Stress Detection Based on Wearable Physiological Sensors: Laboratory and Real-Life Pilot Scenario Application

Vasileios-Rafail Xefteris*, Athina Tsanousa*, Spyridon Symeonidis*, Sotiris Diplaris*, Francesco Zaffanela†, Martina Monego†, Maria Pacelli‡, Stefanos Vrochidis*, and Ioannis Kompatsiaris*
* Information Technologies Institute - CERTH, Thessaloniki, Greece
Email: {vxefteris, atsan, spyridons, diplaris, stefanos, ikom}@iti.gr
† Autorita di Bacino Distrettuale delle Alpi Orientali, Venice, Italy
Email: {francesco.zaffanella, martina.monego}@distrettoalpiorientali.it
‡ Smartex, Prato, Italy
Email: m.pacelli@smartex.it

Abstract*—Stress as a mental/physiological reaction of a person in a challenging situation of high discomfort can affect his/her ability to focus and perform fast and accurate decisions. Thus, stress can be a key factor in cases of emergency, when first responders need to be fast and accurate. Continuous monitoring of the stress levels of the first responders can be crucial in cases of disaster management situations. Wearable devices and physiological sensors provide real-time monitoring of physiological signals, which can be helpful for real-time stress monitoring. This work describes the stress detection module of the xR4DRAMA project and the results of its application during a disaster management pilot scenario. For this cause, a wearable smart vest equipped with an electrocardiograph (ECG) sensor, respiration (RSP) sensor, and an Inertial Measurement Unit (IMU) with an accelerometer, gyroscope, magnetometer, and quaternion sensors has been used. An initial data collection was performed to train the stress detection module, and the trained model was deployed for real-time stress detection of first responders in the pilot scenario. The training performed includes a massive feature extraction from the different modalities, and the test of four machine learning algorithms and six fusion and three feature selection techniques. The results of the continuous valued stress levels detection indicate that the best performing combination is the eXtreme Gradient Boosting (XGB) algorithm with the use of a Genetic Algorithm (GA) feature selection technique, achieving a Mean Square Error (MSE) of 0.0567. Results from the pilot show that the stress level detection module can operate in real-time in real life conditions, offering reasonable results regarding the detected stress levels.

***Index Terms*—Stress level detection, wearable sensors, smart vest, multimodal fusion**

I. INTRODUCTION

Stress is among the most important problems in our society. It can be defined as the reaction of a person when being subject to high discomfort and challenging situations. As stated by World Health Organisation “Work-related stress is the response people may have when presented with work demands and pressures that are not matched to their knowledge and abilities and which challenge their ability to cope” [1]. Stress can impact the mental clarity of a person decreasing his ability of precise and fast decisions. High levels of stress might also influence person’s performance, even in actions they are trained to perform. Thus, stress can be considered one of the most vital aspects of disaster management situations.

Apart from the effects of stress on first responders performance, their exposure to highly stressful events for long periods can result in serious health problems. Mental health issues, such as Post-Traumatic Stress Disorder (PTSD) and major depressive disorder [2], or other physical health problems, such as sleep disturbances and musculoskeletal problems [3], are some of the most common health problems induced by chronic stress. Therefore, monitoring the stress levels of first responders during emergencies is of crucial importance. Simulating a disaster management scenario with first responders or volunteers assists in collecting physiological data and build models for prediction of stress. Protocols that induce stress might be adopted or the exact scenario can be reproduced, such as in [4].

With the development of the Internet of Things (IoT), smart devices are equipped with many sensors able to monitor physiological signals and human body motion attributes. Since stress is a mental/physiological reaction the monitoring of physiological signals can be considered useful in the task of stress detection. Also, in many cases, abnormal human body movements along with certain physiological signal attributes can be beneficial for stress detection applications. The IoT advances with the deployment of multiple sensors in wearable devices and the high computational power of smart devices and computers can lead to real-time stress detection capabilities.

In the current work, an application of an experimental design for stress level detection of first responders is described. The stress level detection module exploits data from a wearable smart vest equipped with sensors, designed for this application, and predicts the levels of stress as a continuous value, which is not the case in most stress detection applications, where only a categorical variable of two or three classes is typically predicted. The stress detection module was trained using data collected through an initial data collection, where

 ISBN: 978-1-68558-057-5

subjects underwent various challenges that induce different levels of stress, and they reported their stress level after each challenge. The trained stress detection module was deployed for real-time stress level detection during the pilot scenario, where subjects had to perform certain tasks simulating a real flood scenario. These tasks include going to certain areas on the field and sending incident reports. Since there was no flood simulation or any other stressor to induce high levels of stress, the pilot scenario mainly tested the ability of the stress detection module to perform real-time stress level monitoring in real life conditions. The current work is an application of stress detection in a general framework of eXtended Reality (XR) technologies for disaster management, as part of the xR4DRAMA project [5], which is a solution that makes use of XR in disasters, or media production scenarios. The pilot scenario is part of the first pilot of the project regarding the disaster management pilot use case, where the need for real-time stress level monitoring using wearable physiological sensors is present.

The rest of the paper is organized as follows; in Section 2 state-of-the-art methods for stress detection are presented. In Section 3 the methods used for the data collection and analysis are described followed by the results of the experiments in Section 4 and the conclusion of our work in Section 5.

II. Related work

The most common stress detection methods based on physiological signals include a feature extraction step that attempt to describe the various affective states. The extracted features are used to train a state-of-the-art machine learning classifier which eventually learns to detect the stress levels of the subjects. A more recent approach attempts to omit the feature extraction step by utilizing a Deep Neural Network (DNN), which can do the representation learning of the different affective states directly from the physiological signals.

Physiological sensors can be exploited separately or in combination for the task of stress detection. Electrocardiography sensors (ECG) are amongst the best performing ones in predicting stress and are often utilized individually. In [6] machine learning algorithms were applied on features extracted from ECG signals to detect stress in drivers. ECG signals were used in [7] in a simulated stress scenario and their performance was compared to electromyogram (EMG) signals. Galvanic Skin Response (GSR) sensors are often combined with ECG signals and other physiological sensors to detect stress. Early fusion was used in [8] to combine features extracted from GSR, Electroencephalogram (EEG) sensor and Photoplethysmogram (PPG), in order to improve the individual performance for monitoring stress.

Schmidt et al. [9] created a benchmark for their publicly available dataset for stress detection using a large number of well-known features (extracted from physiological and motion signals) and common machine learning methods (Decision Tree (DT), Random Forest (RF), AdaBoost (AB), Linear Discriminant Analysis (LDA) and k-nearest neighbor (kNN)). The authors validated their methods on a three-class problem (neutral, stress, amusement) achieving 80.34 % accuracy with the AB classifier, and on a two-class problem (stress, no stress) achieving 93.12 % accuracy with the LDA classifier.

Rusell Li et al. [10] proposed a novel Deep Learning (DL) based method for stress detection, which was trained and evaluated on the same dataset as [9]. This work attempts to address the limitation of the handcrafted features that traditional machine learning methods rely upon and their potential decrease in accuracy due to the misidentification of features. The authors designed a novel 1D Convolutional Neural Network (CNN) and a Multi-Layer Perceptron (MLP) that take as input the raw physiological signals and do not require hand-crafted features but instead extract features from raw data through the layers of the neural networks. The authors validated their classifiers on both the three and two-class problems of [9] achieving 97.48 % for the three-class and 99.14 % for the two-class problem.

Sriramprakash et al. [11] proposed a method for detecting stress during working conditions based on feature extraction and machine learning. The authors trained and validated their data on the SWELL-KW dataset [12]. They utilized a set of 17 statistical features derived from ECG and GSR signals and evaluated which of them are the most dominant to increase accuracies. They trained a kNN classifier and a Support Vector Machine (SVM) classifier. The SVM classifier trained on the dominant selected features achieved the highest classification accuracy of 92.75 % for the stress vs no-stress classification task. Another work based on feature extraction and SVM was reported by Yuan Shi et al. [13]. The authors proposed a set of 26 handcrafted features derived from ECG, GSR, skin conductance, temperature and respiration. They reported an 80 % recall over the binary classification of stress vs no stress problem.

Feng-Tso, et al. [14] extracted statistical features from ECG, GSR, and accelerometer and trained a DT, Bayesian Network (BN), and SVM classifier for stress detection inference combined with physical activities (sitting, standing, and walking). The best classification accuracy (92.4%) was obtained by using the DT classifier with the all-feature combination.

Keshan et al. [15] proposed an ECG-based feature extraction scheme for driver stress detection. They trained and evaluated their data on [16]. They utilized a set of 14 statistical features derived from ECG signals and found that stress levels can be successfully detected from ECG signals alone; with a random tree classifier allowing for the identification of the three classes of stress, low, medium, and high, with 88.24% accuracy, and Naïve Bayes for two stress levels, low and high, with 100% accuracy.

In the work of Nath et al. [17] the authors extracted statistical features from GSR and PPG sensors for stress detection of healthy elders. They utilized the Trier Social Stress Test to induce stress in the subjects and a fingertip sensor to monitor physiological signals. The extracted features were fed into a feature selection algorithm to remove redundant information before utilizing a machine learning algorithm for the final stress detection. They tested kNN, RF, and SVM classifiers along with a deep learning Long Short-Term Memory (LSTM) based classifier and found out that the LSTM classifier performs the best, achieving 0.87 macro F1-score, 0.95 micro F1-score, and 0.81 AUC.

In all of the previous works, the data were derived from publicly available datasets. Even though this makes the comparison of the different methods easier, since all methods are based on the same data, this might influence the performance of the models when deployed in a real-life scenario, where the sensors will be different. Also, all of the aforementioned methods are classification methods, with two or three classes. Our work goes beyond predicting only binary (stress, no stress) or categorical (low, medium, high) variables by using regression models to produce continuous values of stress levels.

III. Methods

In this Section, the main methods of our work are described.

A. Smart vest and sensors

The physiological data were acquired using a sensing platform based on textile sensors fully integrated into a smart vest and a data logger that can record and process data on board and transmit them via Bluetooth 2.1.

Furthermore, an Inertial Measurement Unit (IMU) system is integrated into the data logger, including accelerometer, gyroscope, magnetometer and quaternion sensors with the aim of monitoring the movements of the trunk. The Fig. 1 shows the wearable sensing platform in which its features are presented:

- two textile electrodes to acquire ECG signal
- one textile respiratory (RSP) movement sensor
- one jack connector to plug the garment into the electronic device
- a pocket to hold the electronic device during the activity

Fig. 1. Wearable sensing platform architecture.

B. Data collection protocol

The data collection is divided into two different protocols; the training data collection and the pilot scenario. The training data collection protocol is an experimental design based on interchanges between stressful challenges and relaxing situations. The pilot scenario is designed to evaluate an overall disaster management use case using XR technologies, including the real-time stress detection module and all of the other features of the platform.

Fig. 2. The Stroop test

1) Training data collection protocol: The training data collection protocol has been designed to induce stress in the users followed by calmness. The basis of experimental design is based on known stressors for both psychological and physiological stress. The stressors selected, divided into the two aspects of stress they induce, are the following:

- Psychological:
  - The Stroop test. Is a commonly used task to induce stress [18], in which some slides with certain words of different color names are presented to each user. The words are written in different colors than those they describe (Fig. 2). The user is asked, in a short period of time, to describe the color in which each word is written.
  - The descending subtraction test. In this also commonly used task for inducing stress [19], the user is asked to begin counting backward from a certain number, subtracting each time another certain number. In the context of the training data collection experiment, the users were asked to begin with the number 1324, subtracting 17, until 17. If the users make a mistake, they must start over.
  - Explain a stressful situation in your life.
  - Explain how it has been the day. This is not a stressful challenge, but it is used to get low stress values as well.
  - Listen to relaxing music. This task was also used to get low stress values.
- Physiological:
  - Place a hand in cold water (2º C) for two minutes, make pause, and then place it again.
  - Ascend and descend four levels of stairs.
  - Tie and untie shoes after exercise.

These different challenges were combined in a different order each time, to induce various levels of stress, from calmness to high stress. The users were asked to report their stress levels as a number from 0 to 100 after each challenge. During the whole experiment, the users were wearing the smart vest to collect their physiological data.

2) Pilot scenario: The pilot scenario of the disaster management use case of the xR4DRAMA project was designed to evaluate the overall disaster management solution of the project. During the phases of the pilot, the roles of control room operators, first responders, and citizens were assigned to the participants. The storyline of the pilot scenario can be summarized in two different phases; the pre-emergency phase and the emergency phase.

The pre-emergency phase focuses on the forecasting of flood incidences. In more detail, the storyline starts with the reception of an official warning message by the municipality of Vicenza, dealing with the worsening of safety conditions along the Bacchiglione river. Since the stress detection module is not involved in this phase there is no need for further analyzing the design of the certain phase.

During the emergency phase, the first responders are asked to perform certain tasks from the control room. These tasks include sending incident reports to signal the authorities that there were flooding events in various areas of the city center. For the whole time of the emergency phase, the first responders were wearing the smart vest to monitor their stress levels in real time. There was no simulation of flood events during the experiment, thus the first responders did not experience any certain stressor that could induce high levels of stress.

C. Data analysis

The data analysis is referring to extraction of features from the received data and the training of the different machine learning algorithms and the different fusion and feature selection techniques. The best performing method was selected to be implemented for the disaster management pilot scenario.

After receiving the data from the training data collection, we performed a data analysis involving preprocessing of the data and feature extraction. The preprocessing of the data involves only simple transformation of the data by multiplying them with certain weights. Feature extraction was applied to all the preprocessed data. The features were extracted using a 60-second window with 50% overlap. We used the data of all subjects that were monitored. In total 94 ECG, 28 RSP, and 192 IMU (16 per single-axis data) features were extracted for a total of 314 features. The ECG features include statistical and frequency features regarding the signal and the R-R (the physiological phenomenon of variation in the time interval between heartbeats) intervals, along with Heart Rate (HR) variability time and frequency domain statistical features. For the ECG features, we used the hrv-analysis [20] and the neurokit [21] toolboxes. The respiration features include statistical and frequency features of the signal, breathing rate, respiratory rate variability, and breath-to-breath intervals. The respiration features were also extracted using the neurokit toolbox [21]. The IMU features include simple statistical and frequency features from the IMU signals. These features are mean, median, standard deviation, variance, maximum value, minimum value, interquartile range, skewness, kurtosis, entropy, energy, and 5 dominant frequencies.

For the ground truth values, the self-reported stress levels of the users refer to the whole challenge they performed right before they were asked to report their stress. Thus, each of the 60-second time windows used for the feature extraction was assigned the stress value the user reported for the whole challenge that took place at the certain window. The ground truth values were integer values in the range of 0 to 100.

After extracting the features, the data were split into train and test with an 80/20 ratio. We applied four different ML algorithms; namely SVM, k-Nearest Neighbors (kNN), RF, and eXtreme Gradient Boosting trees (XGB) to perform regression of the stress level since the stress level is a continuous variable. The evaluation was performed using the Mean Squared Error (MSE) metric and 10-fold cross validation. Before computing the MSE we normalized the values of stress level to be in the range of 0 to 1. We tested each modality alone, all different combinations of modalities in early-level fusion (concatenation) and two late-level fusion methods: mean and median of the predicted stress level of each modality. We also tested the performance of three different feature selection algorithms, those being Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and Genetic Algorithm (GA).

IV. RESULTS

In this Section, the main results of our work are presented. First, the training data collection's main results are presented, including the different early and late fusion and feature selection methods. Following are the results of the pilot scenario, including the real-time outcomes of the stress detection module during the disaster management pilot scenario.

A. Training data collection

For the training data collection, seven subjects (4 female, age: 40±7.78) participated, each one performing a series of challenges as described above. The results from all the different fusion methods tested are presented in Table I. From the Table, it can be seen that the IMU modality performs better than the ECG and RSP modalities when used alone. Also, when combining only two of the three different modalities it can be seen that when the IMU modality is used, the results are better. Since IMU sensors are typically used for activity recognition, this might indicate that along all the users, the physiological stressors, which include more specific movements, might have a larger influence on the users' stress levels. The best performing method of all the different tested methods is the early fusion of all the modalities while using the XGB classifier, achieving an MSE score of 0.073.

Since the best performing fusion method was the early fusion of all the modalities, we tested the different feature selection methods on the concatenated feature set of all the different modalities. In Table II the results from the different feature selection methods are presented. All the different

 ISBN: 978-1-68558-057-5

TABLE I
MSE RESULTS OF THE DIFFERENT FUSION TECHNIQUES WITH ALL FOUR DIFFERENT REGRESSORS.

	ECG	RSP	IMU	ECG + RSP	ECG + IMU	RSP + IMU	ECG + RSP + IMU	Late mean	Late median
SVM	0.1709	0.1530	0.1305	0.1723	0.1306	0.1305	0.1305	0.1412	0.1363
kNN	0.1439	0.1553	0.1107	0.1285	0.1106	0.1106	0.1107	0.1170	0.1125
RF	0.1113	0.1280	0.0918	0.1073	0.0916	0.0871	0.0886	0.0984	0.1025
XGB	0.1237	0.1307	0.0844	0.1092	0.0835	0.0858	0.0730	0.0958	0.1006

feature selection algorithms improve the overall performance of the different classifiers, nevertheless the GA feature selection algorithm when again applied with the XGB regressor performs the best, achieving an MSE score of 0.0567. All the feature selection methods retained features from all modalities.

TABLE II
MSE RESULTS OF THE DIFFERENT FEATURE SELECTION TECHNIQUES WITH ALL FOUR DIFFERENT REGRESSORS.

	RFE	PCA	GA
SVM	0.1052	0.1201	0.1305
kNN	0.1023	0.1106	0.1106
RF	0.0790	0.1044	0.0742
XGB	0.0772	0.0953	0.0567

Since in all cases the XGB classifier achieves the best results, it is important to see how the feature selection method improves the overall performance of the stress detection module. In Fig. 3 we present concatenation and GA feature selection results along with the ground truth values in each subfigure respectively. From the figure, it can be seen that the use of GA feature selection improves the overall performance of the XGB regressor, by minimizing the error between the ground truth values and the predictions.

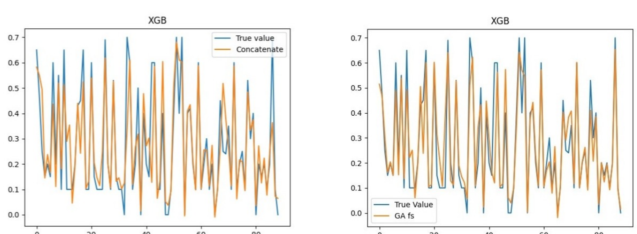

Fig. 3. Plot of the ground truth stress levels reported versus the predicted stress levels using the XGB regressor with and without the use of GA feature selection technique

B. Disaster management pilot scenario

For the pilot, we trained an XGB model using a GA feature selection, since it was the best performing method for stress detection. The model was deployed for real-time stress detection using the data from the smart vest. Four different subjects were participating, having the role of the first responder and performing tasks on the field, as described above. Each subject was wearing a smart vest during the whole experiment.

Data from the smart vest were streamed while the users were following the instruction given to them for the pilot scenario. The streamed data are packed in 5-second packages before being sent to the stress detection module. The streamed data were received from the stress detection module, which stacks them until a full minute of data is collected, and then the feature extraction, feature selection, and final stress detection process are taking place. Therefore a 1 min long time window with 5 seconds step is applied. The full procedure can be seen in Fig. 4, where the stack of the 5-second packages of data along with the main stress detection process including feature extraction, feature selection, and stress detection, are presented.

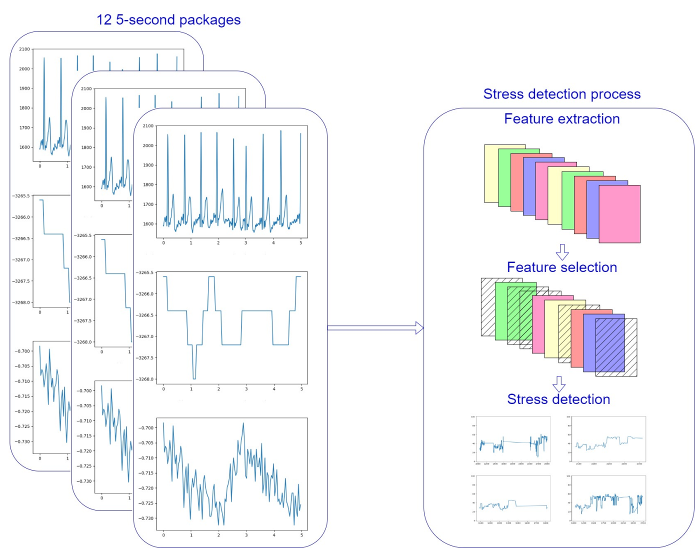

Fig. 4. Workflow of the stress detection module during the pilot.

The results from the pilot can be seen in Fig. 5. Each one of the four different subfigures presents the results of a different user. Knowing that the users during the pilot were performing simple tasks, their stress levels are reasonable to be in a range from 40 to 60. From the Figure, it can be seen that the stress levels are at a medium level indicating that users were calm, which is reasonable considering the tasks they were asked to perform.

V. CONCLUSION

In this paper, we present a solution for real-time stress level detection based on sensors in the general context of XR technologies for disaster management. This work focuses on the training of the sensor-based stress level detection module from data gathered during a training data collection, and its implementation into a real-life disaster management pilot

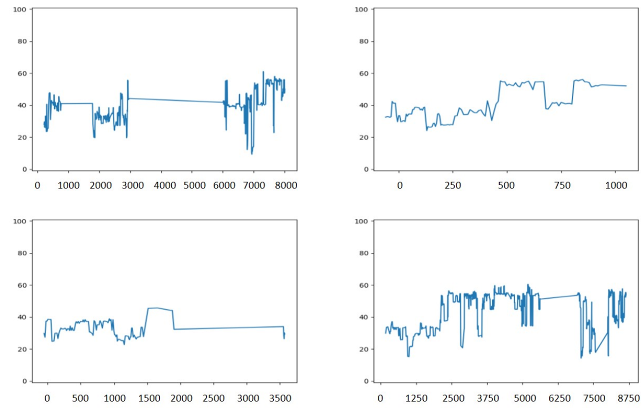

Fig. 5. Stress level results of the stress detection module (x-axis) from data from the pilot over time (y-axis) for each subject.

scenario. The sensor-based stress level detection module is based on data gathered from a smart vest developed for the current application consisting of an ECG sensor, an RSP sensor, and an IMU system with 3-axis accelerometer, gyroscope, magnetometer and quaternion sensors. Data gathered from these sensors are analyzed in order to extract features that are fed into a trained model for the final continuous-valued stress level detection. From the results of the evaluation study, where multiple fusion and feature selection methods were tested using four different machine learning algorithms, it was revealed that the best performing combination was the use of XGB regressor along with GA-based feature selection method, achieving 0.0567 MSE. We retrained the XGB model with the feature sub-set selected from the GA-based feature selection method, and deployed it into a real-world disaster management pilot scenario. Results from four subjects serving as first responders in this pilot scenario indicate that our model works reasonable even in real-life conditions and in real-time. Future work includes performing a second disaster management pilot scenario in the context of the xR4DRAMA project, where a more well defined protocol to induce stress will be implemented. Also in this pilot scenario, the sensor based stress level detection system will be tested alone and in combination with the predicted stress of an audio-based system, through the fusion module of the xR4DRAMA project.

ACKNOWLEDGMENT

This work was supported by the xR4DRAMA project funded by the European Commission (H2020) under the grant number 952133.

REFERENCES

[1] W. H. Organization, "Occupational health: Stress at the workplace." https://www.who.int/news-room/questions-and-answers/item/ccupational-health-stress-at-the-workplace, 2020. [Online; accessed 4-November-2022].

[2] B. Kleim and M. Westphal, "Mental health in first responders: A review and recommendation for prevention and intervention strategies," *Traumatology*, vol. 17, no. 4, pp. 17–24, 2011.

[3] M. J. Friedman and B. S. McEwen, "Posttraumatic stress disorder, allostatic load, and medical illness.," *Trauma and health: Physical health consequences of exposure to extreme stress*, p. 157–188, 2004.

[4] J. Strahler and T. Ziegert, "Psychobiological stress response to a simulated school shooting in police officers," *Psychoneuroendocrinology*, vol. 51, pp. 80–91, 2015.

[5] S. Symeonidis, S. Diplaris, N. Heise, T. Pistola, A. Tsanousa, G. Tzanetis, E. Batziou, C. Stentoumis, I. Kalisperakis, S. Freitag, *et al.*, "xr4drama: Enhancing situation awareness using immersive (xr) technologies," in *2021 IEEE International Conference on Intelligent Reality (ICIR)*, pp. 1–8, IEEE, 2021.

[6] N. Keshan, P. Parimi, and I. Bichindaritz, "Machine learning for stress detection from ecg signals in automobile drivers," in *2015 IEEE International conference on big data (Big Data)*, pp. 2661–2669, IEEE, 2015.

[7] S. Pourmohammadi and A. Maleki, "Stress detection using ecg and emg signals: A comprehensive study," *Computer methods and programs in biomedicine*, vol. 193, p. 105482, 2020.

[8] D. Das, S. Datta, T. Bhattacharjee, A. D. Choudhury, and A. Pal, "Eliminating individual bias to improve stress detection from multimodal physiological data," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 5753–5758, IEEE, 2018.

[9] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, "Introducing wesad, a multimodal dataset for wearable stress and affect detection," in *Proceedings of the 20th ACM international conference on multimodal interaction*, pp. 400–408, 2018.

[10] R. Li and Z. Liu, "Stress detection using deep neural networks," *BMC Medical Informatics and Decision Making*, vol. 20, no. 11, pp. 1–10, 2020.

[11] S. Sriramprakash, V. D. Prasanna, and O. R. Murthy, "Stress detection in working people," *Procedia computer science*, vol. 115, pp. 359–366, 2017.

[12] S. Koldijk, M. Sappelli, S. Verberne, M. A. Neerincx, and W. Kraaij, "The swell knowledge work dataset for stress and user modeling research," in *Proceedings of the 16th international conference on multimodal interaction*, pp. 291–298, 2014.

[13] Y. Shi, M. H. Nguyen, P. Blitz, B. French, S. Fisk, F. De la Torre, A. Smailagic, D. P. Siewiorek, M. al'Absi, E. Ertin, *et al.*, "Personalized stress detection from physiological measurements," in *International symposium on quality of life technology*, pp. 28–29, 2010.

[14] F.-T. Sun, C. Kuo, H.-T. Cheng, S. Buthpitiya, P. Collins, and M. Griss, "Activity-aware mental stress detection using physiological sensors," in *International conference on Mobile computing, applications, and services*, pp. 282–301, Springer, 2010.

[15] N. Keshan, P. Parimi, and I. Bichindaritz, "Machine learning for stress detection from ecg signals in automobile drivers," in *2015 IEEE International conference on big data (Big Data)*, pp. 2661–2669, IEEE, 2015.

[16] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Transactions on intelligent transportation systems*, vol. 6, no. 2, pp. 156–166, 2005.

[17] R. K. Nath, H. Thapliyal, and A. Caban-Holt, "Machine learning based stress monitoring in older adults using wearable sensors and cortisol as stress biomarker," *Journal of Signal Processing Systems*, vol. 94, no. 6, pp. 513–525, 2022.

[18] R. Nawaz, J. T. Ng, H. Nisar, and Y. V. Voon, "Can background music help to relieve stress? an eeg analysis," in *2019 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, pp. 68–72, IEEE, 2019.

[19] M. Tanida, M. Katsuyama, and K. Sakatani, "Relation between mental stress-induced prefrontal cortex activity and skin conditions: a near-infrared spectroscopy study," *Brain research*, vol. 1184, pp. 210–216, 2007.

[20] R. Champseix, "hrv-analysis 1.0.4." https://pypi.org/project/hrv-analysis/, 2021. [Online; accessed 19-September-2022].

[21] D. Makowski, T. Pham, Z. J. Lau, J. C. Brammer, F. Lespinasse, H. Pham, C. Schölzel, and S. Chen, "Neurokit2: A python toolbox for neurophysiological signal processing," *Behavior research methods*, vol. 53, no. 4, pp. 1689–1696, 2021.