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A Non-invasive Multi parameter System for Early Detection of Cardiovascular Stress

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ABSTRACT: Cardiovascular dysfunction is often preceded by subtle changes in skin microcirculation due to disturbances in physiological homeostasis during physical or emotional stress. Early detection of these microcirculatory changes provides important insights into cardiovascular health. This project proposes a multi-sensor system integrating Electrocardiogram (ECG), Pulse Oximeter with Perfusion Index (PI), and Galvanic Skin Response (GSR) to monitor cardiac activity, vascular perfusion, and autonomic responses during stress. The Perfusion Index (PI) obtained from the pulse oximeter serves as an indicator of peripheral blood flow and microvascular perfusion, enabling better assessment of circulatory variations. Data collected from subjects before, during, and after induced stress are processed using signal processing techniques and a Multi-Layer Perceptron (MLP) algorithm to identify patterns associated with cardiovascular variations. A portable skin perfusion monitoring prototype is developed as a low-cost and scalable solution for early cardiovascular stress detection in healthcare monitoring and future long-duration space missions, with system control implemented through an Arduino platform.

KEYWORDS: Cardiovascular Dysfunction, Skin Microcirculation, Electrocardiogram (ECG), Pulse Oximeter, Perfusion Index (PI), Galvanic Skin Response (GSR), Stress Detection, Multi-Sensor System, Arduino-Based Prototype**.**

I. INTRODUCTION

Cardiovascular dysfunction often causes subtle changes in skin microcirculation, which can act as early indicators of physiological imbalance during physical or emotional stress. Monitoring parameters such as skin blood flow, vascular perfusion, and autonomic responses provides valuable insights into cardiovascular health and stress-related physiological changes. Traditional cardiovascular monitoring systems are often complex or invasive, making continuous monitoring difficult outside clinical environments. This creates the need for a portable and non-invasive system capable of assessing cardiovascular responses in real-time, particularly in everyday healthcare monitoring and specialized environments such as long-duration space missions. To address this need, this project proposes a multi-sensor monitoring system integrating Electrocardiogram (ECG), Pulse Oximeter with Perfusion Index (PI), and Galvanic Skin Response (GSR) sensors. The Perfusion Index (PI) obtained from the pulse oximeter provides an indicator of peripheral blood flow and microvascular perfusion, helping to detect circulatory variations during stress conditions. A portable and low-cost prototype is developed using an Arduino-based platform to monitor cardiovascular signals and skin perfusion. The system offers a simple, scalable, and minimally invasive solution for continuous cardiovascular stress monitoring and potential applications in healthcare and space health monitoring.

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II. DATA ACQUISITION AND SYSTEM ARCHITECTURE

A. DATASET COLLECTION

Physiological data for this study were obtained from publicly available biomedical datasets containing cardiovascular-related signals. The dataset includes electrocardiogram (ECG), heart rate (BPM), pulse oximeter measurements with Perfusion Index (PI), and galvanic skin response (GSR). The Perfusion Index (PI) indicates peripheral blood flow and microcirculatory changes. These physiological signals were recorded using wearable or clinical monitoring devices under normal and stress-related conditions and were used to train and evaluate the proposed machine learning model.

Table.1. Dataset Summary

Class	**No. of Samples**	**Training Set**	**Testing Set**
Normal Condition	1,000	800	200
Abnormal Condition	1,000	800	200
Total	**2,000**	**1,600**	**400**

Table2. Sensor Parameters

Parameter	**Description**
ECG Signal	Monitoring electrical activity of the heart
Pulse Oximeter – Perfusion Index (PI)	Indicator of peripheral blood flow and microvascular perfusion
Heart Rate (BPM)	Beats per minute derived from pulse oximeter signal
GSR (μS)	Skin conductance response indicating stress level
Microcontroller	Arduino Nano
Communication Module	ESP8266 Wi-Fi module

Prior to model training, the dataset underwent data preprocessing steps including noise filtering, normalization, and feature extraction to ensure consistency and improve model performance. The processed data were then used to train a Multi-Layer Perceptron (MLP) classifier implemented in Python, which classifies the physiological condition into normal or abnormal cardiovascular states.

III. PROPOSED METHODOLOGY

The proposed system is a multi-sensor platform designed to monitor skin microcirculation and detect cardiovascular stress. It integrates Electrocardiogram (ECG) for cardiac activity monitoring, a Pulse Oximeter to measure heart rate and Perfusion Index (PI), and Galvanic Skin Response (GSR) to detect stress-related autonomic responses. The Perfusion Index (PI) represents the ratio of pulsatile to non-pulsatile blood flow and indicates peripheral perfusion changes. These sensors are connected to an Arduino-based controller for real-time data collection. The acquired signals are processed using signal processing techniques and a Multi-Layer Perceptron (MLP) algorithm to classify cardiovascular stress conditions. The system is designed to be portable, low-cost, and non-invasive, and the collected data are visualized as real-time graphs on the ThingSpeak cloud platform for remote monitoring.

1. Sensor Module

The sensor module is the core data collection unit of the system. It integrates three key sensors: an Electrocardiogram (ECG) sensor for monitoring the heart's electrical activity, a Pulse Oximeter sensor to measure heart rate and Perfusion Index (PI), and a Galvanic Skin Response (GSR) sensor to assess skin conductance as an indicator of stress-induced autonomic responses. The PI parameter helps evaluate peripheral blood flow and microvascular circulation, which can change during stress conditions. These sensors work in parallel to capture real-time physiological data from the subject, and the readings are transmitted to the Arduino controller for further processing.

2. Signal Processing Module

This module is responsible for filtering and pre-processing the raw sensor data. Signal processing techniques Kalman filter and butterworth, such as noise reduction, normalization, and feature extraction, are applied to ensure that the data is clean and suitable for analysis. Key features such as heart rate variability from ECG, perfusion trends from PI

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obtained through the pulse oximeter, and GSR patterns are extracted to detect subtle physiological changes that may indicate stress or early signs of cardiovascular dysfunction.

3. Machine Learning Module

The processed data is then fed into a machine learning algorithm, specifically a Multi-Layer Perceptron (MLP). This module classifies the data based on patterns correlated with cardiovascular stress. The MLP is trained on a dataset containing normal and stress-induced physiological conditions, enabling it to identify deviations in ECG, PI, and GSR parameters. Once trained, the system can classify abnormalities in real time and assist in the early detection of potential cardiovascular issues.

4. Arduino Control Module

This module serves as the interface between the sensors and the processing unit. The Arduino controller manages data acquisition from the ECG, Pulse Oximeter (PI), and GSR sensors, and sends this data to the signal processing and machine learning modules for analysis. The controller ensures that the sensors operate properly and that physiological data are transmitted continuously. It also communicates the processed data to the ThingSpeak IoT platform, enabling real-time visualization and remote monitoring.

5. User Interface Module

The user interface (UI) module is designed for visualization and interaction with the system. It provides a real-time display of physiological parameters, including ECG signals, heart rate, PI values, and GSR responses. The system uploads these parameters to the ThingSpeak cloud platform, where they are displayed as graphical trends and real-time dashboards, allowing healthcare providers or users to monitor cardiovascular stress remotely and receive alerts if abnormal patterns are detected.

6. Prototype

The prototype module is a compact and portable unit that houses the sensors, Arduino controller, communication module, and power supply. The system is designed to be lightweight and easy to use in both clinical and home monitoring environments. A rechargeable battery is used to ensure portability and continuous operation. The power module efficiently distributes power to all sensors and the controller, ensuring stable data acquisition and uninterrupted physiological monitoring.

Working of the System

The system continuously collects physiological data using ECG, Pulse Oximeter, and GSR sensors placed on the subject's body. The ECG sensor records the electrical activity of the heart to determine heart rate and rhythm. The Pulse Oximeter measures blood oxygen saturation (SpO_2), heart rate, and Perfusion Index (PI). The Perfusion Index (PI) represents the ratio of pulsatile to non-pulsatile blood flow and provides information about peripheral perfusion and microcirculatory changes. The GSR sensor measures variations in skin conductance associated with stress responses. In the signal processing stage, the collected signals undergo noise filtering, normalization, and feature extraction. Important features such as heart rate variability from ECG, SpO_2 and PI trends from the pulse oximeter, and GSR patterns are extracted. These features are then analyzed using a Multi-Layer Perceptron (MLP) classifier trained with datasets representing normal and stress-related physiological conditions.

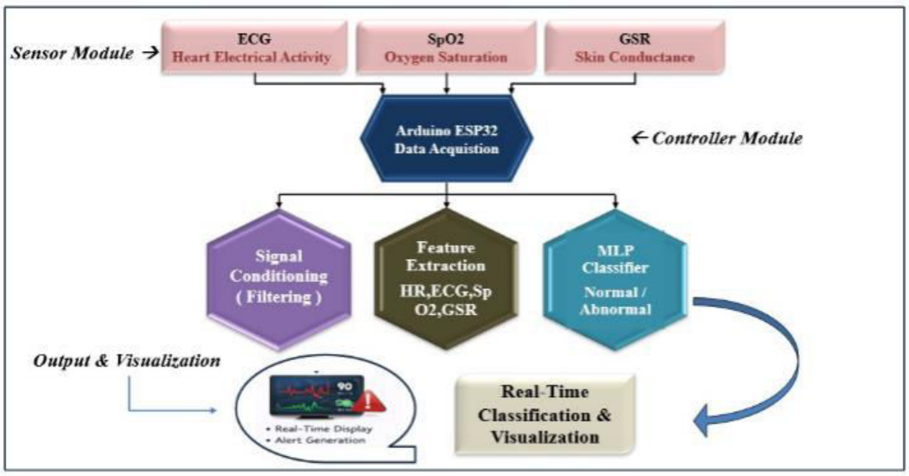

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Table.3. Feature-Based Classification Thresholds For Cardiovascular Stress Detection

Feature	Symbol	Threshold / Range for Abnormal Condition
Heart Rate	HR (BPM)	< 60 BPM or > 100 BPM
Blood Oxygen Saturation	SpO_2 (%)	< 95 %
Perfusion Index	PI	< 0.7 (Low Perfusion) or > 4.5 (High Perfusion)
Galvanic Skin Response	GSR (µS)	> 30 µS

If abnormal patterns are detected, the Arduino controller triggers an alert through the user interface. The physiological data are also transmitted to the ThingSpeak cloud platform, where ECG, SpO_2, PI, and GSR values are displayed as real-time graphs for remote monitoring. The system prototype is powered by a rechargeable battery, making it portable and suitable for continuous cardiovascular stress monitoring in healthcare applications and long-duration space missions.

IV. MULTI-LAYER PERCEPTRON ARCHITECTURE

The Multi-Layer Perceptron (MLP) is a feed-forward artificial neural network widely used for classification and prediction tasks. It consists of three main layers: input layer, hidden layers, and output layer, where neurons are interconnected through weighted connections. MLP models learn complex nonlinear relationships between input features and output classes by adjusting weights during training. Artificial neural networks are inspired by the structure of the human brain, where neurons communicate through synaptic connections. Similarly, in an MLP network, artificial neurons are arranged in layers and transmit information through mathematical operations such as weighted summation, bias addition, and activation functions.

1. Input Layer

The input layer is the first layer of the neural network where raw data is provided to the model. Each neuron in the input layer represents one feature of the dataset. In this study, the input features include physiological parameters such as heart rate, SpO_2, Perfusion Index (PI), and GSR values collected from sensors. The number of neurons in the input layer depends on the number of features used in the dataset. The input layer does not perform complex computations; it simply forwards the input values to the hidden layers for further processing.

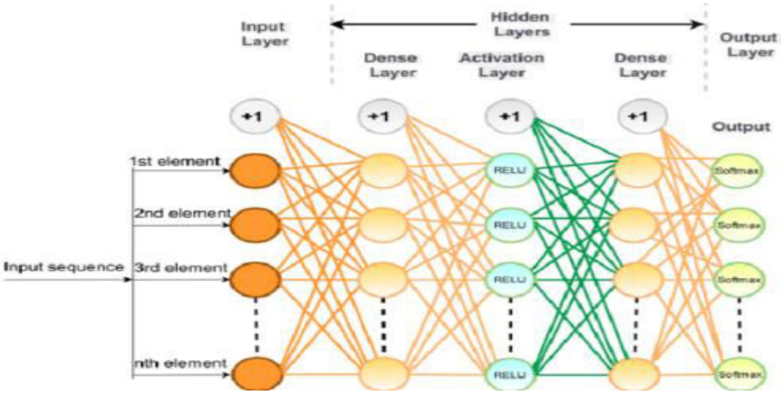
2. Hidden Layers

The hidden layers are responsible for learning patterns and extracting meaningful representations from the input data. Each neuron in a hidden layer is connected to all neurons in the previous layer through weighted connections, forming a fully connected (dense) layer. The output of each neuron is calculated using the following equation:

$$Z = WX + b$$

Where:

- Z is the output of the layer before activation.
- W is the weight matrix (these are learnable parameters).
- X is the input data (or outputs from the previous layer).
- b is the bias (also learnable parameters).



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To introduce non-linearity into the model, an activation function is applied after this transformation. In this system, the ReLU (Rectified Linear Unit) activation function is used, defined as:

$$f(x) = \max(0, x)$$

ReLU converts negative values to zero while retaining positive values, allowing the model to learn complex nonlinear patterns and improving training efficiency.

3. Output Layer

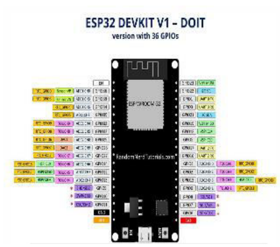
The output layer produces the final classification result of the neural network. In this study, the model performs binary classification, identifying whether the physiological condition is normal or abnormal cardiovascular stress. The output layer uses a Softmax activation function, which converts the network outputs into probability values that sum to one. The class with the highest probability is selected as the predicted output.

Training Process

During training, the network performs forward propagation, where input data passes through the layers to generate predictions. The difference between predicted output and actual label is calculated using a loss function, typically cross-entropy loss for classification tasks. The network then updates its weights using optimization algorithms such as backpropagation and gradient descent, allowing the model to gradually improve its accuracy in detecting cardiovascular stress patterns.

V. HARDWARE DETAILS

1. ESP32 Microcontroller



ESP32 is a low-cost, low-power system-on-chip (SoC) developed by Espress if Systems with integrated Wi-Fi and Bluetooth connectivity. It is powered by a dual-core Tensilica Xtensa processor and includes built-in RF components and power management modules. Due to its high processing capability and wireless communication features, ESP32 is widely used in IoT-based health monitoring systems for real-time data transmission.

2. ECG Sensor

The Electrocardiogram (ECG) sensor is used to measure the electrical activity of the heart. It detects the electrical signals generated during each heartbeat through electrodes placed on the body. ECG signals help determine heart rate, rhythm, and cardiac abnormalities. In this system, ECG data is used to monitor cardiovascular activity and detect irregular heart conditions associated with stress or cardiac dysfunction.

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3. Pulse Oximeter Sensor (MAX30100)

The MAX30100 is an integrated pulse oximeter and heart-rate sensor that measures blood oxygen saturation (SpO_2), heart rate, and Perfusion Index (PI). It uses red and infrared LEDs with a photodetector to measure light absorption in blood vessels. The sensor includes ambient light cancellation, a 16-bit ADC, and low-power operation, and communicates with the microcontroller through an I^2C interface, making it suitable for wearable and medical monitoring systems.

4. GSR Sensor

The Galvanic Skin Response (GSR) sensor measures the electrical conductance of the skin, which varies with sweat gland activity controlled by the sympathetic nervous system. Changes in skin conductance indicate stress or emotional responses. Electrodes attached to the fingers measure these variations, helping to evaluate physiological stress levels.

5. Arduino Microcontroller

Arduino is an open-source microcontroller platform used for building embedded systems and sensor-based applications. It provides multiple digital and analog I/O pins for interfacing with sensors such as ECG, pulse oximeter, and GSR. Arduino boards are programmed using the Arduino IDE with C/C++, enabling efficient data acquisition and processing.

6. Lithium-Ion Battery

A Lithium-ion (Li-ion) battery powers the prototype system. It provides high energy density, low maintenance, and long cycle life, making it suitable for portable medical monitoring devices. Li-ion batteries typically operate around 3.6 V, ensuring stable power supply for continuous system operation.

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VI. HARDWARE IMPLEMENTATION

Figure: (a) Fully developed hardware prototype of the proposed cardiovascular stress monitoring system integrating ESP32/Arduino, ECG sensor, pulse oximeter, and GSR sensor. (b) Finger placement on the GSR sensor and pulse oximeter for real-time acquisition of physiological parameters such as SpO_2, heart rate, perfusion index (PI), and skin conductance. (c) ECG electrode placement used to measure the electrical activity of the heart and obtain ECG signal signals for cardiovascular analysis. (d) LCD display showing the real-time output of the calculated physiological parameters.

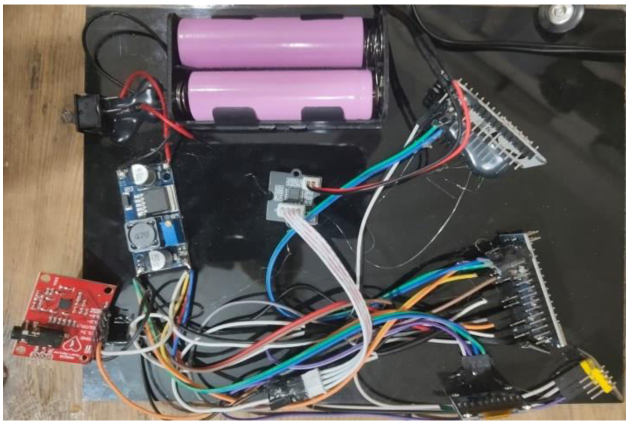


Figure (a)

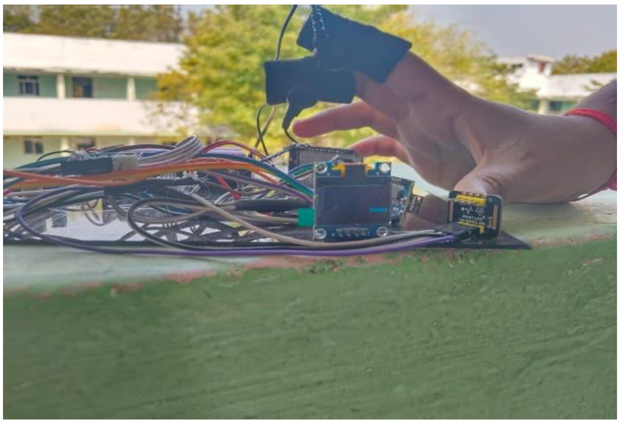
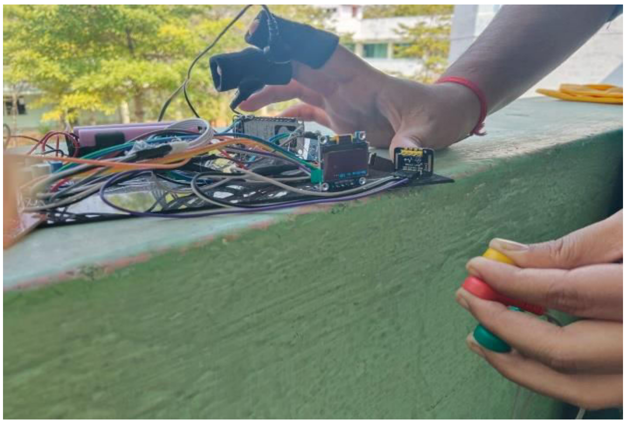


Figure (b)



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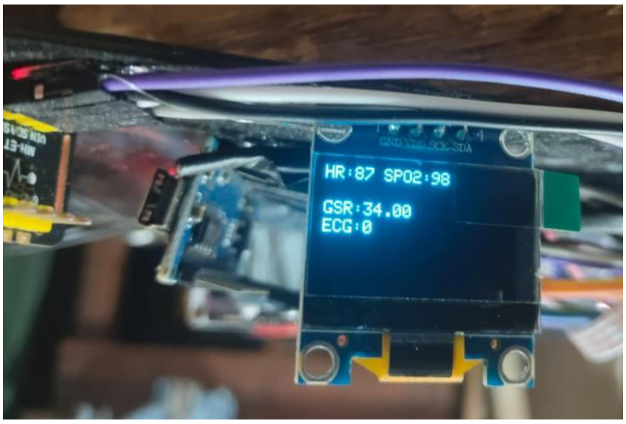

Figure (d)

VII. EXPERIMENTAL RESULTS

Figure: (a) LCD display showing the calculated physiological parameters obtained from the sensors. (b) System message indicating that the collected data is being transmitted to the IoT platform for remote monitoring. (c) Classification output displaying the Normal cardiovascular condition detected by the system. (d) Classification output displaying the Abnormal cardiovascular condition detected by the system.

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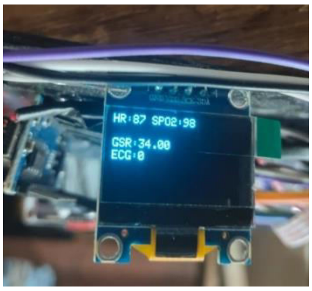
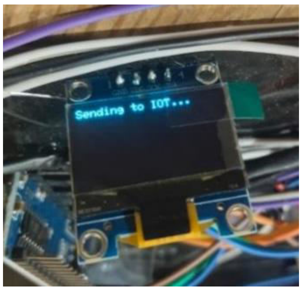


Figure (a)



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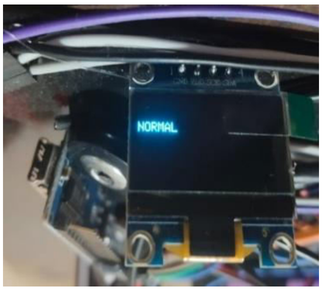

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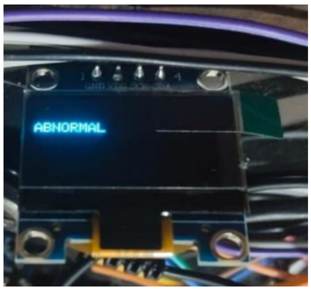

Figure (d)

Figure: (e) Python software interface displaying the calculated physiological parameters obtained from the sensors. (f) IoT ThingSpeak cloud platform showing the real-time graph of BPM and SpO_2 values. (g) Graphical representation of GSR and ECG signals generated from the acquired physiological data. (h) Final classification result graph indicating the detected cardiovascular condition.

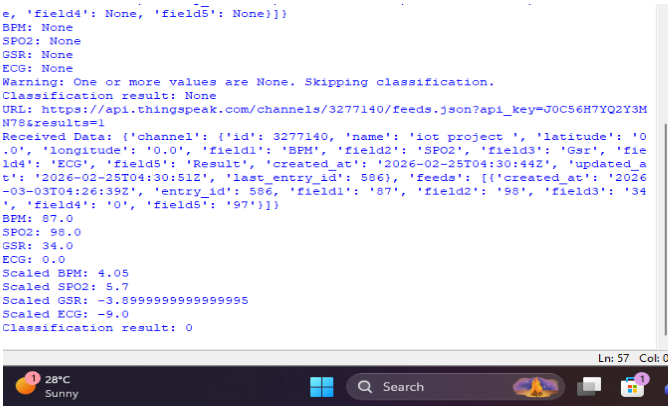

Figure (e)

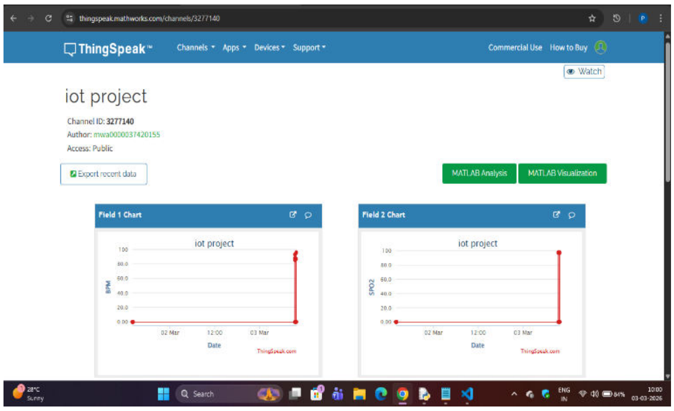

Figure (f)

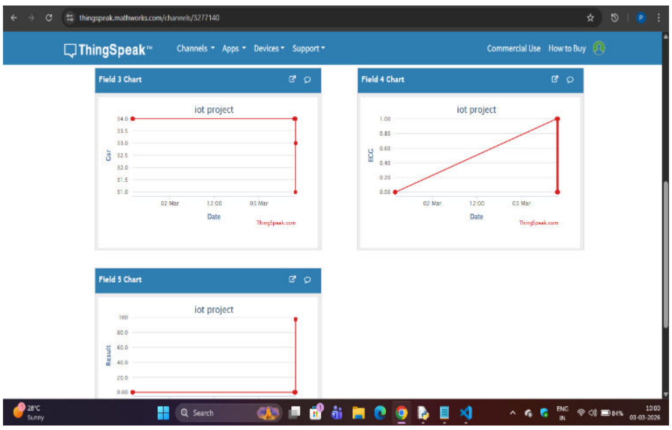

Figure (g)

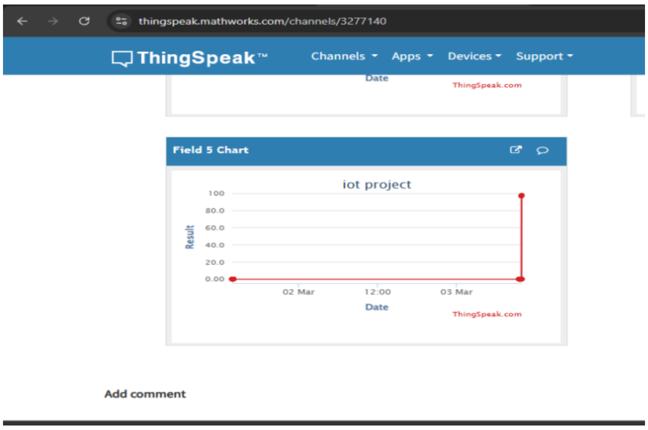

Figure (h)

The results obtained from the multi-sensor system demonstrate its effectiveness in detecting early signs of cardiovascular stress through the analysis of skin microcirculation and physiological responses. The integration of ECG, pulse oximeter, and GSR sensors provides comprehensive insights into cardiovascular health. The ECG sensor captures heart rate variability and electrical cardiac activity, while the pulse oximeter measures blood oxygen saturation (SpO_2), heart rate, and Perfusion Index (PI). The Perfusion Index (PI) reflects the strength of peripheral blood flow and provides valuable information about microcirculatory changes associated with stress conditions. In addition, the GSR sensor monitors skin conductance variations related to autonomic nervous system responses. Signal processing techniques such as noise reduction and feature extraction ensure that the collected data is accurate and suitable for analysis. The Multi-Layer Perceptron (MLP) machine learning model effectively classifies the physiological states into normal and stressed conditions, achieving high classification accuracy during testing. The system is capable of detecting stress-induced variations in parameters such as PI, SpO_2, heart rate, and GSR, even before significant abnormalities become evident, highlighting its potential for early detection and preventive healthcare. The Arduino-based prototype operates efficiently with real-time data acquisition and low power consumption, making it suitable for portable and cost-effective cardiovascular monitoring systems. Future improvements may include enhancing the machine learning model, incorporating larger and more diverse datasets, and integrating the system with cloud-based healthcare platforms for continuous remote monitoring.

VII. CONCLUSION

The proposed multi-sensor system offers a promising solution for the early detection of cardiovascular stress through continuous, non-invasive monitoring of skin microcirculation and related physiological parameters. By integrating ECG, pulse oximeter, and GSR sensors, the system captures important indicators such as heart rate, SpO_2, and Perfusion Index (PI) along with skin conductance responses. The Perfusion Index (PI) provides additional information about peripheral blood flow and microcirculatory changes, enabling more accurate assessment of cardiovascular stress conditions. These physiological signals are processed using signal processing techniques and a machine learning algorithm for effective classification of normal and abnormal states. The use of an Arduino-based prototype ensures portability and cost-effectiveness, making the system suitable for various applications including healthcare monitoring, stress assessment, and remote physiological monitoring. By detecting subtle physiological changes at an early stage, the system supports proactive health management and provides valuable insights into stress-induced cardiovascular responses.

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