Mood Detection Using Heart Rate from Wearable Devices

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***Abstract*—Mood detection in day to day life is important for determining various aspects regarding a persons quality of life, like early diagnosis of depression. Accurate and objective measures for detecting mood is required. With the advent of Internet of things and wide spread use of body wearable devices such as smart watch, we can leverage the sensors such as heart rate monitor to evaluate the mood of the person. In this project we build a android application which can communicate with a smart watch through BLE, and model a classifier for prediction of current mood with the accuracy of 76%. The data collected from the project can be used to further research in the area.**

1. Introduction

Mood detection has been a major research topic for several years. Accurate measurement of mood can be utilized in the diagnosis of various mental health problems such as anxiety, and depression. Through the years various methodologies for mood detections have been developed, from a simple questionnaire in the early days to EEG analysis and recently moving towards more sophisticated fMRI state of art techniques. All these techniques have been administered in the lab environment under various stress conditions to analyze patient responses, as such, there has not been an adequate study on a large group people in day to day life to know the effects of common daily activities such as study and work on the mood of a person. Historically such study has been expensive and has rarely been successfully conducted. But now, however, with the Internet of Things connecting us to various kinds of sensors in daily lives, such a study could easily and inexpensively be taken up.

Emotion recognition is also useful for human-computer interaction. Mood can be a context for any AI system, Expert systems can improve the accuracy of interaction knowing the current user's state of mind. For example, detection of sarcasm from the text, Recommender systems accurate mood detection for the play-list creation and many more.

Wearable technologies have made huge strides in terms of cost, battery life, and accuracy since they first got introduced. They now contain a plethora of sensors embedded in the portable form. Commonly available smartwatches now come equipped with accelerometers to detect motion and activity, Heart rate sensor to detect heart rate (HR) and Heart rate variability (HRV), GPS to track location, Skin conductance to detect galvanic skin response, Skin temperature to detect ambient temperature, and Oxymetry sensor to measure blood oxygen. All of these or some of these can be collectively used to detect various physical parameters of a person, from which we can infer physiological conditions.

Heart rate has been associated to our overall health from a long time [1], it is popularly believed that heart rate reflects our current state of mind and body, for example, heart rate is high when we are in a nervous or anxious state. Many studies [2] have tried to understand the effects of emotions on heart rate, such lab studies have been conducted on people with anxiety disorder or other health conditions, as such they have not been able to produce any reproducible formula or method for detection of heart rate. Machine learning has proved to be effective tool in areas which need data analysis to match patterns and learn predictive functions for classification. However lack of large dataset has prevented complex models be applied on this problem. In this project we propose to use above mentioned sensors in a commonly available smart watch, to collect data which can be used to build a mood classifier. Next sections of the report are divided into Related works, Architecture, Methodology, Evaluation and Results, Conclusion and Future works.

1.1. Problem statement

The problem statement can be defined as a set of multiple objectives to build a IoT based mood detection platform.

- Build an android application to read sensor values from Dynamic Heart Rate Smart Bracelet.
- Store watch and mobile sensor data in cloud for future analysis.
- Build a classifier from existing data sets to predict the mood of the user.

Limitations: The android application is specific to the watch used in this project because of BLE protocol variations, universal application for all kinds of smart watch is out of scope of this project. Due to limited availability of datasets for building a machine learning model, this project is proof of concept for future applications which can be built with the collected data through this project.

2. Related Work

Very little is known about the relationship between stress and cardiovascular responses in everyday settings. Johnston and Anastasiades [3] conducted a study on 32 healthy individuals relating their heart rate with standard ambulatory techniques. They showed that only strong correlation between mood and heart rate was found in minority of subjects who had exhibited signs of anger and anxiety disorder with high blood pressure. For other subjects, no correlation was established.

Salamon and Mouek [5] proposed a unique way to collect Heart rate and sentiment data in daily life, since earlier studies were conducted in lab settings under various stress conditions. They have collected experimental data with common time-line between Heart rate data from the user's Fitbit charge,and Basic Peak wrist bands and the sentiment expressed by the user during the defined period from their Twitter tweets. Their analysis of the data found that negative emotions increase heart rate, while there is no correlation between positive mood and heart rate. They have made their data available online [4].

Some studies have shown that changes in resting Heart rate variability [16] [17] can be associated with negative mood of a person. However the studies are not conclusive, and limitations of current hardware does not let us measure Heart rate variability.

Budner et. al. [6] introduced a system to measure individual happiness based on body sensors from Pebble smart watch tracking activity, heart rate, light level, and GPS coordinates, they also added features through external data such as humidity, temperature from weather api, and day of the week through smart phone. To predict mood on the basis of pleasance and activation they categorize the mood into 9 categories. Using user feedback mechanism they have collected ground truth for 3 months and have trained their machine learning model, achieving up to 94% accuracy. Their experiments have shown that the user mood is strongly affected by weather and Heart rate is a weak indicator. However, they have not made the collected data public and the smart watch is not in production anymore, making it hard to reproduce the results or use it for further analysis.

Study by Kudielka [15] suggests that Mood is also changed based on time of the day and many researchers believe that weather has positive and negative effects on mood of the people. from the works of Keller et. al. [7], Sanders et al [8], and Denissen et al [9], we believe that weather has a strong correlation as shown in the Happimeter experiment [6], We will consider various weather parameters in our study.

Figure 1. Dynamic Heart Rate Health Bracelet

Smart watch	Smart phone	External
Heart rate	GPS day of week Hour of Day	Temperature Humidity Precipitation Cloudiness

TABLE 1. SENSOR DATA CAPTURED

3. Architecture

The overall architecture of the system is shown in figure 2. We have Android smart phone as our gateway device, which collects sensor data from smart bracelet watch shown in figure 1 connected via BLE protocol. We collect weather data based on Smartphone GPS coordinates using Weather API [1]. Data is sent to Cloud system hosting the classifier and the data store through REST service calls. We have three kinds of sensor data used in the system as described in the table 1 , they are a) Smart watch data, b) Smart phone data, and c) External data. Initially only Heart rate will be used in this project, but other sensor data collected will be used in future work for accuracy enhancement.

4. Methodology

Detailed methodology of the experiment is described in the next sections. Code is made available on github [2].

4.1. Wearable Sensor Data

Smart watch is enabled with Bluetooth low energy (BLE) protocol for communication. Here watch acts as a GATT server, and gateway device (smartphone) acts as a client. According to the Oldsmobile wristband

[1] https://openweathermap.org/api
[2] https://github.com/vingk/IoT2017MoodDetect

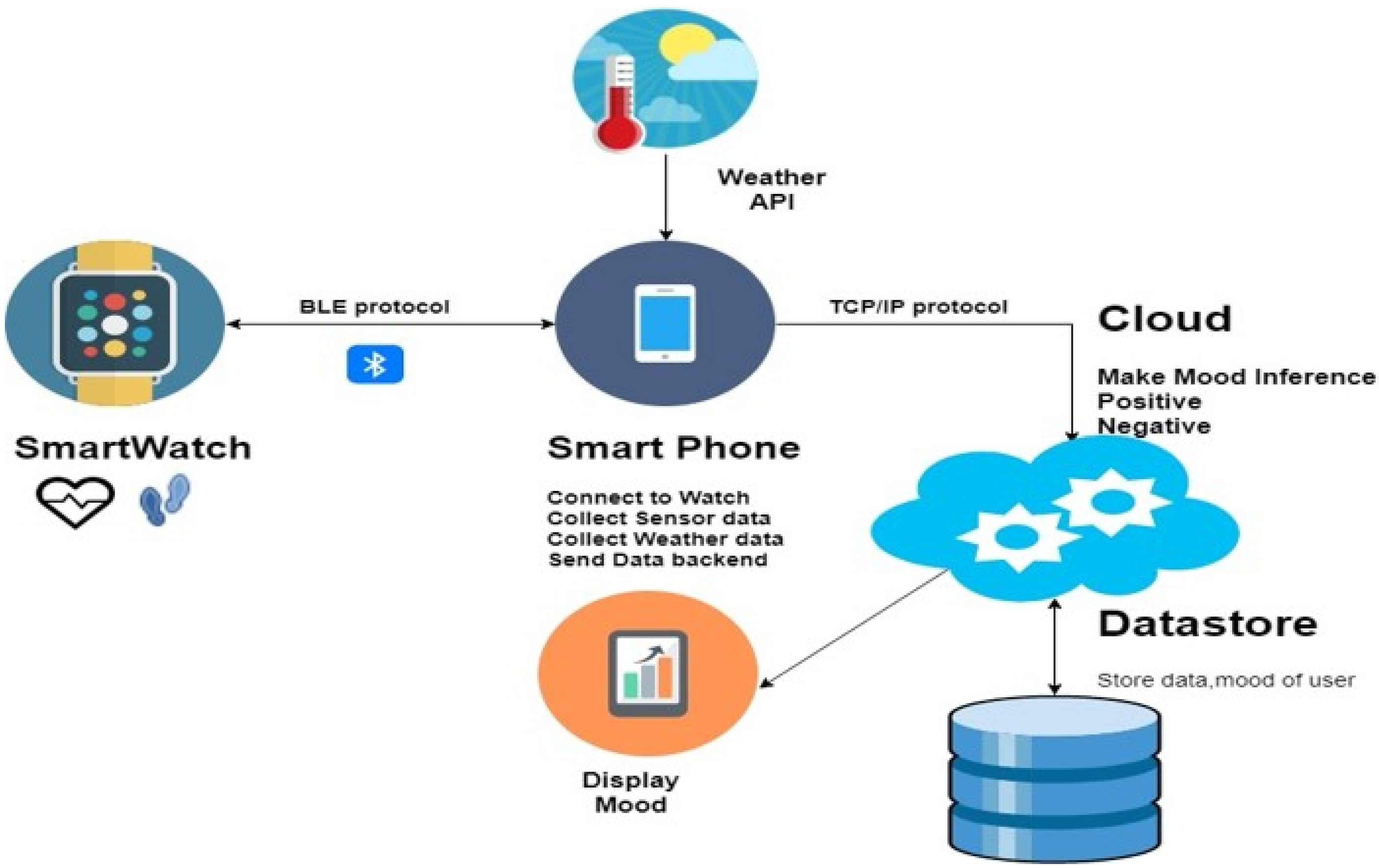

Figure 2. System architeture for Mood Detect system.

Communication protocol specification Version: 1.6.7 dated 2016.9.29 [3], there is only one GATT service required for communication called Retrieval, having two GATT characteristics Read and Write which can be used to request and receive the sensor information. We use listener services in Android to receive the data in real time. Illustration is shown in figure 3.

Device limitations require us to tap on the screen of the watch to start BLE service, HR reading on initialization requires 10 to 15 seconds for data retrieval, As such, we cannot create a background service which will collect the data throughout the day at specified interval. However, with an advanced device data collection can be executed in background.

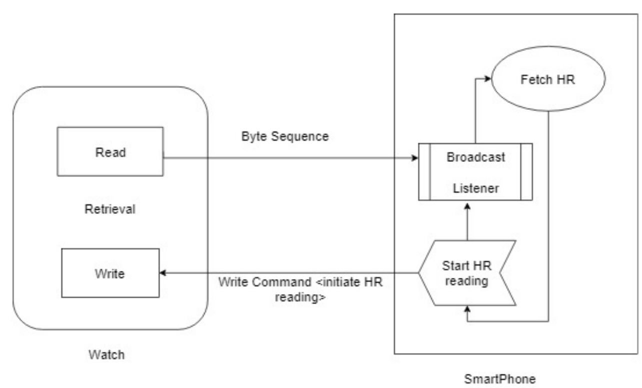

Figure 3. BLE protocol sequence

4.2. Weather Data

We use GPS location of the user retrieved from the smartphone to request weather data from Weather API. Received JSON file is parsed for various weather parameters like Humidity, Temperature, Cloudiness. Sample JSON response is shown below for Edmonton.


```
{"coord":{"lon":-113.52,"lat":53.53},
"weather":[{"id":801,"main":
"Clouds","description":"few clouds",
"icon":"02d"}],"base":"stations",
"main":{"temp":283.67,"pressure":1012,
"humidity":37,
"temp_min":283.15,"temp_max":284.15},
"visibility":14484,
```


[3]https://goo.gl/9hMqVE

”wind”:{”speed”:3.1,”deg”:170},
”clouds”:{”all”:20},”dt”:1525111200,
”sys”:{”type”:1,”id”:3162,
”message”:0.0237,”country”:”CA”,
”sunrise”:1525089563,”sunset”:1525143849},
”id”:5946768,”name”:”Edmonton”,”cod”:200}

From this we can get temperature, humidity, and cloudiness which are added to our heart rate feature vector.

4.3. SmartPhone Data (Gateway Device)

Android application built for the purposes of collected watch data is also the gateway device for connecting to our cloud system. we collect other data from the phone such as GPS location, Date and Time of the phone. From date and time we calculate day of the week and hour of the day as per the designs of Budner et al. [6]. Gateway communicates to the server using REST service calls.

4.4. Mood Cloud

Mood cloud is the server which responds to queries from the gateway device. We use java servlet application for our REST services, along with WEKA [4] machine learning library to classify the data. User information is stored in mySQL database on the cloud along with the requests for Mood detections. With increase in users this system can be migrated to NoSQL database such as MongoDB for better handling of big data.

4.5. Classification Model

From Malik et al. [10] work, We know that resting Heart rate or the average normal heart rate for people is different for each individual, meaning for example say a HR of 90 is normal for person A, but the same HR 90 is elevated HR for person B. As such, it is difficult to have a prediction model which works for all people with just heart rate value. for accurate prediction of the user mood, we would have to collect individual data over 3 months to be able to achieve good accuracy as done by Budner et al. [6]. As a solution to this problem, we have 2 models for the system. a) Generic Model, and b) Individual model.

4.5.1. Generic Model. Generic model for mood prediction is built using Salamon's experiment 1 dataset [4] of HR from Fitbit charge device. We use random forest forest classifier to build our prediction function.

4.5.2. Individual Model. To build a classifier for each individual we will collect their HR value, weather conditions during the day, and other parameters as described in earlier sections. Using Weka library we build a random forest classifier for each user name, for easy and quick detection from trained model, serialized model weights are stored for each user. Which can be periodically updated either by the administrator or by user request.

[4] https://www.cs.waikato.ac.nz/ml/weka/

Heart Rate	Exp-1 Fitbit	Exp-2 Basis Peak
Total number of samples	411,799	69,941
Minsamples per day	6147	961
Max samples per day	9469	1440
Device sampling frequency	Every 5 s	32 times/second
Device recording frequency	Every 5 - 15s	Every 1 minute
Tweets		
Total number of tweets	1029	1017
Average no. of tweets per day	20.56	20.32
Number of positive tweets	780	718
Number of negative tweets	249	299

TABLE 2. DATASET DETAILS

5. Evaluation and Results

5.1. Dataset

Finding dataset is one of the major challenges of this project, we have not found a dataset available which could be used to build a classifier with good accuracy. Following standard biosignals datasets have been explored for emotion recognition.

- DEAP - Database for Emotion Analysis using Physiological Signals by Koelstra et al. [13] , does not contain HR data.
- DECAF - Multimodal Dataset for Decoding Affective Physiological Responses by Abadi et al. [14], does not contain HR data.
- MAHNOB-HCI - Multimodal Database for Affect Recognition and Implicit Tagging by Soleymani et al. [11], does not contain HR data.
- EMDB - Emotional Movie Database by Carvalho et al. [12], contains HR but access has not been granted yet.

We need to build our own ground truth data. However, for the project purposes we combine the twitter and HR data published by Salamon and Mouek [4], and use it as our initial ground truth data set. Data set was created through pilot experiment - 2*50 days, one participant, Twitter - sentiment data, Fitbit Charge HR, Basis Peak - heart rate data, details in table 2. There are only two mood categories considered for this project.

- Positive mood (+1)
- Negative mood (-1)

Dataset Processing: We match the date time features from Twitter and the sensor data. We obtain 1017 samples from experiment 2 and 5909 samples from experiment 1, we further split this data set into 70% train and 30% test. The reported results are on the fitbit test dataset.

5.2. Evaluation Metrics

Since it is a binary classification (positive/negative), correctly classified and Incorrectly classified we will considered in the following metrics to evaluate our model.

	N	P
N	8	415
P	8	1340

TABLE 3. FITBIT TEST CONFUSION MATRIX

Class	Precision	Recall	F-Score
+ Mood (N)	0.76	0.99	0.86
- Mood (N)	0.55	0.02	0.04
Weighted Avg.	0.71	0.76	0.667

TABLE 4. RESULTS ON FITBIT DATASET

- **Accuracy:** Percentage of correct predictions.

$$Accuracy = \frac{Number\ of\ correct\ classification}{Total\ number\ of\ samples}$$

- **Precision:** is the fraction of correct predictions of class c to total number of predictions of class c.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

- **Recall:** is the fraction of correct predictions of class c to total correct number of class c.

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

- **F-Measure:** is the harmonic mean of Recall and Precision, which is taken as a good measure for imbalanced dataset.

$$F - Measure = \frac{2 * Precision * Recall}{Precision + Recall}$$

5.3. Results

Random Forest classifier on our processed dataset, gives us the following results on the two datasets.

5.3.1. Fitbit Charge Dataset Results. With 1773 samples in Test instance, we are able to correctly classify 1350 samples i.e Accuracy of **76.14 %**. which can be seen the confusion matrix shown in table 3. RMSE is 0.42 and average weighted F score is 0.667 as seen from table 4.

5.3.2. Basis Peak Dataset Results. With 305 samples in Test instance, we are able to correctly classify 194 samples i.e Accuracy of **63.61 %**. which can be seen the confusion matrix shown in table 5. RMSE is 0.49 and average weighted F score is 0.60 as seen from table 6.

5.4. Discussion

We have also verified the above results using **Logistic Regression** and **Naive Bayes** which all yield similar results.

	N	P
N	11	75
P	37	183

TABLE 5. BASIS PEAK CONFUSION MATRIX

Class	Precision	Recall	F-Score
+ Mood (P)	0.71	0.832	0.76
- Mood (N)	0.23	0.13	0.16
Weighted Avg.	0.58	0.64	0.60

TABLE 6. RESULTS ON BASIS PEAK DATA

We can see that our best model is using Fitbit charge dataset to train. This achieved accuracy can be further enhanced by using Individual model customized for the user along with the usage of weather data, we must be able to reach the Budner et al [6] reported accuracy of 94%. We also notice from the confusion matrix that due to class imbalance negative mood is not predicted as often, this must be also corrected with further data collection.

6. Conclusion

Wearable technology has made huge strides in terms of availability and accuracy, making it easy to collect data for research activities, analyzing various physiological attributes. Mood detection is important for human computer interactions for context aware systems, and early diagnosis of mental health problems like depression. Earlier studies in mood and various physiological attributes like heart rate are limited to only people with known clinical diseases, because of the cost involved. However, now with wearable IoT devices, such as smart watch, health bracelets having become common, we can leverage it to take advantage of huge number of test subjects to collect the data.

In this project, we use a cheap health bracelet available for 30 to 40$, and check if the Heart rate reported by such a device can be used to predict user mood. Following earlier papers, we add additional data to the HR value, such as Weather, time, and day through the gateway device- Android phone. Because resting HR and the changes in HR are personal to each user and vary according to their physical fitness level, we use the approach of dual prediction models. We have a generic prediction model built with historic data, and a individual model which will be built over time with usage and data collection from user, specific to the user, for higher accuracy.Random Forest technique has been used to construct the prediction model. The model is only as good as the data it has been trained on, and due to limited availability of solid ground truth data, accuracy of the model currently is low 76.14% , which can be improved with individual model after collection of more data.

7. Future Work

One of the major concerns of the project is the lack of availability of public datasets, We have requested access to [name of the data set], which if granted can be used to obtain better ground truth. To reach the accuracy of over 90 percent the model needs to be trained and tested over a longer period of time. We plan to undertake these activities in the future.

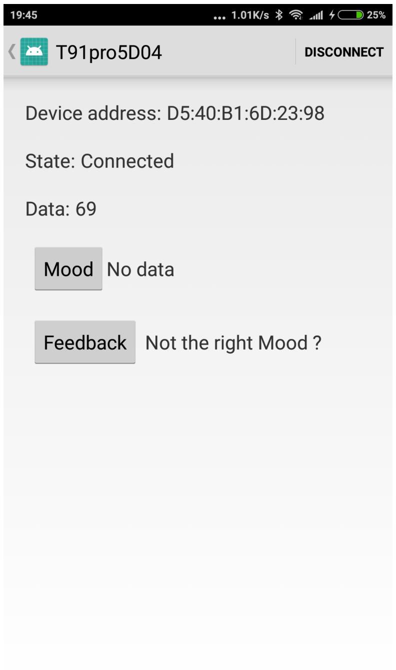

Figure 4. Data shows the current reading Heart rate from the Smart watch

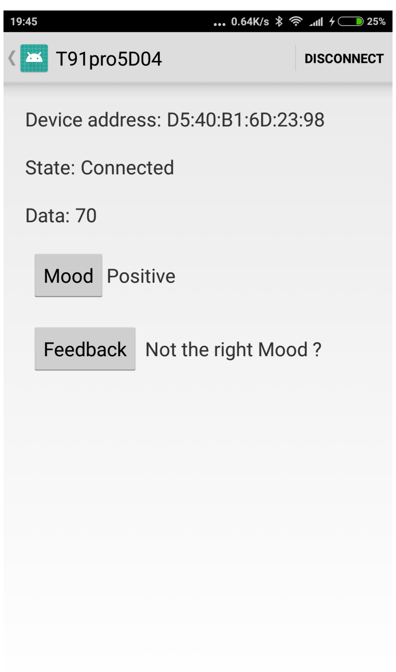

Figure 5. Mood detected from the server for the above HR

References

[1] Thayer, J.F., hs, F., Fredrikson, M., Sollers III, J.J. and Wager, T.D., 2012. A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews, 36(2), pp.747-756.

[2] Caplan, R.D. and Jones, K.W., 1975. Effects of work load, role ambiguity, and type A personality on anxiety, depression, and heart rate. Journal of applied psychology, 60(6), p.713.

[3] Johnston, D.W., Anastasiades, P. and Wood, C., 1990. The relationship between cardiovascular responses in the laboratory and in the field. Psychophysiology, 27(1), pp.34-44.

[4] Salamon, J. and Mouek, R., 2017. Heart rate and sentiment experimental data with common timeline. Data in brief, 15, pp.851-861.

[5] Salamon, J., ern, K. and Mouek, R., Stress Dichotomy using Heart Rate and Tweet Sentiment.

[6] Budner, P., Eirich, J. and Gloor, P.A., 2017. " Making you happy makes me happy"-Measuring Individual Mood with Smartwatches. arXiv preprint arXiv:1711.06134.

[7] Keller, M.C., Fredrickson, B.L., Ybarra, O., Ct, S., Johnson, K., Mikels, J., Conway, A. and Wager, T., 2005. A warm heart and a clear head: The contingent effects of weather on mood and cognition. Psychological science, 16(9), pp.724-731.

[8] Sanders, J.L. and Brizzolara, M.S., 1982. Relationships between weather and mood. Journal of General Psychology.

[9] Denissen, J.J., Butalid, L., Penke, L. and Van Aken, M.A., 2008. The effects of weather on daily mood: A multilevel approach. Emotion, 8(5), p.662.

[10] Malik, M., Frbom, P., Batchvarov, V., Hnatkova, K. and Camm, A.J., 2002. Relation between QT and RR intervals is highly individual among healthy subjects: implications for heart rate correction of the QT interval. Heart, 87(3), pp.220-228.

[11] "A multimodal database for affect recognition and implicit tagging", M. Soleymani, J. Lichtenauer, T. Pun, M. Pantic. IEEE Transactions on Affective Computing. 3: pp. 42 - 55, Issue 1. April 2012.

[12] Carvalho, S., Leite, J., Galdo-lvarez, S. and Gonalves, .F., 2012. The emotional movie database (EMDB): A self-report and psychophysiological study. Applied psychophysiology and biofeedback, 37(4), pp.279-294.

[13] Koelstra, S., Muhl, C., Soleymani, M., Lee, J.S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A. and Patras, I., 2012. Deap: A database for emotion analysis; using physiological signals. IEEE Transactions on Affective Computing, 3(1), pp.18-31.

[14] Abadi, M.K., Subramanian, R., Kia, S.M., Avesani, P., Patras, I. and Sebe, N., 2015. DECAF: MEG-based multimodal database for decoding affective physiological responses. IEEE Transactions on Affective Computing, 6(3), pp.209-222.

[15] Kudielka, B.M., Schommer, N.C., Hellhammer, D.H. and Kirschbaum, C., 2004. Acute HPA axis responses, heart rate, and mood changes to psychosocial stress (TSST) in humans at different times of day. Psychoneuroendocrinology, 29(8), pp.983-992.

[16] Hughes, J.W. and Stoney, C.M., 2000. Depressed mood is related to high-frequency heart rate variability during stressors. Psychosomatic medicine, 62(6), pp.796-803.

[17] Vrijkotte, T.G., Van Doornen, L.J. and De Geus, E.J., 2000. Effects of work stress on ambulatory blood pressure, heart rate, and heart rate variability. Hypertension, 35(4), pp.880-886.