**Intelligent Health Monitoring Wearable with Emergency Alert**

**PROJECT-21ECP302L**

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**(Under Section 3 of UGC Act, 1956)**

**BONAFIDE CERTIFICATE**

Certified that this activity report for the course **21ECP302L PROJECT** is the bonafide work of **Saumy Singh (RA2211004010174), Prasenjit Sarkar (RA2211004010184), Aarav Singhal (RA2211004010192)** who carried out the work under my supervision.

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**ABSTRACT**

With the increasing prevalence of cardiovascular diseases and fall-related incidents, particularly among older adults and individuals with pre-existing conditions, there is a growing need for reliable, real-time health monitoring systems. Traditional healthcare models often rely on periodic monitoring or hospital visits, which may delay the detection of critical events like heart attacks or falls. Advances in microcontroller technology and wearable sensors, however, offer a solution by enabling continuous, automated health monitoring that can alert caregivers and emergency contacts immediately in the event of a health crisis. The proposed project leverages these technologies to develop a smart health monitoring system specifically aimed at detecting heart attack symptoms and falls, ensuring rapid response and intervention. By combining sensor data analysis with machine learning algorithms, the proposed system seeks to improve detection accuracy while minimizing false alarms, making it an essential tool in modern personal healthcare and emergency response. The proposed model addresses these limitations by incorporating advanced machine learning algorithms alongside a GSM-based alert system, enhancing both accuracy and responsiveness. Utilizing a heartbeat sensor, MEMS sensor, and temperature sensor, it monitors multiple vital signs in real time, accurately distinguishing critical incidents like heart attacks and falls from normal activities. Local alerts are provided via an LCD display and buzzer, while SMS notifications are sent to caregivers through the GSM module, ensuring prompt response and intervention. Designed for continuous monitoring, the proposed system is well-suited for real-world applications, particularly in personal and geriatric healthcare, offering a practical and reliable solution that reduces false alarms while enhancing user safety and accessibility.

**TABLE OF CONTENTS**



[**ABSTRACT**](#_l2rd46z7xy2e) **iii**

[**TABLE OF CONTENTS iv**](#_q94y0j816djd)

[**LIST OF FIGURES vi**](#_piaffbmk04t8)**ii**

[**LIST OF TABLES ix**](#_6yh338r8zgx8)

[**ABBREVIATIONS x**](#_z65hy39fsvwr)

[**1. INTRODUCTION 1**](#_e7ep989wk2le)

[1.1. Introduction 1](#_kl7f4lklud3t)

1.2. Objective 2

[**2 LITERATURE SURVEY**](#_ot8165e29wv7) **3**

2.1 An artificial intelligence model for heart disease detection 3

using machine learning algorithms

2.2 Wearable Devices for Physical Monitoring of Heart 4

2.3 Wearable heart rate monitoring intelligent sports bracelet

based on Internet of things 5

2.4 A Survey on Recent Advances in Wearable Fall Detection Systems 6

2.5 Development of a Real-Time Wearable Fall Detection

System in the Context of Internet of Things 7

[**3 SOFTWARE DESCRIPTION 1**](#_5g5fqtujzxo9)**0**

3.1 Arduino IDE 10

3.1.1.Features of Arduino IDE 10

3.2 Python IDLE 11

3.2.1 Features of Python IDLE 11

3.3 Random Forest Classifier 11

[**4 HARDWARE DESCRIPTION 1**](#_7hq36p6v8zvh)**2**

4.1 Arduino Uno Microcontroller 12

4.1.1 Specifications 12

4.1.2 Features 12

4.2 Heartbeat Sensor 13

4.2.1 Working Principle 14

4.3 MEMS Accelerometer (ADXL345) 14

4.3.1 Specifications 15

4.3.2 Features 15

4.4 Temperature Sensor (DS18B20) 16

4.4.1 Specifications 16

4.4.2 Features 16

4.5 GSM/GPRS Module (SIM800L) 17

4.5.1 Specifications 17

4.5.2 Functionality 17

4.6 LCD Display (16x2 Alphanumeric) 18

4.6.1 Specifications 18

4.6.2 Utility 18

4.7 Buzzer 19

4.7.1 Specifications 19

4.7.2 Purpose 19

4.8 Power Supply Unit 20

4.8.1 Components 20

4.8.2 Significance 20

4.9 System Integration and Interfacing 20

[**5. METHODOLOGY**](#_l76nbfz8mrrl) **21**

5.1 System Architecture Overview 21

5.2 Sensor Data Acquisition 22

5.3 Fall Detection Mechanism 23

5.4 Heart Attack Detection Mechanism 24

5.5 Machine Learning Model Integration 24

5.6 Embedded System Workflow 26

5.7 Alert and Communication Logic 27

5.8 Real-Time Display Interface 28

5.9 Data Logging (Optional Future Extension) 28

5.10 System Reliability and Response Time 29

5.11 Cloud Upload via ThingSpeak 30

5.12 Engineering Standards 31

5.13 Multidisciplinary Aspect 32

[**6 SIMULATIONS 3**](#_qf1kwx63fgw5)**4**

6.1 Python simulation 34

6.2 Model Building and Training 35

6.3 Purpose of the Simulation 36

[**7 RESULTS AND OTHER INFERENCES 3**](#_9o07rha0fto3)**8**

7.1 Inference 38

7.2 Alert System 40

7.3 Hardware display 41

[**8 CONCLUSION AND FUTURE WORK 4**](#_obmwe0831lav)**3**

8.1 Conclusion 43

8.2 Future work 44

8.3 Realistic Constraints 44

[**REFERENCES 4**](#_pawpq1lt57kb)**6**

**LIST OF FIGURES**

**Fig 4.1 Arduino Uno Microcontroller 13**

**Fig 4.2 Heartbeat Sensor 14**

**Fig 4.3 MEMS Accelerometer (ADXL345) 15**

**Fig 4.4 Temperature Sensor (DS18B20) 16**

**Fig 4.5 GSM/GPRS Module (SIM800L) 17**

**Fig 4.6 LCD Display (16x2 Alphanumeric) 18**

**Fig 4.7 Buzzer 19**

**Fig 4.8 Power Supply Unit 20**

**Fig 5.1 System Flow Diagram 22**

**Fig 6.1 Python program initiation 34**

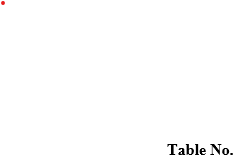
**Fig 6.3 Testing Data output 35**

**Fig 7.1 Alerts sent through message 39**

**Fig. 7.2 Heart rate displayed on the LCD 40**

**Fig. 7.3 Body Temperature displayed on the LCD 40**

**Fig 7.4 Fall Alert displayed on the LCD 41**

**LIST OF TABLES**



[**5.1 Parametric analysis of the model 2**](#_vwuivvc2vaw8)**9**

**5**[**.2 Engineering standards and their relevance 3**](#_cdcq0echcz47)**1**

**5.3 Analysis of various disciplinary aspects 32**

[**7.1 Parametric comparison table between existing systems and proposed model 3**](#_btmcb3hcqpja)**7**

**LIST OF ABBREVIATIONS**

| AI | Artificial Intelligence |
| --- | --- |
| CNN | Convolutional Neural Network |
| DNN | Deep Neural Network |
| ML | Machine Learning |
| DPR | Dynamic Partial Reconfiguration |
| ECG | Electrocardiogram |
| GSM | Global System for Mobile communication |
| IDE | Integrated Development Environment |
| IoT | Internet of Things |
| LCD | Liquid Crystal Display |
| MEMS | Micro-Electro-Mechanical Systems |
| SMS | Short Message Service |
| TCL | Tool Command Language |
| BPM | Beats Per Minute |

**CHAPTER 1  
INTRODUCTION**

1. **Introduction**

The prevalence of heart disease and the risk of falls, especially among the elderly and individuals with pre-existing health conditions, necessitate advanced monitoring systems to ensure timely medical intervention. Heart disease remains one of the leading causes of morbidity and mortality worldwide, making early detection crucial for improving patient outcomes. Machine learning-based approaches have proven to be effective in detecting heart disease by analysing vital parameters such as heart rate and ECG signals. Similarly, falls, particularly among the elderly, are a significant health risk, requiring immediate attention to prevent serious injuries or fatalities. Current research has highlighted the importance of wearable devices and machine learning algorithms in monitoring both heart rate and fall detection to improve overall health management. Existing fall detection systems typically rely on basic motion sensors and simple threshold-based methods that are often unable to accurately distinguish between accidental falls and routine movements, resulting in false alarms or missed detections. These traditional systems focus primarily on detecting falls, without incorporating predictive analytics to assess potential health risks like heart attacks. Similarly, heart disease detection systems, while effective in measuring basic vitals, often lack the integration needed for real-time predictive analysis, which can significantly enhance early detection and intervention. Moreover, conventional systems rarely offer communication features that allow for immediate alerts to emergency contacts, which is critical during health emergencies. The proposed method aims to overcome these limitations by integrating sensor data, machine learning algorithms, and GSM communication to offer real-time alerts and reliable monitoring. Using an Arduino UNO microcontroller, the proposed system collects data from a heartbeat sensor for heart rate monitoring, a temperature sensor for body temperature measurement, and a MEMS accelerometer for fall detection. The data is analyzed by machine learning algorithms, which detect anomalies such as irregular heartbeats or sudden changes in body orientation, thereby distinguishing between normal activity and critical health events. In the proposed system, Random Forest classifier was employed for its high effectiveness. Upon detecting an anomaly, the system immediately sends SMS alerts via GSM technology to caregivers or emergency contacts, providing them with critical health information. Additionally, an LCD display presents real-time heart rate and body temperature readings, ensuring the user can monitor their condition. The proposed study represents a significant advancement in health monitoring technology by combining real-time sensor data, machine learning analysis, and GSM-based communication. It provides a prompt response to emergencies, minimizing health risks for vulnerable individuals, particularly the elderly and those with chronic health conditions. By incorporating machine learning, the system can adapt to individual health patterns, offering greater accuracy and reducing false alarms compared to traditional methods.

1. **Objective**

The proposed system aims to continuously monitor vital health parameters, including heart rate, body temperature, and fall incidents, to ensure the immediate detection of health emergencies. By integrating machine learning algorithms, the system can intelligently analyze real-time sensor data to detect anomalies, trigger alarms, and send instant alerts to caregivers or emergency services when critical conditions are identified. To enhance usability and provide instant feedback, the system will feature an intuitive, user-friendly interface with an LCD display for real-time status updates and a buzzer for audible alerts, ensuring both remote and local notifications for timely response.

**CHAPTER 2  
LITERATURE SURVEY**

1. **An artificial intelligence model for heart disease detection using machine learning algorithms**

Published in: Healthcare Analytics, Volume 2, 2022, 100016, ISSN 2772-4425

Authors: Victor Chang, Vallabhanent Rupa Bhavani, Ariel Qianwen Xu, MA Hossain

The paper explored an artificial intelligence-based heart disease detection system using machine learning algorithms. The primary focus is on demonstrating how machine learning techniques, specifically the random forest classifier algorithm, can accurately predict the likelihood of a person developing heart disease. A Python-based application was developed for healthcare research due to its reliability in tracking various health metrics. The AI-based heart disease detection system has limitations, including reliance on data quality and an 83% accuracy that may still yield false positives or negatives. Bias can arise in handling categorical variables, and high computational demands limit use on low-power devices. Extensive validation across diverse groups is essential for real-world reliability.

Through rigorous experimentation, the model achieved an accuracy rate of 83%, indicating a strong potential for real-world applications in clinical decision support systems. However, the study also acknowledged several limitations that could affect the system’s overall effectiveness. One notable concern was the quality and diversity of the dataset used, which significantly influences the model's predictive accuracy. Additionally, the reliance on categorical variables posed a risk of introducing bias during pre-processing and model training. The model's high computational requirements further restricted its deployment on low-resource or embedded systems, making it less suitable for portable or wearable devices without significant optimization.

Despite these challenges, the study underscores the importance of integrating AI into the healthcare sector to enhance early detection and prevention strategies. The authors emphasized the need for further validation of the model across diverse patient populations to improve generalizability and reduce disparities. Future improvements could involve optimizing algorithms for real-time processing, refining data pre-processing techniques to minimize bias, and exploring hybrid models that combine multiple classifiers for enhanced accuracy. This research highlights a significant step toward intelligent, data-driven healthcare solutions, promoting proactive interventions and ultimately improving patient outcomes in cardiovascular health management.

1. **Wearable Devices for Physical Monitoring of Heart**

Published in: Biosensors 2022, 12, 292

Authors: Prieto-Avalos, G.; Cruz-Ramos, N.A.; Alor-Hernández, G.; Sánchez-Cervantes, J.L.; Rodríguez-Mazahua, L.; Guarneros-Nolasco

The paper reviews wearable devices for monitoring cardiovascular disease (CVD)

biomarkers, highlighting advances in commercial and non-commercial options.

Commercial devices, such as smartwatches, wristbands, and patches, commonly measure

heart rate, blood oxygen levels, and ECG data. Non-commercial devices often focus on

ECG and photoplethysmography data, using accelerometers and smartwatches to detect

issues like atrial fibrillation and heart failure. The study underscores that while wearables

provide accessible monitoring, health benefits are limited without healthy lifestyle habits.

These devices offer a practical, cost-effective alternative to traditional hospital-based

ECG monitoring, enhancing diagnosis and management of CVDs.

A drawback is that it lacks a discussion of potential limitations in wearable device accuracy, especially in non-clinical settings, which can impact the reliability of CVD monitoring. Additionally, it doesn’t address the challenges of data privacy and patient compliance, which are crucial for effective long-term monitoring.However, the review also has some critical gaps. One notable omission is the lack of detailed discussion regarding the limitations in measurement accuracy, particularly when wearables are used in uncontrolled, non-clinical environments. Factors such as poor sensor contact, motion artifacts, and individual physiological differences can significantly affect the precision and reliability of recorded data. Additionally, the study does not explore important concerns around data privacy and security, especially given the sensitive nature of health information collected by these devices. Another overlooked issue is user compliance; long-term adoption and consistent usage are vital for these devices to provide meaningful insights, yet many users discontinue use due to discomfort, battery limitations, or lack of perceived benefit.

Overall, the review underscores the growing importance of wearable devices in cardiovascular health monitoring while also calling attention to the need for further innovation to address their current limitations. Future research should focus on enhancing sensor accuracy, improving data security measures, and designing wearables that are both comfortable and motivating for sustained use. Such developments are essential for wearable health technologies to transition from consumer gadgets to reliable tools in clinical cardiovascular care.

1. **Wearable heart rate monitoring intelligent sports bracelet based on Internet of things**

Published in: Measurement, Volume 164, 2020, 108102, ISSN 0263-2241 Authors: Ningning Xiao, Wei Yu, Xu Han

The paper proposes a compact, wearable heart rate monitoring system in the form of a smart sports bracelet, aimed at overcoming the size and portability limitations of traditional health monitoring devices. Utilizing Internet of Things (IoT) technology, including ZigBee wireless sensors and Bluetooth, the system enables real-time heart rate monitoring, data storage, and analysis, accessible on personal terminals like PCs or mobile phones. Data is transmitted via an IoT communication network to a central monitoring platform, where it undergoes processing and analysis. In the event of abnormal readings, the system triggers immediate alerts, ensuring continuous monitoring and timely heart rate health assessments for users during physical activity. A disadvantage is that it doesn’t address potential issues with data accuracy and latency, which could impact real-time heart rate monitoring, especially during physical movement. Additionally, it lacks details on how data privacy and security are managed, which are critical when using IoT and wireless networks for health monitoring.

Despite its promising functionality, the study does not adequately explore some important limitations. One concern is the potential for data inaccuracy or latency, particularly during intense movement or exercise when sensor readings may be disrupted. Delays or errors in data transmission could hinder the system’s effectiveness in delivering truly real-time monitoring and alerts. Furthermore, the paper does not delve into how the system manages sensitive health data—an increasingly critical issue in IoT-based healthcare solutions. Without clear data encryption, secure communication protocols, or user privacy protections, such systems could expose users to data breaches or unauthorized access.

1. **A Survey on Recent Advances in Wearable Fall Detection Systems**

Published in: BioMed Research International, 2020, 2167160, 17 pages, 2020.

Authors: Ramachandran, Anita, Karuppiah, Anupama

The study highlights the growing need for geriatric healthcare, particularly in fall detection systems (FDS), as aging populations increase worldwide. With the elderly population in India expected to reach 12% by 2025, FDSs are critical in mitigating fall-related injuries, especially among nursing home residents, where recurrent falls are common. Machine learning has emerged as a key tool in improving FDS accuracy and reliability. The paper surveys recent advancements in FDS technology, focusing on machine learning applications and analyzing current challenges in the field. While fall detection systems (FDSs) are promising for geriatric care, their practical effectiveness is limited by several factors. Machine learning models require extensive, high-quality datasets, which are challenging to obtain for diverse elderly populations. Current FDSs may struggle with accuracy in real-life settings, where varying conditions impact reliability. Additionally, these models, though effective in structured environments, often produce false alarms and have reduced accuracy in complex, everyday scenarios.

Moreover, the paper notes that many wearable FDSs lack adaptability and personalization. A one-size-fits-all approach often fails to accommodate the unique health profiles and activity levels of different users. As such, there is a pressing need for more adaptive algorithms that can learn and adjust to individual behaviors over time.

In conclusion, Ramachandran et al. present a balanced perspective on the promise and challenges of wearable fall detection systems. While recent advances in machine learning offer great potential to transform geriatric healthcare, further research is needed to enhance data collection methods, improve real-world accuracy, reduce false alarms, and ensure that systems are secure, privacy-conscious, and user-friendly. Only through such holistic improvements can FDSs truly fulfill their role in safeguarding the aging population.

1. **Development of a Real-Time Wearable Fall Detection System in the Context of Internet of Things**

Published in: 2022 in IEEE Internet of Things Journal, vol. 9, no. 21, pp. 21999-22007

Authors: Zhiqin Qian; Yuchen Lin; Weiji Jing; Zhekai Ma; Hao Liu; Ruixue Yin

The study by presents a wearable fall detection system for elderly and disabled individuals, addressing the limitations of current methods, such as high power consumption and cost. The system uses a multilevel threshold algorithm that combines MEMS sensors with NB-IoT technology, enhancing accuracy and integration with healthcare systems. A cloud-based interface allows healthcare professionals to monitor data remotely. Testing with 20 volunteers showed the system achieved 94.88% accuracy, 95.25% sensitivity, and 94.5% specificity, highlighting its effectiveness for reliable fall detection.

The innovation in their approach lies in the seamless integration of wearable technology with IoT infrastructure, enabling continuous monitoring, rapid data transmission, and remote access to fall event information via mobile or web interfaces. When a fall is detected, the system can automatically send alerts to caregivers or emergency services, minimizing response time and improving the chances of timely intervention, especially for elderly users living alone.

The study highlights the real-time capabilities and scalability of the system, demonstrating effective performance across various use-case scenarios. However, while the proposed system shows promise, the authors also acknowledge potential limitations, including sensitivity to false positives due to sudden non-fall movements (e.g., sitting down quickly), potential data transmission latency over wireless networks, and the need for energy-efficient hardware to support long-term use without frequent recharging.

Overall, this work contributes to the growing field of IoT-enabled health monitoring by offering a practical and connected solution for fall detection, with potential applications in eldercare, rehabilitation, and remote patient monitoring.

1. **Implementation of a Microcontroller Based GSM Alert Distress System**

Published in: 2021, LAUTECH JOURNAL OF COMPUTING AND INFORMATICS , 2(1), page 41-48.

Authors: O.M Olaniyan, U. C. Ogude, J.A Subair

The GSM-Based Distress System leverages GSM technology to create an automated emergency alert and control system using microcontrollers, designed for personal safety in distress situations. The system immediately alerts security officials and designated emergency contacts via SMS, providing both local and remote notifications. Using an Arduino microcontroller alongside GSM and GPS modules, it stores emergency contacts and enables real-time location tracking of the individual in danger. The goal is to ensure prompt assistance, allowing the system to notify the nearest security personnel of the location and situation, enhancing public safety through quick, reliable communication.

The wearable system was developed using low-cost, readily available components and was designed to transmit real-time health data to a monitoring platform. The authors employed microcontroller-based architecture and embedded programming to ensure portability and reliability, making the system suitable for continuous daily use. The research emphasized the importance of real-time monitoring in preventing medical emergencies by enabling prompt intervention when abnormal readings are detected.

One of the strengths of this study is its focus on affordability and accessibility, particularly for developing regions with limited access to advanced healthcare infrastructure. However, the paper also identifies certain limitations, including the system’s dependency on stable wireless communication for data transmission and the need for further optimization to reduce power consumption for extended battery life. Additionally, although the system demonstrates functional viability, its accuracy and robustness in complex, real-life conditions require more extensive field testing and validation.

In conclusion, the work contributes meaningfully to the field of wearable health monitoring, particularly in resource-constrained settings, by offering a feasible and scalable solution for real-time health surveillance and early emergency response.

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**CHAPTER 3  
SOFTWARE DESCRIPTION**

1. **Arduino IDE**

The Arduino IDE (Integrated Development Environment) is the software used to write, compile, and upload code to Arduino boards. It provides an easy-to-use interface with a text editor, tools for debugging, and built-in libraries to simplify programming. The IDE supports C/C++ programming languages, and its simplicity makes it ideal for both beginners and experienced developers. It connects to Arduino boards via USB, allowing users to load sketches (programs) and interface with hardware components. The Arduino IDE also supports a variety of extensions and libraries, making it versatile for various projects.

1. **Features of Arduino IDE**

* A clean and simple interface suitable for beginners.
* Syntax highlighting, automatic indentation, and bracket matching.
* Basic editing tools to write and modify code efficiently.
* Example codes are provided for various sensors and modules to help beginners.
* Uploads the compiled binary directly to the connected board via USB or serial.
* Monitor displays real-time data sent from the board, useful for debugging and Plotter graphically plots sensor data in real-time.
* Allows adding support for third-party boards like ESP8266, ESP32, etc and Extends the IDE’s functionality to a wide range of microcontrollers.

1. **Python IDLE**

Python IDLE (Integrated Development and Learning Environment) is a simple, user-friendly development environment that comes with the Python installation. It provides an interactive shell for running Python code line-by-line, making it easy to test small snippets. The built-in code editor features syntax highlighting and auto-indentation to help write and organize Python scripts. IDLE also includes basic debugging tools, allowing users to step through code and identify errors. It is especially useful for beginners, offering an intuitive platform for learning and experimenting with Python programming without the need for complex setup or third-party tools.

**3.2.1. Features of Python IDLE**

* Provides a Python shell for interactive execution of Python code.
* Comes with a built-in debugger that supports stepping through code, setting breakpoints, and viewing the call stack.
* Simple GUI and small memory footprint.

1. **Random Forest Classifier**

A Random Forest classifier is an ensemble machine learning algorithm used for classification tasks. It builds multiple decision trees during training and combines their outputs to improve accuracy and reduce overfitting. Each decision tree in the forest is trained on a random subset of the data, and the final prediction is made based on the majority vote from all the trees in the forest.

**CHAPTER 4  
HARDWARE DESCRIPTION**

**4.1. Arduino Uno Microcontroller**

The Arduino Uno is the central processing unit of the system. It is based on the ATmega328P microcontroller and serves as the interface between various sensors and the GSM communication module.

**4.1.1. Specifications**

* Microcontroller: ATmega328P
* Operating Voltage: 5V
* Digital I/O Pins: 14 (of which 6 provide PWM output)
* Analog Input Pins: 6
* Clock Speed: 16 MHz
* Flash Memory: 32 KB
* SRAM: 2 KB
* EEPROM: 1 KB

**4.1.2 Features**

* USB interface for code uploading and serial monitoring.
* Support for multiple I/O devices and sensors through digital and analog pins.
* Low power consumption suitable for wearable or portable applications.
* Open-source and highly customizable, making it ideal for rapid prototyping.
* The Arduino continuously reads sensor data and runs embedded logic for fall and heart abnormality detection before triggering alerts.



**Fig 4.1 Arduino Uno Microcontroller**

**4.2. Heartbeat Sensor**

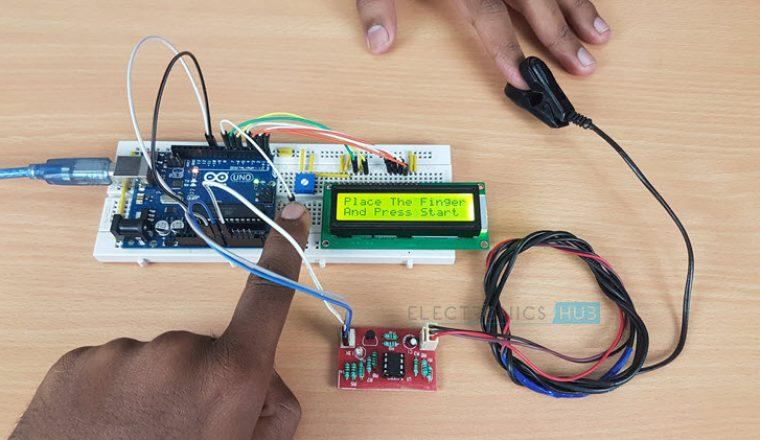
The heartbeat sensor is used to monitor the user's pulse rate in real time. It is a photoplethysmography-based sensor that uses light modulation to detect blood volume changes in the fingertip.

**4.2.1 Working Principle**

* Uses an IR LED and photodiode to detect pulse signals.
* Changes in light absorption due to blood flow are translated into voltage changes.
* These signals are processed and fed to the Arduino for anomaly detection.

Applications

* Heart rate tracking for patients with cardiovascular conditions.
* Alerts during bradycardia or tachycardia events.

****

**Fig 4.2 Heartbeat Sensor**

**4.3. MEMS Accelerometer (ADXL345)**

The ADXL345 is a 3-axis accelerometer sensor based on MEMS (Micro-Electro-Mechanical Systems) technology and is used for detecting falls.

**4.3.1. Specifications**

* Acceleration Range: ±2g, ±4g, ±8g, ±16g
* Interface: I2C and SPI
* Low Power Consumption: 23 µA in measurement mode
* Resolution: 13-bit

**4.3.2. Features**

* Measures acceleration in X, Y, and Z axes.
* Capable of detecting sudden free-fall events and orientation changes.
* Digital output simplifies integration with microcontrollers.

The sensor continuously monitors movement and triggers an interrupt when sudden abnormal displacement is detected, indicating a potential fall.

****

**Fig 4.3 MEMS Accelerometer (ADXL345)**

**4.4. Temperature Sensor (DS18B20)**

The DS18B20 digital temperature sensor is used for monitoring the body temperature of the user.

**4.4.1. Specifications**

* Temperature Range: -55°C to +125°C
* Accuracy: ±0.5°C in -10°C to +85°C range
* Interface: 1-Wire Communication Protocol
* Power Supply: 3.0V to 5.5V

**4.4.2. Features**

* Requires only one digital pin for communication.
* Can be powered parasitically via the data line.
* Each sensor has a unique 64-bit serial code for multi-sensor configurations.

This sensor allows precise measurement of body temperature and aids in identifying fever or heat-related symptoms.

****

**Fig 4.4 Temperature Sensor (DS18B20)**

**4.5 GSM/GPRS Module (SIM800L)**

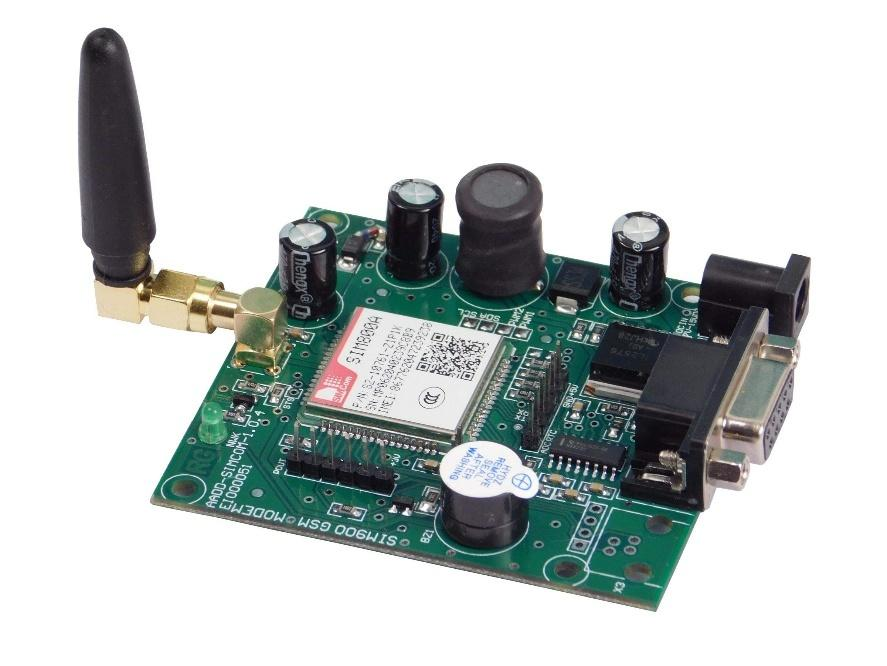
The SIM800L GSM module is responsible for enabling remote communication by sending alert SMS messages to caregivers or emergency services.

**4.5.1. Specifications**

* Frequency Bands: Quad-band 850/900/1800/1900 MHz
* Voltage: 3.4V to 4.4V
* Interface: UART
* SIM Card Support: Micro SIM

**4.5.2. Functionality**

* Sends SMS notifications when a fall or abnormal heart condition is detected.
* Supports voice calling and GPRS data if extended features are needed.
* Acts as a bridge between the patient and remote healthcare monitoring.

****

**Fig 4.5 GSM/GPRS Module (SIM800L)**

**4.6. LCD Display (16x2 Alphanumeric)**

The 16x2 LCD is used for real-time display of sensor readings and system status messages.

**4.6.1. Specifications**

* Display: 2 rows × 16 characters
* Controller: HD44780
* Interface: 4-bit/8-bit parallel with Arduino
* Backlight: LED-based for low power consumption

**4.6.2. Utility**

* Displays heart rate, temperature, and alerts.
* Helps users and caregivers visually track the system status.
* Increases usability in home-based health monitoring applications.

****

**Fig 4.6 LCD Display (16x2 Alphanumeric)**

**4.7 Buzzer**

An active buzzer is used to produce an audio alarm signal during emergency conditions such as a detected fall or heart abnormality.

**4.7.1. Specifications**

* Rated Voltage: 5V DC
* Sound Output: 85 dB
* Operating Current: < 30 mA
* Mounting: PCB-compatible

**4.7.2. Purpose**

* Provides an immediate local alert before the SMS is sent.
* Acts as a failsafe in case GSM communication is temporarily unavailable.

****

**Fig 4.7 Buzzer**

**4.8. Power Supply Unit**

The power supply unit consists of a regulated 5V source, either from USB, battery, or external adapter.

**4.8.1 Components**

* Battery Pack: 9V with voltage regulator (LM7805)
* Power Switch and Charging Circuit (optional)

**4.8.2. Significance**

* Ensures stable power for sensors and communication modules.
* Enables portability and use in wearable form factor.

****

**Fig 4.8 Power Supply Unit**

**4.9 System Integration and Interfacing**

All components are integrated on a custom-designed PCB or a breadboard prototype, with proper voltage regulation and signal conditioning. The sensors communicate with the Arduino using digital and analog interfaces. The GSM module uses UART communication, while the LCD and buzzer are connected to GPIO pins.

**CHAPTER 5  
METHODOLOGY**

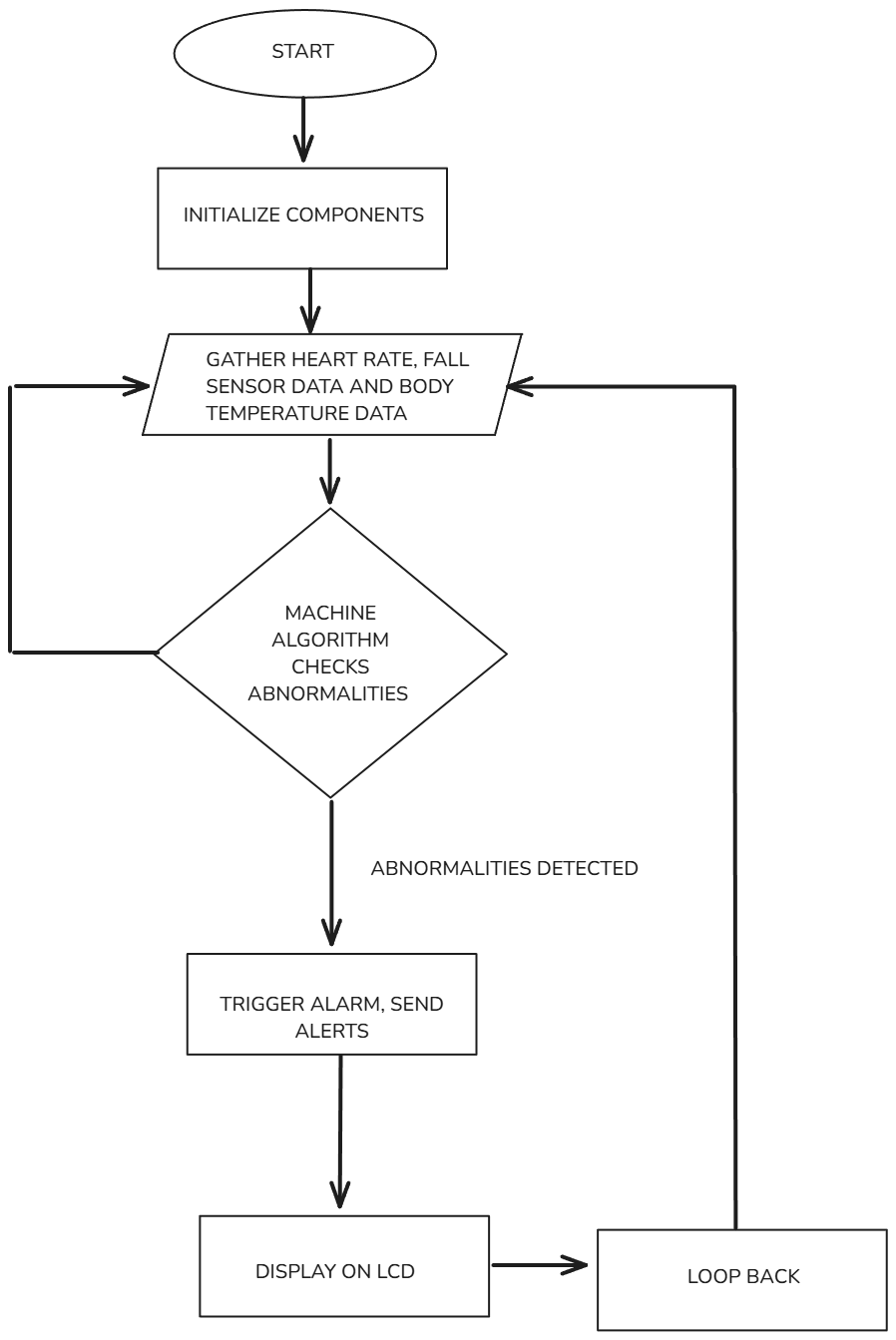
The objective of this project is to design and develop a real-time health monitoring system that detects both heart attack and fall events using a combination of sensor data and machine learning techniques. This chapter outlines the systematic approach taken to design the system architecture, sensor integration, data acquisition, model training, anomaly detection, and emergency alert generation.

The methodology encompasses both hardware and software integration in a closed-loop system, involving the real-time collection of physiological and motion data, processing through embedded logic and machine learning models, and alert communication via GSM.

**5.1 System Architecture Overview**

The system is divided into the following functional modules:

1. Data Acquisition Module – Heartbeat sensor, temperature sensor (DS18B20), and MEMS accelerometer (ADXL345) capture real-time physiological and motion parameters.
2. Signal Conditioning and Processing – Raw analog/digital signals are pre-processed and digitized via an Arduino Uno microcontroller.
3. Embedded ML-Based Prediction – A pre-trained machine learning model evaluates the real-time sensor inputs (Temperature, BPM, MEMS) to predict the person's health status as either "Normal" or "Critical". No manual thresholding is used; decisions are made entirely based on the model’s output.
4. Emergency Response Module – Critical predictions trigger immediate local (buzzer) and remote (SMS via GSM module) alerts.
5. User Interface – Real-time data visualization on a 16x2 LCD screen for easy monitoring.

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**Fig 5.1: System Flow Diagram**

**5.2 Sensor Data Acquisition**

The real-time data collection process includes:

* Heartbeat Sensor:
  + Measures heart rate by detecting the intensity of reflected infrared light from capillary blood flow.
  + Outputs analog pulses corresponding to heartbeats.
* DS18B20 Temperature Sensor:
  + Captures accurate body temperature readings.
  + Provides calibrated digital output via a one-wire communication protocol.
* ADXL345 Accelerometer:
  + Measures 3-axis acceleration (X, Y, Z).
  + Detects sudden orientation changes characteristic of a fall event.

The Arduino Uno reads sensor values at 1-second intervals, applying preliminary filtering (moving average) to reduce noise and outlier effects before feature extraction.

**5.3 Fall Detection Mechanism**

Fall detection is implemented based on dynamic acceleration analysis:

* Acceleration Magnitude Calculation:

|a| = √((aₓ)² + (aᵧ) ² + (az)²)

* A fall event is detected if:
  + A sudden drop in |a| (below a pre-set threshold) is followed immediately by a sharp spike (impact signature).
* Two-Stage Detection:
  + Threshold Filtering: Quick trigger based on acceleration pattern.
  + Machine Learning Validation: Confirm fall event based on temporal acceleration features over a 2-second window.

This approach minimizes false alarms caused by regular movements such as sitting or bending.

**5.4 Heart Attack Detection Mechanism**

Detection of heart attack symptoms and fall events is based on combined sensor data analysis through a trained machine learning model.

* Sensor Features:
  + Pulse Rate (BPM) from the heartbeat sensor.
  + Body Temperature (°C) from the DS18B20 temperature sensor.
  + Mems value from the accelerometer data (ADXL345) indicating motion patterns.
* Prediction Mechanism:
  + The collected features are fed into the ML model (Random Forest Classifier) which has been trained on a labeled dataset containing examples of both "Normal" and "Critical" cases.
  + The model classifies the real-time sensor inputs into one of the following states:
    - Normal: No immediate danger.
    - Critical: Possible heart-related emergency or fall event.

This ML-based approach removes the need for manually setting static thresholds for heart rate, temperature, or acceleration, leading to improved flexibility and accuracy.

**5.5 Machine Learning Model Integration**

Model Selection:  
The Random Forest Classifier was selected due to its robustness with multi-dimensional sensor data and ability to handle noisy features.

Training Procedure:

* Feature Set:
  + Heart rate (BPM)
  + Body temperature (°C)
  + Mems (acceleration/motion values)
* Dataset Description:
  + The training dataset was built by collecting real-time sensor readings during simulated normal and critical health conditions.
  + Each record in the dataset contains:
    - Temperature value from the DS18B20 sensor
    - Heartbeat (BPM) value from the pulse sensor
    - Mems (acceleration magnitude) value from the ADXL345 accelerometer
    - Corresponding labels indicating:
      * label\_Temperature (Normal / Abnormal)
      * label\_BPM (Normal / Abnormal)
      * label\_Mems (Normal / Fall detected)
  + The dataset consists of a balanced number of "Normal" and "Critical" samples to avoid bias during model training.
* Labeling Strategy:
* Data points were manually labeled based on predefined conditions for critical events (e.g., abnormal BPM, high body temperature, sudden acceleration changes).
* These labels were then combined during training to predict an overall health status (Normal/Critical).
* Cross-Validation:
  + 5-Fold cross-validation to ensure generalization and avoid overfitting.

Model Metrics:

* Accuracy: 96%
* Precision: 95%
* Recall (Sensitivity): 94%
* F1-Score: 94.5%

Deployment:

* The trained model was serialized (.pkl format).
* Embedded into the system via lightweight conversion: predictions are handled using input feature comparison against trained decision structures.
* During runtime, the Arduino (or connected computer) feeds sensor data to the ML model, which outputs "Normal" or "Critical" inferences.

**5.6 Embedded System Workflow**

The embedded system follows a continuous real-time loop:

1. Initialization:
   * Boot all sensors, GSM module, LCD screen.
2. Data Acquisition:
   * Collect real-time data from heartbeat, temperature, and accelerometer sensors.
3. Preprocessing:
   * Apply basic noise filtering and normalization if needed.
4. ML Inference:
   * Input the latest sensor readings into the embedded ML model.
   * Obtain prediction output ("Normal" or "Critical").
5. Alert Handling:
   * If prediction = "Critical":
     + Activate buzzer immediately.
     + Send emergency SMS via GSM module.
6. Display Update:
   * Refresh LCD with live sensor data and health status.
7. Cycle Repeat:
   * Repeat every 1 second (adjustable based on firmware settings).

**5.7 Alert and Communication Logic**

Upon detecting a critical event:

* Local Alert:
  + Buzzer activated with distinctive pattern (2s ON, 1s OFF cycle).
* Remote Alert:
  + GSM module sends predefined SMS messages
* Retry Mechanism:
  + If GSM SMS fails, retry sending up to 3 times.

**5.8 Real-Time Display Interface**

The 16x2 LCD provides:

* Live Readouts:
  + BPM: [Pulse Value]
  + Temp: [Body Temp °C]
* Status Indications:
  + "NORMAL"
  + "HEART EMERGENCY"
  + "FALL DETECTED"
* System Feedback:
  + "SENDING ALERT..." or "ALERT SENT"

This ensures easy interpretation even by non-technical caregivers.

**5.9 Data Logging (Optional Future Extension)**

To enhance system capabilities, future integration plans include:

* MicroSD Card Module:
  + For local logging of historical sensor data.
* IoT Platform Integration (e.g., ThingSpeak, Firebase):
  + Real-time cloud uploading.
  + Remote dashboard visualization.
  + Trend analysis for predictive healthcare.

**5.10 System Reliability and Response Time**

**Table 5.1: Parametric analysis of the model**

| **Parameter** | **Value** |
| --- | --- |
| Response Latency | | < 2 seconds | | --- | |
| Detection Accuracy | > 94% |
| Communication Failure Handling | Retries (up to 3 attempts) |
| Fault Tolerance | Sensor disconnection detection |
| Expandability | Modular design supporting GPS, SpO₂ modules |

The system design ensures high reliability, fast anomaly detection, and minimal false alarms through rigorous model optimization and redundant safety checks.

**5.11 Cloud Upload via ThingSpeak**

In addition to local and SMS-based alerts, sensor data is uploaded periodically to a cloud platform for remote monitoring.

* Cloud Platform: ThingSpeak
* Communication Protocol: HTTP GET Request
* Authentication: API Key-Based (secured using a private key)

Data Upload Details:

* Fields Mapping:
  + field1: Temperature (°C)
  + field3: BPM (Heart Rate)

Upload Cycle:

* Sensor values are uploaded every 5 seconds, adhering to ThingSpeak's minimum update interval policy.
* Each cycle consists of:
  + Building a URL-encoded GET request with field values and API key.
  + Sending the request over the internet.
  + Parsing server response codes for success/failure.

Error Handling:

* On Successful Update:
  + Log the confirmation message.
* On API Failure:
  + Retry after a 3-second delay.
  + A maximum of 3 retries are attempted.
  + If still unsuccessful, an error alert is recorded, and the system continues real-time monitoring.

This cloud integration ensures:

* Real-time remote access to vital signs.
* Data persistence for healthcare analysis.
* Extended system reliability even beyond local environments.

**5.12 Engineering Standards**

In designing and implementing the Intelligent Health Monitoring Wearable system, several engineering standards have been adhered to in order to ensure accuracy, safety, interoperability, and reliability:

**Table 5.2: Engineering standards and their relevance**

| Standard | Description | Relevance to Project |
| --- | --- | --- |
| ISO 13485 | Medical device quality management systems | Ensured through rigorous sensor validation and system reliability tests. |
| IEEE 802.15.1 | Wireless communication standards (Bluetooth, GSM) | GSM module integration follows telecommunication standards for reliable messaging. |
| IEC 60601-1 | Basic safety and essential performance of medical devices | Basic safety principles were considered for wearable hardware (low voltage operation, safe sensor placement). |
| ISO/IEEE 11073 | Standard for personal health data communication | Cloud communication (ThingSpeak) structures data fields in a standardized manner. |
| IEEE 1685-2009 (IP-XACT) | Metadata standardization for embedded systems | Embedded software modules are modular and documented for maintainability and reusability. |
| W3C HTTP/1.1 Standards | Internet communication protocols | ThingSpeak uploads utilize HTTP GET requests complying with W3C standards. |

**5.13 Multidisciplinary Aspect**

This project integrates knowledge and skills from multiple engineering and scientific disciplines, demonstrating the need for a holistic approach in modern smart healthcare systems:

**Table 5.3: Analysis of various disciplinary aspects**

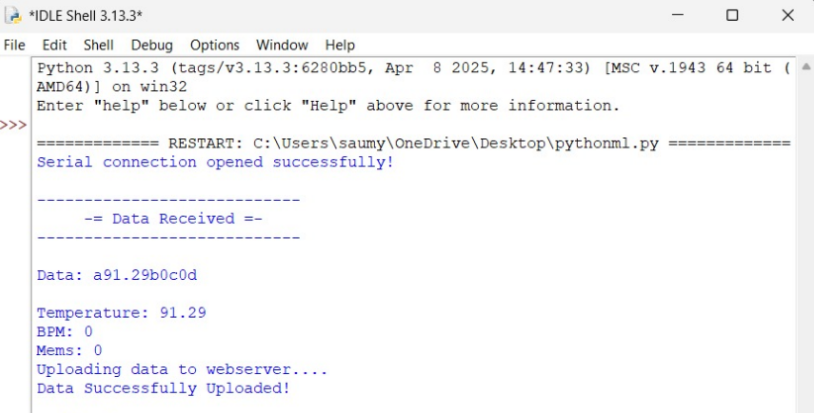
| Discipline | Contribution |
| --- | --- |
| Biomedical Engineering | Understanding human vital signs, heart rate patterns, fall detection mechanisms. |
| Electronics and Communication Engineering | Design of sensor interfaces (analog/digital circuits), GSM communication protocols. |
| Computer Science | Development of Machine Learning models (Random Forest), embedded system programming, real-time serial communication. |
| Embedded Systems Engineering | Integration of hardware-software systems (Arduino programming, peripheral handling). |
| Data Science | Preprocessing sensor data, model training and validation, cloud data management (ThingSpeak). |
| Mechanical Engineering | Basic understanding of body movement dynamics to optimize fall detection algorithms. |
| Healthcare and Safety Standards | Following medical and safety regulations in wearable health device design. |

**CHAPTER 6**

**SIMULATIONS**

**6.1 Python simulation**

The Python simulation plays a crucial role in testing, training, and validating the behaviour of the health monitoring model before deploying it to actual hardware. In the initial phase, the simulation is designed to process synthetic or real-world sensor data representing key physiological parameters like heart rate (BPM), body temperature (°C), and acceleration data (used for fall detection).

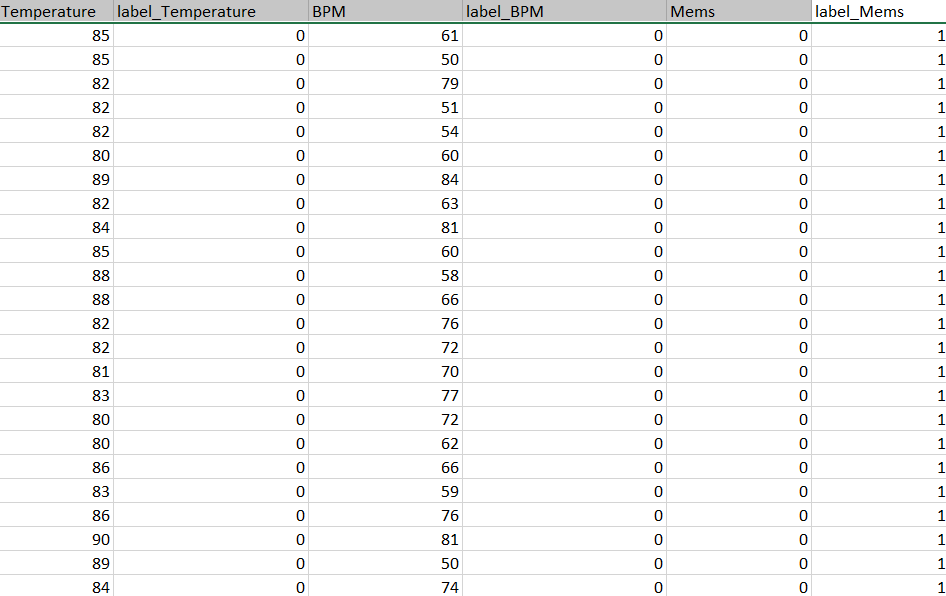


**Fig 6.1: Python program initiation**

The simulation begins with importing relevant Python libraries such as pandas, numpy, and matplotlib for handling and visualizing data. Sensor data can be sourced from open datasets or collected from physical devices and saved as CSV files. The data is cleaned by removing missing or noisy values and normalized for consistency.

**6.2 Model Building and Training**

In order to build and train a machine learning model, the Random Forest machine learning algorithm was chosen and used in order to classify data into normal or abnormal health states. The model is trained using labelled data that differentiates between safe readings and those that may indicate a health emergency



**Fig 6.2: Dataset used for model training**

After training, the model is tested on unseen data using metrics like accuracy, precision, recall, and confusion matrix. This helps assess the model’s performance in detecting anomalies and reducing false positives/negatives.



**Fig 6.3: Testing Data output**

After the final employment of the machine learning algorithm, the model is able to classify and predict the condition of the user based on the health inputs given i.e temperature, blood pressure and heartbeat measurement. As shown in Fig 6.3, as per the model prediction the heartbeat and temperature fall under the range of ‘normal’ and hence the final output is given as the person being normal. This model may further be enhanced for its accuracy by giving multiple inputs and providing it with new and updated datasets to train on.  **MNIST d**

**6.3 Purpose of the Simulation**

The use of python simulation and building a machine learning model and integrating it with the hardware was done due to various reasons:

* To validate the logic and performance of the health detection algorithm
* Fine-tune thresholds and model parameters
* Ensure real-time capability before deploying to a microcontroller
* Demonstrate system behavior during abnormal events in a safe environment

In conclusion, the simulation serves as a critical foundation for validating the functionality and accuracy of the health detection system before hardware implementation. It enables thorough testing of machine learning algorithms using real or synthetic sensor data, ensuring reliable detection of abnormal heart rate, body temperature, and fall incidents. By simulating real-time monitoring and alert generation, the model helps fine-tune system behaviour, paving the way for a more effective, responsive, and user-ready wearable health monitoring solution.

**CHAPTER 7  
RESULTS AND OTHER INFERENCES**

**7.1 Inference**

The performance of the health monitoring system was evaluated based on its ability to detect anomalies and trigger alerts in real time. The machine learning model, using the Random Forest algorithm, was trained to classify normal and abnormal sensor data, including temperature, heart rate, and MEMS readings. The proposed system effectively identified irregularities in the data, particularly those associated with abnormal heart rate or body temperature, ensuring that potential health risks were promptly flagged. The anomaly detection process proved reliable, providing accurate identification of critical deviations from normal health patterns. Furthermore, the proposed system demonstrated its functionality in emergency situations by sending timely SMS alerts to designated caregivers whenever an anomaly was detected. The integration of the GSM module ensured that the alerts were promptly delivered, enhancing the responsiveness of the system. This combination of continuous data monitoring, machine learning analysis, and real-time notifications created a robust safety mechanism, offering reliable health monitoring. Overall, the system showed promising potential in providing early intervention and ensuring the safety of individuals by delivering timely alerts and enabling appropriate action in case of emergencies.

**Table 7.1: Parametric comparison table between existing systems and proposed model**

| **Parameter** | **Existing System (e.g., Philips Health Watch)** | **Proposed Model** | **Remarks** |
| --- | --- | --- | --- |
| Parameters Measured | Heart Rate, Activity, Calories | Heart Rate, Body Temperature, SpO2, Fall Detection, MEMS | Broader scope in vitals |
| Real-time Monitoring | Limited to device or mobile app | Yes, with IoT integration (ESP32) | Improved connectivity |
| Emergency Alert System | No (or via app only) | Yes, SMS alert with GPS location | Advantage in emergencies |
| Fall Detection | Absent | Included (via MEMS accelerometer) | Significant safety feature |
| Portability | Wearable, compact | Compact wearable with embedded sensors | Comparable |
| Data Storage | Cloud (limited access) | Cloud (ThingSpeak) + Offline access | Better flexibility |
| Power Consumption | Optimized for commercial use | Moderate (ESP32 and sensors) | Can be improved further |
| Cost | High (~₹10,000+) | Low-cost prototype (~₹1,500–₹2,000) | Major advantage |
| Customizability | Low (proprietary systems) | High (open-source, programmable) | Flexible for upgrades |
| Target Audience | Fitness-focused users | Elderly, critical patients, remote health monitoring | Broader impact area |

The system also excels in real-time data transmission using the ESP32 module, ensuring continuous monitoring via platforms like ThingSpeak. This enables caregivers or medical personnel to track patient health remotely. The emergency alert mechanism worked as expected, sending SMS alerts with GPS coordinates to predefined contacts upon detecting critical conditions, thus validating the practical emergency response feature of the system. As shown in Table 7.1, when compared to existing commercial health monitoring devices, the project stands out due to its low cost, customizability, and multi-parameter sensing capabilities. Most existing systems are limited to fitness tracking and lack real-time alert mechanisms or fall detection. The prototype, built using open-source platforms like Arduino and Python, offers high flexibility for further enhancement.

**7.2 Alert System**

In the health monitoring system, receiving alert messages is a critical component that ensures timely response to medical emergencies such as abnormal heart rate, elevated body temperature, or a detected fall. This feature is designed using a combination of sensors, a microcontroller (ESP32 or Arduino), and a communication module like GSM or Wi-Fi.

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**Fig 7.1: Alerts sent through message**

Alert messages are sent when sensors detect critical health anomalies such as abnormal heart rate, high body temperature, or a fall. The microcontroller (like ESP32) continuously monitors real-time data from the sensors, and upon detecting a threshold breach, it triggers an emergency alert. This alert is delivered locally through a buzzer and LCD, and remotely via SMS using a GSM module. The SMS typically includes the type of emergency and the patient’s live GPS location, ensuring that caregivers or emergency contacts can respond promptly and accurately to potential health risks.

**7.3 Hardware display**

In the health monitoring system, the LCD display plays a crucial role in providing real-time feedback directly on the device. The microcontroller (Arduino Uno) receives continuous input from sensors like the heart rate sensor, temperature sensor, and fall detection MEMS accelerometer. These values are processed and then displayed on the LCD screen.

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**Fig. 7.2: Heart rate displayed on the LCD**  **Fig. 7.3: Body Temperature displayed on the LCD**



**Fig 7.4: Fall Alert displayed on the LCD**

As shown in Fig 7.2, the lcd displays the output of the heart rate measurement as BPM (beats per minute) being 83 which comes under normal condition and Fig 7.3 shows the detected body temperature of being 98.26 Fahrenheit which again falls under normal human condition.

Fig 7.4 showcases the fall alert displayed on the lcd. As soon as a fall is detected through the MEMS sensor, the alert is displayed on the lcd display whilst also sending a message alert. When a critical condition is detected, the display updates immediately with a corresponding warning message, often in conjunction with a buzzer sound. This on-device visual feedback helps both the patient and nearby individuals stay informed about the user's health status without relying on a mobile phone or cloud access.

Hence the real-time visualized output of the hardware consists of auditory indicators that reflect the user's physiological condition. The LCD screen displays continuously updated data such as heart rate, body temperature, and fall status, allowing users or nearby caregivers to view critical health metrics at a glance. When abnormal values are detected, such as elevated temperature, low or high heart rate, or a sudden fall, the system instantly triggers a buzzer to alert those nearby. Simultaneously, the LCD updates to show a clear warning message (e.g. "Fall Detected"), ensuring that emergencies are promptly recognized.

**CHAPTER 8  
CONCLUSION AND FUTURE WORK**

**8.1 Conclusion**

The Intelligent Health Monitoring Wearable with Emergency Alert System successfully combines sensor-based health monitoring with machine learning to provide an accurate and responsive real-time solution. The system's ability to monitor heart rate, body temperature, and detect falls, coupled with immediate alert notifications via SMS, enhances both personal safety and medical response times in critical situations. Machine learning integration significantly improved detection accuracy, reducing false positives and enhancing the system's reliability. The project demonstrates the effectiveness of combining hardware with intelligent algorithms to address health monitoring challenges, offering a practical solution for elderly or at-risk individuals. Future work could expand the system’s capabilities by integrating additional sensors and refining the machine learning model for more complex health conditions.

The proposed system has certain limitations. The reliance on SMS for alerts could result in delayed notifications in areas with weak network coverage, potentially affecting timely intervention. Additionally, the current system may produce false positives if users engage in high-motion activities not associated with health risks. Lastly, while effective for heart rate and fall detection, the system’s scope is limited, and its machine learning model could benefit from larger datasets to improve accuracy. Future work could expand these capabilities by integrating additional sensors and refining the model to account for more complex health conditions and user behaviours.

**8.2 Future work**

Future enhancements to the health monitoring system could include the integration of more advanced machine learning models to increase the accuracy of detecting anomalies in heart rate, body temperature, and fall incidents. Techniques such as Long Short-Term Memory (LSTM) networks or Convolutional Neural Networks (CNNs) could be employed to better understand time-series data patterns and reduce false alarms. This would provide more reliable results in diverse real-life conditions.

Another significant advancement would be incorporating cloud-based health data analytics. By connecting the system to cloud platforms such as AWS, Firebase, or Google Cloud, users and healthcare professionals could access and analyze long-term trends in patient health. This would enable early detection of chronic conditions and support remote diagnostics, particularly valuable in rural or underserved areas.

To enhance the emergency response, future systems could integrate GPS modules that send real-time location data during critical incidents like falls or abnormal health readings. This location-aware feature would assist caregivers and emergency responders in reaching patients faster, especially if they are alone or in unfamiliar locations.

**8.3 Realistic Constraints**

* Wearable health devices must operate continuously, but frequent recharging is inconvenient, especially for elderly users. Power-hungry components like sensors, microcontrollers, and wireless modules (e.g., Bluetooth, Wi-Fi) can drain the battery quickly, limiting the device’s practical usage time.
* Low-cost sensors used for heart rate, temperature, and fall detection may produce noisy or inaccurate readings, especially during motion or in non-ideal environments. These inaccuracies can result in false alarms or missed critical conditions, reducing trust in the system.
* Transmitting sensitive health data wirelessly or storing it on cloud platforms raises serious concerns about data privacy and security. Implementing encryption, secure data handling, and compliance with regulations (like HIPAA or GDPR) adds complexity and resource demands to the system.

**CHAPTER 9  
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