An investigation into predictive stress monitoring using wearable sensors

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1 Abstract

This paper examines on the use of non-invasive wearable sensor data to determine an individual's stress levels. The findings are analysed, and it is found that the predictive model's performance is promising. More investigation is performed on preventative stress monitoring and the commercial viability of such a device. The experiment's limitations and possible enhancements are also highlighted.

2 Main Findings

2.1 Where did the data come from?

The data was generated by collecting Photoplethysmogram (PPG), 3-axis accelerometer and temperature readings from the Empatica E4 watch of each participant (N=35). The PPG signal was used to obtain the Blood Volume Pressure (BVP), Heart Rate (HR), and time between individuals heart beats (IBI) signal [2] [1].

2.2 Visualizations

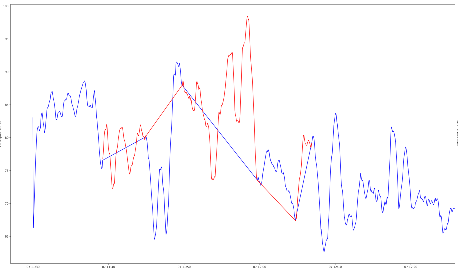
In the interest of brevity, visual analysis was performed on relevant signals from two random subjects.

The experiment consisted of three tests, each putting the individual through a different type of stress. The first was the Stroop Color-Word Test, which placed the individual under mental strain. The Trier Social Scale Test was used to apply emotional stress, and lastly a hyperventilation test was carried out to induce physical stress. There was a rest period of five minutes between tests [2].

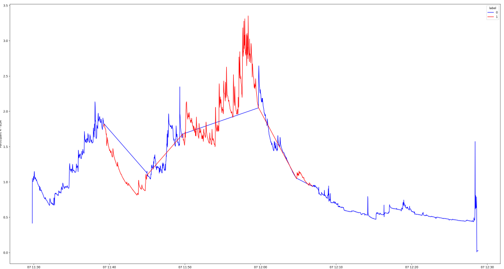
The jagged red line/straight blue line represent the times when the subject was stressed, while the straight red line represents the rest period.

Participant 4 shows a notable change in EDA (Fig. 1b), (Fig. 1a) HR and (Fig. 1c) upward/downward motion signals when under stress.

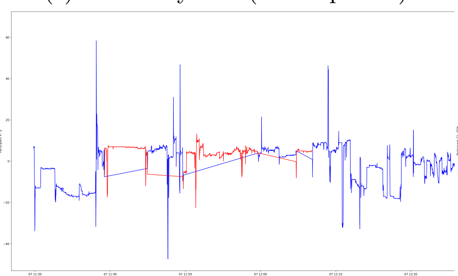
(a) Time vs Heart Rate (Participant 4)



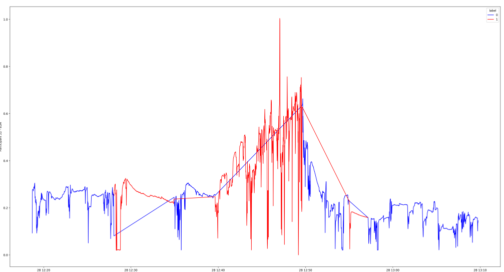
(b) Time vs EDA (Participant 4)



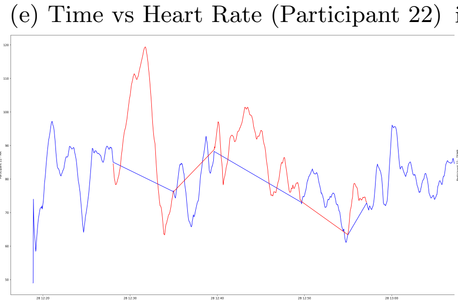
(c) Time vs y-axis (Participant 4)



(d) Time vs EDA (Participant 22)



(e) Time vs Heart Rate (Participant 22)



(f) Time vs Temperature (Celsius) (Participant 22)

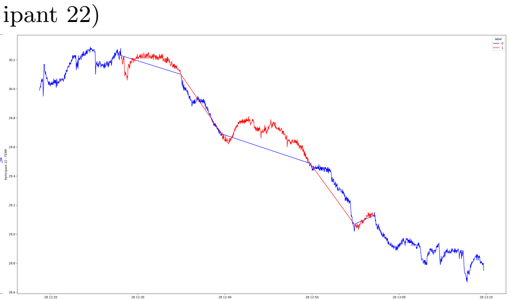


Figure 1: Relevant sensor readings from participant 4 and 22

Participant 22 shows a notable change in EDA (Fig. 1d), (Fig. 1e) HR and (Fig. 1f) TEMP signals when under stress.

3 Discussion

3.1 Insights

Fig. 1a to Fig. 1f show that different participants respond to stress in different ways and at varying intensities. Participants' temperatures, electrodermal activity (perspiration), and z-axis (forward and backward movement) values all increased on average. However, this is not always the case as individuals react differently under physical and psychological stress.

As a result, each participant will require a personalised model tailored to their specific stress responses, with all features except BVP required to be retained.

BVP was not retained because it was discovered to have no correlation with whether or not any participant was stressed.

3.2 Data Partitioning

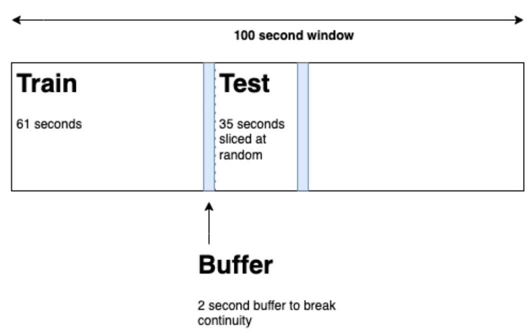


Figure 2: Train-test split

Every participant's data was subjected to a train-test split. Every 100 seconds, a random slice of 35 seconds was captured and moved into the testing set, excluding the buffer, as shown in Fig. 2. The order of the data was preserved.

3.3 Modelling

Five machine learning models were applied to all 30 participants to determine if it was possible to predict whether an individual was stressed based on sensor signals.

The time taken to train and test, as well as the f1 score, are the two most important metrics for this experiment. The f1 score is pertinent as it indicates whether or not the model is speculating.

Fig. 3a and Fig. 3b demonstrate that the K-Nearest Neighbours model is the quickest to train and has the best f1 scores. Therefore, this is the best

(a) Time taken to train and test — Lower is better (Participant 4)

(b) Higher is better (Participant 4)

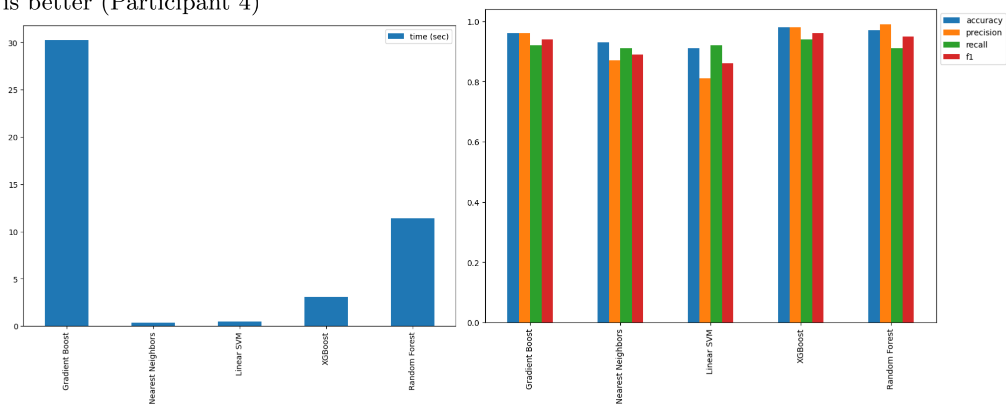


Figure 3: Participant 4 model performance

model to run in production. A similar trend has been observed for the 29 other participants.

3.4 Business Feasibility

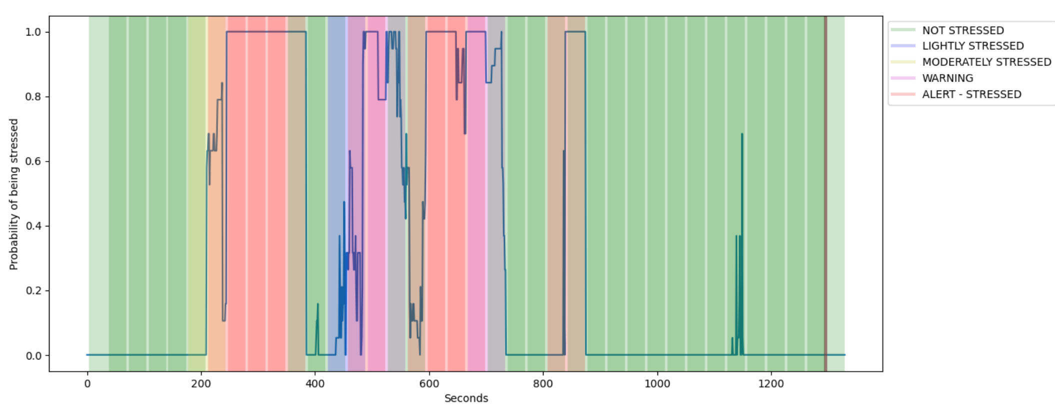


Figure 4: Participant 4 stress probability

The favourable predictive performance suggests that developing a stress monitoring wearable is a feasible business idea. According to Fig. 4, the model may additionally determine the degree to which a person is stressed. Individuals with chronic diseases, as well as healthy people, might benefit from this to monitor their stress levels. For example, the model for participant 22 was found to have an accuracy of 96%. This was accomplished by forecasting stress in 35-second intervals using sensor data.

Fig. 4 also suggests that stress levels usually increase gradually. This is critical when determining when medical intervention is necessary.

4 Conclusion

The investigation demonstrates that the data acquired was indeed useful in monitoring an individual's stress levels, and personalised prediction models were helpful in determining the extent to which an individual was stressed. The excellent performance of this system also allows for further commercial exploration into consumer and medical grade non-invasive stress monitoring devices. To aid in personalisation, the study may have benefited from information regarding an individual's age, gender, ethnicity, BMI, chronic illnesses and activity levels.

References

[1] Iqbal, T., Elahi, A., Ganly, S., Wijns, W., and Shahzad, A. Photoplethysmography-based respiratory rate estimation algorithm for health monitoring applications. *J. Med. Biol. Eng. 42*, 2 (Apr. 2022), 242–252.

[2] Iqbal, T., Simpkin, A. J., Roshan, D., Glynn, N., Killilea, J., Walsh, J., Molloy, G., Ganly, S., Ryman, H., Coen, E., Elahi, A., Wijns, W., and Shahzad, A. Stress monitoring using wearable sensors: A pilot study and stress-predict dataset. *Sensors (Basel) 22*, 21 (Oct. 2022), 8135.