Utilization of Real-time Heart Rate Changes to Classify Emotions Based on Low-cost Device Development

Pramudya Rakhmadyansyah Sofyan
Electrical Engineering Department
Universitas Islam Indonesia
Yogyakarta, Indonesia
17524011@students.uii.ac.id

Rizdha Wahyudi
Electrical Engineering Department
Universitas Islam Indonesia
Yogyakarta, Indonesia
17524067@students.uii.ac.id

Diandri Perkasa Putra
Electrical Engineering Department
Universitas Islam Indonesia
Yogyakarta, Indonesia
17524012@students.uii.ac.id

Alvin Sahroni
Electrical Engineering Department
Universitas Islam Indonesia
Yogyakarta, Indonesia
alvinsahroni@uii.ac.id

Nur Widiasmara
Pscyhology Department
Universitas Islam Indonesia
Yogyakarta, Indonesia
nurwidiasmara@uii.ac.id

Isnatin Miladiyah
Medical Department
Universitas Islam Indonesia
Yogyakarta, Indonesia
isnatin@uii.ac.id

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***Abstract*—Emotion is a complex phenomenon and has an essential role in supporting the quality of life and affecting motivation, perception, cognition, creativity, empathy, education, and making an important decision. Also, negative emotions such as anger, shame, and anxiety usually arise from stress, and it is referring to destructive and threatening to show a relationship between them. Therefore, research on recognizing emotions is still an important issue currently. Fifteen males university students have participated in this study. A fingertip photoplethysmograph (PPG) was used to record the heart rate variable. This study used The International Affective Picture System (IAPS) to induce particular emotions. As a subjective evaluation, we employed Self-Assessment Manikin (SAM) to evaluate the subject's emotions. Then, we compared the SAM evaluation to their heart rate properties for further investigation. The FIR Band Pass Filter was established as a pre-processing method, and a single feature was extracted from a PPG recording called Heart Rate Changes (HCR). Instead of utilizing artificial intelligence or other machine learning classification techniques, we performed if-else classification to recognize negative and positive emotions as basic emotions. We found that the HCR was significantly different between the positive and negative emotions ($p<0.0001$). We achieved ± 50% of accuracy while classifying the two basic emotions. We validated the results by implementing a real-time scheme detection based on a low-cost device and display it on a user-built application. Current results need improvement in future studies. We concluded that a single feature without any advanced methods is still a promising approach for real-time detection. The system was also reliable in future applications on low-cost device development.**

Keywords— Emotions, Heart rate changes, Low-cost device

I. Introduction

Emotion is a complex phenomenon and has an essential role in supporting the quality of life, affecting motivation, perception, cognition, creativity, empathy, education, and making an important decision. Most of our daily activities and jobs are often struggle to address human emotion to be effective [1], [2]. Negative emotions such as anger, shame, and anxiety usually arise from stress, and it is referring to destructive and threatening to show a relationship between them. Previous studies already agreed that stress is closely associated with negative emotions. For instance, depression is a form of stress response [3]. Hence, former studies to evaluate psychological conditions such as mental stress and other feelings objectively are urgently needed currently.

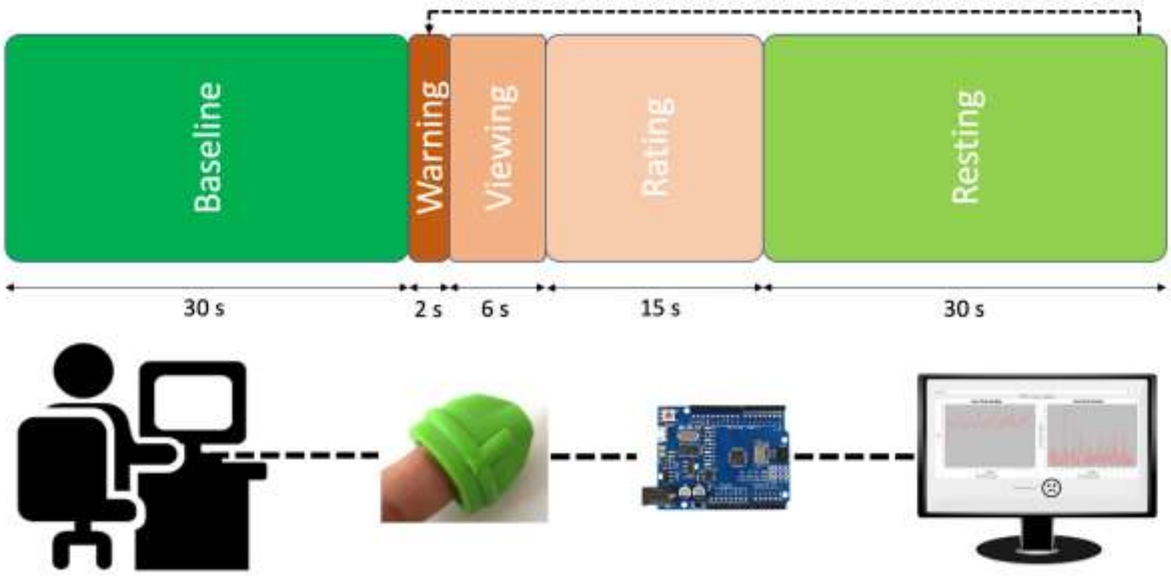


Fig. 1. Experimental design and the scheme of the proposed study

In past decades, the development of mental stress and emotion objective measurement received more attention from researchers. Predominantly, the studies focused on heart rate measurement due to its relationship with Autonomic Nervous System (ANS) activity which regulates the cardiovascular system through sympathetic and parasympathetic components [4]. Heart Rate Variability (HRV) is already well-known as a physiological variable to assess ANS non-invasively. The previous investigation on HRV studies has been conducted to assess mental stress using various HRV properties and can be used as an ANS-related marker of mental stress. In addition, HRV has also been used in combination with other biosignals and or biomarkers to improve its stress detection performance [5]. In common practice, we retrieved HRV features from a conventional Electrocardiograph (ECG). However, the utilization of ECG provoked limitations regarding using multiple electrodes on the chest area. Finally, it raised another issue related to comfortability. Photoplethysmograph (PPG) is considered to substitute the ECG while recording the HRV to overcome its limitations [4], [6]-[9].

Despite the success of HRV parameters from ECG or PPG to assess the psychological aspect, another shortcoming remains, especially for real-time detection. The recording duration of HRV to obtain peak-to-peak intervals varies between literature (1 to 15 mins). However, recent studies revealed that 5 mins recording is the minimum requirement to achieve reliable HRV during seated position and 10 mins for the orthostatic test [10]. Although Zubair et al. were able to get 94.33 % of accuracy during ultra-short HRV recording (1 min), the proposed method is still not reliable for real-time detection [4].

The primary aim of this study is to investigate the possibility of applying heart rate changes as a single parameter to detect different emotions based on low-cost device development. In the beginning, we want to observe the performance of a single parameter to differentiate basic emotions during real-time assessment with a fixed time interval. Finally, the performance result could be a consideration of how to develop real-time detection for further study.

II. Materials and Methods

A. Subjects

Fifteen male participants from university students aged 19 to 22 years have participated in this study. We selected those criteria to avoid any bias of heart rate changes caused by gender and ages effects [11]. They were in healthy conditions without any historical cardiovascular diseases. All participants were required to understand the experiment procedures and got informed prior to the experiment.

B. Experimental Design

The experiment was conducted in a soundproofed room to avoid noise from the outside. The data retrieval was held between 10.00 AM - 02.00 PM. We asked All participants to see images that reflect four basic emotions (happiness, sadness, fear, and anger) from the International Affective Picture System (IAPS) database. At this stage, we simplified the four basic emotions into two types, positive (happiness) and negative (sadness, fear, and anger) emotions. There are twenty-five images showed during this experiment. All participants saw randomized emotion images every one minute. There are five images to represent an emotion.

Fig. 1 shows the detail of our proposed study. It was started from the baseline condition where all participants were sat for thirty seconds and relax before seeing the image. Before seeing the picture of a particular emotion, participants got a warning sign from the display monitor (two seconds) and then followed by viewing the image for six seconds [12]. Finally, the participants need to rate and evaluate their psychological condition by using Self Assessment Manikin (SAM) to reflect

Fig. 2. The low-cost device prototype

the seen picture/image. Participants need to rest for thirty seconds before seeing the following randomized pictures. During the experiment, we recorded their physiological signal from their heart rate every six seconds. We retrieved the data by using our user-built application. During that, we asked the participants to avoid any excessive body movements.

C. Data Recording

There were two recording purposes. The main recording was to get the heart rate properties, and we used it for further analysis while deciding the threshold to classify the emotion during real-time detection later. We developed a low-cost device (Fig. 2) based on Arduino and PPG sensor where it was connected to an analogue to digital (ADC) port in Arduino. This procedure used 50 Hz for the sampling rate following our configuration before the experiment. For the communication protocol, we were using USB serial communication to a computer. Another type of recording is real-time detection, where the low-cost device records the heart rate for classifying it into emotions. An application was also developed to monitor and provide a real-time emotion recognition result. We obtained the main parameter every six seconds as the sampling rate while sending the data to the computer application.

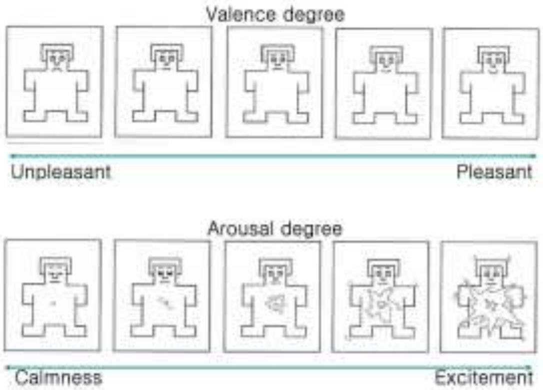


Fig. 3. Self-Assessment Manikin (SAM) is utilized to rate the emotions regarding the valence (top) and arousal (bottom) dimensions

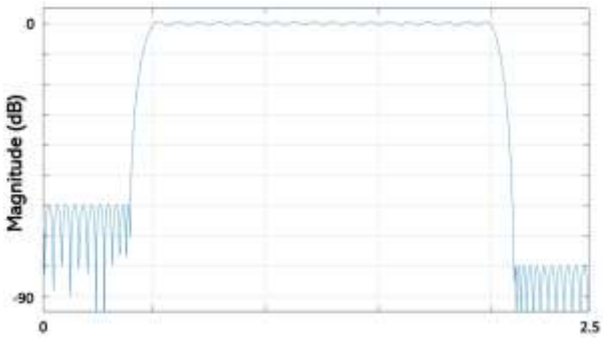


Fig. 4. The FIR band-pass filter with cut-off frequency 0.2 - 2 Hz

D. Self-Assessment Manikin (SAM)

Every participant was doing a subjective evaluation, and it was established by performing the SAM assessment after viewing an image. SAM is a picture-oriented instrument containing five images for each affective dimension (valence and arousal) that the participants should rate after seeing a picture that represents particular emotion [12]. The rating used single-item scales that measure valence/pleasure and perceived arousal between negative to positive scores. (Fig. 3). The study was using -2 to 2 as the SAM rating scale that 0 represents neutral (middle side) and -2 (left side) until 2 (right side) represents negative and positive effects, respectively.

E. Signal Processing and Feature Extraction

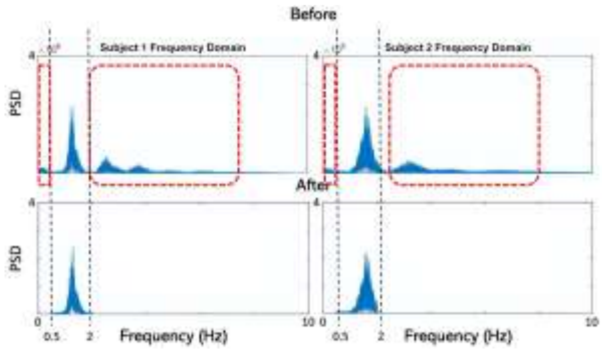
The pre-processing method was conducted by employing the FIR band-pass filter. The purpose was to avoid unnecessary frequency that affects the heartbeat peaks. We designed the cut-off frequency between 0.5 to 2 Hz and 50 Hz sampling rate. We calculated the heart rate changes (HCR) as our main feature (Eq. (1)). The data was sent to the computer every six seconds.

$$HCR(n) = \frac{|HR(n) - HR(n-1)|}{|HR(n-1)|} \quad (1)$$

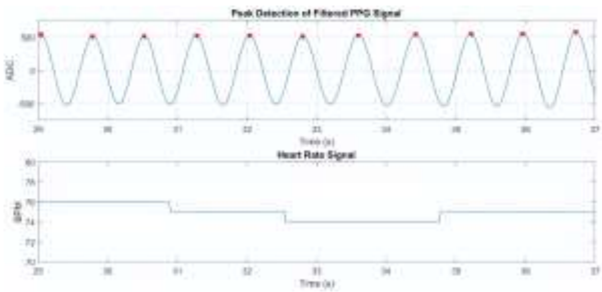
$$Performance = \frac{NCD}{TD} \times 100\% \quad (2)$$

F. Data Analysis

We performed a performance percentage to evaluate the results of the single-feature HCR parameter from the heart rate as presented in Eq. (2), where NCD is the number of correct detection and TD is the number of total data. Also, we evaluated and analyzed the HCR properties based on positive and negative emotions. Statistical representation used mean and standard error, and we performed a non-parametric method for the statistical test.



(a)



(b)

Fig. 5. Pre-processing and feature extraction results. a) the frequency domain comparison; b) the peak detection to measure heart rate

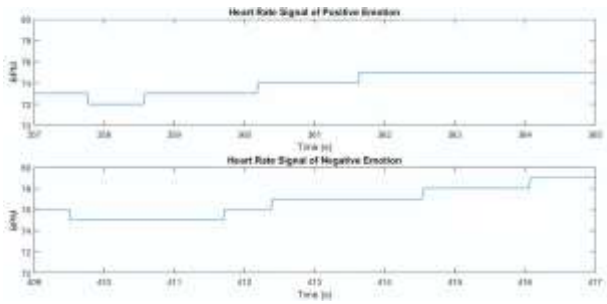


Fig. 6. Heart rate comparison from a subject with different emotions

III. RESULTS

A. Pre-processed and Extracted Feature

Pre-processing data is an essential step prior to feature extraction and analysis. PPG is commonly known as a sensor that is weak to the motion artefact or any body movements. Therefore, the FIR band-pass filter was designed to focus and pass the data on low frequency and reduce any high-frequency data. Also, we can see that the most meaningful data were in between 0.5 to 2 Hz (Fig. 5(a)). Fig. 5(a) showed unnecessary signals in a frequency range less than 0.5 Hz and 2 Hz above. The results of the filtering process are seen in Fig. 5(b). The filtered PPG signals provide clean peaks to be detected, and then it was easier to be followed by extracting the heart rate for every six seconds. To validate the measurement, we compared the developed device with the standard clinical electrocardiograph. We observed 24 trials of heart rate measurement on different subjects during sitting and relaxed positions. We obtained the average error of the heart rate measurement comparison between our developed device and standard ECG to 0.79 BPM, where we considered to error is still low.

B. Heart Rate Changes : Positive Vs Negative Emotions

We already know that different psychological conditions can be evaluated from our heart rate as a physiological signal. Fig. 6 depicted a participant's heart rate properties for six seconds while viewing the IAPS image. According to Fig. 6, we can observe that negative emotions reflect higher heart rate changes than positive emotions. The pleasure or positive emotion had fewer alterations between 72 to 74 BPM. Contrarily, the unpleasant feeling yields higher heart rate changes from 75 to 79 BPM. The results showed that the heart rate changes provide more information rather than the well-known heart rate measurement. Thus, while significant psychological state changed, the heart rate changes followed it significantly as well.

We established a statistical analysis to investigate the HRC parameter to distinguish the positive and negative emotions. This study employed Mann-Whitney U-Test to find a significant difference between those two emotions. Then, we found that the HRC was significantly different between the pleasant and unpleasant emotions ($p < 0.0001$). This finding was successfully strengthened that the heart rate changes or HCR can be applied as a physiological feature to discriminate basic emotions. Thus, the average HRC was used as the threshold to detect the positive and negative emotions.

C. Performance

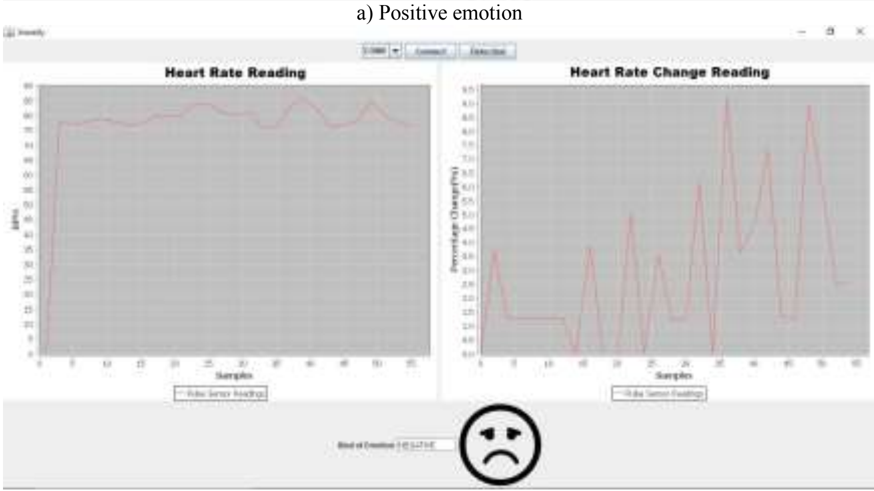
Fig. 7 represents the real-time detection both in positive (Fig. 7(a)/upper figure) and negative (Fig. 7(b)/lower figure) emotions by using our low-cost device development. Regarding the accuracy of the detection system, we obtained 210 data represent positive and negative emotions. However, we found that seventeen data were removed due to the heart rate changes false measurement caused by the misdetection of the heart rate peaks. Then, we calculated the performance of the HRC feature to discriminate the positive and negative emotions. By using a threshold value, we tested several thresholds based on Table 1 results. We tested 2.7675, 2.9145, and 3 as the thresholds, and we obtained 50.78%, 46.11%, and 46.11% of accuracy, respectively. According to the classification system study, these results still need to be improved in many aspects. Therefore, future studies to develop new feature and or classification algorithms are still needed.

TABLE I.
THE MEAN AND STANDARD ERROR (SE) OF SAM DIMENSIONS (AROUSAL AND VALANCE) AND PERCENTAGE OF HRC DURING DIFFERENT STATES

	Positive Emotion		Negative Emotion	
	Mean	**SE**	**Mean**	**SE**
Arousal	0.0159	0.1386	-0.6462	0.0823
Valence	1.1270	0.1049	-0.5692	0.0699
HCR (%)*	2.7675	0.2083	2.9145	0.1637

*p<0.0001

a) Positive emotion



b) Negative emotion

Fig. 7. Real-time detection during different emotional states

IV. Discussion

Previous studies on how to detect emotions already yield compelling findings. The most important of this research is the usage of cardiac measurement to evaluate psychological properties. Mental stress and emotional characterization are the common issues regarding cardiac utilization and yield good accuracy by establishing complex mathematical techniques to extract potential and meaningful features [9]. The purpose of this study is based on the reliability of cardiovascular through the ECG or PPG to draw the reactions caused by an activation of the autonomic nervous system and by the release of particular hormones (adrenalin, noradrenaline, testosterone, and cortisol) [6]. The consequences of this are the respiration and heart rate also getting raised.

The measurement of the accuracy of heart rate to quantify the psychological changes such as emotions are varies. However, the rule of thumb of this performance is proportional to the number of parameters were used. Our proposed method is only performing a single parameter, heart rate changes (HCR). We also established this study by developing a low-cost device based on an Arduino system to find out the performance of this system. Our study successfully found that the emersion of negative emotion is increasing the HCR values. The increase of HCR values reflects the heart rate fluctuation. The higher HCR depicts more negative or unpleasant feelings. Our studies successfully confirmed the latest HRV study as a biomarker to assess emotions objectively [8]. Although the study was not utilizing the same feature, the direction of heart rate represents the same properties as ours.

We realized that the accuracy of our proposed system was still not good enough to classify the primary binary emotion classification (positive or negative), where the accuracy was still less than 80% compared to other studies. While considering a real-time classification system and the computation aspect, our study is promising to be developed as a wearable device for daily use compared to the common studies. Previous studies used heart rate variability (HRV) properties to measure and classify different psychological characteristics. HRV needs a longer recording time between 5 to 20 mins and many parameters to be extracted to achieve higher accuracy [13]. The ultra-short HRV was established to assess mental stress during a one-minute recording [4]. Nevertheless, our proposed method is still superior that needs only six seconds of recording.

We realized that this study faced particular issues and needed to be resolved in future investigations. The classification's accuracy (±50%) as the performance measurement also demands a higher priority for future improvement. Those issues consisted of the interference and artefacts during PPG recording, the consistency of HCR to represent more emotions, and the reliability of this system to be applied in a standard psychological procedure. Finally, we believed this study could be the solution for assessing psychological state in a real-time scheme, together with the low development cost so that the technology can be massively manufactured.

V. Conclusion

In this study, we developed a low-cost device to classify positive and negative emotions. Also, we confirmed that negative emotion is related to the rise of heart rate changes or HCR values as reported in the previous studies with different approaches. We obtained a significant difference of positive and negative feelings regarding the HCR values ($p<0.0001$). Also, we can classify two basic emotions with the performance of 50.76% by using HCR as a single parameter (threshold = 2.7675). Despite the accuracy issue, our proposed study can be a solution for real-time emotion detection. However, further study to increase the number of emotions is urgently needed. To achieve higher accuracy and recognize more emotions, features development also needs to be considered.

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References

[1] H. K. Palo and M. N. Mohanty, "Wavelet based feature combination for recognition of emotions," Ain Shams Engineering Journal, vol. 9, no. 4, pp. 1799–1806, Dec. 2018, doi: 10.1016/j.asej.2016.11.001.

[2] B. H. Kim and S. Jo, "Deep Physiological Affect Network for the Recognition of Human Emotions," IEEE Transactions on Affective Computing, pp. 1–1, 2018, doi: 10.1109/taffc.2018.2790939.

[3] E. M. Sternberg, "The Stress Response and the Regulation of Inflammatory Disease," Annals of Internal Medicine, vol. 117, no. 10, p. 854, Nov. 1992, doi: 10.7326/0003-4819-117-10-854.

[4] M. Zubair and C. Yoon, "Multilevel mental stress detection using ultrashort pulse rate variability series," Biomedical Signal Processing and Control, vol. 57, p. 101736, 2020.

[5] B. Zhang, Y. Mor`ere, L. Sieler, C. Langlet, B. Bolmont, and G. Bourhis, "Reaction time and physiological signals for stress recognition," Biomedical Signal Processing and Control, vol. 38, pp. 100–107, Sep. 2017, doi: 10.1016/j.bspc.2017.05.003.

[6] S. Hey, A. Gharbi, B. von Haaren, K. Walter, N. K¨onig, and S. L¨offler, "Continuous noninvasive pulse transit time measurement for psychophysiological stress monitoring," In 2009 International Conference on eHealth, Telemedicine, and Social Medicine, IEEE, Feb. 2009, pp. 113-116.

[7] A. Goshvarpour, A. Abbasi, and A. Goshvarpour, "Fusion of heart rate variability and pulse rate variability for emotion recognition using lagged poincare plots," Australasian Physical and Engineering Sciences in Medicine, vol. 40, no. 3, pp. 617–629, Jul. 2017, doi: 10.1007/s13246-017-0571-1.

[8] J. W. Yee Chung, H. C. Fuk So, M. M. Tak Choi, V. C. Man Yan, and T. K. Shing Wong, "Artificial intelligence in education: using heart rate variability (HRV) as a biomarker to assess emotions objectively," Computers and Education: Artificial Intelligence, vol. 2, p. 100011, 2021.

[9] E. Mej´ıa-Mej´ıa, K. Budidha, T. Y. Abay, J. M. May, and P. A. Kyriacou, "Heart Rate Variability (HRV) and Pulse Rate Variability (PRV) for the Assessment of Autonomic Responses," Frontiers in Physiology, vol. 11, Jul. 2020, doi: 10.3389/fphys.2020.00779.

[10] N. Bourdillon, L. Schmitt, S. Yazdani, J. M. Vesin, and G. P. Millet, "Minimal Window Duration for Accurate HRV Recording in Athletes," Frontiers in Neuroscience, vol. 11, Aug. 2017, doi: 10.3389/fnins.2017.00456.

[11] M. Estévez-Báez *et al.*, "Influence of Heart Rate, Age, and Gender on Heart Rate Variability in Adolescents and Young Adults," *Advances in Medicine and Medical Research*, pp. 19–33, 2018, doi: 10.1007/5584_2018_292.

[12] M. M. Bradley and P. J. Lang, "Measuring emotion: The self-assessment manikin and the semantic differential," Journal of Behavior Therapy and Experimental Psychiatry, vol. 25, no. 1, pp. 49–59, Mar. 1994, doi: 10.1016/0005-7916(94)90063-9.

[13] G. Ramos, M. Alfaras, and H. Gamboa, "Real-time approach to HRV analysis," in *BIOSIGNALS*, Funchal, Portugal, 2018, pp. 208–215, Accessed: 08, 2021. [Online]. Available: https://www.scitepress.org/Papers/2018/66414/66414.pdf.