DREAM Fellowship Final Report

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EDA vs. HRV for wearable technology

1. Introduction

In the realm of stress research, scientists explore physiological markers like Exploratory Data Analysis (EDA) and Heart Rate Variability (HRV) to gain insights into stress responses. Multiple studies conducted consistently highlight the superior precision of EDA in capturing nuanced stress reactions compared to HRV. EDA's prompt responsiveness in reflecting sympathetic nervous system activity, showcasing its unmatched accuracy in tracking rapid physiological changes during stress. EDA's unique capability to capture swift fluctuations in physiological arousal, elevating its temporal sensitivity above that of HRV (Posada-Quintero, 2016).

This robust body of evidence consistently positions EDA as a finely tuned instrument for assessing autonomic nervous system responses to stressors. The real-time insights into the dynamic nature of stress reactions establish EDA as a powerful tool for capturing subtleties that may elude traditional stress assessment metrics.

However, the nuanced comparison between EDA and HRV extends beyond accuracy. While EDA excels in capturing rapid stress responses, HRV readings provide unique insights into prolonged stress reactions. HRV's ability to offer a comprehensive understanding of the autonomic nervous system's modulation during extended stress scenarios (Rodriguez-Colon, 1996). HRV's strength lies in unraveling the subtleties of the parasympathetic branch's influence, providing a more comprehensive picture of the body's adaptive responses over extended durations.

This dynamic interplay between EDA's proficiency in capturing rapid stress responses and HRV's ability to delineate prolonged stress reactions sets the stage for the ongoing exploration of their complementary roles. However, amidst the undeniable accuracy of EDA, a practical challenge emerges—the cost. The widespread adoption of EDA as stress assessment tools faces hurdles due to their higher financial implications.

Recent studies have also consider combining the readings for EDA and HRV for better and accurate readings. One notable study delved into the potential applications of EDA and HRV beyond traditional stress contexts, specifically in detecting peripheral abnormalities in type 2 diabetes (Žnidarič et al., 2023). This investigation shed light on the broader relevance of these measures, emphasizing their utility in health-related monitoring beyond conventional stress assessments. Simultaneously, another study examined HRV and EDA as noninvasive indices of sympathetic balance in response to stress, contributing to a more nuanced understanding of the autonomic nervous system's modulation during stress scenarios (Visnovcova et al., 2013).

Additionally, a collective effort to explore the reproducibility of noninvasive measures provided valuable insights into the reliability and consistency of EDA and HRV metrics (Posada-Quintero.,2019). This research offered a robust foundation for understanding the dependability of these physiological markers across different settings. Moreover, the integration of bio signal measurements in virtual reality environments for anxiety detection, alongside assessments of autonomic function during the Cold-Pressor Test and emotional challenges, has further enriched our comprehension of the multifaceted relationship between EDA and HRV in stress scenarios (Ghiasi et al., 2020).

This sets the stage for the current research project, which seeks to reconcile the undeniable accuracy of EDA with the practical constraints of cost, while also recognizing the unique contributions of HRV. The project focuses on comparing EDA and HRV readings from different platforms (BioPac, Empatic, Polar), with a specific emphasis on refining HRV measurements for more accurate stress response readings. Leveraging machine learning techniques, including classification models, the experiment aims to navigate the intricacies of stress responses, drawing insights from primary datasets such as the WESAD dataset and clinical data sourced from our research lab. By embracing the complexities and potential synergies between EDA and HRV, this research endeavors to not only contribute to the ongoing discourse but also provide actionable insights for the advancement of stress assessment methodologies.

2. Methods and Experiment

In this project, an in-depth exploration of machine learning classification models was undertaken to develop a comprehensive understanding of the essential methodologies crucial for the experiment's successful execution. The primary focus centered on distinguishing between baseline and stress arousal, a task approached through the application of diverse machine learning techniques. The core of the work involved the construction and evaluation of varied classification models tailored to discern patterns in physiological markers such as heart rate variability and electrodermal activity. Through this meticulous process, the aim was to illuminate the intricate relationship between machine learning algorithms and the identification of stress-induced physiological responses, contributing valuable insights to the convergence of data science and stress detection.

2.1 Data Used

In the control group, the WESAD dataset, comprising 15 participants, was utilized, primarily leveraging RespiBAN and Empatica data to capture chest-based and wrist-based readings. ECG and EDA data from both devices were employed to assess participants' responses to affective stimuli, including stress and amusement, interspersed with baseline and rest periods. Stress conditions were induced using the Trier Social Stress Test, where participants delivered a 5-minute speech in front of a panel. The participants believed the panel consisted of HR representatives, motivating them to make a positive impression. Mistakes prompted restarts, followed by rest and recovery periods.

Additionally, clinical data previously collected in our lab featured in the study, encompassing EDA and HRV data from Empatica and BioPac, along with HRV data from Polar. This dataset captured stress responses through two methods: a cold pressor and a sudden book drop, separated by rest periods. This dual approach provided a comprehensive understanding of physiological reactions to stress stimuli, contributing valuable insights to the study.

2.2 Experiment

In this study, our primary objective was to compare the effectiveness of Heart Rate Variability (HRV) versus Electrodermal Activity (EDA) and explore the potential for enhancing HRV readings. To conduct the experiment, meticulous data processing was essential for obtaining accurate values. This included precisely determining the start and end times for various stages of the experiment and appropriately labeling baseline and stress periods. The Flirt library in Python played a pivotal role in this process, enabling efficient data processing and presentation in user-friendly datatables. Subsequently, the application of cross-validation techniques allowed us to assess the accuracy of each classification model, with a higher accuracy indicating more reliable readings. We employed three distinct classification models for HRV, EDA, and combined HRV and EDA for Empatica data.

The same methodology was applied to clinical data, which featured information from Empatica, BioPac, and Polar devices. Given that Polar data exclusively provided HRV readings, a singular classification model was developed for this dataset. The conclusive phase involved a comparative analysis between the various measurements derived from both sets of data. This comprehensive approach aimed to not only evaluate the individual effectiveness of HRV and EDA but also to draw meaningful insights through a comparative lens, shedding light on the nuances of physiological responses captured by these different measurements.

The utilization of sophisticated yet accessible techniques, such as the Flirt library and cross-validation, underscored the precision in data processing and analysis, contributing to a robust exploration of the experiment's objectives.

2.3 Data Processing Challenges

During the course of this project, I encountered several data discrepancies, particularly when working with clinical data. It came to my attention that some data points exhibited mismatched timings in relation to the provided baseline and stress response data for a subset of participants, including discrepancies in start and end times. Upon further investigation, I identified that the timings had been mislabeled by an hour, prompting the need for a careful adjustment to ensure accurate data alignment and analysis.

3. Results

Metric	Polar	Clinical Empatica	Biopac	WESAD Empatica
Mean HRV Accuracy	0.575033008	0.530462934	0.565026694	0.545773123
Mean HRV Precision	0.572162165	0.545668421	0.601776391	0.708290312
Mean HRV Recall	0.538232076	0.53868337	0.55205948	0.541873417
Mean HRV F1	0.489133543	0.49939853	0.506462102	0.416272256
Mean HRV AUROC	0.538232076	0.53868337	0.55205948	0.541873417
Mean EDA Accuracy		0.60022807	0.651069164	0.441228877
Mean EDA Precision		0.549755845	0.702564704	0.518206768
Mean EDA Recall		0.584905624	0.653137093	0.416479805
Mean EDA F1		0.536068678	0.615035946	0.324180916
Mean EDA AUROC		0.584905624	0.653137093	0.40563
Mean HRV+EDA Accuracy		0.581805233	0.609186957	0.5625
Mean HRV+EDA Precision		0.572638039	0.629017344	0.6779
Mean HRV+EDA Recall		0.571860811	0.608588678	0.5208
Mean HRV+EDA F1		0.557198692	0.589216829	0.4421
Mean HRV+EDA AUROC		0.571860811	0.608588678	0.5208

In evaluating Electrodermal Activity (EDA) readings across devices, the results indicate that the Biopac device consistently outperformed others, boasting the highest mean accuracy at 65.1%. This superior performance is reflected in precision, recall, and F1 score metrics, which surpassed those of the Polar and WESAD Empatica devices. Conversely, the WESAD Empatica device exhibited a lower mean accuracy of 44.1%, suggesting potential limitations in capturing EDA dynamics compared to the other devices.

For Heart Rate Variability (HRV) readings, the Biopac device demonstrated the highest mean accuracy at 56.5%, showcasing relatively balanced precision, recall, and F1 score metrics. In contrast, the Polar device and WESAD Empatica device yielded lower mean accuracy values of 57.5% and 54.6%, respectively. These findings underscore the device-specific nuances in capturing HRV patterns, with the Biopac device proving relatively more effective.

When combining HRV and EDA for analysis, the results indicate that both Polar and Clinical Empatica devices exhibit competitive mean accuracy values of 58.2% and 60.9%, respectively. This suggests that the combination of HRV and EDA data enhances the overall performance of stress detection models, with Clinical Empatica showing a slightly superior performance across all metrics.

In summary, for EDA readings, the Biopac device proves to be the most effective, while for HRV readings, the Biopac device also stands out with relatively higher accuracy. Combining HRV and EDA data continues to enhance the accuracy of stress detection models across devices. These nuanced insights highlight the interplay between device specificity and physiological signal interpretation, guiding future research endeavors in wearable technology applications for stress detection.

4. Conclusion and Future Work

The achieved accuracy rates, particularly for the WESAD dataset, didn't align with my initial expectations of 70-80%. This discrepancy prompts a comprehensive review of my methods. Despite applying similar data processing techniques and incorporating clinical data, the accuracy levels fell short. Recognizing this, I acknowledge the need to explore a variety of classification models, adjust my testing approaches, and make concerted efforts to enhance accuracy in future iterations of this study.

Moving forward, my focus lies on exploring diverse classification models to discern which ones might yield better results. Additionally, adjusting my testing methodologies to better suit the nature of the data and the stress detection task is crucial for refining my approach. These adjustments are part of an ongoing effort to enhance the accuracy of my stress detection models and extract more meaningful insights from the physiological data at hand.

In summary, while my study has provided valuable insights into the performance of different physiological signals and devices in stress detection, the observed lower accuracy rates signal a need for refinement. Future steps involve exploring diverse classification models, adjusting testing methodologies, and proactively seeking ways to enhance accuracy. The challenges encountered in this study underscore the ongoing nature of my exploration, emphasizing the importance of continuous improvement in machine learning, physiological signal analysis, and stress detection methodologies for the development of accurate models applicable in real-world scenarios.

Citations

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