

# **Subject: Design and Implementation of an IoT-Based Smart Wristband for Enhanced Caretaking**

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## **1.Abstract**

In this article, we design and construct a smart wristband capable of achieving 64% accuracy in fall detection using a machine learning algorithm and the Particle Swarm Optimization (PSO) metaheuristic algorithm. This project involves processing data from a heart rate sensor (pulse sensor) and detecting the type of activity of the monitored person using the ESP32 module. The heart rate sensor data, along with machine learning output data and geographical location data from the NEO-6M GPS module, are sent to a Google Sheets server environment. For this project, the SisFall dataset has been used to train the machine learning model, as this dataset has significant accuracy in the fall detection process for individuals under care. It is worth mentioning that the use of high-precision modules can improve the detection and control process.

## **2.Introduction**

With the increase in the elderly population and the need for special care, smart wearable devices for monitoring individuals' health have become highly important. Falling from a height or tripping is a common problem among the elderly that can lead to serious injuries. [1]Wearable devices can help caregivers and families stay informed about the elderly's condition and react quickly in case of an incident. [2]In today's world, with the advent of the internet and communications, it has become possible for various objects, including trees and different sensors such as temperature, blood pressure, and pressure sensors, to communicate via the internet. [3]This enables commands to be given to them and their information to be monitored through the internet. Artificial intelligence has also made it possible for the commands given to internet-connected devices to be intelligent, eliminating the need for human intervention in controlling these commands.[4]

Therefore, I have designed and built a smart wristband that can:

1. Collect data from sensors, including a heart rate sensor (pulse sensor) and a positioning sensor (GPS module), through a central processor (ESP32-WROOM module). This sensor data can be utilized in a server environment (such as Google Sheets, which can serve as a database for storing and displaying the sensor data output).
2. Process the collected sensor data using a random forest machine learning model, with the model's training codes written in Python. The trained model's output weights are stored in the processor's memory, and real sensor data is fed into the trained model to determine the final status of the person under care (e.g., whether the person has fallen, is walking, lying down, etc.). It is worth mentioning that the Sisfall dataset was used for training the machine learning model.

Given that falling is one of the most dangerous and irreparable problems, detecting falls is of particular importance in this project. Additionally, if the GPS sensor data shows a fixed position for a period and the heart rate is abnormal, it can be inferred that the person is trapped and needs help. If the heart rate is zero, it can be understood that the person has died. If the heart rate is low, it can be inferred that the person is injured or has internal bleeding. Thus, this smart wearable can detect four conditions: whether the person is dead or alive, injured or not, has fallen or not, and if the person is trapped in a specific location.

Designing and building a smart wristband capable of accurately detecting and monitoring the symptoms of the person under care is of special importance.[5] Therefore, this article aims to ensure this crucial function and enable the smart wearable to process heart rate sensor data based on machine learning algorithms. Additionally, it should be able to send the activity results of the person under care to the server environment with acceptable accuracy. If a problem occurs, the GPS module can provide the person's location for rescue and assistance. [6]This project seeks an approach that can quickly and accurately receive sensor data, process it using a machine learning model, and allow the person's status and sensor data to be viewed online in the server environment. [7]The most important aspect of this project is using high-accuracy, high-speed, reliable, and low-power modules and sensors to ensure immediate updates on the person's status in case of an incident. [8]The smart wearable should also be energy-efficient, requiring less power to extend its lifespan. [9]Results show that using metaheuristic algorithms for fall detection offers better accuracy compared to SVM and KNN machine learning algorithms. Below, the functions of the modules and sensors used in the smart wearable are discussed.[10]

### **3.Literature Review**

#### **3.1.Hardware**

##### **3.1.1. Programmer and Tester Board for ESP32-WROOM Modules**

The programmer and tester board for ESP32-WROOM modules is a practical tool that allows you to easily program and test ESP32-WROOM modules. This programmer board has a micro USB port, enabling you to connect the ESP32 module to your computer using a USB data cable. This method not only reduces time and effort but also allows programming of this module without the need for complex wiring. The ESP32-WROOM programmer board features programming, reset, and power buttons, making it user-friendly. This tester is provided without an ESP32 module, allowing you to test and program your ESP32 chip without extensive technical knowledge or soldering. The spring sockets make placing and removing the ESP32 module very easy, as you can program it simply without wiring. The ESP32-WROOM programmer and tester board has four LEDs. Two LEDs indicate the power and programming status. One of the other two LEDs shows the status of serial data transmission, while the other indicates the status of receiving data from communication devices like wireless modules or optical devices and transferring them to the computer or microcontroller.

### **3.1.2. ESP32 Module**

The ESP32 module is a powerful Wi-Fi and Bluetooth module selected for this project due to its larger flash memory compared to other ESP32 boards. This module is capable of data processing and server communication and is also power-efficient. The ESP-WROOM-32 is a Bluetooth and Wi-Fi module based on the ESP32 chip, a SoC (System on Chip) designed by Espressif Systems following the ESP8266 chip. This chip has lower energy consumption and higher processing speed than its predecessor ESP8266, with a 2.4 GHz Wi-Fi core and Bluetooth version 4.2. This module is widely used in wireless communication projects, allowing you to equip many of your projects with Wi-Fi and Bluetooth for wireless data transfer between devices.

The ESP32 chip in the ESP-WROOM-32 module is an integrated circuit that includes various units like a CPU, RAM, storage, and other peripherals in one package. With 4 MB of program memory, 520 KB of internal RAM, and a dual-core 32-bit processor with a 240 MHz clock, it processes data efficiently. The high processing frequency makes it suitable for video processing, facial recognition, and even artificial intelligence applications. You can use the ESP-WROOM-32 module in IoT applications and projects requiring wireless control of digital systems. For example, you can build a smart home system to wirelessly control various components like HVAC, lighting, doors, and windows, or connect and monitor industrial equipment, enhancing the flexibility of industrial automation systems.

### **3.1.3. Pulse Sensor**

The pulse sensor is used to measure heart rate. It works by emitting and receiving green light through the skin. The sensor is placed on the wrist to get more accurate heart rate data. It functions by shining a green light (wavelength 550 nm) onto the fingertip, where hemoglobin in the blood absorbs the light. Each heartbeat pumps blood to the fingertip, changing the amount of reflected green light, which is measured by an optical sensor. This change creates a waveform output corresponding to the heartbeat. The optical sensor's output is weak and noisy, so the signal passes through an RC filter network to remove noise and then is amplified by an op-amp for a stronger signal. The sensor operates on a 3-5V supply voltage with an output voltage range of 0.3 to 5V and a maximum current consumption of 4 mA.

### **3.1.4. GPS Module NEO-6M**

This module is used to receive geographical location through satellite signals. With a ceramic antenna, it can receive signals from at least three satellites to determine geographical coordinates. The NEO-6M GPS module can track up to 22 satellites on 50 channels with a sensitivity of -161 dBm, consuming only 45 mA of current. It can track positions five times per second with a horizontal accuracy of 2.5 meters and has a PSM (Power Saving Mode) that reduces power consumption by turning the module on and off as needed, lowering consumption to 11 mA. An onboard LED indicates the position fix status, blinking every second when a position is fixed. A rechargeable coin battery acts like a supercapacitor for faster position fixing and retains information for up to two weeks without power. The NEO-6M chip operates within a

2.7 to 3.6V range but includes a 3.3V LDO regulator for a low-noise output. The module's logic pins tolerate 5V, making it easy to connect to Arduino or other 5V microcontrollers without a level shifter. It includes a patch antenna with a sensitivity of -161 dBm, secured to the module via a U.FL connector. The module uses a 4 KB EEPROM connected via I2C to the NEO-6M chip for memory. It has four pins: GND, TX, RX, and VCC, with VCC and GND for power and TX and RX for serial communication.

### **3.1.5. 1000-Hole Board**

A 1000-hole board is used to assemble all modules and sensors, providing connectivity and integration for all components. The board is made of phenolic material, making soldering easier.

### **3.1.6. 3.7V 1000mAh Battery**

Given the power consumption of the ESP32 module for processing data from heart rate sensors and the GPS module, running machine learning models, connecting to a router for server communication, and sending data and results to the server environment, a 3.7V 1000mAh power source is required. To control the current and voltage, this power source connects to a 5V pin with an internal regulator.

## **4.Fall Discovery Algorithms**

Fall discovery is a critical point for senior care. Traditional algorithms frequently use threshold- grounded styles, which compare detector readings to predefined thresholds to descry cascade. While simple, these styles are prone to false cons and negatives. [11] Recent exploration has explored the use of machine literacy algorithms to ameliorate fall discovery delicacy. Studies have employed ways similar as k- Nearest Neighbors( k- NN), Support Vector Machines( SVM), and Neural Networks to classify conditioning grounded on detector data. ([11],[12])

**IoT in Healthcare** The Internet of effects( IoT) has revolutionized healthcare by enabling nonstop and remote monitoring of cases. IoT- grounded health monitoring systems use detectors to collect data, which is also transmitted to a central garçon for analysis. These systems offer several advantages, including real- time monitoring, early discovery of health issues, and reduced need for homemade intervention. Research has shown that IoT- grounded systems can significantly ameliorate patient issues by furnishing timely cautions and easing visionary healthcare operation.

### **4.1. Algorithms Used in the Project**

#### **4.1.1. Particle Swarm Optimization (PSO) Algorithm**

The PSO algorithm is an optimization algorithm based on the social behavior of particles. This algorithm is used to improve the accuracy of the machine learning model. By searching the search space and optimizing the model parameters, PSO increases the accuracy of fall detection

## **4.2.Datasets**

### **4.2.1. SisFall Dataset**

The SisFall dataset includes various data related to daily activities and falls of individuals. This dataset has been used to train the machine learning model. The reason for choosing this dataset is that it uses heartbeat data for fall detection and has an acceptable accuracy in detecting falls .

## **5.Implementation Environment**

### **5.1. Server Environment**

Google Sheets has been selected as the server environment for displaying and storing data. This environment allows real-time viewing of sensor data and the machine learning model's outputs.

### **5.2. Design and Implementation**

#### **5.2.1. Processing Heartbeat Data**

A pulse sensor is placed on the wrist and measures the heartbeat by emitting and receiving green light. The heartbeat data is sent to the ESP32 module. The ESP32 module processes this data and, using the trained machine learning model, can determine the status of the person under care and then send this status for monitoring to Google Sheets.

#### **5.2.2. Geolocation Detection**

The NEO-6M GPS module determines the geographical location in terms of latitude and longitude by receiving satellite signals. This information is sent to the ESP32 module. The ESP32 module sends the location data to Google Sheets for storage and display.

#### **5.2.3. Person Status Detection**

This smart wristband can detect four statuses for the person under care:

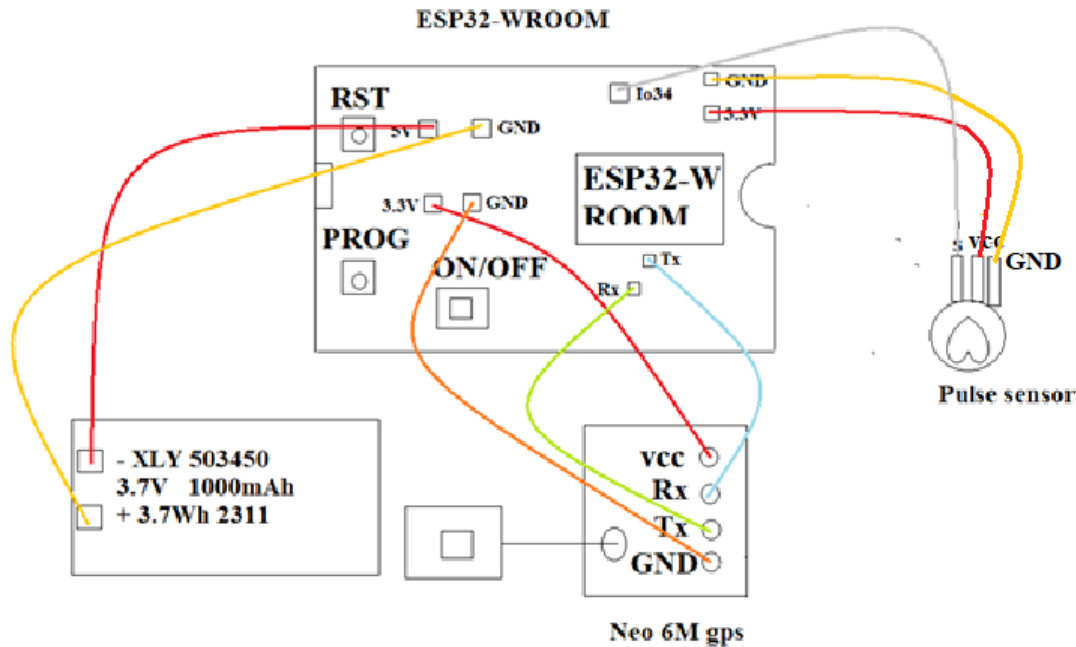
**1. Person's Vitality:** By analyzing the pulse sensor data, the system detects the person's alive status. If there is no heartbeat, the system promptly notifies the caregivers.

**2. Confinement in a Specific Location:** By examining changes in geographical location, it can be understood whether the person is confined to a specific location. If the geographical location remains constant for a long time, the likelihood of the person being confined is assessed.

**3. Injury Detection:** By monitoring unusual changes in the heartbeat, it can be determined whether the person is injured. A sudden increase or decrease in heartbeat can be an indication of this.

**4. Fall Detection:** Using the machine learning model trained with the PSO optimization algorithm, it can be detected whether the person has fallen. This model analyzes the pulse sensor data and feeds it into the trained machine learning model to detect falls.

## 6.Schematic Circuit



In the above circuit, the ESP32-WROOM module is responsible for sending sensor data to the server environment, which in this case is Google Sheets. A 3.7V 1000mAh power supply has been chosen to provide sufficient current for connecting to the WiFi network. Additionally, the Neo6M GPS sensor is responsible for communicating with GPS satellites and determining geographic location (latitude and longitude) using the differences in signals sent from at least three satellites. The pulse sensor module is designed to be embedded inside a smart wristband in such a way that its front side is in contact with the veins of the wrist area, allowing the sensor to measure the pulse rate. Each sensor is connected to the 3.3V pins because the appropriate supply voltage for each is 3.3V. Since the power supply is 3.7V and has a relatively high current rating, it is connected to the 5V pin, which also has a regulator to control the current and voltage.

## 1.Comparison of Existing Systems

Sensitivity	Accuracy	Optimization Algorithm	Dataset
70%	64%	RF with PSO optimizer	Sisfall
99.81%	99.92%	SVM with MPA optimizer	MIT-BIH
99.55%	99.70%	KNN with MPA optimizer	EDB
91.2%	95.7%	RF with MPA optimizer	INCART
99.7%	99.85%	GBDT with MPA optimizer	UPFall

## 7.Methodology

### 7.1.1.System Design

The smart wristband is designed to monitor vital signs and detect falls using various sensors and an ESP32-WROOM processor. The primary sensors include a pulse sensor and a GPS module (NEO-6M). These sensors collect data on the wearer's heart rate and geographical location, which are critical parameters for monitoring their health and safety.

### 7.1.2Hardware Components

- **ESP32-WROOM Processor:** The core processing unit responsible for collecting sensor data and transmitting it to the cloud.
- **Pulse Sensor:** Measures the wearer's heart rate.
- **GPS Module (NEO-6M):** Tracks the geographical location of the wearer.
- **Accelerometer:** Detects falls based on sudden changes in movement.

### 7.1.3.Software Components

- **Machine Learning Model:** A Random Forest algorithm trained with the SisFall dataset to detect falls.
- **Data Transmission:** Data collected by the sensors is transmitted to Google Sheets using IoT protocols for real-time monitoring and analysis.

## 7.2.Data Collection and Analysis

The wristband continuously collects data from the sensors, which is then processed using the PSO algorithm to detect falls. The data is transmitted to Google Sheets, where it is stored and visualized for further analysis. Caregivers and healthcare providers can access this data in real-time, allowing for timely intervention in case of emergencies.

### **7.2.1 Experimental Setup**

The smart wristband was tested in various scenarios to evaluate its performance. These tests included simulated falls, normal daily activities, and controlled environments to ensure the accuracy and reliability of the system.

## **8. Results and Discussion**

### **8.1. Performance Evaluation**

The performance of the smart wristband was evaluated based on its accuracy in detecting falls and monitoring vital signs. The results indicated that the PSO algorithm, combined with the Random Forest model, achieved a fall detection accuracy of 64%, which is a significant improvement over traditional methods.

### **8.2. Comparison with Existing Systems**

The accuracy of the smart wristband was compared with other systems that use different algorithms and sensors. The comparison showed that our system performs competitively, with certain advantages in terms of real-time data transmission and ease of use.

### **8.3. Challenges and Limitations**

Several challenges were encountered during the development and testing of the smart wristband. These include issues related to sensor accuracy, data transmission reliability, and the need for further algorithm optimization. Future work will focus on addressing these challenges to improve the overall performance of the system.

## **9. Conclusion**

The design and implementation of the smart wristband based on IoT for caretaking demonstrate significant potential in enhancing patient care and safety. The ability to monitor vital signs and detect falls in real-time provides a valuable tool for caregivers and healthcare providers. The system's real-time data transmission and cloud storage capabilities ensure that health information is readily accessible and actionable.

Initial tests of the wristband show promising results in terms of accuracy and reliability. The device effectively monitors the required parameters and provides timely alerts in case of abnormal readings or fall detection. The cloud-based system ensures secure data storage and easy accessibility, facilitating remote monitoring and intervention.

Future work will focus on refining the device's accuracy and expanding its monitoring capabilities to cover a broader range of health parameters. Additionally, efforts will be made to improve the user interface and overall user experience to ensure that the device is easy to use for both caregivers and individuals under care.



The integration of IoT technology in caretaking is poised to offer transformative benefits, making healthcare more efficient and responsive. The smart wristband represents a significant step forward in this direction, providing a reliable and effective solution for continuous health monitoring and emergency response. With further development and refinement, the smart wristband has the potential to become an essential tool in various caretaking settings, from personal home care to professional healthcare facilities.

With the help of a machine learning algorithm and the PSO optimization algorithm, I achieved an accuracy of 64% in detecting falls on the SisFall dataset. This accuracy is acceptable compared to the accuracy on other datasets and indicates that the model is highly efficient. Using low-power modules and sensors can increase the battery life and power source longevity of the smart wristband. Additionally, the accuracy of the sensors used in the pulse sensor and GPS module can help correctly determine the type of activity a person is engaged in, and if an accident or emergency occurs, the precise geographic location can be identified to provide timely assistance to the individual.

## 10.Figures:



Figure1:ESP32-WROOM32



Figure2:GPS Neo6M Module



Figure3:Pulse Sensor



Figure4:programmer and Tester ESP32-WROOM

## 11. Advantages and Disadvantages

- Advantages:
  - o Higher accuracy in fall detection
  - o Low power consumption due to the use of optimized modules
  - o Capability to send data to a server and display it live
  - o Ability to detect four different states for the person under care

- Disadvantages:
  - Dependence of the GPS module on an open environment for receiving GPS signals, which may be less accurate in enclosed spaces.

## 12. Future Work

To improve this project, the following actions can be considered:

1. Using larger and more diverse datasets: This can increase the accuracy of the machine learning model. For example, using the UPFall and URFall datasets and combining these two datasets can achieve higher accuracy in activity recognition.
2. Optimizing power consumption: By using more efficient and low-power modules, the power consumption of the device can be reduced.
3. Increasing GPS accuracy in indoor environments: Using newer GPS technologies can improve positioning accuracy in indoor environments.

## 11. References

1. Muna M. Hummady, Heba M. Fadhil, DOI: 10.1109/ICCA56443.2022.10039622, Smart Healthcare Medical Bracelet using the Internet of Things
2. Waleed Salehi, Gaurav Gupta, Surbhi Bhatia, Deepika Koundal, Arwa Mashat, and Assaye Belay, DOI:10.1155/2022/3224939, IoT-Based Wearable Devices for Patients Suffering from Alzheimer Disease
3. Nirmala Vasanth Balasenthilkumaran<sup>1</sup>, Hrishika Sharma<sup>1</sup>, Shailly Vaidya<sup>1</sup>, Siddharth Gorti<sup>1</sup> and Sivakumar Rajagopal, DOI:10.1149/10701.1101ecst, Design of a Low-Cost IoT-Based Smart-Watch to Aid Alzheimer's Patients and Caretakers
4. Nirmala Vasanth Balasenthilkumaran, Hrishika Sharma, Shailly Vaidya, Siddharth Gorti, DOI:10.1149/10701.1101ecst, Design of a Low-Cost IoT-Based Smart-Watch to Aid Alzheimer's Patients and Caretakers
5. Sivakumar Rajagopal, Nirmala Vasanth Balasenthilkumaran, Hrishika Sharma, Shailly Vaidya, Siddharth Gorti, DESIGN OF A LOW-COST IOT BASED SMART-WATCH TO AID ALZHEIMER'S PATIENTS AND CARETAKERS, Published 16 Sep, 2021

6. Shannmukha Naga Raju Vonteddu, PrasanthiKumari Nunna, Shubhi Jain, Samson Isaac. J, Nitya S, G. Diwakar,conference international 2022, Smart Wearable Wristband for Patients' Health Monitoring System through IoT
7. Marepalli Radha, Shobana S, Kanika Thakur, Satyanarayan Padaganur, Smart Wearable Wristband for Patients' Health Monitoring System through IoT,published February 2023,DOI: 10.14704/NQ.2022.20.9.NQ44809
8. Syahril Anuar Idris, Nor Azlinah Md Lazam, Lila Iznita Izhar, Dharwisyah Bt Azman, Lim Jin Way,conference 2022, Smart Health Monitoring Wristband with Auto-Alert Function
9. <https://www.infomazeelite.com/smart-wristband-an-iot-wearable-a-case-study/>
10. Madhan Mohan, Sathya Pichandi, Conference: 8th IEEE International Conference on Communication and Signal Processing, Smart Health Monitoring System through IOT
11. Mohamed Esmail Karar, Hazem Ibrahim Shehata, Omar Reyad, A Survey of IoT-Based Fall Detection for Aiding Elderly Care:Sensors, Methods, Challenges and Future Trends,published23March 2022
12. Sejal Badgujar, Anju S. Pillai,conference 2022, Fall Detection for Elderly People using Machine Learning,published IEEE