Real-Time Stress Detection Using Single-Lead ECG Signal Analysis

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***Abstract*—Stress detection is an active research field with ongoing challenges, particularly in real-time data analysis. This pilot study aims to implement a real-time stress detection algorithm that utilizes cardiac and respiratory information extracted from a single-lead ECG signal. Novel methods are combined to extract physiological indices, which are then processed using the XGBoost machine learning technique to provide per-second inferences. ECG signal processing is conducted over a storage buffer to ensure low processing time, with sliding-window analysis applied to extract cardiac indices in the time domain, frequency indices with the orthogonal subspace projection decomposition method, and respiratory indices in both time and frequency domains from ECG-derived respiration. A single-subject experiment, including a relaxation stage, musical stimuli stage, and stressor stage, is conducted to evaluate the algorithm's performance. The comparison between indices extracted via offline and real-time processing yielded a Pearson correlation coefficient average of 0.98 for 21 indices, demonstrating the method's effectiveness. Additionally, the stress probabilities inferred by the model during the experiment clearly distinguish between stages, as supported by visual descriptive statistics and significant differences found in ANOVA and post-hoc tests.**

***Index Terms*—real time, stress detection, single-lead ECG, EDR, XGBoost.**

I. Introduction

In recent years, the study of stress has become increasingly important in various scientific fields, as its treatment or management are essential for promoting human well-being. This purpose has led to the combined efforts of multiple disciplines, including psychology, computer science, engineering, and medicine. However, combining multiple disciplines often imply not only improvements or benefits in traditional methods but also new challenges that must be addressed [1]. For instance, it is beneficial the transition from sporadic to continuous monitoring of physiological data in a patient, but it requires the development of appropriate sensors along with adequate real-time processing. Consequently, real-time processing of physiological signals is a widely studied topic, as explored in [2]–[4].

A potential initial step in studying stress is its detection. In this regard, the debate focuses on aspects such as the physiological signals used, the methods for processing the information, and the types of temporal processing employed. Concerning physiological signals, a wide range can be utilized, including electrocardiogram (ECG), blood pressure, electrodermal activity, respiratory signal, electroencephalogram, photoplethysmogram, electromyogram, skin temperature, and impedance cardiogram [5]. While some methods rely on a single physiological signal for stress detection, others use multimodal signals [6], [7]. Although using multiple physiological signals can enhance detection accuracy, it can also increase the demands on hardware and processing. Consequently, an alternative approach is to utilize a single signal and extract additional information through novel methods. For example, [8] demonstrated the extraction of ECG-derived respiration from ECG signals.

Moreover, as an alternative to traditional statistical analysis of indices, machine learning techniques such as SVM, random forest, decision trees, XGBoost, neural networks, and CNNs are increasingly applied in signal analysis for stress detection [9]–[11]. These techniques aim to identify patterns in data to make accurate inferences. Furthermore, some studies have demonstrated the feasibility of incorporating machine learning into real-time processing not only for disease detection [12], [13] but also for stress detection. Various signals have been utilized in this context, including electrodermal activity [14], heart rate and galvanic skin response [15], ECG [16], and multimodal approaches as seen in [17].

Despite the advances in the field, real-time stress detection remains an area of active interest. There are still opportunities to enhance detection systems by optimizing the physiological signals used, refining the indices extracted from these signals, or improving the processing tools employed for the data obtained. Therefore, the purpose of this pilot study is to implement an algorithm for real-time stress detection that utilizes cardiac and respiratory information extracted from a single-lead ECG. This algorithm employs rigorous methods to extract the signal indices, which are then processed using machine learning techniques to provide inferences on a per-second basis.

The remainder of this paper is structured as follows: Section II outlines the methods employed in this research. Section III details the results, which are discussed in Section IV. Finally, Section V presents the conclusions.

II. Materials and Methods

A. Acquisition and Processing of the ECG Signal

We decided to use only one physiological signal for stress detection to minimize resource and time requirements during processing. Consequently, we measured a single-lead ECG signal using the OpenBCI 8-channel Cyton Biosensing Board, with the ECG signal acquired on one channel at a sampling frequency of 250 Hz. Hydrogel snap electrodes with an Ag/AgCl layer were placed in a Lead II configuration for electrode placement.

Subsequently, the signal processing method included a filtering stage, followed by a wavelet-based algorithm to detect heartbeats [18] and the identification of ectopic beats as described in [19] to obtain the instantaneous heart rate variability (HRV) signal. Additionally, we extracted respiratory indices from the ECG-Derived Respiration (EDR) signal according to [20]. Using both HRV and EDR signals, we calculated the frequency indices of HRV, estimating the respiratory influence on the heart rate signal using decomposition based on orthogonal subspace projections (OSP) [21]. The indices extracted from the acquired ECG signal are shown in Table I.

Commonly, in offline processing, the complete signal is processed first, and later, the indices are extracted using a sliding-window method. In contrast, for real-time analysis, there is an incremental signal that grows over time as data is continuously acquired. In this context, the indices were extracted by processing windows of 60 seconds with a 1 second slide. These parameters allowed us to obtain indices in real time each second, while ensuring the minimum time requirements for respiration and HRV frequency indices estimation. Due to processing time limitations in real time, it is not possible to store and process the entire incremental signal. However, to provide a more robust analysis for the wavelet-based algorithm and ectopic beat detection, 180 seconds of the signal were saved in a storage buffer, updated every second. Additionally, to avoid edge artifacts due to the limitations of the interpolation and filtering algorithms at the boundaries of the signal, we defined an exclusion zone by omitting a small margin of one second at the end of the signal segment. Fig. 1 shows the schematic of the ECG signal processing in real time, where the last second marked in red corresponds to the exclusion zone.

TABLE I
Extracted Indices

Type of indices	Index	Description
Cardiac time**	mHR	Mean heart rate
	SDNN	Standard deviation of normal to normal* intervals
	SDSD	Standard deviation of differences between adjacent NN intervals
	RMSSD	Root mean square of successive NN interval differences
	pNN20	Percentage of successive NN intervals differing by more than 20 milliseconds
	pNN50	Percentage of successive NN intervals differing by more than 50 milliseconds
	pNN100	Percentage of successive NN intervals differing by more than 100 milliseconds
	SD1	Standard Deviation 1
	SD2	Standard Deviation 2
	S	Area of ellipse
	SD1/SD2	The ratio of SD1/SD2
HRV frequency***	LFres	Power in low frequency of residual component
	LFresp	Power in low frequency of respiration component
	HFresp	Power in high frequency of respiration component
	SBn	Sympathovagal component
	SBnprima	Normalized sympathovagal component
	TP	Total power
	Px	Relative power of respiratory component
Respiratory	mBR	Mean breathing rate
	mBwr	Mean of respiratory bandwidth
	SDBwr	Standard deviation of respiratory bandwidth

* Normal to normal (NN) intervals refer to the intervals between consecutive heartbeats that are classified as normal, excluding any ectopic or abnormal beats.
** Indices obtained from the NN interval series.
*** Indices derived from the HRV signal obtained through the IPFM model.

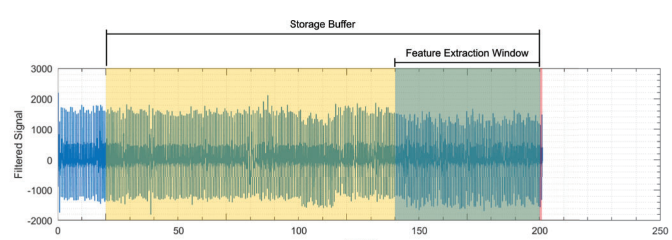

Fig. 1. ECG signal processing overview.

All algorithms were implemented in Matlab (R2024a, MathWorks, Natick, MA, USA). Although OpenBCI provides its own software tool for managing the boards, we preferred using the BrainFlow library to acquire data from the Cyton board directly in Matlab. This approach allowed us to control the execution time within a single software environment, which is fundamental for real-time processing. The pseudocode of this processing is shown in Algorithm 1.

Algorithm 1 Pseudocode for Real-Time Processing of the ECG Signal, as Described in Section II-A.

REPEAT EVERY 1 SECOND:
- **Read** Cyton board channel
- **Update** storage buffer
- **Process** complete buffer signal
- **Extract** indices from 60s window before exclusion zone
- **Store** extracted indices

To validate the performance of the real-time processing algorithm, we tested it by acquiring and processing a 5-minute ECG signal, storing the extracted indices, and recording the raw ECG data. Subsequently, we processed the raw ECG signal offline, extracting the indices for comparison with those obtained through real-time processing.

B. Stress Detection Using Machine Learning

For the training of the machine learning model, we utilized single-lead ECG signals from 40 participants provided by the ES3 project database [22], focusing specifically on data from the baseline and arithmetic task stages of the stress session. After processing the signals and extracting the features, we implemented a classifier using the Extreme Gradient Boosting (XGBoost) algorithm through the DMLC XGBoost Python Package [23]. The hyperparameters were tuned using a grid search approach in combination with the Leave-One-Subject-Out cross-validation (LOSO) technique. Finally, the best resulting model was saved in JSON format.

For the inference stage, we used the *pyrun* function in Matlab to execute a short Python script that loads the XGBoost classifier model and predicts the probability every second. Consequently, this script is run after the index extraction step, as shown in Algorithm 2.

Algorithm 2 Pseudocode for Real-Time Stress Detection

REPEAT EVERY 1 SECOND:
- **Read** Cyton board channel
- **Update** storage buffer
- **Process** complete buffer signal
- **Extract** indices from 60s window before exclusion zone
- **Infer** probabilities using *predict_proba*
- **Store** extracted indices and prediction

As mentioned above, the entire algorithm was implemented using Matlab on a general-purpose laptop equipped with an AMD Ryzen 7 5700U processor, 16GB of RAM, and a 64-bit operating system.

C. Single-Subject Experiment for Real-Time Stress Detection

We evaluated the performance of the complete algorithm, including ECG signal processing, index extraction, and stress detection, by conducting a single-subject experiment. According to the self-diagnosis of the Institutional Review Board (IRB) at the School of Engineering at Universidad de los Andes, the minimal risk was mitigated because the subject was one of the authors of this pilot study, who knew in detail the experiment phases and their implications. Three electrodes were connected to record the single-lead ECG signal during the experiment. The experiment consisted of three stages, each lasting 5 minutes, as follows:

- Relaxation stage: The subject was induced into a relaxed state using an audio guide based on the Schultz method [24].
- Musical stimuli stage: The subject was further encouraged to relax by listening to a classical music piece. The chosen piece was Pachelbel's Canon in D major, which has been shown to induce relaxation in previous studies [25].
- Stressor stage: As a stressor, we used the arithmetic task from the TSST [26] protocol. The subject was asked to subtract 13 from 1022 repeatedly, as quickly and accurately as possible. If a mistake was made, the subject had to restart from 1022.

III. Results

A. Performance of the Real-Time Algorithm

To assess the performance of the real-time algorithm in comparison to the offline algorithm, we recorded and processed a 5-minute single-lead ECG signal while the subject listened to a classical musical piece. Simultaneously with the real-time extraction of indices, the raw ECG signal was recorded for subsequent offline processing and extraction of indices. Fig 2 presents the results for several temporal indices (mHR and pNN50), nonlinear indices (SD2 and SD1/SD2), frequency indices (TP, LFresp, and Px), and respiratory indices (mBR and mBwr). The red line represents the results from offline processing, where the entire signal was processed and indices were extracted using sliding windows. The blue line represents the results from real-time processing, where a 180-second buffer of the signal was processed, and indices were extracted using sliding windows. In most of the graphs, the results are identical, and in cases where they differ, the real-time indices follow the same trend.

The similarity of the indices extracted using the two algorithms was assessed by calculating the Pearson correlation coefficient for each index. The results are presented in Fig. 3, where the lowest correlation was observed for the Px index, with a coefficient value of 0.9056.

Given the fundamental importance of ensuring correct real-time processing, we measured the processing time for each second during the execution of the algorithm. The results,

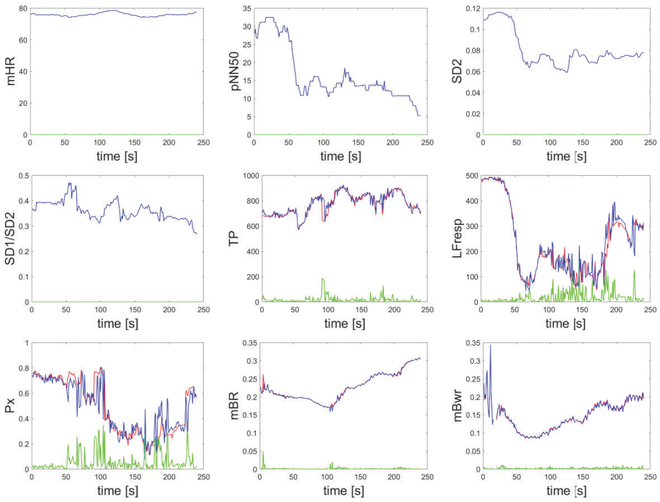

Fig. 2. Comparison of indices extracted through offline processing (red), real-time processing (blue), and the difference between them (green).

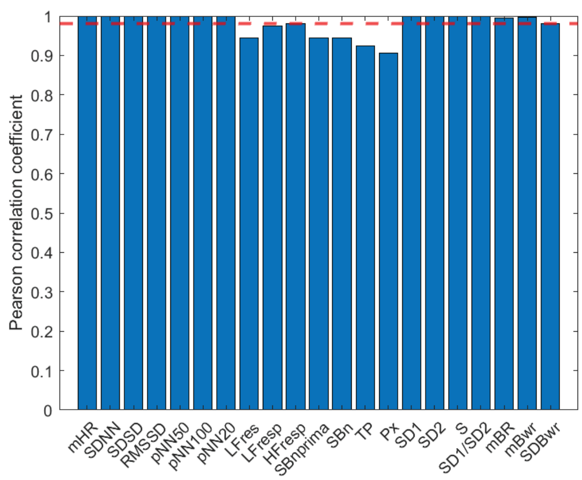

Fig. 3. Pearson correlation coefficient for 21 indices extracted using the offline and real-time algorithms.

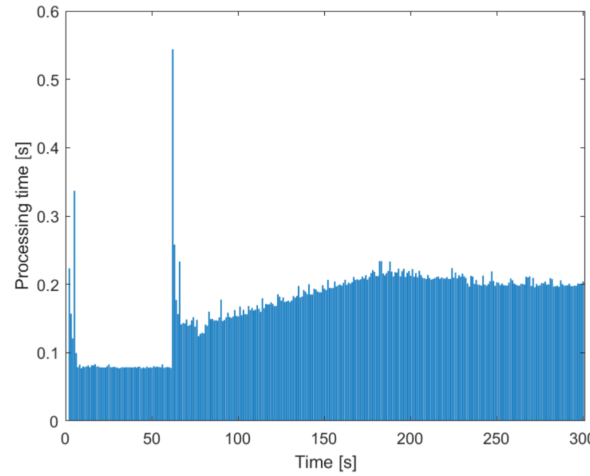

Fig. 4. Processing time per second for the real-time algorithm.

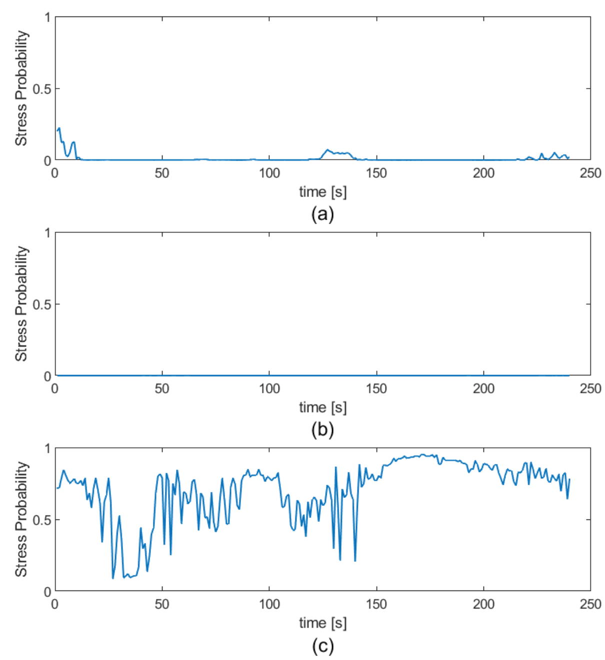

Fig. 5. Predicted stress probabilities for Relaxation Stage (a), Musical Stimuli Stage (b), and Stressor Stage (c).

showing the processing time for each second over a total of 300 seconds of recording, are presented in Fig. 4. The highest value recorded was 0.54 seconds, and the mean processing time was 171.7 ± 55.4 ms.

B. Single-Subject Experiment Results

It is important to emphasize that the inference of the classifier using the function *predict_proba*, provide us with a prediction of the probability of a class occurring, in this case, stress. Consequently, the reader should not confuse the probability results with the level of stress. With this in mind, the predicted stress probabilities for the stages of the experiment are depicted in Fig. 5.

Although obvious differences in the results are obtained, descriptive statistics were computed and are presented in Fig. 6. The statistics reveal a median value close to 0 for the Relaxation and Musical Stimuli stages, whereas the Stressor stage shows a median value of 0.77.

Due to time constraints inherent to real-time algorithms, processing time is a critical parameter for analyzing the results. Therefore, we measured the processing time throughout the experiment to ensure that the condition of acquiring data every second was met and that no data was missing. The results are summarized through the calculation of descriptive statistics for processing time at each stage, as shown in Fig. 7. The median values were 231.41 ms for the Relaxation Stage, 226.9 ms

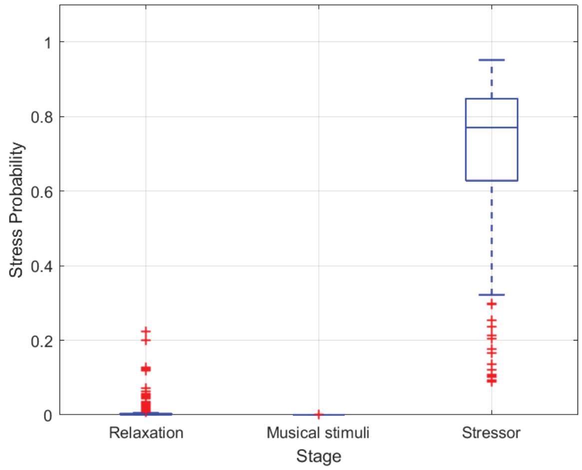

Fig. 6. Descriptive statistics of predicted stress probabilities for the stages.

for the Musical Stimuli Stage, and 242.34 ms for the Stressor Stage.

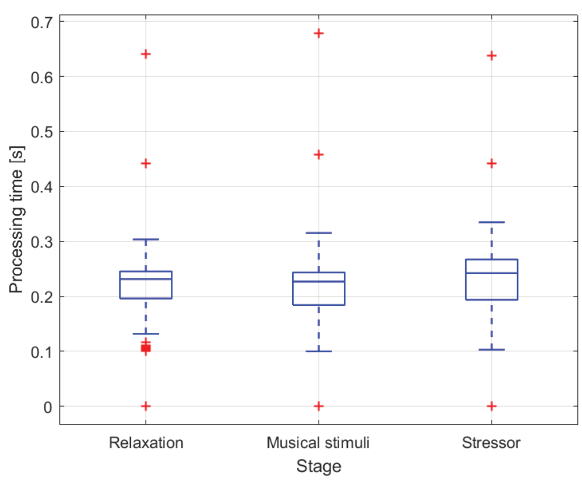

Fig. 7. Descriptive statistics of processing time per stage.

IV. Discussion

This article presents an algorithm for real-time stress detection using a single-lead ECG signal analysis. Various novel methods were applied to extract respiratory indices from the ECG signal, resulting in a comprehensive set of indices from two organ systems. The performance of the real-time algorithm, when compared to the offline processing algorithm, was successful, as illustrated graphically in the indices shown in Fig. 2 and mathematically in the Pearson correlation coefficients presented in Fig. 3, with all coefficients exceeding 0.9. This measure suggests that the proposed processing methodology is as effective as offline processing, yielding reliable results. According to the indices, those in the frequency domain, such as TP, LFresp, or Px shown in Fig. 2, appear to be more susceptible to variations in algorithm computations, resulting in higher error margins compared to other indices. We believe this could be due to the extensive processing involved in extracting these indices—first obtaining the EDR and then applying the OSP method, combined with the reduction of the signal for buffer storage.

Regarding the experiment results, the predicted stress probabilities shown in Fig. 5 align well with the nature of the stages, displaying a very low probability of stress for the Relaxation and Music Stimuli stages, and a high probability of stress for the Stressor stage of the arithmetic task. The descriptive statistics of these results, as presented in Fig. 6, clearly differentiate between the first two stages and the Stressor stage. As expected, an Analysis of Variance (ANOVA) reveals significant differences between the stages (p-value = 0). A post-hoc test with paired t-tests was conducted for pairwise comparisons. The results for Relaxation vs. Stressor (p-value = 3.96×10^{-131}) and Music Stimuli vs. Stressor (p-value = 4.51×10^{-133}) indicate significant differences, as expected. Interestingly, the result for Relaxation vs. Music Stimuli (p-value = 5.09×10^{-8}) also shows significant differences, despite this not being visually apparent in the graphical results. However, a closer inspection demonstrates that the results are consistent. Although these stages have significant differences, for practical purposes, both could be considered non-stress stages.

Regarding the processing time, the outlier values throughout the entire experiment did not exceed 0.7 s as depicted in Fig. 7, with only two upper outliers observed for each stage. Considering that this experiment was conducted on a general-purpose laptop, results demonstrate the feasibility of implementing this real-time algorithm with a high level of reliability.

A limitation of this research, particularly in the single-subject experiment, is the limited statistical representation due to the small sample size. However, the primary objective of this study was to validate the real-time algorithm. Future work involving experiments with a larger population could further confirm the results regarding the predicted stress probabilities across different stages as presented in this article. Additionally, optimizing the code and executing it on a specialized computer could enhance processing time, allowing for the expansion of tasks related to stress analysis.

V. Conclusions

An algorithm for real-time stress detection was implemented and evaluated through a single-subject experiment. This research demonstrated the feasibility of developing a rigorous processing approach based on information from two organ systems, meeting the time processing requirement of less than one second. This processing included ECG signal pre-processing, extraction of the respiratory signal from a single-lead ECG, and the derivation of a comprehensive set of indices using sliding window analysis. Additionally, the results suggested that offline processing of the entire signal is equivalent to using buffer storage, and that choosing the XGBoost model was the right decision due to its performance in the inference process. An additional benefit was the ability to obtain predicted stress probabilities as continuous values, which can be useful for further applications in future work.

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REFERENCES

[1] S. Subramaniam, M. Akay, M. A. Anastasio, V. Bailey, D. Boas, P. Bonato, A. Chilkoti, J. R. Cochran, V. Colvin, T. A. Desai *et al.*, "Grand challenges at the interface of engineering and medicine," *IEEE Open Journal of Engineering in Medicine and Biology*, vol. 5, pp. 1–13, 2024.

[2] L. F. Brown and S. P. Arunachalam, "Real-time estimation of the ECG-derived respiration (EDR) signal," *Biomed Sci Instrum*, vol. 45, pp. 59–64, 2009.

[3] A. Badr, A. Badawi, A. Rashwan, and K. Elgazzar, "Xbeats: A real-time electrocardiogram monitoring and analysis system," *Signals*, vol. 3, no. 2, pp. 189–208, 2022.

[4] C. Crema, A. Depari, A. Flammini, and A. Vezzoli, "Efficient R-peak detection algorithm for real-time analysis of ECG in portable devices," in *2016 IEEE Sensors Applications Symposium (SAS)*. IEEE, 2016, pp. 1–6.

[5] A. A. Jiménez-Ocaña, A. Pantoja, M. A. Valderrama, and L. F. Giraldo, "A systematic review of technology-aided stress management systems: Automatic measurement, detection and control," *IEEE Access*, vol. 11, pp. 116 109–116 126, 2023.

[6] A. Arza, J. M. Garzón-Rey, J. Lázaro, E. Gil, R. Lopez-Anton, C. de la Camara, P. Laguna, R. Bailon, and J. Aguiló, "Measuring acute stress response through physiological signals: towards a quantitative assessment of stress," *Medical & biological engineering & computing*, vol. 57, pp. 271–287, 2019.

[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] C. Varon, J. Morales, J. Lázaro, M. Orini, M. Deviaene, S. Kontaxis, D. Testelmans, B. Buyse, P. Borzée, L. Sörnmo, P. Laguna, E. Gil, and R. Bailón, "A comparative study of ECG-derived respiration in ambulatory monitoring using the single-lead ECG," *Scientific reports*, vol. 10, no. 1, p. 5704, 2020. [Online]. Available: https://drive.google.com/file/d/1fNXZ2OX6Zt2Oqo9XwQi4D4DzE2Tr-YyO/view

[9] F. Suni Lopez, N. Condori-Fernandez, and A. Catala, "Towards real-time automatic stress detection for office workplaces," in *Information Management and Big Data: 5th International Conference, SIMBig 2018, Lima, Peru, September 3–5, 2018, Proceedings 5*. Springer, 2019, pp. 273–288.

[10] M. Abd Al-Alim, R. Mubarak, N. M. Salem, and I. Sadek, "A machine-learning approach for stress detection using wearable sensors in free-living environments," *Computers in Biology and Medicine*, vol. 179, p. 108918, 2024.

[11] A. Greco, G. Valenza, J. Lazaro, J. M. Garzon-Rey, J. Aguilo, C. de la Cámara, R. Bailón, and E. P. Scilingo, "Acute stress state classification based on electrodermal activity modeling," *IEEE Transactions on Affective Computing*, vol. 14, no. 1, pp. 788–799, 2021.

[12] T. Jeon, B. Kim, M. Jeon, and B.-G. Lee, "Implementation of a portable device for real-time ECG signal analysis," *Biomedical engineering online*, vol. 13, pp. 1–13, 2014.

[13] P. Wang, Z. Lin, X. Yan, Z. Chen, M. Ding, Y. Song, and L. Meng, "A wearable ECG monitor for deep learning based real-time cardiovascular disease detection," *arXiv:2201.10083*, 2022.

[14] S. de Vries, F. van Oost, H. Smaling, N. de Knegt, P. Cluitmans, R. Smits, and E. Meinders, "Real-time stress detection based on artificial intelligence for people with an intellectual disability," *Assistive Technology*, vol. 36, no. 3, pp. 232–240, 2024, pMID: 37751530. [Online]. Available: https://doi.org/10.1080/10400435.2023.2261045

[15] A. de Santos Sierra, C. S. Ávila, J. G. Casanova, and G. B. Del Pozo, "Real-time stress detection by means of physiological signals," *Recent application in biometrics*, vol. 58, pp. 4857–65, 2011.

[16] P. Zhang, F. Li, R. Zhao, R. Zhou, L. Du, Z. Zhao, X. Chen, and Z. Fang, "Real-time psychological stress detection according to ECG using deep learning," *Applied Sciences*, vol. 11, no. 9, p. 3838, 2021.

[17] J. Minguillon, E. Perez, M. A. Lopez-Gordo, F. Pelayo, and M. J. Sanchez-Carrion, "Portable system for real-time detection of stress level," *Sensors*, vol. 18, no. 8, p. 2504, 2018.

[18] J. P. Martínez, R. Almeida, S. Olmos, A. P. Rocha, and P. Laguna, "A wavelet-based ECG delineator: Evaluation on standard databases," *IEEE Trans. on Biomedical Engineering*, vol. 51, no. 4, pp. 570–581, 2004. [Online]. Available: https://drive.google.com/file/d/1F3eJlt-qy7xyhs3JWDrpdEDMeQMMsonI/view

[19] J. Mateo and P. Laguna, "Analysis of heart rate variability in the presence of ectopic beats using the heart timing signal," *IEEE Trans. on Biomedical Engineering*, vol. 50, no. 3, pp. 334–343, 2003. [Online]. Available: https://drive.google.com/file/d/1O1NeSKUy34EBp4oKBrm2PRKA-u9KDK4q/view

[20] S. Kontaxis, J. Lázaro, V. D. Corino, F. Sandberg, R. Bailón, P. Laguna, and L. Sörnmo, "ECG-derived respiratory rate in atrial fibrillation," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 3, pp. 905–914, 2019.

[21] C. Varon, J. Lázaro, J. Bolea, A. Hernando, J. Aguiló, E. Gil, S. Van Huffel, and R. Bailón, "Unconstrained estimation of HRV indices after removing respiratory influences from heart rate," *IEEE journal of biomedical and health informatics*, vol. 23, no. 6, pp. 2386–2397, 2018.

[22] A. Arza, J. Garzón, A. Hemando, J. Aguiló, and R. Bailón, "Towards an objective measurement of emotional stress: Preliminary analysis based on heart rate variability," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2015, pp. 3331–3334.

[23] DMLC, "XGBoost python package documentation," https://xgboost.readthedocs.io/en/stable/python/index.html, accessed: Mar. 30, 2024.

[24] F. Stetter and S. Kupper, "Autogenic training: a meta-analysis of clinical outcome studies," *Applied psychophysiology and biofeedback*, vol. 27, pp. 45–98, 2002.

[25] W. E. Knight and N. S. Rickard, "Relaxing music prevents stress-induced increases in subjective anxiety, systolic blood pressure, and heart rate in healthy males and females," *Journal of music therapy*, vol. 38, no. 4, pp. 254–272, 2001.

[26] C. Kirschbaum, K.-M. Pirke, and D. H. Hellhammer, "The 'trier social stress test'–a tool for investigating psychobiological stress responses in a laboratory setting," *Neuropsychobiology*, vol. 28, no. 1-2, pp. 76–81, 1993.