Recording and Analysis of BVP Signals Using the MAX30105 Sensor for Machine Learning-Based Stress Monitoring

Md Santo Ali
Department of Electrical and Electronic Engineering
Rajshahi University of Engineering and Technology,
Rajshahi-6204, Bangladesh
E-mail: shantorueteee19@ieee.org

Al Mahruf Rahman
Department of Electrical and Electronic Engineering
Rajshahi University of Engineering and Technology,
Rajshahi-6204, Bangladesh
E-mail: almahrufrahman@gmail.com

Objectives

- Recording Blood Volume Pulse (BVP) signals using the MAX30105 sensor for physiological monitoring.
- Deploying machine learning techniques to analyze BVP signals for stress detection and classification.

Introduction

Stress is a natural response to challenging situations, leading to mental tension and physiological reactions that help individuals adapt and manage difficulties. Chronic stress may further manifest as various mental and physical health issues, including anxiety, depression, cardiovascular diseases, weakened immune function, sleep disturbances, and cognitive impairments. Modern society, driven by rapid technological advancements and evolving lifestyle demands, has contributed to rising stress levels among individuals, impacting both mental and physical well-being. This necessitates frequent stress monitoring in daily life to ensure timely intervention and management.

Analyzing physiological signals such as electrocardiography (ECG), electroencephalography (EEG), electrodermal activity (EDA), electromyography (EMG), and blood volume pulse (BVP), alternatively known as photoplethysmography (PPG), in combination with machine learning (ML) techniques, has become a leading approach for effective stress monitoring. BVP is a practical surrogate for ECG signals, measuring the electrical activity of the heart through blood volume changes in the microvascular bed tissue. BVP sensors are more cost-effective than ECG and other sensors, making them ideal for intensive use in stress monitoring. This has led to the integration of BVP sensors into commercially available wearables.

BVP sensors utilize low-intensity infrared light to measure changes in blood volume. As light passes through biological tissues, it is absorbed more by blood than the surrounding tissues, allowing PPG sensors to detect variations in blood flow through changes in light intensity, as demonstrated in Fig. 1. The resulting voltage signal is proportional to the blood volume in the vessels, enabling the detection of even minor fluctuations with high precision.

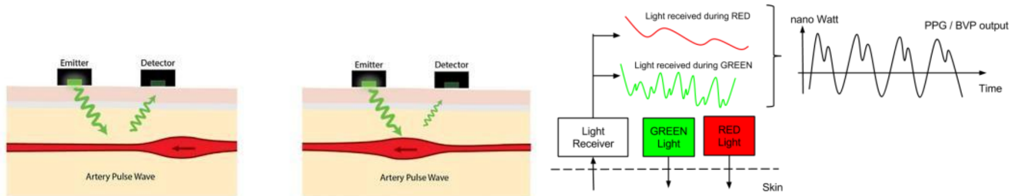

Fig. 1. Illustration of BVP signal acquisition and an Ideal BVP waveform. [1][2]

As mentioned earlier, analyzing physiological signals using machine learning (ML) techniques has become a leading approach for stress monitoring. More specifically, a variant of ML, deep learning (DL), has demonstrated outstanding performance in extracting complex patterns from physiological data, enhancing the accuracy and reliability of stress detection. In this project, we deployed a pretrained deep learning (DL)based model for stress assessment, utilizing BVP signals recorded from a MAX30102 sensor. The subsequent sections describe the materials and methods, deployment, results, discussion, and conclusions.

Materials and Methods

This section provides an overview of the methodology used in this project, including the materials utilized, preprocessing steps, and the prediction system.

Materials

Sensor Module: MAX30102 optical sensor was used to record Blood Volume Pulse (BVP) signals.

Processing Unit: Data acquisition and processing were performed using a microcontroller-based system using Arduino uno.

Software & Libraries: Python-based data processing, filtering, and deep learning (DL) model deployment were conducted using TensorFlow/Keras, NumPy, and SciPy.

Signal Acquisition

The MAX30102 sensor recorded raw BVP signals in real time. The sensor provides raw signals at a sampling frequency of 32Hz. The raw signals contain artifacts and baselines. The raw signals are then preprocessed. The signal acquisition was performed using an Arduino Uno, which interfaced with the MAX30102 sensor to collect and transmit data. The hardware setup and the corresponding output from the Arduino serial plotter are demonstrated in Fig. 2.

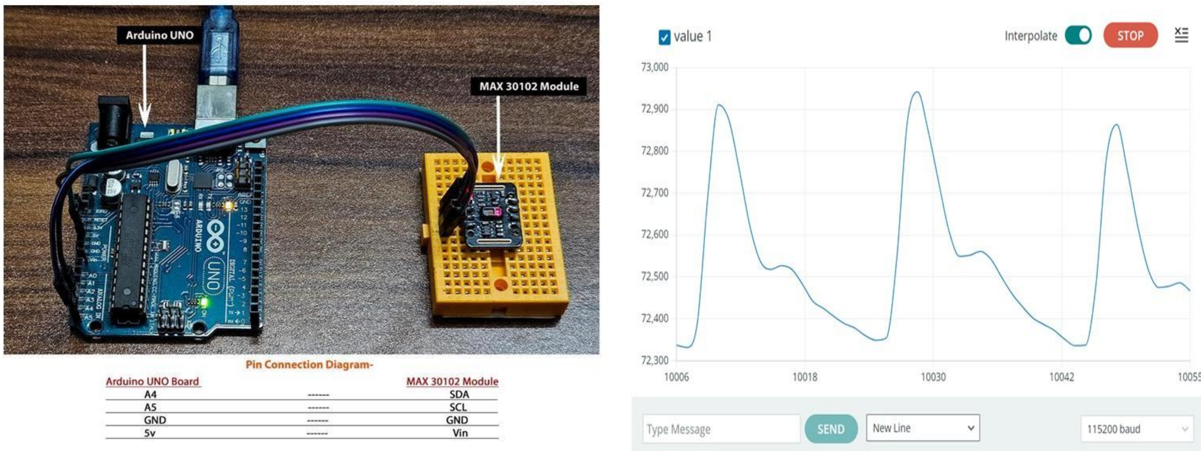

Fig. 2. Illustration of the hardware connection and real-time BVP signal output from the Arduino serial plotter.

Preprocessing

To enhance signal quality and ensure reliable feature extraction, the raw BVP signals undergo the following preprocessing steps:

1. **High-Pass Filtering**: A 2nd-order Butterworth high-pass filter with a cutoff frequency of 0.5 Hz was applied to remove baseline wander and low-frequency noise.
2. **Segmentation**: The filtered signals were divided into fixed-length windows to ensure uniform input for the deep learning model.
3. **Normalization**: **Z-score normalization** was applied to maintain the signal within a standardized range, improving model robustness and convergence.

Prediction Framework

After preprocessing, the segmented BVP signals were fed into a pre-trained deep learning model for stress classification. The model processes the input signals and predicts stress levels based on learned patterns.

The overall workflow, including filtering, preprocessing, and prediction, is illustrated in Fig. 3.

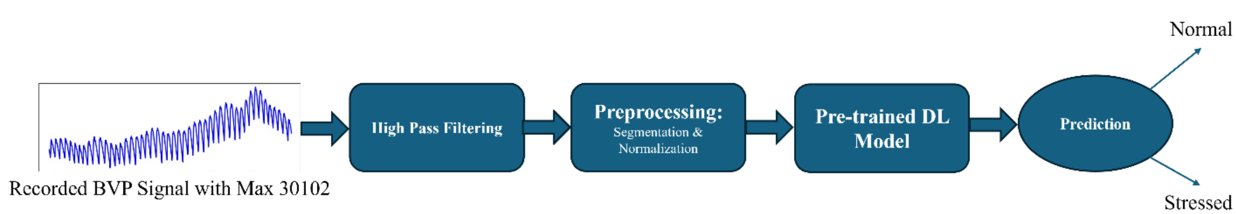

Fig. 3. Block diagram of the stress assessment system, showing BVP signal acquisition, preprocessing (high pass filtering and normalization), and classification using a pretrained deep learning model.

Result

This section presents a comprehensive analysis of the stress monitoring system's performance. The evaluation includes the effectiveness of the preprocessing techniques, the classification accuracy of the deployed deep learning model, and a comparison with existing approaches. The results are analyzed to assess the reliability of the system in real-time stress detection.

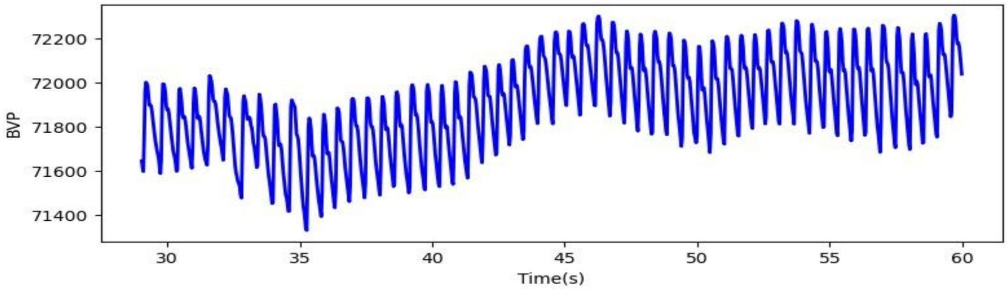

Fig.4 Raw BVP signal collected from MAX 30102 sensor

Fig. 4 presents the raw BVP signal, where the Y-axis values are relatively high, ranging from approximately 71,400 to 72,200. These values represent the direct sensor readings, which include both the DC component (baseline) and the AC component (fluctuations related to heartbeats). However, the presence of baseline drift and noise can make further analysis challenging.

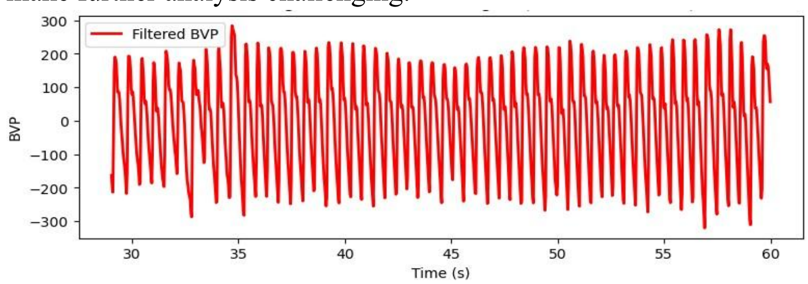

Fig. 5. High-pass filtered BVP signal

To address this, Fig. 5 shows the BVP signal after applying a high-pass filter, which removes the lowfrequency baseline drift while retaining the essential high-frequency variations. As a result, the Y-axis values shift to a much smaller range, approximately between -300 and 300, centering the signal around zero. This transformation highlights the actual fluctuations in blood volume changes while eliminating unnecessary background noise.

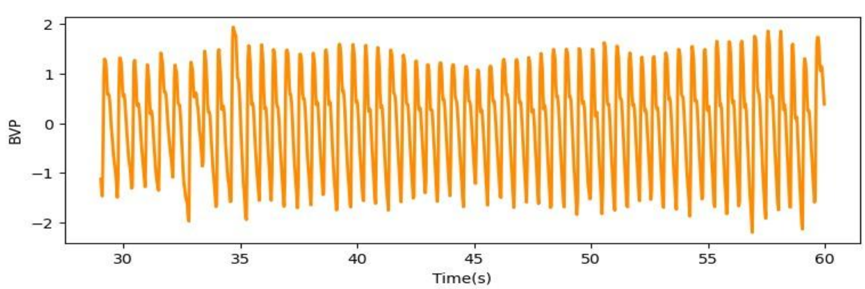

Fig.6. Normalized BVP signal

Finally, Fig. 6 presents the normalized BVP signal, where the amplitude is further adjusted to a standardized scale, typically between -2 and 2. Normalization ensures consistency across different recordings, making the data more suitable for machine learning models. The stepwise changes in the Y-axis across the figures reflect the progressive refinement of the BVP signal, from raw acquisition to a clean, standardized format for stress analysis.

Fig. 7 illustrates the prediction outputs for two cases: one corresponding to a normal state and the other indicating a stressed condition.

```
#Prediction'
y_pred_prob = model.predict(X_scaled.reshape(-1, 960, 1))

y_pred = np.argmax(y_pred_prob, axis=1)
for pred in y_pred:
    if pred == 1:
        print("Stressed")
    else:
        print("Normal")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 193ms/step
Stressed
```

```
#Prediction'
y_pred_prob = model.predict(X_scaled.reshape(-1, 960, 1))

y_pred = np.argmax(y_pred_prob, axis=1)
for pred in y_pred:
    if pred == 1:
        print("Stressed")
    else:
        print("Normal")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 382ms/step
Normal
```

Fig. 7. Prediction Outputs for Normal and Stressed States.

The results demonstrate significant potential for real-time stress monitoring in real-world settings.

Discussion and Conclusions

This project demonstrates the effectiveness of using the MAX30102 sensor for real-time Blood Volume Pulse (BVP) signal acquisition and machine learning-based stress detection. The preprocessing steps—high-pass filtering and normalization—enhanced signal quality, allowing accurate stress classification. The deep learning model successfully distinguished between normal and stressed states, proving the system's potential for real-time stress monitoring in real-world settings. Compared to traditional methods, BVPbased monitoring is cost-effective, portable, and accurate, making it ideal for wearable devices. While the results are promising, further improvements can be made by refining the model with diverse data and realtime adjustments for individual variability. Overall, this approach holds significant promise for continuous, non-invasive stress monitoring and can be integrated into wearable technology for personalized health management.

References

[1] Ansys, "Modeling Human Skin and Optical Heart Rate Sensors," [Online]. Available: https://www.ansys.com/blog/modeling-human-skin-and-optical-heart-rate-sensors. [Accessed: 11Feb-2025].

[2] Empatica, "Utilizing the PPG/BVP Signal," [Online]. Available: https://support.empatica.com/hc/en-us/articles/204954639-Utilizing-the-PPG-BVP-signal. [Accessed: 11-Feb-2025].