Preface

This study explores the optimization of Electrodermal Activity (EDA) signals for classifying human emotional states, leveraging advanced signal processing techniques and machine learning algorithms. The motivation for this work arises from the crucial role emotion recognition (ER) plays across various sectors, including healthcare, human-computer interaction, and well-being. By exploring EDA signals, my research aims to enhance the accuracy and reliability of emotion detection systems, thereby contributing to the development of personalized and sophisticated wearable devices that cater to individual emotional needs.

The journey to this dissertation has been both challenging and rewarding, marked by numerous insights and advancements in the field of emotion recognition. The choice of EDA signals, known for their ability to capture the subtle variations in skin conductance associated with different emotional states, provides a robust foundation for developing an accurate and efficient ER system. My focus on optimizing EDA components through sophisticated feature extraction and classification techniques has been pivotal in achieving significant improvements in emotion classification accuracy.

In this research, my primary objectives have been to identify effective methods for decomposing EDA signals into phasic and tonic components, explore optimal segmentation strategies for phasic signals, analyze various windowing approaches, and determine the most effective two-dimensional representation techniques for emotion classification. These objectives have guided the development of a comprehensive process pipeline that systematically addresses each aspect of EDA signal processing and emotional state classification.

The methodology employed in this study encompasses several key stages: data pre-processing, decomposition optimization, segment optimization, and windowing optimization. Initially, EDA signals obtained from the publicly available CASE dataset were pre-processed to eliminate noise using a Butterworth low-pass filter and downsampled to 20Hz for efficient processing. The decomposition of these filtered EDA signals into phasic and tonic components was achieved using cvxEDA and Bayesian EDA algorithms, followed by temporal feature extraction to optimize the EDA components and decomposition methods. The significance of the extracted features was evaluated using Kruskal–Wallis statistical significance tests to ensure their relevance for classification tasks. These significant features were then used to train and test machine learning models, including Support Vector Machine (SVM), Random Forest (RF), and XGBoost (XGB), to classify four distinct emotional states: amusing, boring, relaxing, and scary. The performance of these classifiers was assessed using various metrics, including accuracy, sensitivity, specificity, precision, F1-score, and the area under the curve (AUC), incorporating 10-fold cross-validation and GridSearchCV for robust evaluation and hyperparameter tuning.

One notable finding of this study is the superior performance of phasic EDA signals in emotion detection compared to tonic signals. The cvxEDA decomposition method proved particularly effective, achieving impressive classification accuracy with the XGB model. Additionally, the segmentation of phasic signals revealed that the Second-half of the phasic signals provided more valuable information for emotion detection than the First-half and the whole phasic signal. Finally, the nine-window approach applied to the Second-half of phasic signals further enhanced classification accuracy, demonstrating the importance of optimizing segmentation and windowing techniques.

The results of this research underscore the critical role of EDA signal optimization in refining emotion recognition systems. By focusing on the nuances of phasic signals and employing advanced feature extraction methods, this study achieved a remarkable classification accuracy of 97.08% with the SVM classifier, setting a new benchmark for EDA-based emotion recognition. The implications of these findings extend across a wide range of applications. In healthcare, the advanced emotion recognition system developed in this study can enhance patient monitoring and personalized treatment plans, contributing to better mental health management. Human-computer interaction can improve user experiences by enabling more responsive and emotionally aware interfaces. Other potential applications include stress management, educational platforms, virtual reality experiences, and automotive safety systems, where accurate emotion detection can significantly enhance user safety and comfort.

This dissertation represents a significant step forward in the field of emotion recognition, offering valuable insights and practical solutions for optimizing EDA signals. The methodologies and findings presented here provide a solid foundation for future research and development, paving the way for more advanced and reliable emotion detection technologies.