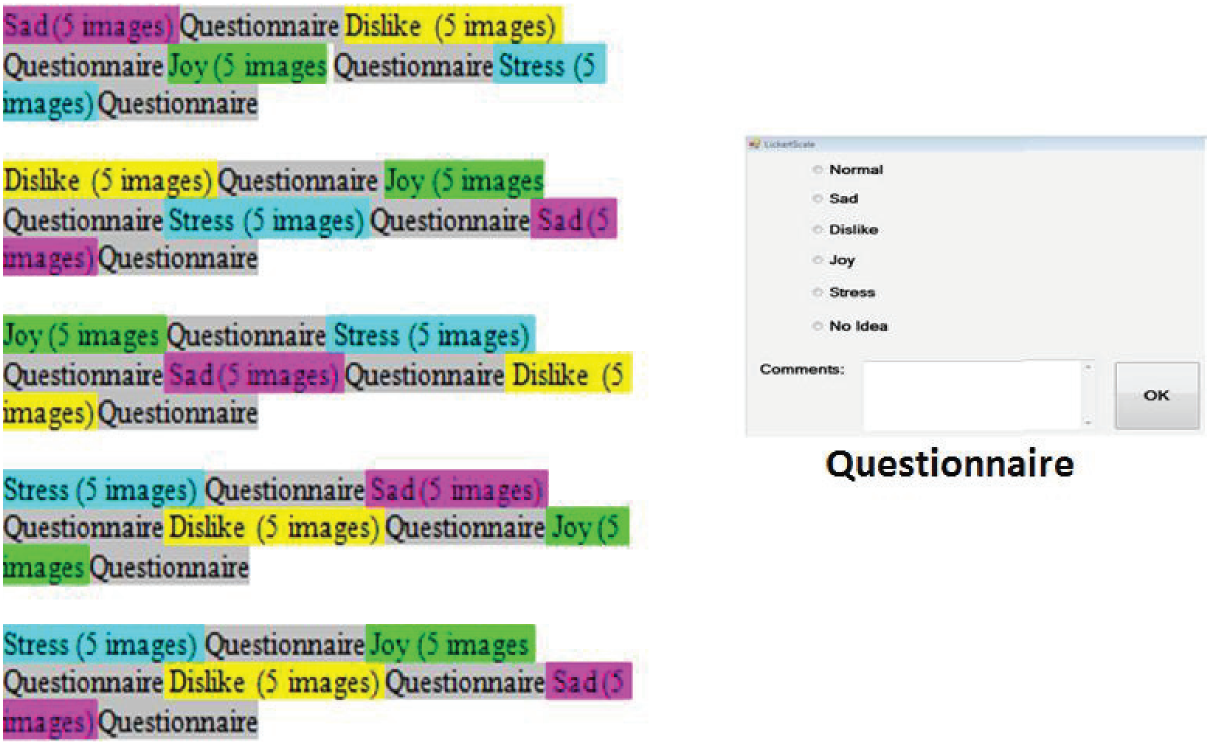

Figure 11: Appearances of IAPS images

4.2 Experiments

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 as shown in Figure 12. 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.
We recruited 26 participants (21 males, 5 females) for our experiment setup; two of them could not participate in the second experiment because of their busy schedules 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 the experiments twice on different days. As described earlier, the intention behind the first experiment was only the 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.

In the second experiment, all participants already knew about the setup and 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 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 the image application was logging the participants' feedback to the same laptop with time stamp to compare the standard meaning of IAPS images with the personal interpretation. We merged both files to generate a single file for post analysis.

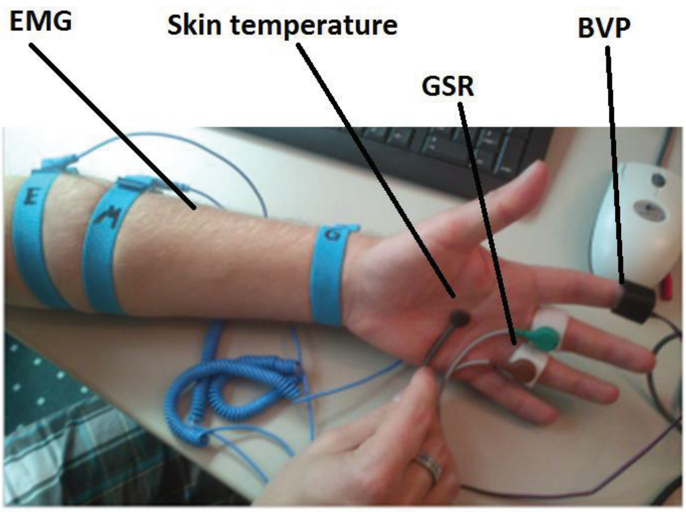

Figure 12: Participant with physiological sensors

Our experimental setup for the user study was able to change emotional states with results as shown in Table 4.

Table 4: 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 out of 24 participants chose all emotional states as given. This was due to the fact that it was hard for the participants to distinguish as they mentioned between sad, dislike and stress especially. To distinguish between joy and normal was also not straightforward. That explains why some emotional states were ignored by participants (as shown in Table 4).
“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” [70].
Therefore, we generated another dataset from our experimental data; we categorized emotional states into two collections:

(1) ‘Positive’ which contained ‘joy’ and ‘normal’.
(2) ‘Negative’ which contained ‘sad’, ‘dislike’ and ‘stress’.

We excluded ‘No-idea’. Participants were not sure about their emotional state which could be any state. The two types of datasets were:

- Type1: {Normal, Sad, Dislike, Joy, Stress and No-idea},
- Type2: {Positive and Negative}.

As the WEKA [38] application was not able to process the data of all 24 participants at a time, we divided the dataset into six groups containing data of four participant each; group 1 with the four participants who chose all emotional states, the other groups were assigned in alphabetic order.
We received values from sensors i.e. EMG, BVP, GSR and Temperature with the sampling rate of around 650Hz.

The two types (i.e. Type 1 and Type 2) were analyzed in three different ways:

(1) Individuals

We applied machine learning algorithm on the dataset of each participant

(2) Group-wise

We divided the participants in 6 groups and applied machine learning algorithm on the dataset of each group.

(3) Portioned data

As mentioned earlier due to the limitations of processing huge datasets in WEKA, we chose small portions of data randomly pertaining to each emotional state from each participant.

4.3 Comparison and results

The “Two-Class” and “Six-class” were analyzed on “Individual”, “Group” and “Portioned” basis. We applied J48 based decision tree classifier with different combinations of sensors on above types of datasets; we used 10-fold cross validation. We took data of each participant and applied J48 based decision classifier and then took an average of ‘Individual’ data. We took the integrated data from each group; applied J48 based decision tree classifier and then took an average of ‘Group’ data. We took a small portion of data randomly from each participant and applied J48 based decision tree classifier on the data.

We used different combinations of physiological sensors in order to see the importance of each physiological sensor.

Table 5: Result comparison; six emotional states

Sensors	Individuals	Groups	Portioned data
EMG, BVP, GSR, ST	99.13%	98.67%	98.47%
BVP, GSR, ST	98.84%	98.56%	98.63%
EMG, GSR, ST	98.68%	98.39%	98.61%
EMG, BVP,ST	98.51%	98.04%	98.06%
BVP, EMG, GSR	96.55%	95.96%	96.5%
EMG, ST	96.69%	95.87%	97.02%
BVP, ST	96.19%	96.04%	96.39%
EMG, BVP	93.34%	92.81%	93.88%
GSR, ST	91.57%	89.87%	91.28%
EMG, GSR	91.56%	90.82%	93.57%
BVP, GSR	91.05%	90.23%	92.64%

Table 6: Result comparison; two emotional states

Sensors	Individuals	Groups	Portioned data
EMG, BVP, GSR, ST	99.40%	99.3%	99.33%
BVP, GSR, ST	99.33%	99.21%	99.27%
EMG, GSR, ST	99.35%	99.19%	99.3%
EMG, BVP,ST	99.13%	98.88%	99.01%
BVP, EMG, GSR	98.14%	97.62%	97.76%
EMG, ST	98.21%	97.89%	98.34%
BVP, ST	97.54%	97.52%	98.15%
EMG, BVP	95.81%	95.53%	96.02%
GSR, ST	95.72%	94.87%	96.08%
EMG, GSR	95.41%	94.98%	96.35%
BVP, GSR	94.94%	94.66%	95.52%

Table 5 and Table 6 represent the accuracies of correctly classified instances from ‘Individuals (average)’, ‘Groups (average)’ and ‘All participants’ based on different combinations of physiological sensors. The results are similar from the approaches ‘Individual’, ‘Groups’ and ‘All participants’.

One can recognize the aforementioned emotional states with an accuracy of up to 98% by using physiological devices and J48 based decision tree classifier. Results have shown that ‘EMG’ and ‘BVP’ are also sufficient for recognizing the required emotional states with an acceptable accuracy rate as shown in Table 5 and 6.

This is only a "proof of concept" showing that one can identify the above mentioned emotional states independently of BMI (body mass index) and age group. Details of this research will be published as a book chapter [39] and are part of the thesis as an appendix; three articles on different aspects of this research have been published on conferences and in a journal [101,102 and 103].

4.4 Exploitation

The results show that one can recognize positive versus negative emotional states with up to 98% probability using four physiological devices. Results with different combinations of physiological sensors are shown in Table 5 and Table 6. The off-the-shelf physiological sensors proof that the system is not dependent on any particular physiological device; and in the future off-the shelf wireless devices or smart phones might be used for it.
There are off-the-shelf physiological devices which come with their software, and raw data can be retrieved [26, 27, 28 and 29] using a smart phone application as shown in Figure 13. However, the user acceptance is still a major issue.

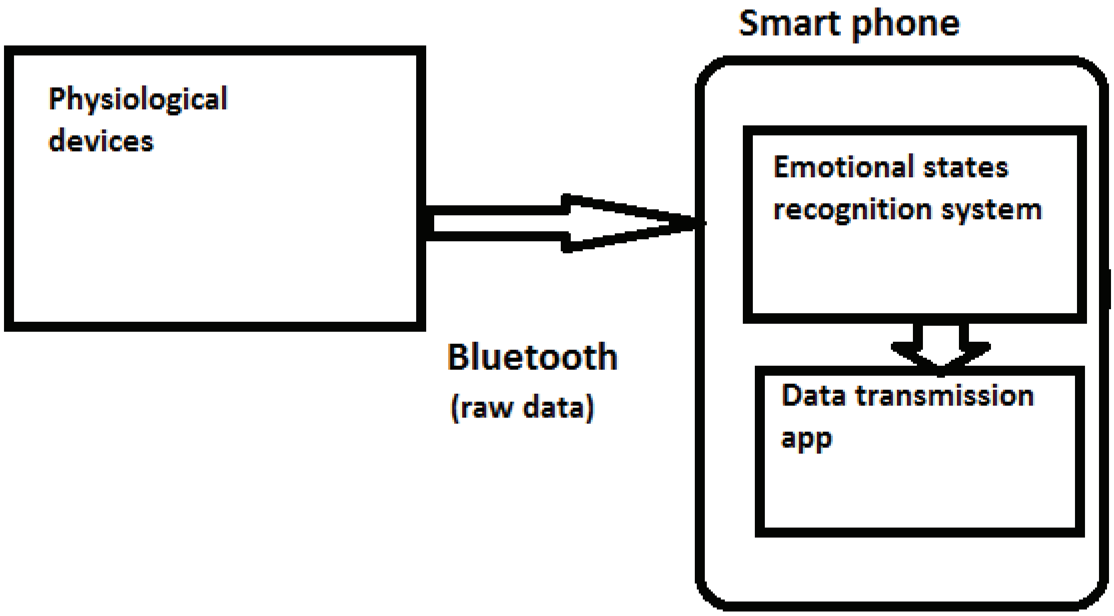

Figure 13: Proposed solution for physical activities exploitation

The physiological sensors have to be fixed properly on the left arm of the user in order to predict the user's emotional states successfully. Although, the usability of a sensor fixture as shown in Figure 12 might be appropriate in a lab setting, it will be not for any 24/7 wearable design. Here further research is required in order to have more reliable results. However, in principle one can recognize emotional states using the physiological device with sufficient accuracy. For further research the collected data is stored here [105].

5. Conclusion

The discussion with health experts initiated is research on Wearable Health Monitoring Systems (WHMS) for heart patients. The information about physical activities, emotional states and physiological data together are mandatory for any health expert in order to assess the heart patients' health conditions remotely as the sensor data itself is not sufficient. With the approach shown here, the needed physical activities one can detect with just one 3D accelerometer with an accuracy of around 90%. The needed emotional states one can recognize using physiological devices with the accuracy from 54% (one physiological device) to 99% (four physiological devices).

Any combination with three physiological devices achieved an accuracy of more than 95%; the combination of two physiological sensors (i.e. EMG, skin temperature and BVP, skin temperature) also achieved the accuracy of 95%.

The needed physiological devices and 3D accelerometer sensor can be worn as they are commercially available i.e. Empatica E4 wristband [27], Myo band [28], Microsoft Band [106] etc. But further developments are required for the practical use. The proposed solution could reduce medical cost and increase patients' satisfaction by reducing visits to hospitals or clinics. It gains time for patients and doctors as technology measures, recognizes and transmits the needed information on request [100]. The system does not require patients to be at their homes for the physiological measurements unlike [40].

We did not perform any clinical study since it was a computer science research and not a medical research. Nevertheless, we got a positive feedback from health experts, for the presented "proof of concept" supporting both physicians and patients.

This research identified physical activities and emotional states being essential for medical doctors to judge the health status of heart patients; this has to be taken into account while developing any WHMS for heart patients. The developed wearable health monitoring system for heart patients recognized these needed physical activities as well as emotional states. This system is not restricted to stationary settings; it can be used outside as well. However as shown in Figure 10 the usability of the sensors to gain the physiological data is not yet sufficient.

One can recognize some physical activities with a 3D accelerometer and recognize emotional states using at least two physiological devices (EMG and BVP). The importance of each physiological device in terms of accuracy was investigated.

List of Abbreviations

WHMS	Wearable Health Monitoring System
ECG	Electrocardiography
EMG	Electromyogram
BVP	Blood Volume Pulse
GSR	Galvanic Skin Response
BMI	Body Mass Index
CSV	Comma-separated values
EEG	Electroencephalography

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Appendix

Draft of planned article "Recognizing emotional states using physiological devices" which would be published as a book chapter in "Clinical Rehabilitation Experience utilizing Serious Games"

Recognizing emotional states using physiological devices

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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 classifier. In this chapter, 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%.

Key words: Emotional states; Electromyogram; Blood volume pulse; Galvanic skin response; Skin temperature; 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. In next chapter, “Related work” will be discussed, “Hypothesis and research question” will be discussed in the 3rd chapter, “Experimental methodology” will be discussed in the 4th chapter, “Results and analysis” will be discussed in the 5th chapter and “Conclusion and future work” will be in the last.

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, 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, 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 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 target is to produce a large set of emotionally-evocative, standardized, color photographs, inter nationally-accessible that includes contents under semantic categories. The IAPS (pronounced eye-aps) is being produced and distributed by the Center for Emotion and Attention (CSEA) at the University of Florida [32].

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

Physiological Devices	Emotional States	Participants	Accuracy	Stimuli	References
GSR, HR	Stress	80 females (19 to 32)	99.5%		[45]
EEG (Forehead), GSR (fingers -> mouse), pulse sensor (earlobe)	Joy, Anger, Sad, Fearness, Relax	12; age: 21-25; males; Native Japanese	41.7%	Audio visual clips	[20]
ECG	Happiness, Sad, Fear, Surprise, Disgust, Neutral	7 males, 8 females; age: 21 to 24	comparison between low and high frequency	Audio visual clips	[21]
ECG, EMG, Skin conductance, Respiration sensor	Joy, anger, Sadness, Pleasure		97%	Music songs	[22]
GSR, BVP, Pupil diameter (PD), Skin temperature	Stress and relaxed	32 (ages 21 -42)	90%	Stroop Effect; computer game'	[46]
Electrocardiogram (EKG), Electromyogram, skin conductance and respiration	Stress	24	97%	car simulator	[47]
EMG, ECG, SC and respiration rate	Joy, Anger, pleasure and happiness		80%	Music	[48]

EMG, ECG, SC and respiration rate	Joy, Anger, sadness and pleasure	1	75 to 85%	Music	[49]
EMG, BVP, GSR and Skin temperature	Stress, Joy/Happy, Sad, Normal/neutral, Dislike, No-idea, Positive and Negative	24 (19 males and 5 females); Native chinese	98%	IAPS images	Our proposed method

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), we also evaluated our research with different combination as well as quantity of sensors. Above mentioned researchers used different parts of body but in our research we used only left arm for the sensor placement.

3.Hypothesis and Research question

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 machine learning classifier.

In this chapter, we investigate some practical aspects of creating an automatic, personal emotional states recognition system. Through our experiments, we want to find the answer to the following question:

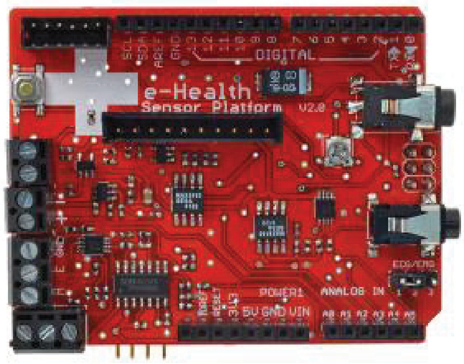
- Is it possible to recognize a person's emotional state (Sad, Dislike, Joy, Stress, Normal, No-Idea) by using different combinations of physiological devices i.e. EMG, blood volume pulse, temperature and skin conductance sensor.

4.Experimental methodology

We developed following systems for the user study.

4.1 eHealth platform and application

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



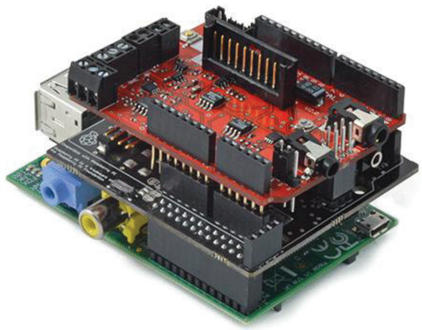


Figure 1: eHealth platform **Figure2: Raspberri pi with eHealth platform**

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] which we purchased separately as shown in Figure 3.

Figure 3: Pulse sensor

"*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 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 in the following structure.

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

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 [42].

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 [42].

Galvanic skin response

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 [42].

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 [42].

4.2 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

4.3 IAPS and its application (Application for Stimulus)

We got an access to IAPS[32] images and we found literature where researchers used IAPS images from different categories like ‘Pleasant’, ‘Neutral’, ‘Unpleasant’, ‘Mutilations’, ‘Attack’, ‘Household Objects’, ‘Families’, ‘Erotica’, ‘Non-threatening animals’, ‘Neutral people’, ‘Neutral scenes’ and ‘Snakes’. We grouped IAPS image in the following groups:

- Sad
- Dislike
- Joy
- Stress
- Joy=> Pleasant
- Normal => Neutral, household objects
- Sad/Dislike => Unpleasant, Negative
- Stress => Mutilations, attack, snakes

4.4 Criteria for choosing IAPS images

IAPS images are used by several researchers and they identified different emotional states/categories i.e. ‘Pleasant ’, ‘Neutral’, ‘Negative’, ‘Un-pleasant’, ‘Mutilations, ’Attack’’, ‘Household objects’, ‘Families’, ‘Erotica’, ‘Non-threatening animals’, ‘Neutral people’,’ Neutral scenes’, ‘Snakes’ [33,34,35,36,37,38,39]
We grouped IAPS image in the following groups:

- Sad
- Dislike
- Joy
- Stress

Joy => Pleasant category

Normal => Neutral, household objects category
Sad/Dislike => Unpleasant, Negative category
Stress => Mutilations, attack, snakes category

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 (as shown in figure: 4) approach. This application generates text file with this information (participants' feedbacks) for each emotional state and IAPS image with timestamp in a following structure:

Test setup

International Affective Picture System (IAPS) stimuli used in this experiment 2 include 'Dislike' (35) 3210, 3500, 3530, 3550, 5120, 6190, 6200, 6210, 6211, 6212, 6230, 6250, 6260, 6300, 6350, 6370, 6510, 6821, 6830, 6831, 6834, 6838, 9250, 9250, 9254; 'Joy' (26) 1440, 1500, 1590, 1600, 1850, 2250, 2304, 2510, 2560, 5300, 5890, 7200, 7260, 7280, 7284, 7352, 7410, 7460, 7481, 8090, 8116, 8280, 8320, 8400, 8465, 8510; 'Sad' (25) 3210, 3500, 3530, 3550, 5120, 6190, 6200, 6210, 6211, 6212, 6230, 6250, 6260, 6300, 6370, 6510, 6821, 6830, 6831, 6834, 6838, 9070, 9250, 9252, 9254; 'Stress' (25) 1019, 1052, 1070, 1080, 1090, 1110, 1111, 1113, 1300, 1930, 3030, 3071, 3080, 3101, 3110, 6370, 6510, 6821, 6830, 6831, 6834, 6838, 9250, 9252, 9254.

Real setup

International Affective Picture System (IAPS) stimuli used in this experiment 2 include 'Dislike' (25) 1111, 1201, 1280, 1300, 1303, 1930, 2691, 2730, 2750, 9006, 9008, 9040, 9090, 9290, 9300, 9341 ,9432, 9440, 9470, 9480, 9490, 9592, 9611, 9912, 9921; 'Joy' (25) 1340, 1463, 1750, 1920, 2070, 2165, 2208, 2340, 2341, 2360, 2791, 4611, 4641, 4651, 4652, 4653, 5600, 5621, 7330, 8080, 8120, 8180, 8200, 8370, 8420; 'Sad' (25) 2120, 2205, 2520, 2590, 2800, 3180, 3181, 5970, 5971, 6020, 7380, 9001, 9010, 9040, 9041, 9102, 9180, 9470, 9560, 9561, 9611, 9622, 9800, 9912, 9921; 'Stress' (25) 1050, 1051, 1114, 1120, 3000, 3010, 3015, 3051, 3053, 3060, 3064, 3068, 3069, 3100, 3102, 3120, 3130, 3150, 3168, 3170, 3266, 3400, 6540, 9181, 9405.

Timestamp; IAPS image-group (i),
Timestamp; IAPS image-group (i),
Timestamp; IAPS image-group (i),
Timestamp; IAPS image-group (i),
Timestamp; IAPS image-group (i),

Timestamp; Participant's feedback (i.e. Sad, Dislike, Joy, Stress, Normal or No-Idea)

We chose 100 IAPS images from different categories and presented it in following order
100 IAPS images in 5 iterations

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

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

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

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

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

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 as shown in Figure: Questionnaire form. It also stores the participants' personal information i.e. age, gender, height and weight.

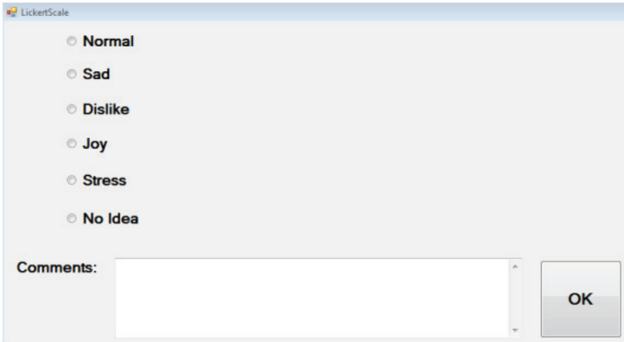


Figure 4: Questionnaire form

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 (as shown in 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.

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 little bit nervous due to physiological devices and long cables and this could adversely influence our data. For this reason the results from the first experiment was never used for analysis.

Second experiment

In 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 (see Figure: 4). 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.Data collection

We got a data from 24 participants, each experiment took from 11 to 12 minutes and the sample rate was around 650 Hz.

Total amount of data: ~11 minutes (660 seconds) X ~650 Hz X 24 participants

6.Application for post-analysis

We implemented another application in Java for post analysis. This application requires two input files; one text file from "Application for Stimulus" and the text file from "Application for reading sensors from eHealth platform". Firstly, it filters needed data from the sensor file based on the time stamp and generates training data sets in ARFF format.

7.Results and Analysis

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 conduct the experiment twice and on different days. They were asked to choose one of the following 'Emotional states' during experiments:
Normal, Sad, Dislike, Joy, Stress and No-Idea
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*” [43]. 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 application [44] to process the data of all 24 participants together. Therefore, we divided our datasets into six groups, each group contains 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 3: Groups

Groups	Age	Gender	BMI	Chose Emotional states
Group 1	25, 24, 25, 26	3 Males, 1 Female	23.4, 20.5, 20.8, 21	Normal (4), Sad (4), Dislike (4), Joy (4), Stress (4) and No-Idea (4)
Group 2	24,25,25,38	4 Males	23, 23.9, 21.2, 26	Normal (0), Sad (3), Dislike (4), Joy (4), Stress (4) and No-Idea (2)
Group 3	24,24,25,44	3 Males, 1 Female	19.1, 20.8, 26.6, 19.4	Normal (3), Sad (3), Dislike (4), Joy (4), Stress (4) and No-Idea (1)
Group 4	20,25,25,33	2 Males, 2 Females	20.5, 20.2, 18.7, 20	Normal (2), Sad (4), Dislike (4), Joy (4), Stress (2) and No-Idea (1)
Group 5	22,24,24,25	3 Males, 1 Female	19.7, 19.6, 21, 22.3	Normal (3), Sad (3), Dislike (4), Joy (4), Stress (3) and No-Idea (2)
Group 6	24,25,25,27	4 Males	25, 19.2, 21.7, 20.9	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 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 following three different ways:

1. **Individuals**

   We applied ML algorithm on the dataset of each participant
2. **Group-wise**

   We divided the participants in 6 groups (as shown in Table 3) and applied ML algorithm on the dataset of each group.
3. **Portioned data**

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

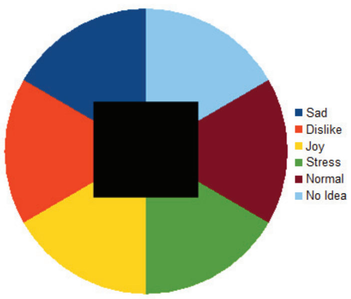


Figure 6(a): Type 1

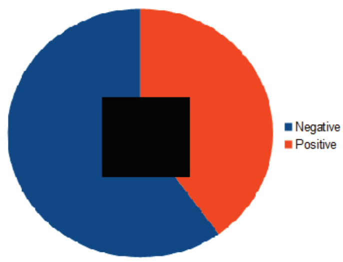


Figure 6(b): Type 2

8.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 different combinations of sensors on above types of datasets. We used 10-fold cross validation.

Two-Class

Four sensors (BVP, EMG, GSR and Temperature)

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. We took confusion matrix from all participants and summed it up, 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**. We took confusion matrix from each group and summed it 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. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

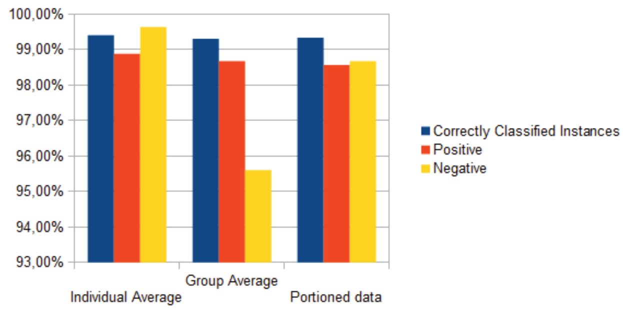


Figure 7: Comparison

We also 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.

Three sensors (BVP, GSR and Temperature)

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 99.33%; Min: 98.65%; Max: 99.68% and SD: 0.29. We took confusion matrix from all participants and summed it up, 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 98.73% and 99.62% 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 99.21%; Min: 98.93%; Max: 99.45%; SD: 0.2**. We took confusion matrix from each group and summed it 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 98.47% and 99.56% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 99.27% and it was also able to predict positive and Negative emotional states with the accuracy of 98.26% and 99.71% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

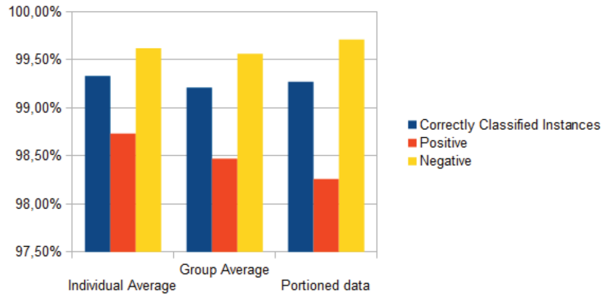


Figure 8: Comparison

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

Three sensors (BVP, EMG and Temperature)

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: 97.76%; Max: 99.71% and SD: 0.39. We took confusion matrix from all participants and summed it up, 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 98.23% and 99.51% 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 98.88%; Min: 98.62%; Max: 99.18%; SD: 0.21**. We took confusion matrix from each group and summed it 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 97.79% and 99.39% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 99.01% and it was also able to predict positive and Negative emotional states with the accuracy of 91.08% and 97.85% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

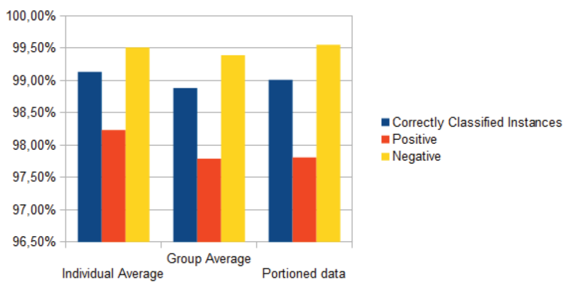


Figure 9: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 9 which shows that there is not much difference in results among all categories.

Three sensors (BVP, EMG and GSR)

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 98.14%; Min: 94.04%; Max: 99.71% and SD: 1.41. We took confusion matrix from all participants and summed it up, 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 96.39% and 98.95% 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 97.62%; Min: 96.42%; Max: 98.22%; SD: 0.63**. We took confusion matrix from each group and summed it 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 95.2% and 98.73% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 97.76% and it was also able to predict positive and Negative emotional states with the accuracy of 95.09% and 98.94% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

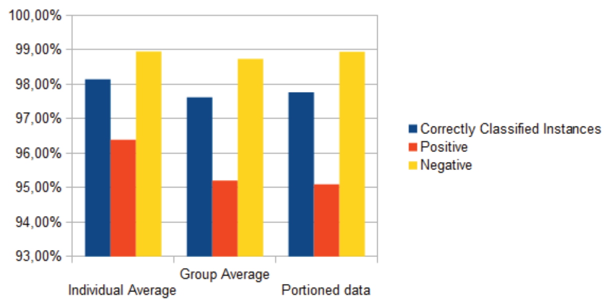


Figure 10: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 10 which shows that there is not much difference in results among all categories.

Three sensors (EMG, GSR and Temperature)

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 99.35%; Min: 98.59%; Max: 99.7% and SD: 0.32. We took confusion matrix from all participants and summed it up, 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 98.74% and 99.64% by J48 classifier respectively**.

2. Group-Summation

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 99.19%; Min: 98.89%; Max: 99.38%; SD: 0.21**. We took confusion matrix from each group and summed it 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 98.41% and 99.536% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 99.3% and it was also able to predict positive and Negative emotional states with the accuracy of 98.5% and 99.65% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

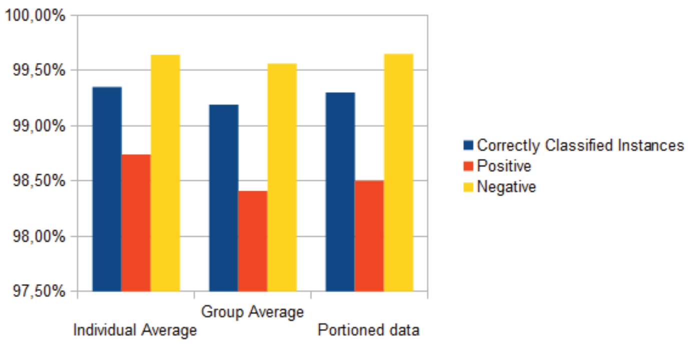


Figure 11: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Figure 11 which shows that there is not much difference in results among all categories.

Two sensors (BVP and GSR)

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 99.94%; Min: 89.75%; Max: 97.78% and SD: 2.39. We took confusion matrix from all participants and summed it up, 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 89.49% and 97.35% 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 94.66%; Min: 92.73%; Max: 96.32%; SD: 1.17**. We took confusion matrix from each group and summed it 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 89.16% and 97.17% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 95.53% and it was also able to predict positive and Negative emotional states with the accuracy of 90.78% and 97.63% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

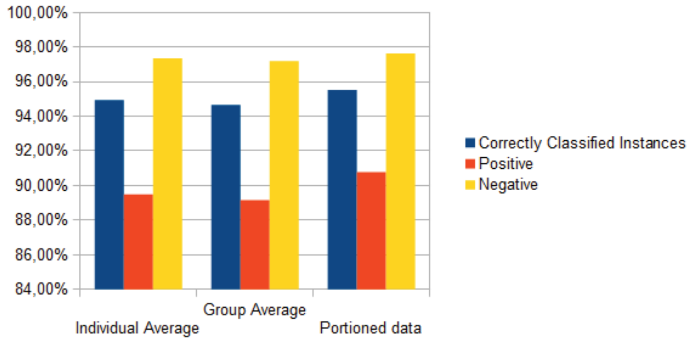


Figure 12: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 12 which shows that there is not much difference in results among all categories.

Two sensors (BVP and Temperature)

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 97.54%; Min: 92.92%; Max: 99.45% and SD: 1.69. We took confusion matrix from all participants and summed it up, 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 94.88% and 98.68% 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 97.52%; Min: 96.92%; Max: 98.07%; SD: 0.48**. We took confusion matrix from each group and summed it 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 95.01% and 98.69% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 98.15% and it was also able to predict positive and Negative emotional states with the accuracy of 96.36% and 98.94% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

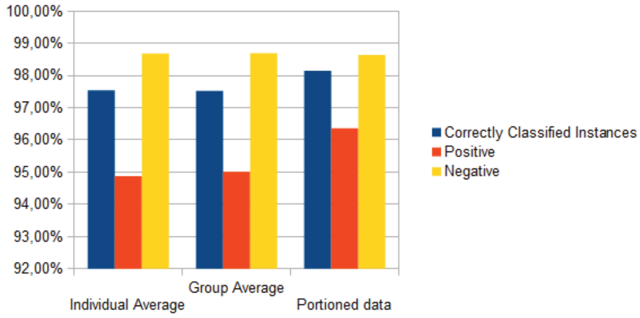


Figure 13: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 13 which shows that there is not much difference in results among all categories.

Two sensors (EMG and BVP)

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 95.81%; Min: 88.04%; Max: 99.61% and SD: 3.44. We took confusion matrix from all participants and summed it up, 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 91.29% and 97.68% 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 95.53%; Min: 93.3%; Max: 97.955%; SD: 1.74**. We took confusion matrix from each group and summed it 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 91% and 97.55% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 96.02% and it was also able to predict positive and Negative emotional states with the accuracy of 91.86% and 97.87% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

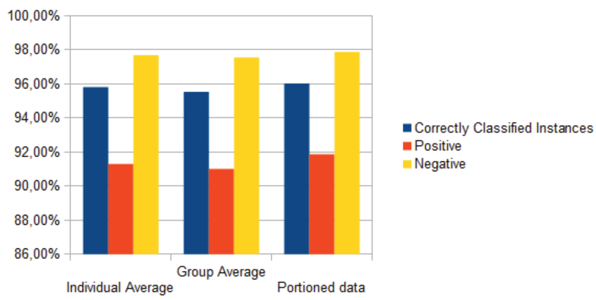


Figure 14: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 14 which shows that there is not much difference in results among all categories.

Two sensors (EMG and GSR)

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 95.41%; Min: 87.63%; Max: 98.65% and SD: 2.57. We took confusion matrix from all participants and summed it up, 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 91.13% and 97.41% 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 94.98%; Min: 93.12%; Max: 96.35%; SD: 1.31**. We took confusion matrix from each group and summed it 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 90.07% and 97.27% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 96.35% and it was also able to predict positive and Negative emotional states with the accuracy of 92.39% and 98.11% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

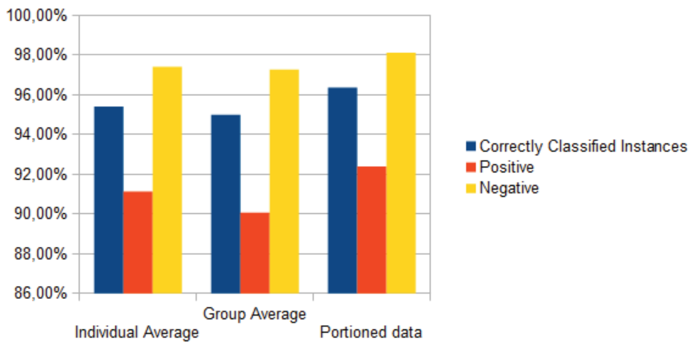


Figure 15: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 15 which shows that there is not much difference in results among all categories.

Two sensors (EMG and Temperature)

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 98.21%; Min: 93.84%; Max: 99.25% and SD: 1.12. We took confusion matrix from all participants and summed it up, 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 96.23% and 99.07% 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 97.89%; Min: 99.82%; Max: 98.42%; SD: 0.55**. We took confusion matrix from each group and summed it 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 95.63% and 98.94% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 98.34% and it was also able to predict positive and Negative emotional states with the accuracy of 96.47% and 99.17% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

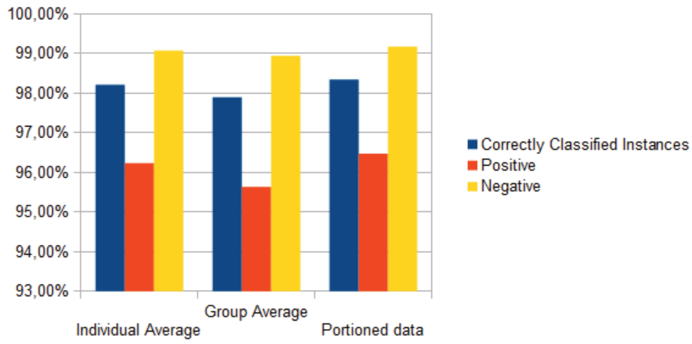


Figure 16 Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 16 which shows that there is not much difference in results among all categories.

Two sensors (Temperature and GSR)

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 95.72%; Min: 89.84%; Max: 98.33% and SD: 2.66. We took confusion matrix from all participants and summed it up, 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 91.08% and 97.85% 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 94.87%; Min: 92.76%; Max: 97.31%; SD: 1.55**. We took confusion matrix from each group and summed it 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 86.63% and 97.82% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of **96.08%** and it was also able to predict positive and Negative emotional states with the accuracy of 90.29% and 98.65% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

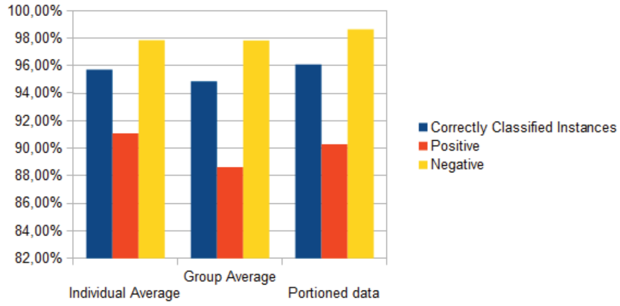


Figure 17: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 17 which shows that there is not much difference in results among all categories.

Single sensor (BVP)

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 86.8%; Min: 69.3%; Max: 94.06% and SD: 6.25. We took confusion matrix from all participants and summed it up, 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 69.94% and 94.23% 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 85.31%; Min: 83.27%; Max: 88.21%; SD: 1.74**. We took confusion matrix from each group and summed it 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 86.46% and it was also able to predict positive and Negative emotional states with the accuracy of 70.63% and 93.47% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

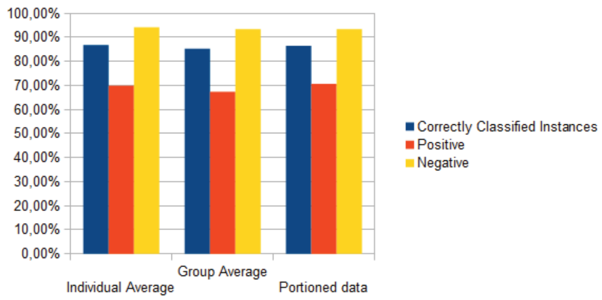


Figure 18: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in **Figure 18** which shows that there is not much difference in results among all categories.

Single sensor (EMG)

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 86.62%; Min: 74.69%; Max: 95.3% and SD: 5.69. We took confusion matrix from all participants and summed it up, 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 75.26% and 94.44% 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 87.07%; Min: 85.22%; Max: 89.83%; SD: 2.03**. We took confusion matrix from each group and summed it 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 72.26% and 93.84% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 89.41% and it was also able to predict positive and Negative emotional states with the accuracy of 78.34% and 94.31% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

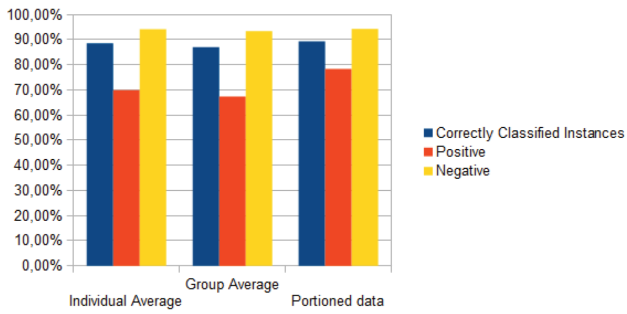


Figure 19: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 19 which shows that there is not much difference in results among all categories.

Single sensor (GSR)

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 80.31%; Min: 71.35%; Max: 87.33% and SD: 4.07. We took confusion matrix from all participants and summed it up, 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 54.02% and 92.66% 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 78.58%; Min: 75.87%; Max: 82.44%; SD: 2.16**. We took confusion matrix from each group and summed it 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 45.99% and 93.66% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 79.72% and it was also able to predict positive and Negative emotional states with the accuracy of 48.36% and 93.61% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

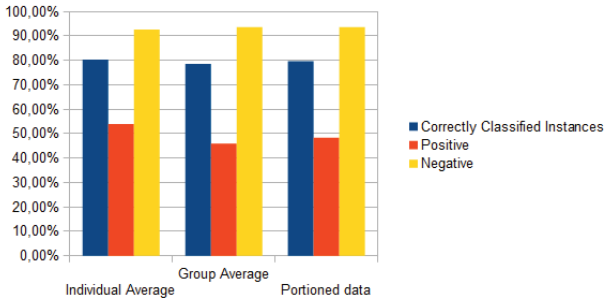


Figure 20: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 20 which shows that there is not much difference in results among all categories.

Single sensor (Temperature)

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 89.49%; Min: 76.8%; Max: 96.78% and SD: 5.89. We took confusion matrix from all participants and summed it up, 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 75.15% and 96.05% 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 86.56%; Min: 82.94%; Max: 91.91%; SD: 3.16**. We took confusion matrix from each group and summed it 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 66.74% and 95.84% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of **88.63%** and it was also able to predict positive and Negative emotional states with the accuracy of 69.47% and 97.47% respectively. We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

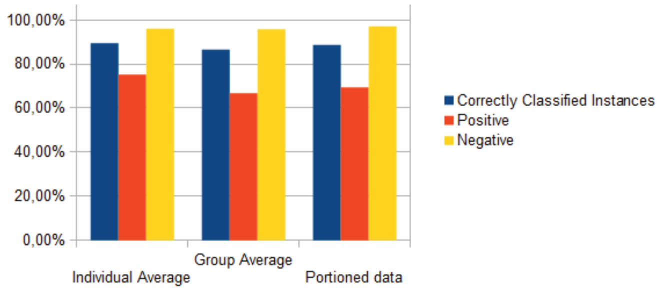


Figure 21: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 21 which shows that there is not much difference in results among all categories.

Six-Class

Four sensors (BVP, EMG, GSR and Temperature)

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. We took confusion matrix from all participants and summed it 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**. We took confusion matrix from each group and summed it 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.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

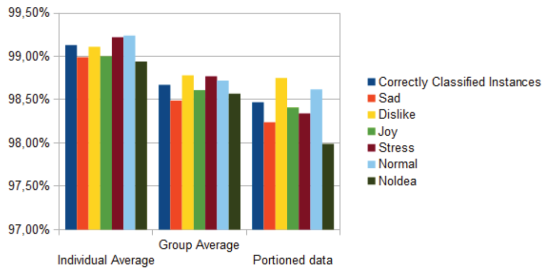


Figure 22: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in **Figure 22** which shows that there is not much difference in results among all categories.

Three sensors (BVP, GSR and Temperature)

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 98.84%; Min: 97.8%; Max: 99.64% and SD: 0.53. We took confusion matrix from all participants and summed it 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 98.6%, 99%, 98.85%, 98.87%, 98.82% and 98.86% 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 98.56%; Min: 98.2%; Max: 98.92%; SD: 0.31**. We took confusion matrix from each group and summed it 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 98.3%, 98.73%, 98.55%, 98.58%, 98.54% and 98.73% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of **98.63%** and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 98.33%, 98.97%, 98.35%, 98.63%, 98.73% and 98.42% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

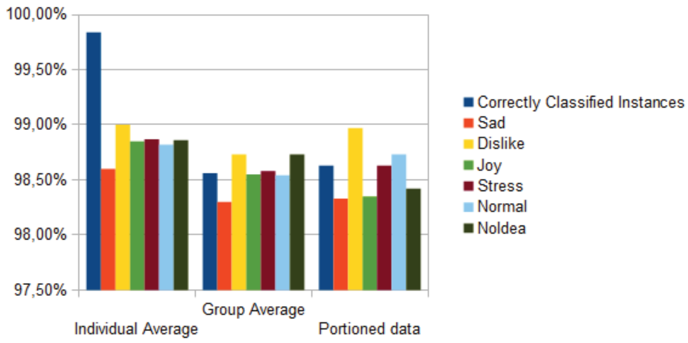


Figure 23: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Figure 23 which shows that there is not much difference in results among all categories.

Three sensors (BVP, EMG and Temperature)

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 98.51%; Min: 96.53%; Max: 99.18% and SD: 0.64. We took

confusion matrix from all participants and summed it 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 98.18%, 98.66%, 98.32%, 98.64%, 98.66% and 98.75% 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 98.04%; Min: 97.55%; Max: 98.46%; SD: 0.34**. We took confusion matrix from each group and summed it 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 97.68%, 98.25%, 97.91%, 98.12%, 98.17% and 98.29%by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 98.06% and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 97.75%, 98.37%, 97.93%, 97.86%, 98.37% and 97.82% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

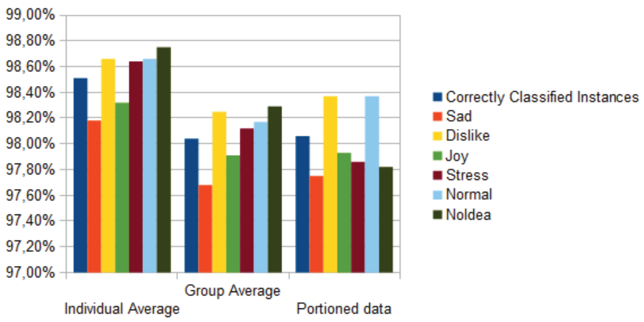


Figure 24: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Figure 24 which shows that there is not much difference in results among all categories.

Three sensors (BVP, EMG and GSR)

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 96.55%; Min: 91.37%; Max: 99.32% and SD: 2.82. We took confusion matrix from all participants and summed it 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 96.42%, 96.86%, 95.93%, 96.44%, 97.41% and 97.29% 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 95.96%; Min: 94.49%; Max: 96.73%; SD: 0.79**. We took confusion matrix from each group and summed it 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 95.77%, 96.23%, 95.34%, 95.8%, 96.85% and 96.66%by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 96.5% and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 96.78%, 98.78%, 95.95%, 96.46%, 96.74% and 96.82% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

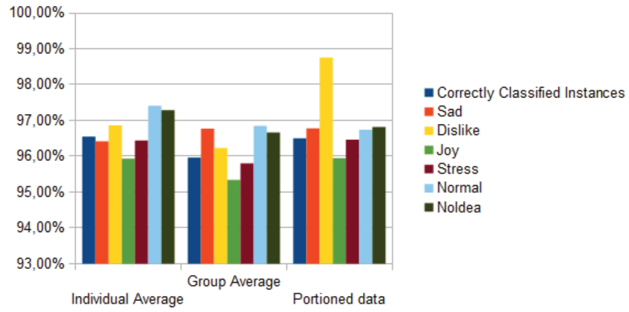


Figure 25: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Figure 25 which shows that there is not much difference in results among all categories.

Three sensors (EMG, GSR and Temperature)

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 98.68%; Min: 96.92%; Max: 99.57% and SD: 0.78. We took confusion matrix from all participants and summed it 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 98.37%, 98.88%, 98.63%, 98.76%, 98.97% and 98.46% 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 98.39%; Min: 97.73%; Max: 98.94%; SD: 0.42**. We took confusion matrix from each group and summed it 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 98.03%, 98.63%, 98.37%, 98.36%, 98.62% and 98.17% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 98.61% and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 98.51%, 98.92%, 98.37%, 98.42%, 99.01% and 97.93% respectively.

We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

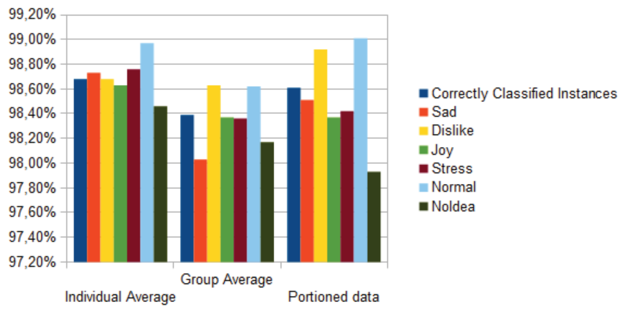


Figure 26: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Figure 26 which shows that there is not much difference in results among all categories.

Two sensors (BVP and GSR)

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 91.05%; Min: 79.04%; Max: 96.8% and SD: 4.98. We took confusion matrix from all participants and summed it 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 90.68%, 92.04%, 89.55%%, 90.23%, 93.44% and 91.38%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 90.23%; Min: 81.76%; Max: 93.27%; SD: 2.2**. We took confusion matrix from each group and summed it 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 89.83%, 91.36%, 89.05%, 89.29%, 92.46% and 90.32% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 92.64% and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 92.86%, 93.9%, 90.75%, 91.77%, 93.58% and 93.04% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

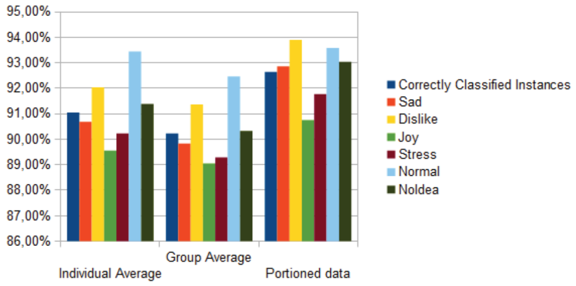


Figure 27: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 27 which shows that there is not much difference in results among all categories.

Two sensors (BVP and Temperature)

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 96.19%; Min: 88.82%; Max: 99.07% and SD: 2.44. We took confusion matrix from all participants and summed it 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 95.64%, 97.11%, 95.55%, 96.21%, 94.91% and 96.82% 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 96.04%; Min: 94.76%; Max: 96.43%; SD: 0.77**. We took confusion matrix from each group and summed it 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 95.01%, 96.57%, 95.2%, 95.54%, 94.45% and 96.16% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 96.39% and it was also able to predict 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea' emotional states with the accuracy of 95.22%, 97.07%, 96.57%, 96.77%, 95.1% and 96.84% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

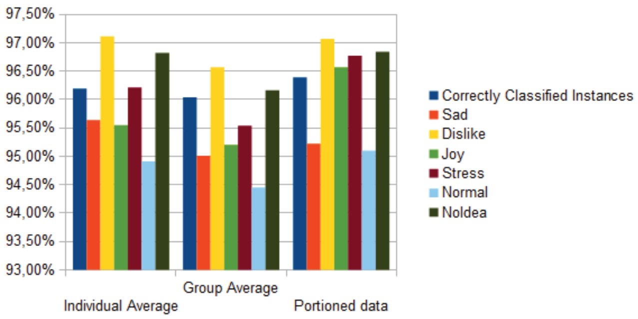


Figure 28: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 28 which shows that there is not much difference in results among all categories.

Two sensors (EMG and BVP)

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 93.35%; Min: 76.58%; Max: 99.35% and SD: 6.07. We took confusion matrix from all participants and summed it 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 92.63%, 93.83%, 91.2%, 93.08%, 96.04% and 98.88% 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 92.81%; Min: 89.15%; Max: 96.58%; SD: 2.89*. We took confusion matrix from each group and summed it 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 92.35%, 93.23%, 91.08%, 92.26%, 95.62% and 96.38% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 93.88% and it was also able to predict 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea' emotional states with the accuracy of 93.18%, 94.21%, 92.17%, 94.11%, 97.75% and 96.84% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

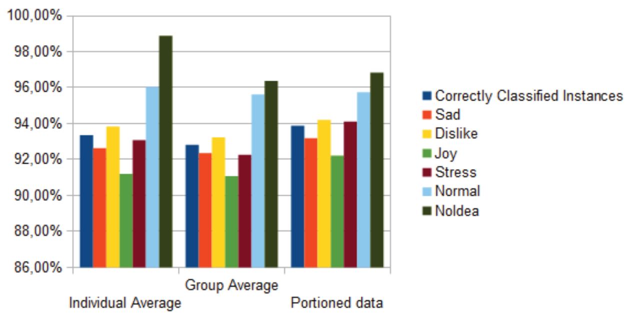


Figure 29: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 29 which shows that there is not much difference in results among all categories.

Two sensors (EMG and GSR)

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 91.56%; Min: 80.57%; Max: 91.56% and SD: 4.27. We took

confusion matrix from all participants and summed it 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 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 90.82%; Min: 87.93%; Max: 93%; SD: 1.93**. We took confusion matrix from each group and summed it 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 88.81%, 92.57%, 89.74%, 90.96%, 92.15% and 89.93% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 93.57% and it was also able to predict 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea' emotional states with the accuracy of 93.76%, 94.13%, 92.17%, 93.16%, 95.45% and 92.72 respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

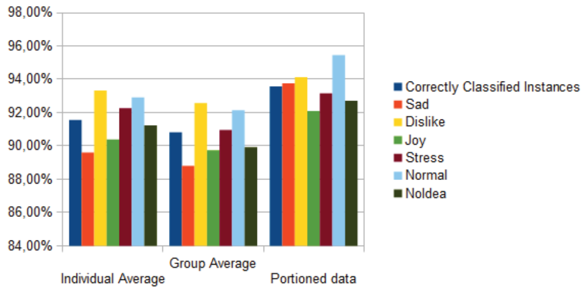


Figure 30: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 30 which shows that there is not much difference in results among all categories.

Two sensors (EMG and Temperature)

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 96.69%; Min: 89.74%; Max: 99.36% and SD: 2.14. We took confusion matrix from all participants and summed it 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 95.93%, 97.23%, 96.4%, 96.98%, 96.97% and 95.59% 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 95.87%; Min: 94.3%; Max: 96.55%; SD: 0.83**. We took confusion matrix from each group and summed it 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 95.23%, 96.49%, 95.68%, 95.93%, 96.06% and 95% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 97.02% and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 97.04%, 97.99%, 95.84%, 96.27%, 97.88% and 96.8% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

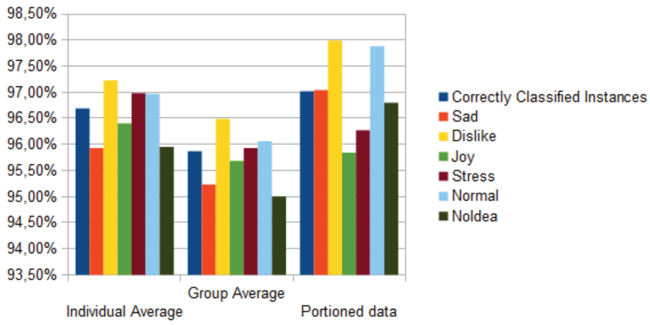


Figure 31: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Figure 31 which shows that there is not much difference in results among all categories.

Two sensors (Temperature and GSR)

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 91.57%; Min: 79.18%; Max: 91.57% and SD: 4.93. We took confusion matrix from all participants and summed it 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 91.31%, 93.04%, 90.77%, 92.03%, 91.41% and 87.23% 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 89.87%; Min: 87.67%; Max: 94.51%; SD: 2.58**. We took confusion matrix from each group and summed it 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 89.12%, 91.98%, 89.36%, 89.96%, 87.85% and 86.21% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 91.28% and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 89.41%, 95.83%, 88.48%, 91.03%, 90.58% and 82.49% respectively.

We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

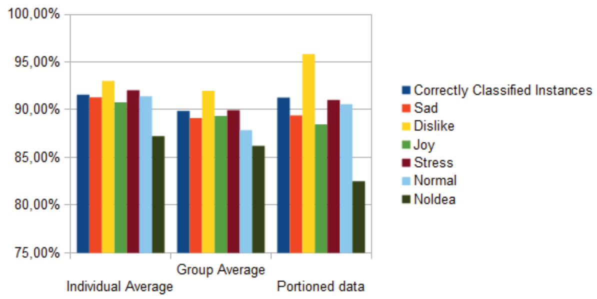


Figure 32: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Figure 32 which shows that there is not much difference in results among all categories.

Single sensor (BVP)

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 74.84%; Min: 54.08%; Max: 87.84% and SD: 11.21. We took confusion matrix from all participants and summed it 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 73.12%, 78.3%, 67.73%, 73.3%, 81.01% and 78% 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 71.3%; Min: 65.38%; Max: 77.16%; SD: 4.69**. We took confusion matrix from each group and summed it 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 69.76%, 75.56%, 65.82%, 68.82%, 76.7% and 73.29% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 73.93% and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 71.31%, 79.54%, 70.68%, 66.72%, 80.31% and 75.62% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

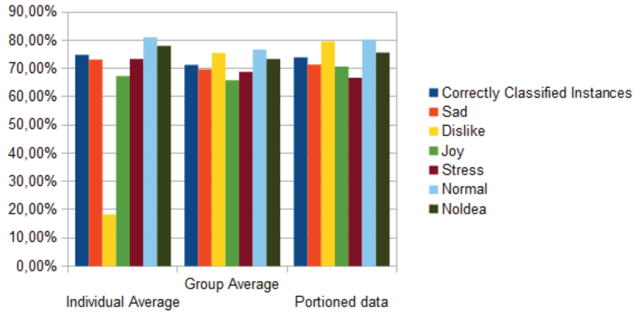


Figure 33: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and '**Portioned' as shown in Figure 33 which shows that there is not much difference in results among all ca**tegories.

Single sensor (EMG)

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 78.91%; Min: 55.47%; Max: 91.04% and SD: 10.37. We took confusion matrix from all participants and summed it 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 75.25%, 81.98%, 73.24%, 82.14%, 80.83% and 82.18% 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 75.79%; Min: 71.11%; Max: 80.39%; SD: 3.6**. We took confusion matrix from each group and summed it 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 72.42%, 80%, 70.42%, 76.57%, 77.8% and 78.69% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 80.27% and it was also able to predict 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea' emotional states with the accuracy of 79.29%, 82.91%, 78.38%, 76.09%, 84.04% and 83.26% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

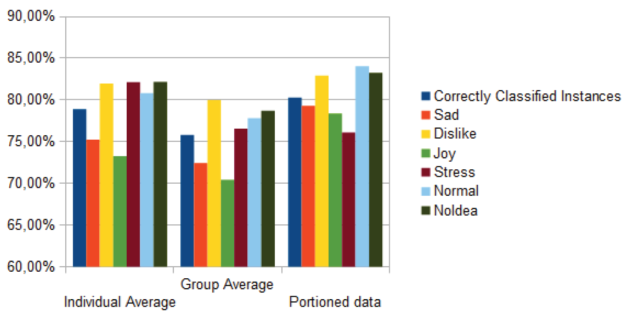


Figure 34: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 34 which shows that there is not much difference in results among all categories.

Single sensor (GSR)

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 60.48%; Min: 43.29%; Max: 83.63% and SD: 8.82. We took confusion matrix from all participants and summed it 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 56.88%, 69.17%, 48.79%, 66.24%, 64.26% and 44.86% 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 55.9%; Min: 50%; Max: 60.66%; SD: 3.99**. We took confusion matrix from each group and summed it 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 49.53%, 73.14%, 39.64%, 57.95%, 51.23% and 43.23% by J48 classifier respectively**.

3. **Portioned data**

Our results show** that J48 was able to correctly classify the instances with the accuracy of 54.36% and it was also able to predict 'Sad', 'Dislike', 'Joy', 'Stress', 'Normal' and 'No-Idea' emotional states with the accuracy of 45.41%, 82.15%, 41.71%, 43.07%, 46.52% and 17.81% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

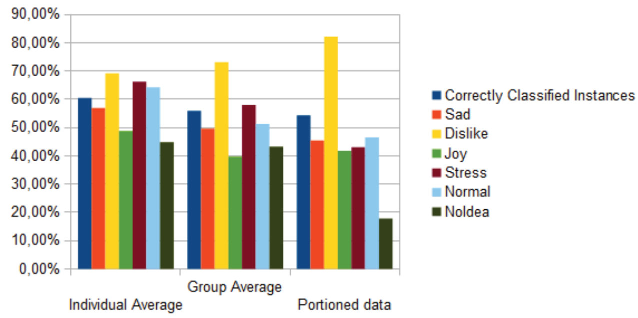


Figure 35: Comparison

We also compared among all categories i.e. 'Individual', 'Group' and 'Portioned' as shown in Figure 35 which shows that there is not much difference in results among all categories.

Single sensor (Temperature)

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 79.22%; Min: 61.59%; Max: 91.87% and SD: 9.81. We took

confusion matrix from all participants and summed it 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 77.42%, 82.76%, 73.73%. 82.9%, 78.58% and 72.77% 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 72.4%; Min: 68.17%; Max: 79.77%; SD: 4.3**. We took confusion matrix from each group and summed it 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 65.81%, 86%, 69.02%, 67.2%, 64.82% and 63.13% by J48 classifier respectively**.

3. Portioned data

Our results show** that J48 was able to correctly classify the instances with the accuracy of 74.66% and it was also able to predict ‘Sad’, ‘Dislike’, ‘Joy’, ‘Stress’, ‘Normal’ and ‘No-Idea’ emotional states with the accuracy of 68.79%, 91.26%, 65.96%, 73%, 68.65% and 42.29% respectively.
We took some data from each emotional state (50,000 instances) and generated graphs in order to visualize our sensor data for better understanding as shown in Figure***.

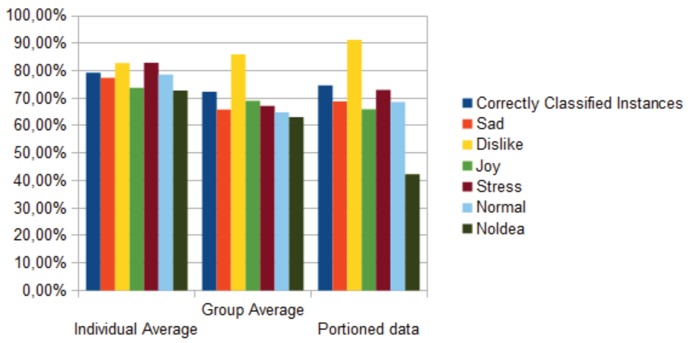


Figure 36: Comparison

We also compared among all categories i.e. ‘Individual’, ‘Group’ and ‘Portioned’ as shown in Figure 36 which shows that there is not much difference in results among all categories.

9.Conclusion 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

We also used different combinations of physiological sensors in order to see the importance of each of them.

Table 4: Results for Six classes

Sensors	Correctly classified instances (Individual); Average	Correctly classified instances (Groups); Average	Chunks from all participants
EMG, BVP, GSR, TMP	99.13%	98.67%	98.47%
BVP, TMP, GSR	98.84%	98.56%	98.63%
EMG, BVP, TMP	98.51%	98.04%	98.06%
EMG, BVP, GSR	96.55%	95.96%	96.5%
EMG, GSR, TMP	98.68%	98.39%	98.61%
BVP, GSR	91.05%	90.23%	92.64%
BVP, TMP	96.19%	96.04%	96.39%
EMG, BVP	93.35%	92.81%	93.88%
EMG, GSR	91.56%	90.82%	93.57%
EMG, TMP	96.69%	95.87%	97.02%
GSR, TMP	91.57%	89.87%	91.28%
BVP	74,84%	71.3%	73.93%
EMG	78,9%	75.79%	80.27%
GSR	60,48%	55.9%	54.36%
Temperature	79,22%	72.4%	74.66%

This Table 4 represents the results of all six emotional states. According to Table 4, accuracy decreased when we used less physiological sensors. Our results show that we achieved good results when we used all four sensors, we were still able to get good results (above 98 %) when we took EMG/BVP out of the experiment and we achieved the same results (above 95 %) when we considered only EMG and temperature sensor.

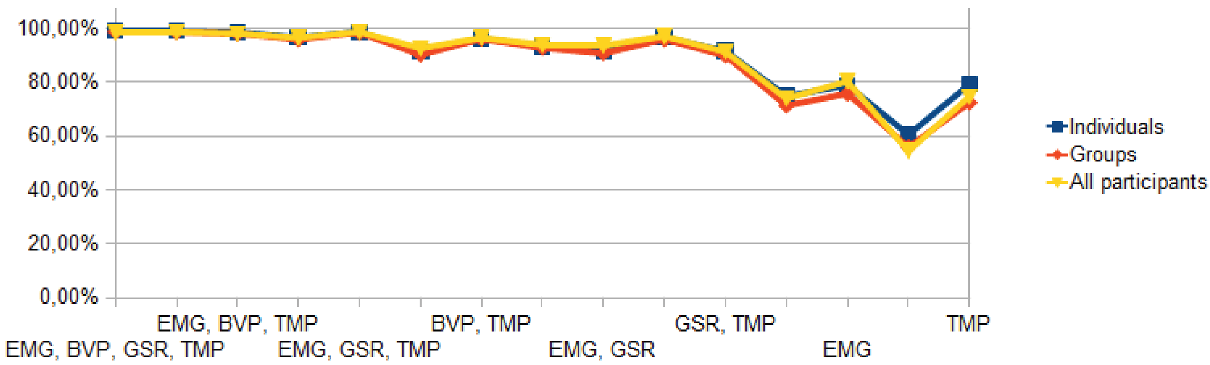


Figure 37: Result comparison

Figure 31 represents the accuracies of correctly classified instances from 'Individuals (average)', 'Groups (average)' and 'All participants' based on different combinations of physiological sensors. We also noticed that we received similar results from all the above approaches i.e. 'Individual', 'Groups' and 'All Participants'.

Table 5: Results for Two classes

Sensors	Correctly classified instances (Individual)	Correctly classified instances (Groups)	Chunks from all participants
EMG, BVP, GSR, TMP	99.4%	99.3%	99.3289%
BVP, TMP, GSR	99.33%	99.21%	99.2664%
EMG, BVP, TMP	99.13%	98.88%	99.0125%

EMG, BVP, GSR	98.14%	97.62%	97.7584%
EMG, GSR, TMP	99.35%	99.19%	99.2987%
BVP, GSR	94.94%	94.66%	95.5263%
BVP, TMP	97.54%	97.52%	98.1468%
EMG, BVP	95.81%	95.53%	96.0205%
EMG, GSR	95.41%	94.98%	96.3525%
EMG, TMP	98.21%	97.89%	98.3365%
GSR, TMP	95.72%	94.87%	96.0839%
BVP	86,8%	85.31%	86.4565%
EMG	88,62%	87.07%	89.4084%
GSR	80,31%	78.58%	79.7173%
Temperature	89,49%	86.56%	88.6275%

This Table 5 represents the results of two emotional states i.e. ‘Positive’ and ‘Negative’. According to Table 5, accuracy decreased when we used less physiological sensors. Our results show that we achieved good results when we used all four sensors, we were still able to get good results (above 99 %) when we took EMG/BVP out of the experiment and we achieved the same results (above 97 %) when we considered only EMG and temperature sensor.

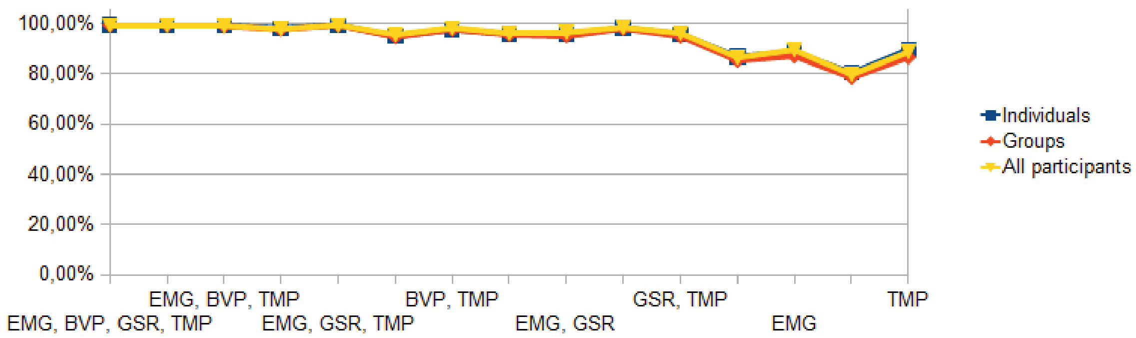


Figure 38: Result comparison

Figure 32 represents the accuracies of correctly classified instances from ‘Individuals (average)’, ‘Groups (average)’ and ‘All participants’ based on different combinations of physiological sensors. We also noticed that we received similar results from above approaches i.e. ‘Individual’, ‘Groups’ and ‘All Participants’.

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.

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* Please see Results and analysis.docx

** Please see Results and analysis_Appendix.docx

*** Please see Results and analysis_Figures.docx

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