Pit-a-Pat: Haptic-based Expressive Biosignal to Enhance the Social Support from Partner to Tame Anxiety

Tae-Hoon Lee, Hye Soo Park
School of Computing, KAIST
{th.lee, hyehye}@kaist.ac.kr

1. Summary

We implemented a system called Pit-a-Pat[1], which detects one's stress level and express it to a partner. A Pit-a-Pat transmits the two types of information (heart rate and the detected stress level). Partner's device receives the information and vibrates to the heart rate. Plus, the amplitude of vibration is changed depending on the stress level.

To detect the stress level, our model performs the binary classification of detecting stress and non-stress. In our experiments, the accuracy and f1-score were 88.65% and 83.11% using WESAD dataset [6], which is the popular dataset in the affective computing field. Furthermore, we evaluated our model on the dataset from Arduino, and the accuracy and f1-score are 81.11% and 84.62%, respectively. We achieved over 80% accuracy with the dataset from Arduino even though the different sensors are used in the training and the evaluation phase. Our findings highlight that the extracted features are sufficient to describe sensor data and the proposed model is generalizable.

2. Statement of need

Recently, expressing and sharing biosignals have gained a significant attention in HCI field. In previous studies, the biosignal was represented as numbers [3]. Beste Ozcan et al., [4] have proposed an interactive pillow that is designed to promote an intimate interaction between two partners by giving feedback on their heartbeats.

Heartbeats are an important cue for empathizing with people's emotions. R. Michael Winters et al., [8] have asked participants to see pictures of human faces and self-report how well you feel what they were feeling in different conditions. They have revealed that the participants tend to be more empathetic to emotion of others when they hear heartbeats.

Joris H. Janssen et al., [2] have found that hearing heartbeats increases intimacy between two partners. The participants were put into a virtual environment, and they were asked to report how intimate they feel to a virtual partner. The results have shown that intimacy is higher when hearing someone's heartbeat compared to silence. In addition, the authors have argued that hearing a heartbeat has the same effect as looking at each other. Thus, heartbeat sharing is a promising way to increase intimacy.

In the previous works, the expression of biosignals in a visual and auditory manner has been extensively studied. In this way, personal physiological information is publicly exposed to arbitrary people. However, there is lack of research on whether the expression of biosignals in a private way enhances connectedness. Furthermore, it has not been studied whether expressing biosignals offers an opportunity to provide social support.

Therefore, our goal is to make the tool that expresses the partner's heartbeat by vibration. To tame the partner's anxiety, it is necessary to infer the partner's stress level in real time and on-device manner. It is challenging that inferring human stress from few sensors collected from an Arduino in real time. Thus, our research question is to investigate whether we can use TinyML for real-time stress detection using BVP and temperature sensors only.

Table 1: The data used in the study and the sampling rate.

Placement	Type of modality	Modality	Sampling rate
Wrist	Physiological	BVP	64 Hz
		TEMP	4 Hz

3. Implementation

3.1. Dataset

3.1.1 WESAD Dataset

WESAD dataset [6] was collected from both a chest-worn device RespiBAN and a wrist-worn device E4. It contains motion and physiological data such as Accelerometer, Temperature (TEMP), Blood volume pulse (BVP), and so on. In our study, we focus only on data from the wrist-worn device

[1] Detailed explanation of implementation is available in our Github. https://github.com/Kaist-ICLab/final-submission-team-4-20233344-20235290

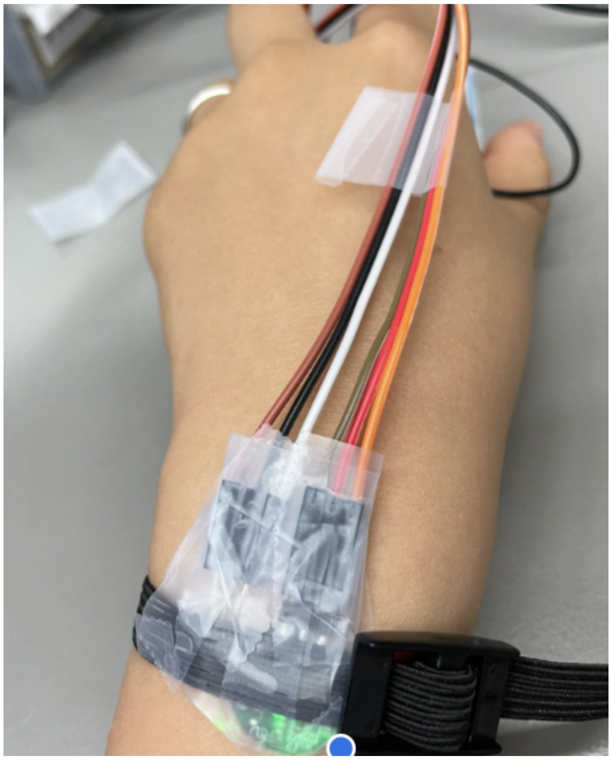

Figure 1: Data collection for BVP and TEMP data from Arduino.

because our prototype is worn on the wrist. Table 1 shows the used sensors in our study and their sampling rate.

During the data collection, subjects went through various condition such as baseline, amusement, and stress condition. Previous studies used the study protocol conditions as labels. Since our interest is how stressed subjects were, we treated the labels as stress condition and non-stress condition (i.e., baseline condition).

3.1.2 Dataset We Collected from Arduino

As shown in Fig 1, we collected dataset from Arduino with TEMP and BVP sensors. We asked participants to perform two task that are meditation for non-stress condition and Mental Arithmetic task for stress condition for three minutes. Mental Arithmetic task is one of popular stressors [5], which was used in WESAD as well.

3.2. Feature Extraction

The window size is 30s and overlapped rate is 0.9. Table 2 shows the definition of the extracted features used in our study. We created BVP_n_peak feature based on the findings that stress is associated with heart rate [7].

Table 2: The definition of the extracted features.

Modality	Feature	Description
BVP	BVP_min	Minimum value
	BVP_max	Maximum value
	BVP_mean	Mean
	BVP_std	Standard deviation
	BVP_n_peak	# of peaks per sec in a window
TEMP	TEMP_min	Minimum value
	TEMP_max	Maximum value
	TEMP_mean	Mean
	TEMP_std	Standard deviation

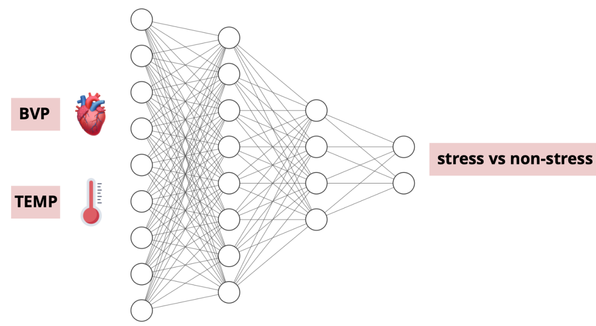

Figure 2: The structure of the proposed model.

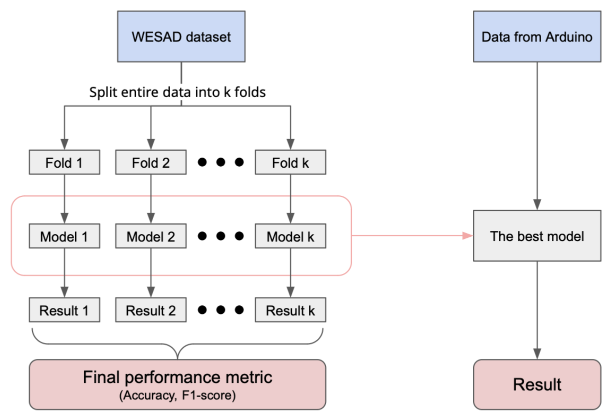

Figure 3: The overview of the evaluation process.

3.3. Model Description

We adopted a simple neural network as shown in Fig. 2. The used model structure follows the model proposed by a previous study [1]. They achieved 95.21% of accuracy using WESAD for stress detection. Their model performs well despite being a lightweight model.

The input to our model has 9 features as described previously. The model performs the binary classification of detecting stress vs non-stress. Therefore, the output is 0 (non-stress) and 1 (stress).

4. Evaluation

Fig 3 shows the overview of the evaluation process. We used two datasets which are WESAD and the dataset we collected from Arduino. WESAD is used to train and evaluate the model. Once we find the optimal hyperparameters based on the final performance metric, we evaluate the best model with the data from Arduino.

As shown in Table 3, the accruacy and f1-score were 88.65% and 83.11% obtained through leave-one-subject-out (LOSO) validation. Among the models trained with the LOSO validation, we selected the best model for evaluation with the dataset from Arduino. The accuracy and f1-score of the best model on the dataset are 81.11% and 84.62%, respectively.

Table 3: The accuracy and f1-score on the WESAD dataset and the dataset we collected from Arduino.

Data	Accuracy	F1-score
WESAD	88.65	83.11
From Arduino	81.11	84.62

5. Discussion

Through the experiment, we revealed that stress can be detected on TinyML in real-time using few sensors (i.e., BVP and temperature sensors). We achieved over 80% accuracy with the dataset from Arduino even though the different sensors are used in the training phase (i.e., E4) and the evaluation phase (i.e., Arduino with sensors). Our findings highlight that the extracted features are sufficient to describe sensor data and the proposed model is generalizable.

We have two direction for the future work. First, we can conduct research on whether sharing heartbeat through device's vibration strengthen the connectedness between two partners. Second, it will be interesting to experiment whether the intervention of vibration amplitude change based on the partner's stress level can be a trigger to increase social support.

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