

Photoplethysmography-based Stress Detection using Machine Learning

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Abstract— Stress-related health issues are growing day by day. Therefore, it is important to find easier ways for accurate stress tracking on a daily basis. This research is an attempt to use photoplethysmography sensors to track stress levels in individuals. Photoplethysmography is a non-invasive optical technique used to detect blood volume changes in the microvascular bed of tissue. PPG sensors use various features like heart rate variability and pulse amplitude. The main aim is to achieve real-time stress detection on a day-to-day basis. The system utilizes various machine learning algorithms to analyze signals and track stress patterns in people for stress management. The system also includes the use of different classifiers including Random Forest (RF), k-Nearest Neighbors (kNN), and Support Vector Machine (SVM). The paper focuses on providing an effective way to track and manage stress without interfering in the individual's day-to-day activities.

Index Terms— Photoplethysmography, PPG signals, Stress detection, Stress level, Pulse sensor.

I. INTRODUCTION

Modern lifestyle has increased the risk of stress-related disorders that can prove harmful to the overall human well-being. Hence there is an ever-growing need to incorporate effective and easy methods to track stress to ensure the complete mental well-being of an individual on an everyday basis. Photoplethysmography sensors and wearable technology are two methods that can be combined to provide easy and effective stress management. The PPG sensors provide continuous tracking of stress-related physiological signals. This method is easier because it does not interfere with day-to-day activities. Machine learning is a tool that can be used to access an individual's stress patterns thereby providing room for stress management. There are various algorithms that use machine learning to gain insight into an individual's stress patterns. These algorithms can also adapt to each user's specific needs in order to provide personalized stress level detection. Most of the current researches related to stress detection only focus on stress tracking in controlled settings. Therefore there is a need to incorporate innovative ways to track stress in an everyday setting and doing daily activities. This paper explores various machine learning algorithms that provide accurate and effective tracking of stress patterns in day-to-day settings.

A. System Architecture and Block Diagram

In this paper, a sequential technique is used to detect stress using PPG sensors. The system architecture block diagram is displayed in Fig. 1. First, wearable devices are used to gather raw PPG signals. Preprocessing is applied to these signals to improve their quality, such as baseline correction and noise reduction. Important physiological

indicators of stress, like pulse rate and heart rate variability, are retrieved. After then, labeled datasets are used to train machine learning models on these features in order to identify patterns linked to stress. Performance and generalizability of the resulting model are assessed, and it may be customized to take individual differences into consideration.

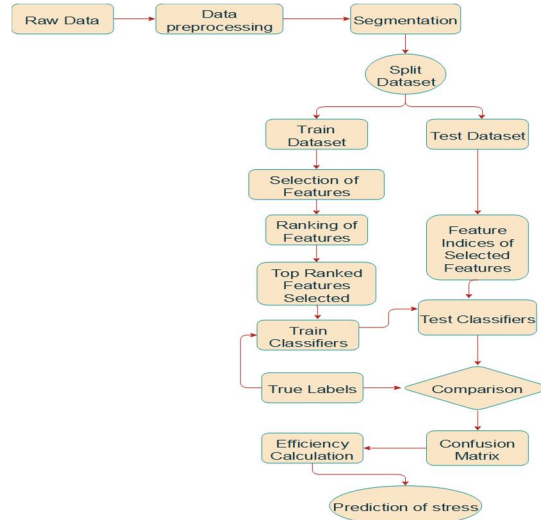


Figure 1. Block Diagram of System Architecture

II. METHODOLOGIES

This section provides information about the methodology we used and the steps we followed including data collection, preprocessing, feature extraction, and selection and classification.

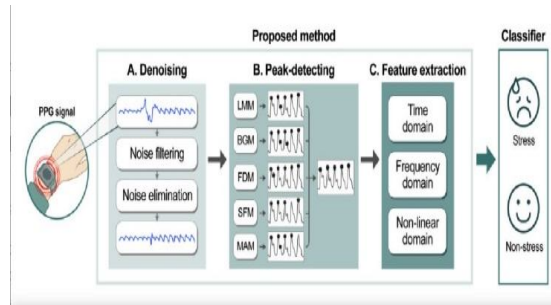


Figure 2. Methodology [1]

A. Data Collection

Collecting data for stress detection using PPG sensors involves continuous monitoring of physiological signals. The PPG sensor, typically part of a wearable device, records real-time information on blood volume changes in peripheral blood vessels[14]. For this study, a readymade dataset was acquired from the ‘kaggle’ website. This dataset includes the data of twenty-seven healthy bachelor students (15 male and 12 female) with a mean age of 21 ± 2 who participated in a study to collect PRV data. A susceptible, low-cost, low-power consumption, and RoHS-compliant PPG sensor was used to collect data from the wrist of the subject. This data was then processed to extract features like heart rate variability and pulse rate, forming personalized profiles for stress detection algorithms. [1]

B. Preprocessing

In the intricate preprocessing phase of Photoplethysmography (PPG) signal analysis, several meticulous steps are taken to refine the raw signals and ensure the accuracy and reliability of subsequent analyses. The initial stage involves Signal Enhancement, wherein bandpass or adaptive filtering techniques are applied to the raw PPG signals as shown in Fig. 2. This process serves to effectively eliminate undesirable noise and motion artifacts that might

distort the true representation of blood volume changes[2]. Fig. 3 shows the Savitzky-Golay filter being applied for smoothing and noise reduction. Following this, Temporal Segmentation comes into play, effectively dividing the continuous PPG signal into distinct time segments. This segmentation enables a more granular analysis, particularly in isolating individual heartbeats and identifying temporal patterns. Fig. 4 shows the ppg signals being divided into interpolated and non-interpolated data for temporal segmentation. The subsequent application of Baseline Correction is crucial for stabilizing the PPG signal. This involves employing methods such as polynomial fitting and wavelet denoising to address any inherent drift or variations in the baseline. By doing so, the stability and consistency of the PPG signal are enhanced, providing a more reliable foundation for subsequent analyses. The final step in the preprocessing phase involves Artifact Removal and Quality Assessment. This step is pivotal for enhancing the robustness of stress detection models. Advanced algorithms are utilized to meticulously identify and eliminate potential disturbances, including motion artifacts, outliers, and low-quality data points[12]. The meticulous removal of these artifacts and the thorough assessment of data quality contribute significantly to the overall reliability of stress detection models, ensuring that the analyzed PPG data accurately reflects the physiological changes associated with stress while minimizing the impact of unwanted influences.

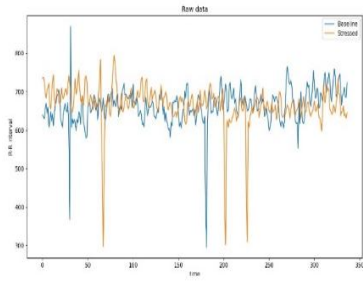


Figure 2. Raw PPG data

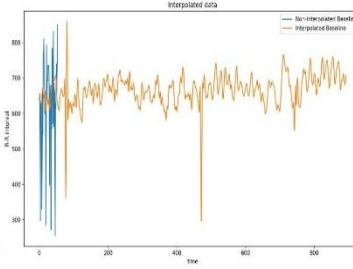


Figure 3. Interpolated data

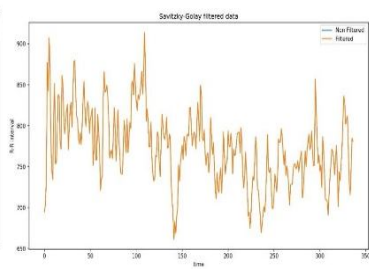


Figure 4. Savitzky-Golay filtered data

C. Feature Extraction

The process of feature extraction plays a pivotal role in discerning relevant physiological patterns associated with stress. Extracting meaningful features from PPG signals involves analyzing various aspects of the signal to capture distinctive characteristics during stress-inducing conditions[5][6].

These are the domains from which the features are extracted

i) Energy Domain

$$P(f) = \int_{f_1}^{f_2} |X(f)|^2 df$$

The energy domain features extracted from PPG signals can provide valuable information about the cardiovascular system. One commonly used energy feature is the Spectral Power.

ii) Heart Rate Variability (HRV)

$$HRV = \sqrt{\text{Var}(RR)}$$

HRV measures the variation in time between successive heartbeats. One common HRV feature is the standard deviation of RR intervals.

iii) Frequency Domain Features

$$\text{Energy Feature} = \int_{f_{\min}}^{f_{\max}} \text{PSD}(f) df$$

iv) Time Domain

$$\text{PPG}(t) = \text{AC} \cdot P(t) + \text{DC}$$

In the time domain, the PPG signal typically consists of a series of peaks and troughs corresponding to the pulsatile nature of blood flow. The most commonly observed peaks are associated with the cardiac cycle.

Here are the extracted features from the domains that are mentioned above

TABLE I FEATURES[3]

Features	Formula	Description
Mean	$\frac{\sum_{i=1}^N X_i}{N}$	This formula calculates the average value of the feature X over all the data points in the PPG signal. The specific feature X can vary based on what you are interested in measuring
Var	$\frac{\sum_{i=1}^N (Feature_i - Mean\ Feature)^2}{N}$	In this formula, you calculate the squared difference between each individual data point of the feature and the mean value of that feature. Summing up these squared differences and dividing by the total number of data points N gives you the variance.
Median	Odd: $Value\ at\ Position\ (\frac{N+1}{2})$ Even: $\frac{Value\ at\ Position\ (\frac{N}{2}) + Value\ at\ Position\ (\frac{N+1}{2})}{2}$	The median represents the middle value in a dataset when it is sorted in ascending or descending order. If the dataset has an even number of values, the median is the average of the two middle values.
A_{max}	$A_{max} = \max(PPG_{signal})$	A_{max} is simply the highest value observed in the PPG signal. This feature is commonly used to represent the peak amplitude of the pulsatile component of the PPG waveform, which is often associated with the arterial blood volume changes.
Range	$Range = \max(Feature) - \min(Feature)$	Refers to the range of values within a certain feature of the PPG signal. The range is calculated as the difference between the maximum and minimum values of that feature.
RMSSD	$RMSSD = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (RR_{i+1} - RR_i)^2}$	The Root Mean Square of the Successive Differences (RMSSD) is a time-domain feature commonly used in heart rate variability (HRV) analysis, particularly for PPG signals
SDSD	$SDSD = \sqrt{\frac{\sum_{i=1}^{N-1} (RR_i - meanRR)^2}{N-1}}$	"SDSD" commonly stands for "Standard Deviation of Successive Differences," and it is often used in the analysis of heart rate variability (HRV).
NNI	$NNI = \frac{\sum_{i=1}^N NNI_i}{N}$	"NNI" typically stands for Normal-to-Normal Interval, which is a term commonly used in the context of heart rate variability (HRV) analysis.
Avg_{HR}	$Avg_{HR} = \frac{Total\ Number\ of\ Heartbeats}{Total\ Time} \times 60$	To calculate the average heart rate Avg_{HR} feature from PPG (Photoplethysmogram) signals, you typically need to identify the individual heartbeats in the signal and then compute the average number of heart beats per minute.
Std_{HR}	$Std_{HR} = \sqrt{\frac{\sum_{i=1}^N (HR_i - Mean_{HR})^2}{N}}$	The standard deviation of heart rate Std_{HR} is a statistical measure that quantifies the amount of variation or dispersion in heart rate values over a period of time.
min_{HR}	$min_{HR} = \frac{60}{\max_{RR}}$	The min_{HR} feature in the context of PPG sensors typically refers to the minimum heart rate calculated from the PPG signal. The heart rate is commonly derived by identifying the time intervals between consecutive heartbeats.
Energy	$Energy = \sum_{i=1}^N x_i^2$	The energy feature is often associated with the calculation of signal energy. Signal energy is a measure of the total "energy" or magnitude of the signal over a specific time interval. For PPG signals, this can be used to capture the overall intensity or amplitude variations in the signal.
abs_sum_diff	$abs_{sum_diff} = \sum_{i=2}^N PPG_i - PPG_{i-1} $	Refers to the absolute sum of differences between consecutive data points in the PPG signal. This feature is a measure of the overall variability or change in the PPG signal.
Peak_VLF	$peak_{VLF} = \max(PPG_{Amplitude_{VLF}})$	The VLF range typically refers to frequencies below 0.04 Hz. In practice, you would perform a frequency analysis, such as Fourier transform or wavelet transform, on the PPG signal to obtain the amplitude values within different frequency bands. The $peak_{VLF}$ would then be the maximum amplitude value within the VLF range.

TABLE II. NUMBER OF SAMPLES AND LABELS COLLECTED FROM EACH SUBJECT [1]

Subject#	Samples	Total labels	Used labels
S01	4,580	228	217
S02	2,164	101	92

S03	1,764	67	42
S04	2,580	56	53
S05	2,267	68	59
S06	17,552	376	370
S07	10,087	105	101
S08	2,752	96	93
S09	1,236	53	50
S10	7,910	119	104
S11	2,555	73	60
S12	1,2296	956	942
S13	3,738	47	45
S14	1,332	61	55

D. Feature Selection

The features that are crucial for achieving the desired level of accuracy, where selected from all the features that we had got in the feature extraction step from different domains. Within the time domain, Mean and Variance were specifically chosen as pivotal indicators, shedding light on overarching shifts in the heart rate signal that could be indicative of stress correlations. The addition of Amplitude of Maximum Peak (amax) was instrumental in uncovering alterations in blood volume associated with stress dynamics..[12]Venturing into the frequency domain, the inclusion of Very Low Frequency (VLF) emerged as significant, shedding light on prolonged regulatory mechanisms tethered to stress responses. Complementary features such as RMSSD, SDSD, NNI_50, and pNNI_50 were deemed essential due to their sensitivity to variations within the nervous system, offering profound insights into the nuanced levels of stress. The incorporation of Average Heart Rate (avg_hr) was instrumental in monitoring the customary elevation in heart rate often associated with stress events. In the energy domain, deliberate choices were made with the inclusion of both Energy and Absolute Sum of Differences (abs_sum_diff). These selections afford a broader perspective, encompassing the overall signal content and capturing stress-related variations in peak differences. The meticulous curation of these features ensures a holistic and comprehensive analysis of physiological responses to stress, thereby enhancing the accuracy.[1]

E. Classifiers

This part investigates the feasibility of using the gathered signals to forecast stressful vs non-stressful periods. Our stress detection models were trained using both individual and broad datasets to assess effectiveness. Various machine learning classification techniques, including Random Forest (RF), k-Nearest Neighbors (kNN), and Support Vector Machine (SVM), were used for stress detection. For ensemble learning in classification[1], RF built several decision trees during training and outputted the class that was the mean of the classes of each individual tree. To predict the sample's class, kNN used the k nearest points and a majority vote. SVM divided the sample space into distinct classes and located hyperplanes. The dataset was used to train each of these classifiers and machine learning techniques and the F1 score as an evaluation metric to analyze their performance[1]. It's important to note that, despite the limitations imposed by small datasets, this investigation has produced insightful knowledge about stress detection and classification techniques.

III. RESULTS

It is difficult to identify stress in daily situations based just on PPG signals . K-Fold cross-validation (K = 5) is how the validity of the models was assessed. In K-Fold Using cross-validation, the data was divided into K equally-sized segments, or folds, and utilized 1 fold for assessment and K-1 folds for training for each iteration. To guarantee that each fold accurately represents the entire, the data is stratified before being divided into K folds. Classifiers under Section II introduce and explain the machine learning techniques were employed. Macro-F1 score² was utilised to assess each method's performance on the gathered dataset. Table. 1 displays the average and standard deviation ($\mu \pm \sigma$) of the F1 scores across the K folds[1]. There were different levels of bias in the physiological data (signals and labels) for individual or group datasets [5]. Consequently, the influence of customization and its ability to raise the dataset's prediction accuracy was showcased. In order to do this, three patients (subjects S06, S10, and S12) were considered for which more information was available. One subject (let's

say, S06) had its data removed first, all other subjects' data was used for training, and half of S06's randomly chosen data was used for testing. The other half of the S06 data was then used for training (together with the data from other users), and the first half of the S06 data was used to test the converted model[1]. An increase in label collection from the user allowed to anticipate stress levels more precisely. To illustrate this method, the data from a single person who had a substantial quantity of accessible labels (Subject S12) was used. For this experiment, a random forest classifier was also employed. The 100 samples were divided randomly and used for testing. The model was initially trained using only 100 samples, and then the training size was increased. This allowed us to use the remaining data incrementally. The trained model was tested using the test data (all from S12) at each step. Figure 2 shows the improvement in prediction performance. As the subject's data size was increased to roughly 300, the model improved. Test and training data were selected for each step 100 times, and the values in the graphic represented the mean of those repetitions, along with the standard deviation of the F1 score over the course of these 100 trials[1].

IV. FUTURE WORK

The future work will focus on addressing the limitations encountered in this research, primarily stemming from a scarcity of datasets. To overcome this challenge, a more extensive set of datasets will be acquired. This expanded data pool enables to delve into a broader exploration of classification techniques, including but not limited to Support Vector Machine (SVM) and Random Forest (RF). By augmenting the dataset and incorporating diverse classification methods, the aim is to enhance the robustness and depth of the analyses, paving the way for a more comprehensive understanding of the subject.

V. CONCLUSIONS

The difficulties of gathering photoplethysmogram (PPG) signals in ordinary environments with adequate labelling are covered in the paper. The study, which used leave-samples-out validation to identify stressful and non-stressful situations based on PPG signals, involved 14 active volunteers. The research customized the classifier and produced encouraging outcomes, with binary classification macro-F1 scores as high as 76%. The favourable results encourage further research into using more sophisticated techniques, such as variations of active learning, in labelling processes. With the use of user activity categories and heart rate variability (HRV), this method seeks to create classifiers that may identify mental health disorders, providing useful resources for the individualized diagnosis and treatment of stress and anxiety in everyday life. The future aim is to broaden the exploration of testing data by incorporating a more extensive array of classification methods. The current study faced limitations in this aspect due to insufficient datasets. This will not only improve the analysis' thoroughness but also lead to a stronger comprehension of stress detection and categorization techniques.

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