Multimodal Physiological Signals and Machine Learning for Stress Detection by Wearable Devices

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***Abstract*—Wearable technology is growing in popularity, and wearable devices, such as smartwatches, are used in many applications, from fitness tracking and activity recognition to health monitoring. As the affordability and popularity of such devices increase, so does the amount of personal and unique data that they provide. At the same time, advantages in microprocessor and memory technology enable multiple physiological signal sensors integrated into wearable devices to collect personal and unique data. After the data is extracted, machine learning classification algorithms can help investigate the insights of the data. In this work, we examine the performance of a real-time stress detection system based on physiological signals collected from wearable devices. Specifically, three physiological signals, electrodermal activity (EDA), electrocardiogram (ECG), and photoplethysmograph (PPG) that can be collected through smartwatches, are examined for stress classification. Six machine learning methods are used for the classification in a post-acquisition phase, at a computer, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, Naive Bayes, Logistic Regression, and Stacking Ensemble Learning (SEL). Data from two publicly available datasets are used for training and testing. We examine the accuracy of each modality and the combination of all modalities. According to evaluation results, EDA has the best accuracy when SEL is used for classification. Also, the accuracy of EDA outperforms the other signals and combinations, in comparison with any of the other machine learning approaches, for both datasets. EDA collected from the wearable device has a great potential to be used for a real-time stress detection system.**

***Index Terms*—EDA, ECG, PPG, physiological signals, wearable device, machine learning, affective computing, SVM, KNN, random forest, logistic regression, stacking ensemble learning, ehealth.**

I. Introduction

Mental health includes emotional, psychological, and social well-being. Mental health disorders can affect our mood, thinking, and behavior. The factors that may affect the mental health of an individual range from minor changes in their everyday routine to major changes such as those from the recent pandemic. Several studies examine the impact of lockdown stress and loneliness during the COVID-19 pandemic on mental health [1]–[3]. Meanwhile, as in most surveys that include human subjects, data collection and availability are key aspects for reliable insights. It is important not only to be able to collect the data but also to have a sufficient number of subjects. Advantages in machine learning and data processing can help better analyze the data and provide valuable insights and data correlation [4]. Powerful machine learning methods can be executed fast and provide reliable results. However, a significant issue is the data availability since a large amount of data is needed for a method to provide results.

Wearable technology has become increasingly prominent in our everyday lives. Through tiny, accurate, and cost-efficient sensors, it can be used to track people's movement, collect biometric signals and analyze daily activities [5]. One of the most popular products of consumer wearables is smartwatches. They act as mini smartphones with computational and data transmission capabilities. The rise of popularity in wearable devices is especially of interest to the healthcare industry as there is now the opportunity to access a pool of data from patients remotely. Providing information remotely can be tremendously helpful for proper treatment, as medical professionals can provide personalized care through real-time monitoring of patients' health information. Meanwhile, the amount of data is sufficient to be used with machine learning methods.

The combination of wearable devices with machine learning capabilities has excellent potential for many ehealth applications, in real-time. Signals regarding the Electrodermal activity (EDA), Electrocardiogram (ECG), and Photoplethysmography (PPG) of the patient can be collected through wrist-worn device. These signals can provide lots of information regarding a patient's health. In [6], the authors utilized the Support Vector Machine Recursive Feature Elimination (SVM-RFE) method to detect major depressive disorder based on EDA and achieved an accuracy of 74%. In [7], EDA was used to examine the patients' presurgery stress in a hospital in India, and an accuracy of 85.06% was obtained. In [8], EDA was used to assess the participants' emotional patterns that were aroused by audio-visual stimuli, and the results were 79% for arousal while 69.8% for valence and 71.2% for dominance.

When it comes to ECG and PPG signals, they can also help in emotion detection. In [9], the authors applied classical machine learning methods to tackle the ECG-based emotion recognition task on the AMIGOS database, and the accuracy for valence and arousal achieved 88.8% and 90.2%. In [10], the single pulse feature was extracted from the PPG signal and used to train a 1D-Convolutional Neural Network for short-term emotion detection. The model was tested on the DEAP dataset, which was established with similar experimental activities as the dataset that the authors created for training the model. The method obtained an accuracy of 75.3% and 76.2% for the valence and arousal status respectively. Since multimodal physiological signals have more joint features which can be utilized to train the classification model, they

have the potential to offer better performance than a single signal. As a result, not only is EDA adopted solely for emotion recognition, other physiological signals such as ECG and PPG are often combined with EDA to perform the tasks. In [11], EDA, PPG, Electroencephalography (EEG), and pupil size were utilized to evaluate the anxiety of drivers when they were facing different road conditions.

In this work, we examine the accuracy of a stress detection system based on multimodal physiological signals collected from wearable devices. We examine three signals, EDA, ECG, and PPG, which can be collected from commercially available smartwatches. For the classification, we use six machine learning methods. To examine the performance of our proposed system, we use data from two publicly available databases.

The rest of this paper is organized as follows: Section II discusses the characteristics of the three signals that are used in this work. Section III presents the methodology of our system and Section IV is the results and the discussion. Section V concludes this work.

II. Physiological signals

Emotion monitoring has become an important research area since emotions, such as joy, sorrow, excitement, and anxiety, positively or negatively influence humans' decisions and behaviors. Among the most widely used emotion detection sensors include EDA (or galvanic skin response (GSR)) [12], ECG [13], PPG [14], Electroencephalogram (EEG) [15], Electromyography (EMG) [16], and piezoelectric/electromagnetic generation. Each physiological signal is generated due to different neural or physical activities. In this work, the first three are examined.

A. Electrodermal Activity, Electrocardiogram and Photoplethysmography

Sweating is common to happen when being excited, doing exercises, or in hot weather. The secretion of sweat will change the skin conductance during the process, and this property is called EDA or GSR. As an indicator of how much a human is sweating, skin conductivity can reflect the human's emotions and physiological response. Hence, EDA can be utilized as a physiological indicator to detect emotional changes [17].

Two primary components of an EDA signal are the tonic level and the phasic level. The first is the slow-responsive component of the signal, and it acts as a background feature. Depending on the individual's reaction, skin moisture level, and autonomous adjustment ability, the slow-responsive component is featured with slow rising and slow falling over time and is represented by the skin conductance level (SCL), which is the baseline of EDA. The other component of the EDA is the opposite of SCL's features. The measurement of the phasic level is skin conductance response (SCR). SCR is an instantaneous and rapid fluctuation in the skin conductance level [18]. SCR is a physiological and psychological activation state caused by stimulation.

ECG is a test that records the electrical activity of the heart. ECG can be collected from several points on the human body, while it can be used for a plethora of identification and verification applications [19]. A complete ECG signal cycle consists of a QRS wave, P wave, and T wave. These waveforms are helpful features for analyzing ECG signals. The P wave is a low frontal wave at the beginning of the ECG waveform group, reflecting the electrical excitation of the left and right atrial depolarization process. After the P wave, the sharp and narrow wave group with high amplitude and often composed of several waves is called the QRS complex. The QRS complex represents the whole process of ventricular muscle excitation. After the end of the QRS wave, there is a low, blunt, and broad wave called a T wave. T wave reflects the potential changes during ventricular repolarization.

Finally, the PPG signal is a non-invasive approach to detecting the change in blood volume resulting from heart activity. PPG has a periodic pulse composed of the Systolic and Diastolic phases. In each pulse, PPG consists of a Systolic peak, Dicrotic notch, and Diastolic peak. The systolic peak is always prominent, while other points can quickly be disappeared or are not clear. Similarly, PPG signals include patterned wave groups as well as ECG signals.

B. Wearable Devices

For measuring and collecting physiological signals, the devices have been developed from simple attachable electrodes, cables, and sources of which the mobility is not as satisfactory as wrist-worn devices, which allow the users to perform more activities with ease. Wearable devices such as Empatica E4 [20] and Shimmer3 [21] are widely used for EDA, PPG, and ECG data collection. In [22]–[24], the authors evaluated and compared the feasibility and reliability of using wearable devices, especially Empatica E4 and Shimmers3, to measure physiological signals. Both devices are non-invasive devices that can collect physiological signals in real-time.

Skin temperature (SKT), Blood Volume Pulse (BVP), EDA, and accelerator (ACC) sensors are integrated into Empatica E4. The sampling rate of SKT and EDA is 4Hz, while 64Hz for BVP and 32Hz for ACC. Bluetooth Low Energy (BLE) is used to forward the Empatica E4 signals to a smartphone in real-time. Also, the convenience of the wristband allows users to perform more activities so that the advantages of investigating the insights of physiological signals have been increased.

Unlike Empatica E4, Shimmer3 GSR+ unit has external sensors instead of integrated ones. The GSR+ unit has two electrodes attached to two fingers of one hand. The sampling rates of the Shimmer3 GSR+ unit, which has EDA and PPG sensors, and the ECG unit are all 256 Hz. Again Bluetooth is used for synchronization with a computer.

C. Datasets

Two public datasets, the WESAD (Wearable Stress and Affect Detection) [25] and the CLAS (Cognitive Load, Affect and Stress Database) [26] are used in this study. The physiological signals in the two datasets were collected with Empatica E4 and Shimmers3, respectively. The WESAD dataset is designed for stress and affect detection. Empatica E4 (wrist-worn)

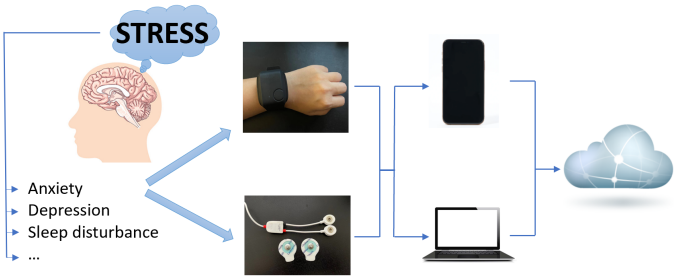


Fig. 1: A wearable stress detection system.

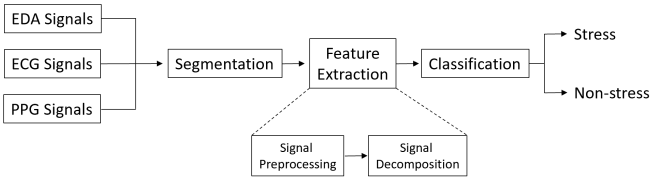


Fig. 2: The pipeline of signal processing and classification.

collected the EDA, BVP, body temperature, and acceleration, while RespiBAN (chest-worn) measured ECG, EMG, EDA, respiration, body temperature, and acceleration. There are 17 participants that were asked to read magazines, watch videos, deliver a public speech, and count numbers while collecting the physiological signals for establishing WESAD, and the signals of 15 participants were successfully recorded.

The signals in CLAS can be utilized for psychological-related research such as mental states, emotion recognition, and stress detection. The authors collected ECG, PPG, EDA, and accelerator data from 62 participants in three experiments with different objectives. The participants attended math, logic, and Stroop tests in the experiments. The sensors used to collect physiological signals for CLAS were Shimmer3 with GSR+ and ECG unit. Specifically, the EDA signals were collected from the fingers via two electrodes in the GSR+ unit.

The main reason for choosing these two datasets in this study is that both datasets have EDA, ECG, and PPG signals, and they were collected during similar activities such as solving math problems so that the comparison between the results based on each dataset could be more informative. Moreover, the EDA data in the two datasets were collected from different skin parts of the participants, which could offer the possibility of discussing the EDA signal quality and validity from different skin parts. Finally, there are three ground truth states (baseline, amusement, and stress) for the data. In our study, we have excluded the data labeled as amusement since it is not aligned with the objective of our study.

III. Methodology

The general framework of the proposed stress detection system is shown in Fig. 1. Data are collected when different stimuli are applied to the subjects, causing them to feel under stress. Wearable devices collect physiological signals, either wrist-based or from the fingers. The signals are forwarded to smartphones or computers for further processing. When the computational tasks are beyond the processing capability of smartphones or computers, the pre-processed data will be sent to the cloud for further processing.

Since physiological signals were usually collected during long activities, more significant insights can be investigated by segmenting the signals into shorter episodes as segmentation can extract more features from time-series data. In the meantime, segmentation can also reduce the computation cost of processing each sample. In this work, we segmented all signals into 30-second episodes and then applied filters and feature extraction methods to process the data. After the procedures, machine learning models train the data and perform stress and non-stress status prediction. The pipeline of signal processing and classification in this study is shown in Fig. 2.

A. Segmentation

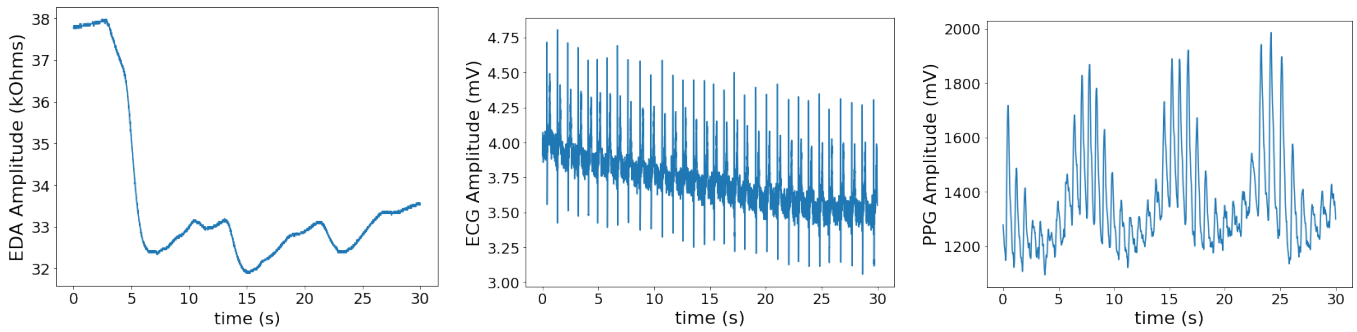
Segmentation is an essential step in data processing, which refers to dispersing data into separate physical units to be processed independently to improve data processing efficiency. After segmentation, the data in the small unit is relatively independent, which is faster and easier to process. A 30-second sliding window was applied to slice all signals into 30-second episodes in our study. Samples of segments from EDA, ECG, and PPG are shown in Fig. 3.

B. Pre-processing

Since each physiological signal has many features, passing all the features to the classification models wastes the computational capability. As a result, only essential features are extracted to train the models. In this study, all signal filtering and feature extracting were processed by the Python NeuroKit2 toolbox. NeuroKit2 is a Python toolbox for processing raw biosignals such as EDA, ECG, and PPG and analyzing the processed signals [27]. Functions in the NeuroKit2 toolbox include automatically applying the cvxEDA method [28] to filter the EDA signals and bandpass filter to ECG and PPG signals for removing the noise.

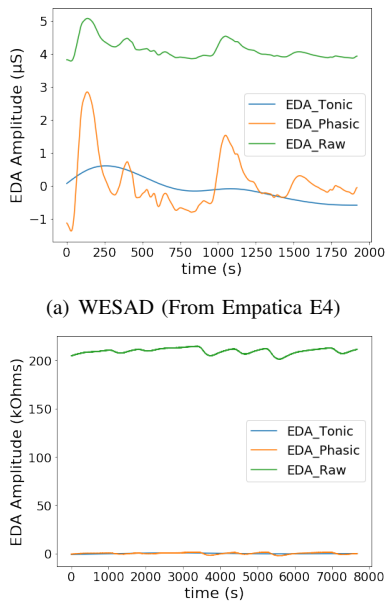
1) EDA feature extraction: Examples of tonic and phasic levels from the EDA signals in WESAD and CLAS datasets are shown in Fig. 4. In [25], the authors of the WESAD dataset explained the features they extracted from the EDA signals in WESAD. Based on this, we determined to extract the features mean_EDA, min_EDA, max_EDA, std_EDA, mean_SCR onsets, mean_SCR amp, mean_SCR recovery in this study. The fluctuations of SCR in EDA signals are displayed in the form of bursts or peaks, shown in Fig. 5. The onset, amplitude, and recovery of SCR can be extracted from the fluctuations.

2) ECG and PPG feature extraction: The peak detection in ECG signals is shown in Fig. 6. The 0, 1, 2, and 3 dotted lines denote the P-peaks, T-peaks, Q-peaks, and S-peaks. The raw PPG signals and processed PPG signals are shown in Fig. 7.



(a) EDA (b) ECG (c) PPG

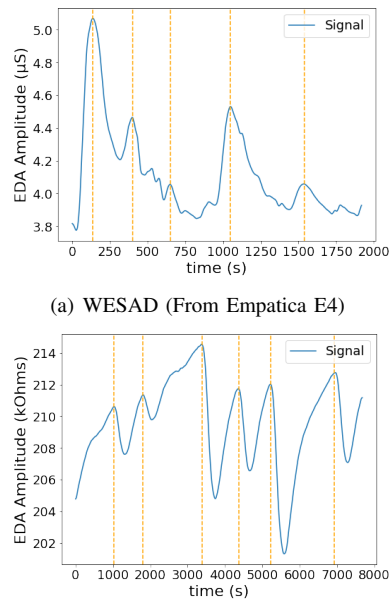
Fig. 3: Samples of different signal segments from CLAS (extracted by Shimmer3 GSR+ Unit and ECG Unit).



(a) WESAD (From Empatica E4)

(b) CLAS (From Shimmer3 GSR+ Unit)

Fig. 4: Extracting components in EDA signals from the two datasets.



(a) WESAD (From Empatica E4)

(b) CLAS (From Shimmer3 GSR+ Unit)

Fig. 5: Detecting peaks in EDA signals from the two datasets.

C. Classification

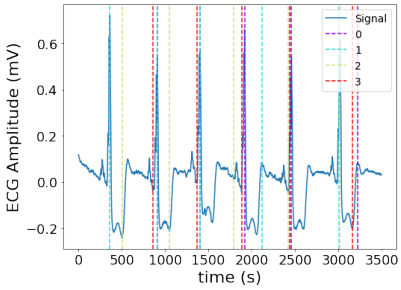
After the pre-processing step, six traditional machine learning methods, Support Vector Machine, K-Nearest Neighbors, Random Forest, Naive Bayes, Logistic Regression, and Stacking Ensemble Learning, are applied to build the classification models. Since these models are less complex and require fewer resources than deep learning models, they are more suitable for this feasibility study.

1) Support Vector Machine (SVM): SVM aims to find the optimal boundary that can divide samples into two classes as far away from any sample as possible. Therefore, the classification task can be converted to an optimization problem if the data is linearly separable. SVM can solve nonlinear classification problems with kernel tricks as well.

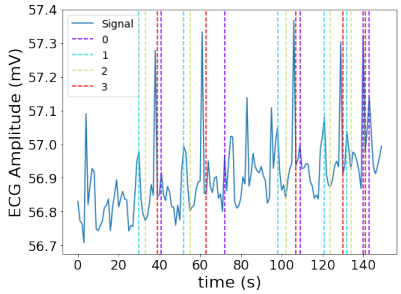
2) K-Nearest Neighbors (KNN): The basic idea of KNN is that the categories of an unknown sample's K nearest neighbors will determine the category of the unknown sample. When addressing the classification problem, the distance between the unknown and other samples needs to be calculated first. Then, according to the principle of majority-voting, the category of the unknown sample is classified as the category with most of K nearest neighbor samples.

3) Random Forest (RF): A random forest is a classifier that consists of multiple Decision Trees, and the categories it outputs are determined by most of the category outputs by the individual trees.

4) Naive Bayes (NB): The Naive Bayes classifier is based on the Bayesian probability theory. Its basic assumption is that the components of the eigenvectors are conditionally independent. The Naive Bayes classifier first examines the class assignment probability under each feature component

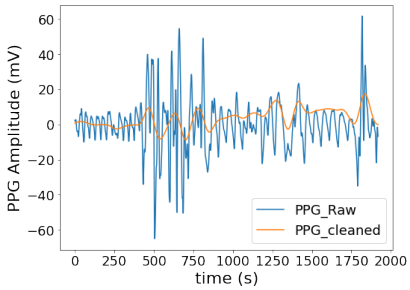


(a) WESAD (From RespiBAN)

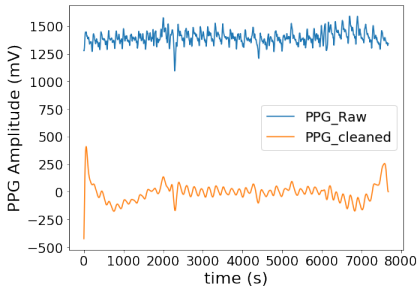


(b) CLAS (From Shimmer3 ECG Unit)

Fig. 6: Samples of detecting peaks in ECG signals.



(a) WESAD (From Empatica E4)



(b) CLAS (From Shimmer3 GSR+ Unit)

Fig. 7: Samples of filtering PPG signals.

separately and then combines the conditional probability of each feature component according to Bayesian probability theory to obtain the final decision result.

5) Logistic Regression (LR): Logistic Regression is a generalized linear model. It assumes that the dependent variable follows a Bernoulli distribution. The result of the LR is not a probability value in the mathematical definition and cannot be used directly as a probability value. This result is often used for weighted summation with other eigenvalues rather than multiplication directly.

6) Stacking Ensemble Learning (SEL): The ensemble learning algorithm is to combine multiple classifiers (base models) to achieve a final classifier (meta model) with a better prediction result. Stacking is one of the ensemble learning methods and is a layered model integration framework suitable for combining different classifiers. In this study, the base models for SEL are SVM, KNN, Decision Tree, NB, and LR, while the meta model is Logistic Regression.

WESAD	SVM	KNN	RF	NB	LR	SEL
EDA	**0.839**	**0.754**	0.763	**0.746**	**0.737**	**0.864**
ECG	0.644	0.381	0.669	0.559	0.517	0.678
PPG	0.678	0.602	**0.788**	0.644	0.559	0.695
ALL*	0.593	0.424	0.636	0.593	0.508	0.678

Table I: Prediction accuracy of applying different models to WESAD. *ALL: EDA+ECG+PPG.

CLAS	SVM	KNN	RF	NB	LR	SEL
EDA	**0.699**	**0.688**	**0.645**	**0.634**	**0.651**	**0.723**
ECG	0.677	0.603	0.602	0.423	0.559	0.670
PPG	0.645	0.581	0.629	0.597	0.629	0.677
ALL*	0.667	0.570	0.618	0.339	0.559	0.677

Table II: Prediction accuracy of applying different models to CLAS. *ALL: EDA+ECG+PPG.

IV. Results and Discussion

Table I and Table II show the classification accuracy with six machine learning models for WESAD and CLAS respectively. The SEL for the binary detection based on the EDA signal in the WESAD dataset has achieved an accuracy of 86.4%, which is the best prediction result in this study.

Additionally, the tables show that the overall prediction accuracy based on EDA signals is more promising than the other modalities for both WESAD and CLAS, except for the Random Forest for WESAD. The reason can be that EDA signals can reflect emotional changes more than ECG and PPG signals. Minor emotional changes that might not affect the participants' ECG and PPG signals could still influence the sensitive EDA signals. For other stress-detection research that compared different combinations of physiological signals, training with multimodal signals does not always offer the optimal results. Multimodal signals are usually fused at three levels: sensor-level fusion, feature-level fusion, and decision-level fusion. In our study, the signal fusion was realized at the feature level, which means the data were from different sensors and combined before being fed into the classifiers. However, the feature-level fusion usually produced a large scale of feature vectors with redundant information, and no statistical test was adopted to prove the significance. Also, signal fusion at the feature level highly depends on feature normalization and selection. The data qualities from different

sensors can also affect the effectiveness of multimodal signal fusion. As a result, multimodal signals fusion at the feature level is not necessarily better than a single signal.

Furthermore, it can be noticed from the tables that the EDA signals in WESAD provide higher prediction accuracy than the EDA signals in CLAS, with all six machine learning methods. The device used to collect the signals for WESAD is Empatica E4, while the one used for CLAS was Shimmer3. Empatica E4 is a wrist-worn device that can sense the signals with more stability than a finger-worn device such as Shimmer3 since artifacts are often produced when the participants move their hands, even if it is a slight movement. Consequently, artifacts can affect the data quality and eventually cause the inaccuracy of model training and prediction.

V. Conclusion

This study aims to assess the feasibility of detecting stress and non-stress mental state with multimodal physiological signals extracted by wearable devices and machine learning methods. Two public datasets, WESAD and CLAS, evaluate the signals with six machine learning models. The SEL method obtained an accuracy of 86.4% based on the EDA signal, which outweighs the other models and signals. Moreover, the overall accuracy of wrist-based EDA in the WESAD dataset is better than that of the finger-based EDA in the CLAS dataset. The research shows that biosignals can predict stress and non-stress states with machine learning methods, especially EDA signals. In further research, the quality and reliability of signals extracted from different devices and different parts of the skin will be explored in detail.

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