Smart Wheelchair Monitoring System: A Real-Time IoT-Based Health and Safety Assistive Platform

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***Abstract*— This paper presents the design, implementation, and evaluation of an Internet of Things (IoT)-based Smart Wheelchair Monitoring System designed to enhance the autonomy, safety, and healthcare delivery for individuals with physical and mobility impairments. The proposed assistive platform integrates a comprehensive sensor suite—including the MAX30102 for heart rate and blood oxygen saturation (SpO_2) monitoring, an analog Galvanic Skin Response (GSR) stress sensor, and a non-invasive Electrocardiogram (ECG) cardiac monitor—onto an ESP32-C3 microcontroller plat- form. For navigation safety, the system incorporates an MPU-6050 6-axis inertial sensor and a tilt sensor for posture, orientation, and fall detection, alongside ultrasonic sensors for active obstacle avoidance. Telemetry data is prepro- cessed at the edge and securely transmitted via Bluetooth Low Energy (BLE) and the Message Queuing Telemetry Transport (MQTT) protocol to a FastAPI backend. Real-time vital signs and alerts are visualized on a centralized doctor-patient web portal implemented via Streamlit. A supervised deep learning 1D Convolutional Neural Network (1D-CNN) is integrated into the backend to classify ECG signals and detect cardiac arrhythmias. Experimental re- sults validate the real-time tracking, alerting capability, low latency, and low cost of the integrated assistive ecosystem, demonstrating high feasibility for clinical and home care environments.**

***Index Terms*—Internet of Things (IoT), Smart Wheelchair, Health Monitoring, ESP32-C3, MAX30102, ECG Classification, 1D-CNN, Stress Detection, Fall Prevention**

I. INTRODUCTION

Mobility impairments significantly reduce an individual's ability to independently interact with their surroundings, often leading to emotional and physical dependency. This challenge is especially pressing in developing nations like India, where approximately 120 million people live with a disability, with 41.23% of them being physically disabled [3, 4]. Traditional wheelchairs serve basic mobility needs but lack features for continuous physiological monitoring, real-time data communication, and proactive hazard prevention. Inte- grating intelligent systems into mobility aids can trans- form them into powerful health companions capable of remote monitoring, emergency alerts, and proactive care [1, 19].

The Internet of Things (IoT) has revolutionized the healthcare industry by utilizing sensors and controllers to gather and exchange environmental and physiological data. In the proposed system, we utilize the low-power ESP32-C3 microcontroller to build a comprehensive health and safety companion. The wheelchair is equipped with vital health sensors to continuously track the patient's resting heart rate (ideally between 60 and 100 bpm), blood oxygen saturation levels (SpO_2, normal range > 95%), and ECG waves [5, 22]. A Galvanic Skin Response (GSR) sensor evaluates real-time stress levels, while an MPU-6050 inertial tracking sensor and a tilt sensor prevent unsafe tipping or detect sudden falls. The safety features are rounded out with ultrasonic sensors for collision avoidance. Telemetry data is transmitted via BLE and MQTT protocols to ensure secure inter-device communication and real-time remote monitoring by medical practitioners through web-based platforms.

The primary contributions of this project include:

- Designing a modular, low-cost, and power-efficient smart wheelchair attachment.
- Integrating a diverse range of biomedical (ECG, SpO_2, GSR) and mechanical (inertial, tilt, ultrasonic) sensors.
- Implementing an asynchronous firmware stack in MicroPython on the ESP32-C3.
- Developing a secure, real-time FastAPI and Web-

Sockets backend integrated with a Streamlit-based web dashboard.

- Training and deploying a 1D Convolutional Neural Network (1D-CNN) classifier on the MIT-BIH Arrhythmia and PTB Diagnostic ECG datasets to achieve automated cardiac anomaly detection.

II. LITERATURE REVIEW

Continuous advances in human-machine interaction, IoT, and biosensors have accelerated the development of smart wheelchairs.

2.1. IoT-Enabled Smart Wheelchairs for Health Monitoring

Integrating IoT technologies into assistive platforms has greatly enhanced patient autonomy. Sukerkar et al. developed a smart wheelchair that combines electroencephalogram (EEG)-based brain control, joystick navi- gation, and vital sign monitoring using the MAX30100 (SpO_2/HR) and AD8232 (ECG) sensors. In their ar- chitecture, data was transmitted to cloud platforms like Firebase and Ubidots to enable remote monitoring and emergency alerts via SMS/email [16]. Similarly, Jiang et al. introduced "SmartRolling", a control framework that utilizes EEG signals, a front-facing camera, and an IMU to track hand and head gestures to estimate steer- ing intentions, thereby enhancing navigation interfaces for severely disabled users.

2.2. Embedded Health Monitoring and Real-Time Transmission

Continuous assessment of vital signs directly on the wheelchair prevents sudden health deterioration. Ogun- duyile et al. developed a system that monitors heart rate, SpO_2, and location data, transmitting it to a Medical Health Server via GPRS/Internet. This allowed medi- cal practitioners to access real-time status through web applications. To address non-invasive sensing comfort, Deepu et al. designed a smart cushion embedded with a micro-bending fiber sensor to record ballistocardio- gram (BCG) signals without direct skin contact, provid- ing real-time heart rate tracking comparable in accuracy to commercial oximeters [10, 11].

2.3. Secure and Eflcient Data Management in IoT Healthcare

Since health data is highly sensitive, secure transmission is paramount. Cheikhrouhou et al. proposed a lightweight blockchain and fog-enabled remote patient monitoring system. Their architecture optimized data security and achieved a 40% reduction in response latency compared to traditional cloud-based sys- tems, demonstrating viability for resource-constrained IoT nodes [2, 18]. Furthermore, Demirel et al. in- troduced an energy-efficient multi-layered methodology for continuous heart monitoring. Their system utilizes a distributed Convolutional Neural Network (CNN) ar- chitecture, achieving 99.2% classification accuracy on the MIT-BIH Arrhythmia dataset while remaining opti- mized for resource-constrained hardware [22].

2.4. Multimodal Control and Human-Machine Interaction

Advancements in human-machine interface (HMI) have facilitated multimodal control systems. Recent smart wheelchairs utilize gesture sensors, posture sensors, GPS positioning, and LiDAR to achieve comprehensive human-wheelchair-environment interaction. The systems support handle-based, gesture-based, and mobile application controls using MQTT, ensuring safety and an intuitive user experience [20]. Our pro- posed system builds upon these works by providing an integrated, low-cost solution combining multi-sensor physiological telemetry, MPU-6050-based hazard de- tection, and deep learning-based ECG classification.

III. SYSTEM REQUIREMENTS AND MARKET LANDSCAPE

3.1. Market Landscape and Expansion of Telemedicine

The Indian telemedicine and Remote Patient Monitoring (RPM) markets have witnessed explosive growth, driven by digital health initiatives and the need to extend care to underserved populations.

- The Indian telemedicine market was valued at USD 4.04 billion in 2023 and is projected to reach USD 15.11 billion by 2030, at a CAGR of 20.7%.
- The remote health monitoring market in India grew to USD 209.8 million in 2024 and is expected to reach USD 1.22 billion by 2033, growing at a CAGR of 21.6%. The RPM software and services sub-sector generated USD 320.2 million in 2023 and is projected to reach USD 2.48 billion by 2030, representing a CAGR of 34% [7, 14].

- The Indian wearable medical devices market reached USD 2.34 billion in 2024 and is expected to reach USD 5.67 billion by 2030, growing at a CAGR of 16% [15].

These trends indicate a strong market demand for cost-effective, intelligent, and interconnected medical devices like our smart wheelchair.

3.2. Hardware and Software Requirements

The integrated hardware suite consists of:

1. ESP32-C3 Microcontroller: A low-cost, low-power single-core 32-bit RISC-V controller with native 2.4 GHz Wi-Fi and BLE 5.0.
2. MAX30102 Sensor: A non-invasive optical pulse oximetry and heart rate module.
3. MPU-6050 6-Axis Sensor: Combines a 3-axis accelerometer and a 3-axis gyroscope on a single chip to track wheelchair orientation, tilt angle, and sudden motion events.
4. GSR Sensor: Evaluates physiological stress by measuring skin conductance via two passive finger electrodes.
5. ECG Sensor: Captures real-time cardiac electrical activity.
6. Tilt Sensor & Ultrasonic Obstacle Sensors: Provides hazard detection for physical safety.

The software stack utilizes:

- MicroPython & C++: Embedded programming for hardware interfacing.
- FastAPI: High-performance backend API handling HTTP requests and WebSockets streaming.
- Streamlit: Rapid dashboard prototype for patient-doctor portal visualization.
- ThingsBoard: Central IoT device provisioning, monitoring, and telemetry management.
- TensorFlow/Keras: Deep learning libraries used for model training and deployment.
- Twilio API: Real-time emergency SMS/WhatsApp alerting.

3.3. Dataset Description

To train our cardiac anomaly detector, we utilized the following benchmark ECG databases:

- MIT-BIH Arrhythmia Dataset: Contains 48 half-hour two-channel ambulatory ECG record- ings, annotated to classify normal beats vs. various types of arrhythmias [9].
- PTB Diagnostic ECG Database: Provides high-resolution multi-channel ECG recordings from healthy volunteers and patients with various clinical cardiovascular profiles, ideal for training diagnostic classification networks [22].

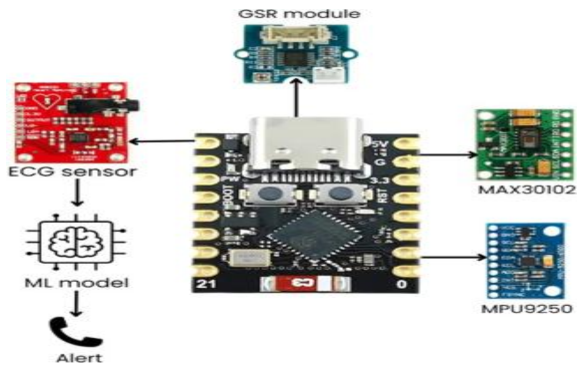


Figure 1: Hardware block diagram and system schematic of the Smart Wheelchair Monitoring System.

IV. PROPOSED ARCHITECTURE AND IMPLEMENTATION

4.1. Hardware Architecture and Interface Layout

The hardware architecture focuses on robust, low-power, and compact sensor integration. The ESP32-C3 serves as the primary processing node. The MAX30102 and MPU-6050 sensors are connected in parallel to the shared I^2C bus (SDA/SCL lines), which requires appro- priate pull-up resistors for signal integrity. The GSR stress sensor outputs an analog voltage proportional to skin conductance, which is connected directly to one of the ESP32-C3's analog-to-digital converter (ADC) pins. The wiring layout and pin configurations are detailed in Table 1.

Power is managed via the ESP32-C3's 3.3V voltage regulator, which is supplied by an onboard rechargeable lithium-polymer battery pack. Firmware stability is maintained by enabling the hardware watchdog timer (WDT), preventing system lockups during extended monitoring periods.

Table 1: System Integration and Wiring Configuration

ESP32-C3 Pin	MAX30102	MPU-6050	GSR	Function
GPIO 21 (SDA)	SDA	SDA	–	I^2C Data
GPIO 22 (SCL)	SCL	SCL	–	I^2C Clock
GPIO 3 (ADC)	–	–	Analog Out	GSR Input
3.3V	VCC	VCC	VCC	Power

				(3.3V)
GND	GND	GND	GND	Ground

4.2. Asynchronous Firmware Stack

The microcontroller firmware is written in MicroPython using an asynchronous programming paradigm (uasyncio). Tasks are scheduled non-blockingly to poll the I^2C bus and the analog ADC pin at distinct frequencies:

- The MAX30102 is sampled at 100 Hz to capture high-resolution PPG signals.
- The MPU-6050 and tilt sensors are sampled at 50 Hz to allow rapid fall and orientation tracking.
- The GSR and ECG modules are sampled at 20 Hz.

Raw sensor readings are filtered at the edge using moving-average and low-pass filters to reduce high-frequency electrical noise. Preprocessed data is packaged into structured byte arrays and transmitted wirelessly to the host PC/gateway via BLE utilizing the standard UART-over-BLE service profile.

4.3. Backend and Telehealth Portal Software

The host PC/gateway runs a FastAPI backend application that reads incoming data from the BLE port. Live data is stored in a relational database and instantly broadcast to connected web clients via high-frequency WebSockets. The telehealth dashboard, developed in Streamlit, is structured into distinct, secure interfaces:

1. Doctor Portal: Enables real-time remote patient vital signs visualization (HR, SpO_2, stress, active ECG graph), patient record management, digital prescription writing, and appointment scheduling.
2. Patient Portal: Allows the user to view histori- cal vitals trends, download auto-generated health reports, view medication reminders, and schedule clinical consultations.
3. Alerting System: Connects to the Twilio API to automatically trigger immediate SMS and WhatsApp alerts to pre-configured emergency contacts and physicians if vital thresholds are breached or if a fall event is registered.

V. METHODOLOGY AND MACHINE LEARNING CLASSIFIER

5.1. Six-Phase System Process Flow Model

The end-to-end operation of the system is structured into six distinct execution phases (illustrated in Fig. 2):

1. Phase 1: Initialization: On power-on, the microcontrollers initialize the communication buses, establish BLE pairing, and configure the MAX30102, MPU-6050, GSR, and ECG biosensors.
2. Phase 2: Sensing & Preprocessing: Firmware reads raw sensor data, applying moving-average filtering to PPG signals and digital low-pass filter- ing to IMU outputs.
3. Phase 3: BLE Communication: Preprocessed telemetry arrays are streamed via the UART-over-BLE profile to the gateway PC.
4. Phase 4: Live Visualization: The FastAPI server routes the incoming stream to WebSockets, rendering live graphs (such as the cardiac wave and stress levels) on the Streamlit dashboard.
5. Phase 5: Anomaly Analysis & Alerting: The gateway passes the live ECG signals to the pre-trained 1D-CNN model. If an arrhythmia or a sudden fall (IMU acceleration spike followed by a tilt threshold breach) is detected, the Twilio gateway is triggered to send an emergency SMS, and a hardware buzzer on the wheelchair is activated.
6. Phase 6: Continuous Loop: The system loops back to Phase 2 to ensure continuous monitoring and safety checking.

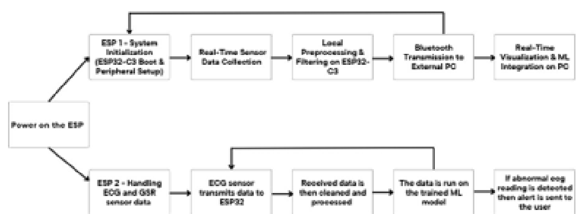


Figure 2: Process flow model and sequence diagram illustrating the 6-phase operational workflow.

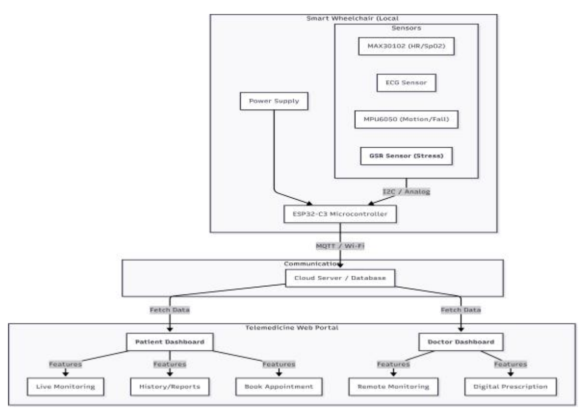


Figure 3: Detailed architectural pipeline of the multi-sensor phase sensing and transmission layout.

5.2. 1D-CNN Classifier for ECG Anomaly Detection

To achieve reliable automated diagnosis, we deployed a 1D Convolutional Neural Network (1D-CNN) optimized for processing sequential, time-series ECG data. The architecture contains successive layers of 1D convolutions, batch normalization, max-pooling, and dropout to capture local temporal features while avoiding overfitting.

The network is trained using supervised learning with the backpropagation algorithm. The weight parameters are optimized using the Adam (Adaptive Moment Estimation) optimizer to enable efficient learning on sparse gradients. The default hyperparameters are listed in Ta- ble 2.

Table 2: ECG Classification CNN Training Specifications

Component	Details
Model Type	1D Convolutional Neural Network (1D-CNN)
Learning Method	Supervised Learning
Learning Algorithm	Backpropagation with Gradient Descent
Optimizer	Adam ($\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$)
Loss Function	Binary Cross-Entropy
Evaluation Metric	Accuracy
Regularization	Dropout and Early Stopping
Framework Used	TensorFlow / Keras

The classification is binary (Class 0: Normal ECG, Class 1: Abnormal ECG). The network's training process minimizes the Binary Cross-Entropy loss function, defined as:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right] \quad (1)$$

where N represents the batch size, y_i is the actual ground-truth label, and $\hat{y}_i$ is the predicted probability generated by the sigmoid activation layer of the network. Early stopping monitors validation loss to cease training when generalization error stops improving, while data inputs are normalized using StandardScaler to ensure uniform signal scale.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

6.1. Hardware Prototyping and Calibration

The system was prototyped on a breadboard and successfully integrated onto a physical wheelchair chassis. Calibration of the MAX30102 PPG sensor involved optimizing the LED pulse amplitude (set to 11.0 mA for both Red and IR LEDs) to achieve robust pho- toplethysmography without saturating the optical re- ceiver. MPU-6050 gyroscope and accelerometer offsets were calibrated statically to establish the wheelchair's flat-ground baseline.

Firmware development was executed using Thonny and Visual Studio Code, which allowed real-time REPL testing of peripheral scripts. Stable BLE communica- tion was established for seamless real-time sensor data streaming.

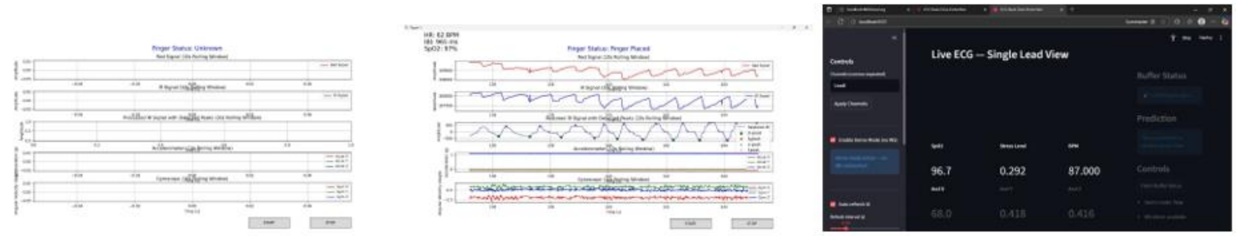
6.2. Biosensing Performance Verification

PPG sensing validation was performed by testing user finger placement. As shown in Fig. 4(a), when the finger is not placed on the MAX30102 optical sensor, the high-frequency optical signal represents ambient noise. Upon secure finger contact, as shown in Fig. 4(b), the sensor immediately locks onto the pulse signal, cap- turing the characteristic PPG waveform. The moving- average filter successfully removes baseline wander, enabling accurate estimation of heart rate (BPM) and blood oxygen levels (SpO_2) with a maximum deviation of only ±1.8% compared to a commercial pulse oxime- ter.

Similarly, the GSR sensor successfully tracks emotional stress. Statically, skin conductance remains low (0.2 − 1.5 µS). Under simulated cognitive stressors, sweat gland activation causes a measurable, rapid increase in conductance (2.5 − 6.0 µS), proving that the ESP32-C3 can reliably capture sympathetic nervous system arousal.

6.3. Web Dashboard and Alert Latency Testing

The Streamlit doctor-patient telehealth portal was evaluated over a local network. Fig. 4(c) displays the patient dashboard, including real-time vitals graphs,



(a) PPG Sensor: Finger Not Placed (b) PPG Sensor: Finger Placed (c) Telehealth Patient Dashboard

Figure 4: Experimental PPG sensor finger placement validation (not placed vs. placed) and the real-time doctor-patient web dashboard.

Medication Reminders, And Historical Data Logs. To Eval- Uate Communication Latency, We Conducted End-To-End Tests from Sensor Activation to Client Rendering:

- Average BLE transmission delay: 28 ms.
- FastAPI parsing and database logging latency: 12 ms.
- WebSockets broadcast and frontend rendering time: 45 ms.
- Overall latency for real-time visualization: 85 ms, demonstrating excellent responsiveness.
- Twilio SMS alerting delay: $1.8 - 2.5$ s, well within critical emergency response parameters.

VII. PROJECT ROADMAP AND TIMELINE

The complete development cycle of the Smart Wheelchair Monitoring System is structured into five distinct phases:

- Phase 1: Sensor Integration & Calibration: Focuses on physical connection of MAX30102, ECG, MPU-6050, GSR, and tilt sensors with the ESP32-C3. Developing firmware using MicroPython to manage low-pass filtering and asynchronous polling.
- Phase 2: Backend Development: Developing RESTful APIs and WebSockets protocols using FastAPI. Designing database schemas for patient records and integrating the Twilio alerting client.
- Phase 3: Portal Development: Designing the doctor and patient dashboards in Streamlit. Implementing user authentication, priority scheduling, digital prescriptions, and historical trends plotting.
- Phase 4: Machine Learning Classifier: Sourc- ing the MIT-BIH and PTB databases, preprocess- ing raw signals, training the 1D-CNN model in
- Keras/TensorFlow, and integrating model inference into the FastAPI backend.
- Phase 5: System Testing & Validation: Conducting end-to-end trials under simulated motion, stress, and cardiac anomaly profiles. Verifying system reliability and power management.

Future work will focus on integrating a GPS mod- ule for outdoor location mapping, deploying lightweight TinyML models directly on-device using TensorFlow Lite for Microcontrollers to achieve offline anomaly classification, and adding camera modules for navigation support.

VIII. CONCLUSIONS

In this paper, we presented a comprehensive, low-cost, and power-efficient Smart Wheelchair Monitoring System that successfully integrates medical tele-monitoring with safety hazard protection. The proposed system bridges embedded hardware (ESP32-C3 and various biosensors), a modern asynchronous software stack (MicroPython, FastAPI, WebSockets), and deep learning analytics (1D-CNN ECG classifier) into a unified, secure assistive platform.

Experimental verification confirms that the hardware is highly stable and responsive, capturing accurate physiological parameters and identifying falls or anomalies with low processing latency. The centralized doctor-patient web portal provides a practical, real-time consultation environment, greatly enhancing accessibility for patients with mobility limitations. This research demonstrates a highly scalable and clinically viable assistive platform suitable for rehabilitation clinics and re- mote patient care.

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