

Development of a Wearable Device for Stress Index Using Photoplethysmography Signal Analysis

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# Development of a Wearable Device for Stress Index Using Photoplethysmography Signal Analysis

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### Abstract

This study focuses on developing a device that can measure PPG signals while wearing a wearable band and measuring HRV-based stress index using PPG signals measured at the wrist. We propose an evaluation method for HRV parameters using deep learning of PPG signals. An integrated model of 1D Convolutional Neural Networks (1DCNN) and Residual Networks (ResNet) are used to learn a model for the parameters. The model was uploaded to a microprocessor through quantization for edge computing and calculated into a stress index of the PPG signals. The device uses an ESP32 microprocessor and a MAX30105 PPG sensor module to measure PPG signals. This study aims to implement a system that optimizes edge device computing algorithms through PPG measurement in wearable devices.

This study aims to implement a system that optimizes the stress index algorithm through edge device computing of PPG signals measurement on wearable devices.

**Keywords:** Photoplethysmography, Heartrate variability, Stress index, Edge device computing

## **1. Introduction**

The prevalence of wearable devices has seen a remarkable surge in recent years, providing an unprecedented opportunity to monitor physiological signals for individual health assessment.

Of particular significance is the growing emphasis on stress management, prompting the utilization of wearable devices for stress measurement. Wearable bands offer the convenience of continuous monitoring of stress levels during daily activities, primarily by measuring Heart Rate Variability (HRV). This approach not only enables real-time assessment but also provides valuable insights for effective stress management [1-3]. By leveraging such technology, individuals can enhance their health and well-being while potentially mitigating the risk of stress-related disorders.

Stress assessment methodologies encompass a range of psychological and biological measures, including cortisol and amylase levels, alongside HRV. HRV, in particular, serves as a pivotal indicator of the heart's responsiveness to both internal and external stimuli. A reduction in HRV typically signifies a more uniform and predictable heartbeat pattern, which consistently correlates with compromised autonomic nervous system (ANS) function. This suggests a decreased ability of the body to effectively cope with stressors [4].

Among the array of stress assessment techniques, researchers are increasingly turning to HRV measurement due to its non-invasive nature and its capability to capture ANS activity through electrocardiography.

This study aims to develop a device capable of measuring Photoplethysmography (PPG) signals via wearable bands, enabling the calculation of an HRVbased stress index. We propose an innovative evaluation method for HRV parameters utilizing deep learning algorithms trained on PPG signals obtained from the wrist.

## 2. Method

2.1 Device implementation

In this study, PPG signals were measured using a wearable band-type device after an edge device was developed. For this purpose, signals were measured and processed using an ESP32 microprocessor and a MAX30105 PPG sensor module. ESP32 was used by compiling applications for signal processing such as signal filtering, noise removal, peak detection, and heart rate measurement. The PPG signal measured in MAX30105 is calculated as a stress index through a learning model in ESP32.



Figure 1. Development board for PPG measurement and edge device computing

	RED reflection	IR reflection
1.4	1.4	
1.2	u	
·		
0.0	0.0	
0.6	0.6	
1 1 20 40		<u> </u>
	Heartbeat rate	5e02
1		
0.8	0.8	
0.6	0.6	
0.4	0.4	
0.2	0.2	
·0 0		
ModeSelection O Discover	read waid:00002aw6-0000-1000-0000-0000998.346	*
@ Connect	hande 25 properties:	
O Disconnect	read service usid data 201-18/5-408e-8kc-c5ctc 301914b	
O File Save	usid beb5403e-361-4008-b3%-ea07301b26a8 handle 41	
View Log	properties: read	
OP, button	write notify	
is clicked	try to activate notify.	v

Figure 2. PPG signal monitoring app

#### 2.2 Learning model

This study used data from 22 healthy subjects collected at the University of Sydney. Data was collected from a device similar to a commercial pulse oximeter containing a commercial sensor in a 3D printed finger clip. A three-lead ECG records the heart's electrical signals in parallel [6].

The ecg data was calculated into time domain, frequency domain, and non-linear domain through FFT analysis, and was finally classified into 6 levels through sdnn. The PPG signal from the data was calculated as a learning data set through FIR filter and band-pass filtering. The data was cropped in 3-minute and prepared as input data. The learning model trains and evaluates a 1D CNN-based ResNet using TensorFlow's Keras [7].

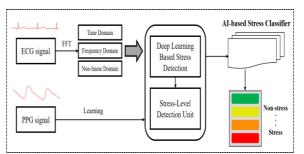


Figure 3. Learning model schematic diagram

# 3. Result

This study utilized the PPG signals from the Mehrgardt et al. dataset as training data. The preprocessed data was then used as input for training a ResNet model based on 1DCNN to calculate stress indices. The model was trained to classify HRV states into 6 categories based on sdnn, achieving an AUROC of 0.969 and an accuracy of 0.842. The trained model was optimized through quantization and uploaded to a microprocessor, enabling real-time stress index analysis to be performed.

# 4. Conclusion

In this study, we focused on the precise measurement of PPG signals, particularly in wearable devices. PPG signals may exhibit biases in signal measurement due to factors such as the measurement environment, highlighting the need for technological advancements to ensure accurate measurements. We recognized the need for detecting changes in blood flow within the epidermis, emphasizing the distinct requirements compared to traditional PPG measurement at the finger. To address this challenge, we developed a sensor module and a learning model capable of robustly capturing pulse and stress indices even during active motion.

Our approach involved signal processing of PPG signals acquired through an ESP32-based edge computing hardware platform. This platform enabled real-time data collection and analysis, essential for accurately measuring PPG signals in dynamic environments.

Moving forward, our platform serves as a foundation for further research aimed at optimizing algorithms for PPG signal analysis across diverse environmental conditions. By leveraging this technology, we anticipate significant advancements in the field of wearable biosensing, facilitating applications ranging from health monitoring to performance tracking.

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