Netaji Subhas University of Technology

Hardware and Software Tools
TinyML Project

Srishti 2023UCM3581
Vandana 2023UCM2820

Instructor:
Ms. Saurabhi Choudhary

TinyML-Based Multi-Parameter Smart Healthcare Monitoring System

🔗 GitHub Repository

https://github.com/srishnagar/tinyml-health-monitor

Abstract

This project presents a TinyML-based smart health monitoring prototype implemented using an Arduino microcontroller. The system performs real-time health condition classification using **simulated physiological parameters**, including body temperature, muscle activity (flex sensor), heart signal simulation (potentiometer), and motion detection (PIR sensor).

A lightweight neural network model was trained offline on a dataset of 150 labeled samples categorized into three classes: **NORMAL, STRESS, and CRITICAL**. The trained model parameters were then embedded into the microcontroller to enable on-device inference without relying on cloud connectivity.

The system provides immediate user feedback through an LCD display and a buzzer alert during critical conditions. This project demonstrates the feasibility of deploying machine learning models on resource-constrained embedded systems and highlights the potential of TinyML for low-power, real-time health monitoring applications.

Introduction

TinyML refers to the deployment of machine learning models on low-power microcontrollers that operate under strict memory and computational constraints. Unlike traditional cloud-based AI systems, TinyML enables real-time inference directly on edge devices without requiring continuous internet connectivity. This makes it suitable for portable and low-latency monitoring applications.

Conventional healthcare devices often rely on fixed threshold logic (for example, triggering alerts when temperature exceeds a predefined limit). However, such rule-based approaches cannot effectively capture relationships between multiple physiological parameters. Machine learning models provide a more adaptive solution by combining several inputs to generate intelligent predictions.

The objective of this project is to design and implement a **multi-parameter health monitoring prototype** using TinyML principles. The system utilizes simulated sensor inputs to classify a user's condition into three categories:

• NORMAL
• STRESS
• CRITICAL

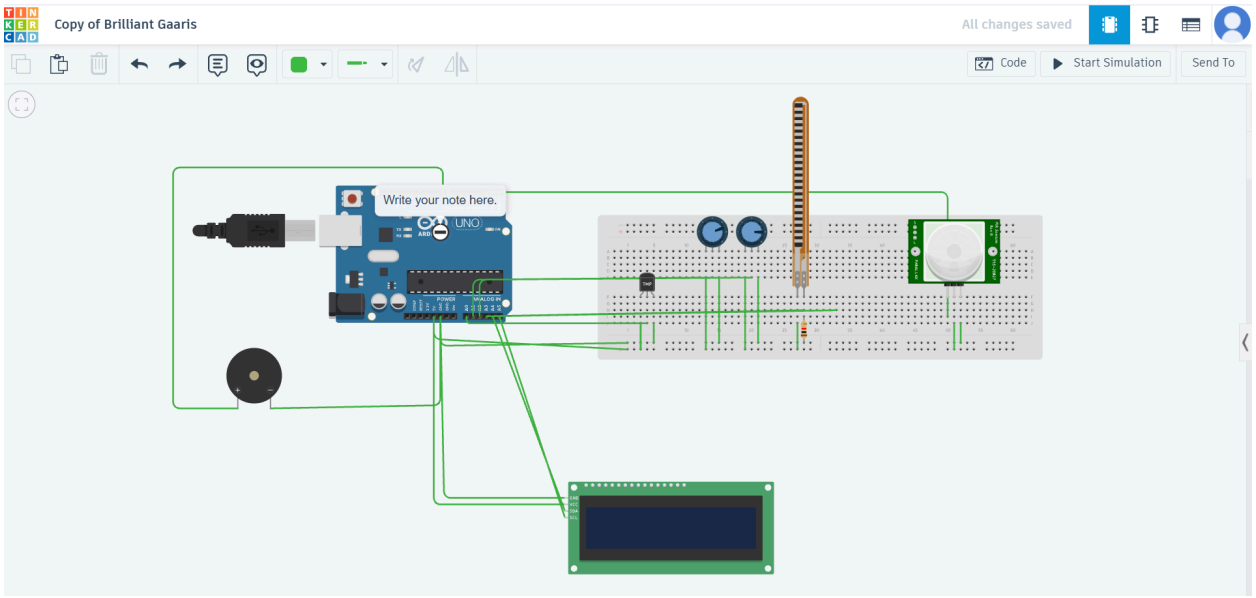
This project demonstrates an end-to-end TinyML workflow including dataset creation, preprocessing, model training, parameter deployment, and real-time embedded inference on a microcontroller.

System Architecture

The system consists of the following components:

Hardware Components

- Arduino Uno (Microcontroller)
- TMP36 Temperature Sensor
- Flex Sensor (Muscle strain simulation)
- Potentiometer (Heart intensity simulation)
- PIR Sensor (Motion detection)
- I2C 16x2 LCD Display
- Piezo Buzzer



System Flow

Sensors
→ Data Acquisition
→ Feature Normalization
→ Neural Network Inference
→ Classification Output
→ LCD Display & Alert System

The Arduino reads sensor values, applies normalization using precomputed mean and standard deviation values, performs forward propagation through a neural network, and selects the output class using an argmax function.

Dataset Generation

A dataset was collected using hardware-based simulation of physiological parameters. The dataset consists of 150 samples distributed equally among three classes:

- 50 NORMAL samples
- 50 STRESS samples
- 50 CRITICAL samples

Each sample contains four features:

- Temperature (°C)
- Flex sensor value (0–1023)
- Heart intensity (0–1023)
- Motion state (0 or 1)

Feature ranges were designed to represent realistic physiological conditions:

Class	Temperature	Flex	Heart	Motion
NORMAL	36–37°C	Low	Low	1
STRESS	37.5–38.5°C	Medium	Medium	0
CRITICAL	39–40.5°C	High	High	0

The dataset was normalized using StandardScaler to ensure proper scaling before training.

Model Training

The model was trained using Python in Google Colab with Scikit-learn's `MLPClassifier`.

Model Architecture:

- Input Layer: 4 neurons (Temp, Flex, Heart, Motion)
- Hidden Layer: 4 neurons
- Activation Function: ReLU
- Output Layer: 3 neurons (Softmax-style argmax classification)

The model achieved approximately **96% Training Accuracy**, indicating effective learning from the hardware-simulated sensor data.

After training, the following parameters were extracted:

- Hidden layer weight matrix
- Hidden layer bias vector
- Output layer weight matrix
- Output layer bias vector
- Feature normalization means and standard deviations

The trained model parameters were embedded into the Arduino program to enable **real-time on-device inference without requiring cloud connectivity**.
The lightweight neural network ensures low memory usage and fast prediction, making it suitable for resource-constrained embedded systems.

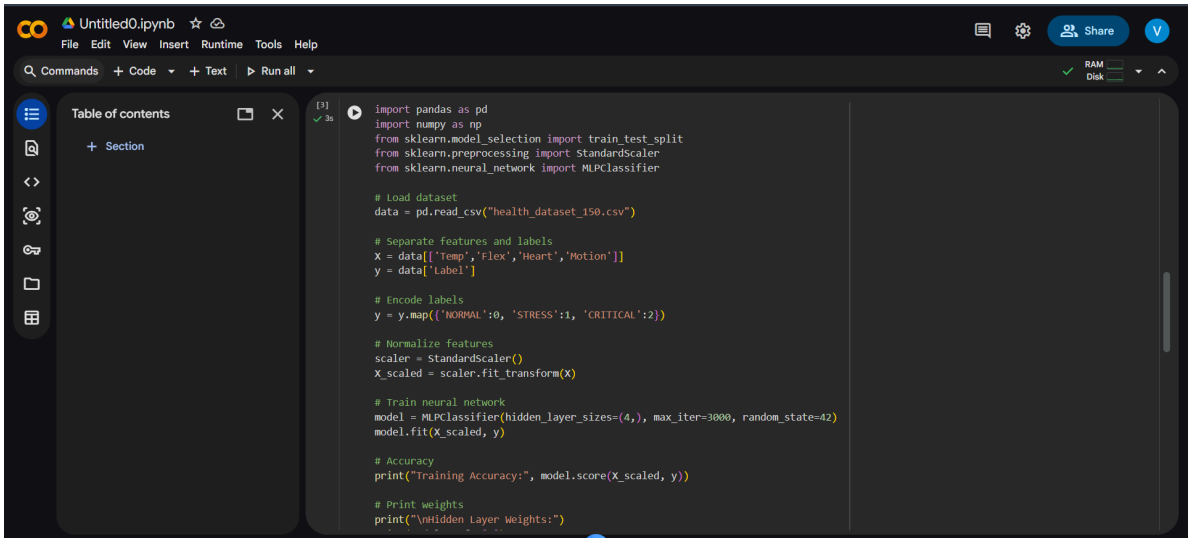

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Table of contents
+ Section
[3] 3s
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPClassifier
# Load dataset
data = pd.read_csv("health_dataset_150.csv")
# Separate features and labels
X = data[['Temp','Flex','Heart','Motion']]
y = data['Label']
# Encode labels
y = y.map({'NORMAL':0, 'STRESS':1, 'CRITICAL':2})
# Normalize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
# Train neural network
model = MLPClassifier(hidden_layer_sizes=(4,), max_iter=3000, random_state=42)
model.fit(X_scaled, y)
# Accuracy
print("Training Accuracy:", model.score(X_scaled, y))
# Print weights
print("\nHidden Layer Weights:")

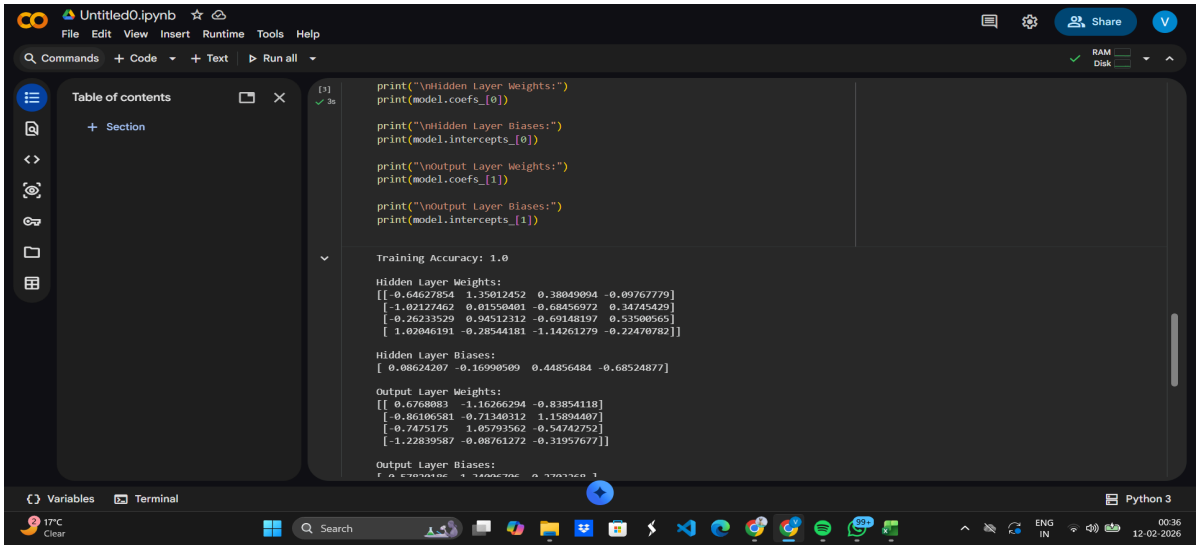
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Table of contents
+ Section
[3] 3s
print("\nHidden Layer Weights:")
print(model.coefs_[0])
print("\nHidden Layer Biases:")
print(model.intercepts_[0])
print("\nOutput Layer Weights:")
print(model.coefs_[1])
print("\nOutput Layer Biases:")
print(model.intercepts_[1])
Training Accuracy: 1.0
Hidden Layer Weights:
[[-0.64627854 1.35012452 0.38049094 -0.09767779]
[-1.02127462 0.01550401 -0.68456972 0.34745429]
[-0.26233529 0.94512312 -0.69148197 0.53500565]
[1.02046191 -0.28544181 -1.14261279 -0.22470782]]
Hidden Layer Biases:
[0.08624207 -0.16990509 0.44856484 -0.68524877]
Output Layer Weights:
[[0.6768083 -1.16266294 -0.83854118]
[-0.86106581 -0.71340312 1.15894407]
[-0.7475175 1.05793562 -0.54742752]
[-1.22839587 -0.08761272 -0.31957677]]
Output Layer Biases:
Variables Terminal
Python 3
17°C Clear
Search
ENG IN
00:36 12-02-2026

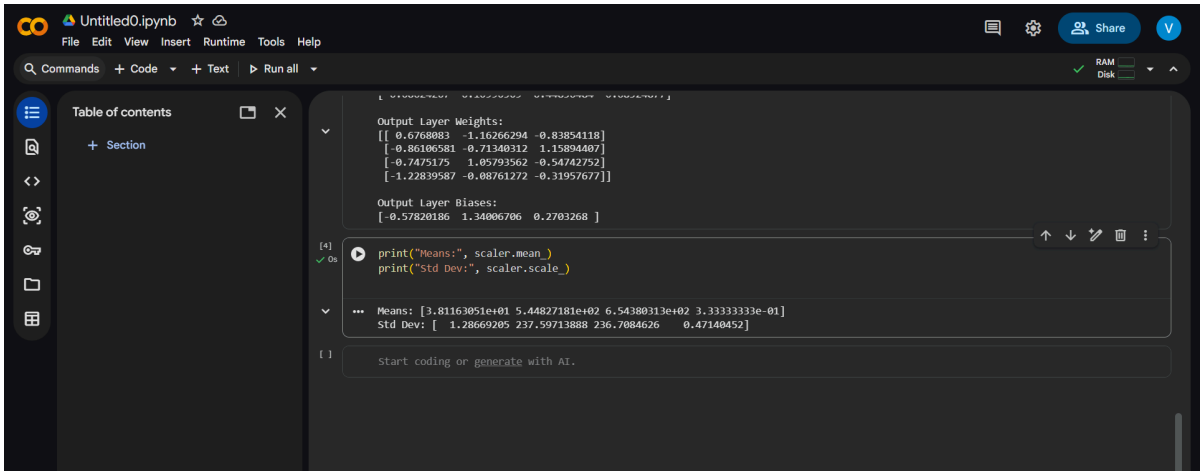
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Table of contents
+ Section
Output Layer Weights:
[[0.6768083 -1.16266294 -0.83854118]
[-0.86106581 -0.71340312 1.15894407]
[-0.7475175 1.05793562 -0.54742752]
[-1.22839587 -0.08761272 -0.31957677]]
Output Layer Biases:
[-0.57820186 1.34006706 0.2703268]
[4] 0s
print("Means:", scaler.mean_)
print("Std Dev:", scaler.scale_)
Means: [3.81163051e+01 5.44827181e+02 6.54380313e+02 3.33333333e-01]
Std Dev: [1.28669205 237.59713888 236.7084626 0.47140452]
[ ]
Start coding or generate with AI.

Embedded TinyML Deployment

The trained neural network was implemented on the Arduino Uno using:

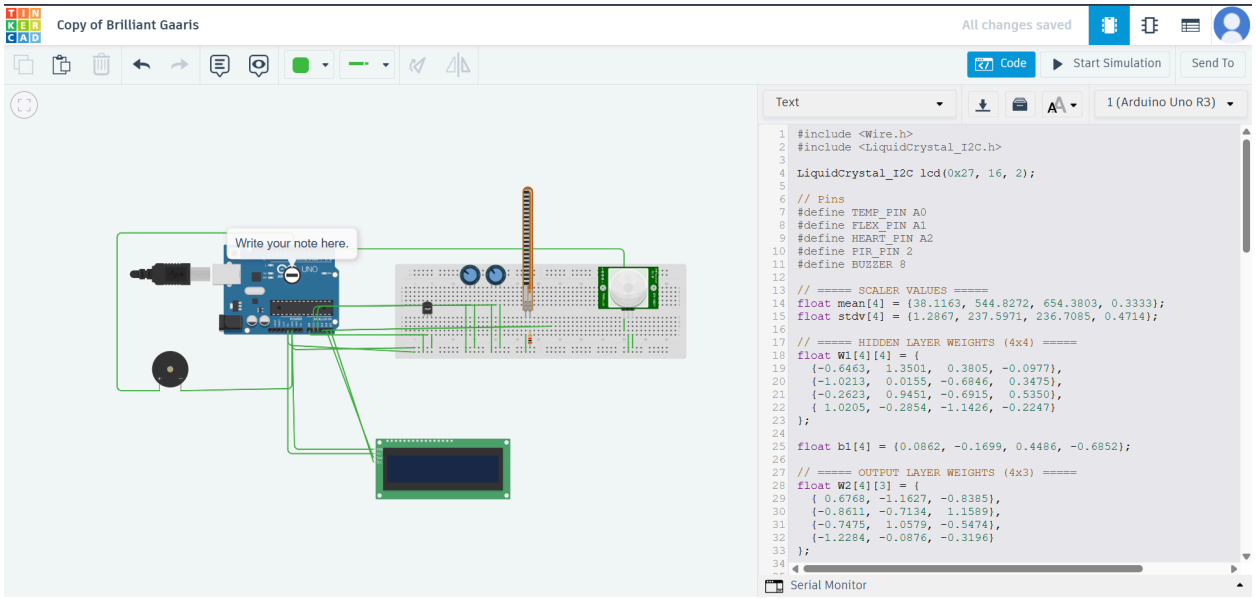
1. Feature scaling using stored mean and standard deviation
2. Matrix multiplication for hidden layer
3. ReLU activation
4. Output layer computation
5. Argmax classification

The inference process runs continuously inside the Arduino loop function.

Based on prediction:

- NORMAL → No alert
- STRESS → Intermittent buzzer alert
- CRITICAL → Continuous buzzer alert

The classification result is displayed on the LCD screen.



CODE :

```
#include <Wire.h>

#include <LiquidCrystal_I2C.h>

LiquidCrystal_I2C lcd(0x27, 16, 2);

// Pins
#define TEMP_PIN A0
#define FLEX_PIN A1
#define HEART_PIN A2
#define PIR_PIN 2
#define BUZZER 8

// ===== SCALER VALUES =====
float mean[4] = {38.1163, 544.8272, 654.3803, 0.3333};
float stdv[4] = {1.2867, 237.5971, 236.7085, 0.4714};

// ===== HIDDEN LAYER WEIGHTS (4x4) =====
float W1[4][4] = {
  {-0.6463,  1.3501,  0.3805, -0.0977},
  {-1.0213,  0.0155, -0.6846,  0.3475},
  {-0.2623,  0.9451, -0.6915,  0.5350},
  { 1.0205, -0.2854, -1.1426, -0.2247}
};

float b1[4] = {0.0862, -0.1699, 0.4486, -0.6852};

// ===== OUTPUT LAYER WEIGHTS (4x3) =====
float W2[4][3] = {
  { 0.6768, -1.1627, -0.8385},
  {-0.8611, -0.7134,  1.1589},
  {-0.7475,  1.0579, -0.5474},
  {-1.2284, -0.0876, -0.3196}
};

float b2[3] = {-0.5782, 1.3401, 0.2703};

void setup() {
  Serial.begin(9600);
  pinMode(PIR_PIN, INPUT);
  pinMode(BUZZER, OUTPUT);
```

```
  lcd.init();
  lcd.backlight();
  lcd.print("TinyML Health");
  delay(2000);
  lcd.clear();
}

void loop() {

  // ===== READ SENSORS =====
  int tempRaw = analogRead(TEMP_PIN);
  int flexRaw = analogRead(FLEX_PIN);
  int heartRaw = analogRead(HEART_PIN);
  int motion = digitalRead(PIR_PIN);

  float voltage = tempRaw * (5.0 / 1023.0);
  float temperature = (voltage - 0.5) * 100.0;

  float input[4] = {temperature, (float)flexRaw, (float)heartRaw, (float)motion};

  // ===== SCALE INPUT =====
  for(int i=0; i<4; i++){
    input[i] = (input[i] - mean[i]) / stdv[i];
  }

  // ===== HIDDEN LAYER =====
  float hidden[4];
  for(int i=0; i<4; i++){
    hidden[i] = b1[i];
    for(int j=0; j<4; j++){
      hidden[i] += input[j] * W1[j][i];
    }
    if(hidden[i] < 0) hidden[i] = 0;  // ReLU
  }

  // ===== OUTPUT LAYER =====
  float output[3];
  for(int i=0; i<3; i++){
    output[i] = b2[i];
    for(int j=0; j<4; j++){
      output[i] += hidden[j] * W2[j][i];
    }
  }
```

```
  // ===== ARGMAX =====
  int prediction = 0;
  float maxVal = output[0];
  for(int i=1; i<3; i++){
    if(output[i] > maxVal){
      maxVal = output[i];
      prediction = i;
    }
  }

  // ===== DISPLAY =====
  lcd.clear();

  if(prediction == 0){
    lcd.print("Status:NORMAL");
    digitalWrite(BUZZER, LOW);
  }
  else if(prediction == 1){
    lcd.print("Status:STRESS");
    tone(BUZZER, 1000);
    delay(200);
    noTone(BUZZER);
  }
  else{
    lcd.print("Status:CRITICAL");
    tone(BUZZER, 2000);
  }

  lcd.setCursor(0,1);
  lcd.print("AI Active");

  delay(2000);
}
```

Results and Observations

The system successfully performs real-time classification based on simulated sensor inputs.

Testing scenarios:

- Normal physiological values → Classified as NORMAL
- Elevated temperature and heart intensity → Classified as STRESS
- High temperature and high strain values → Classified as CRITICAL

The system demonstrates:

- Accurate multi-class classification
- Stable embedded inference
- Real-time response
- Efficient use of microcontroller resources
- Input validation was added to prevent unrealistic out-of-distribution sensor values from affecting predictions.

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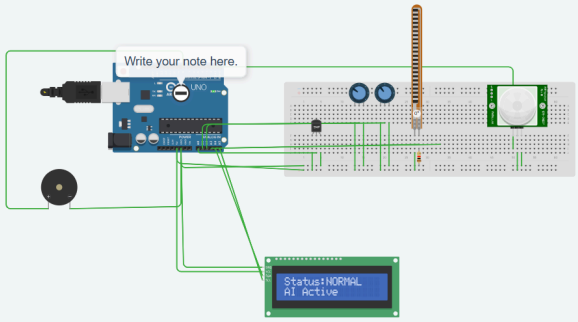
All changes saved

Simulator time: 00:00:05

Code | Stop Simulation | Send To

1 (Arduino Uno R3)

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```

Serial Monitor

```
24.78,0,41,0
24.78,0,41,0
24.78,0,41,0
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```

Copy of Brilliant Gaaris

All changes saved

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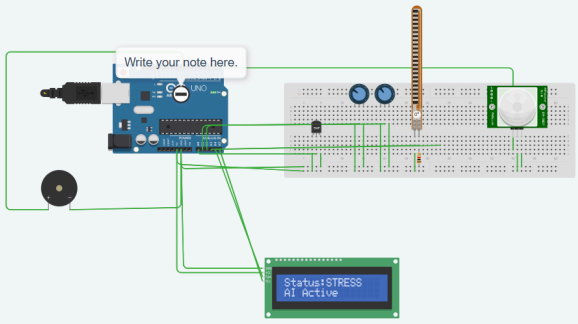
Code | Stop Simulation | Send To

1 (Arduino Uno R3)

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24.78,0,41,0
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Copy of Brilliant Gaaris

All changes saved

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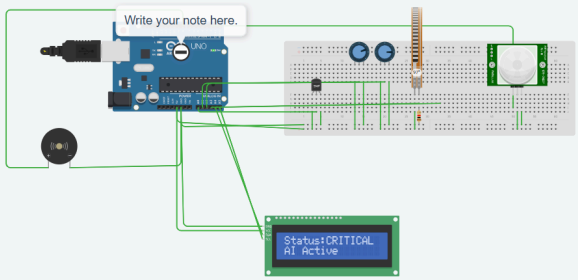
Code | Stop Simulation | Send To

1 (Arduino Uno R3)

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24.78,0,41,0
```

Conclusion

This project demonstrates the design and implementation of a TinyML-based health monitoring system using an Arduino microcontroller and simulated sensor data. Multiple physiological parameters — temperature, muscle strain (flex), heart signal, and motion — were used to classify health conditions into NORMAL, STRESS, and CRITICAL categories.

A lightweight neural network was trained offline and successfully deployed onto the microcontroller for real-time, on-device inference. The system provided immediate feedback through an LCD display and buzzer alerts, illustrating how machine learning can enhance traditional sensor-based monitoring.

Overall, the project validates the feasibility of running compact machine learning models on resource-constrained embedded systems and highlights the potential of TinyML for developing low-cost, portable health monitoring solutions. It also provided practical exposure to the complete TinyML pipeline, including data collection through hardware simulation, model training, and embedded deployment.