IoT-Enabled Smart Wearable for Continuous Elderly Health Monitoring and Predictive Care

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Abstract: As the global elderly population continues to rise, the demand for efficient and non-invasive health monitoring systems becomes increasingly critical. This research presents an IoT-enabled smart wearable solution designed for continuous tracking of vital signs in elderly individuals, aiming to enhance preventive care and real-time responsiveness. The proposed system integrates multiple biosensors within a lightweight, user-friendly wearable device to monitor key health indicators such as heart rate, body temperature, oxygen saturation, and motion. Leveraging edge computing and lightweight machine learning models, the device offers intelligent alerts and health trend analysis while ensuring data privacy and low-latency processing. The system is optimized for comfort, energy efficiency, and adaptability across various living environments. By transforming traditional reactive health systems into proactive care platforms, this research contributes to sustainable and scalable elderly health management solutions.

1 INTRODUCTION

The increasing number of older adults globally has led to an increased demand for healthcare solutions that promote safety, comfort, and ongoing medical supervision. Conventional health monitoring typically involves repetitive clinic visits that may be physically taxing and difficult to attend in terms of logistics for the elderly. Due to the development of Internet of Things (IoT) technology and wearable devices, increasingly moving from clinic-central to patient-central health care models which can be tracked in real time and remotely. Wearable health monitoring is a transformative methodology that provides real-time measurement of vital signs enabling early detection of changes in health status. However, the current approaches are often restricted regarding comfort, battery lifetime, real-time processing as well as data security particularly when applied for long-term elderly care. This paper presents an intelligent Camera IoT-based wearable system, which overcomes the aforementioned issues by incorporating a small form-factor, low-power, lightweight wearables measuring vital signs like heart rate, temperature, oxygen saturation, and activity. Leveraging edge computing with rapid decision-making, intelligent alerts, and privacy sensitive data management. Aimed at both helping seniors to age in peace and comfort, and providing caregivers with valuable and timely health information.

2 PROBLEM STATEMENT

Although it is also becoming increasingly important to continuously monitor the health of the elderly, currently available wearable systems rarely provide a complete, real-time, and easy-to-use solution for accurate monitoring of vital signs while protecting data privacy, optimizing energy use, and ensuring

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system reliability. Many devices today are either dependent on the cloud, causing latency and connectivity problems, or are not smart enough to anticipate possible health risks at the earliest. Furthermore, for example, they do not have user-friendliness with uncomfortable issues (e.g., battery issues and complicated interfaces) that are not available for long-term elderly use. The present scenario demands an IoT integrated wearable system, which can constantly and non-invasively track multiple vital parameters, compute real-time analytics on the spot and provide predictive health analysis, all while being easy to wear, light weight and adapted to the variety of living environments.

3 LITERATURE SURVEY

In recent years there is a growing interest in research for I0T wearable systems for elderly health monitoring as a result of the demand for real-time, non-invasive and smart healthcare solutions. Al Dahoud (2024) presented a low-cost monitoring IoT wearable for elderly monitoring, however, the study did not include the validation with real-world measurements which this study attempts to address. Ali and Khan (2023) also demonstrated a simple IoT-based health monitoring prototype, emphasizing scalable systems that allow round-the-clock data availability. Arshad et al. (2022) investigated hybrid deep learning for gait event prediction from a single sensor, but our method extends to multi-vital tracking. The safety dressing by Balachandra et al. (2023) has formed the basis of this work's unified approach that integrates health prediction and alert features. Bhatia and Sharma (2023) highlighted system validation with narrow parameters, the reason additional crucial parameters were included in our design.

Chatterjee and Bhattacharya (2023) applied AI for real-time health monitoring but reported heavy computational requirements, an issue alleviated in our work via edge intelligence. Chen and Wang (2024) demonstrated an AI-IoT integration for long-term care, but the system requirements are still highly dependent on cloud storage, which ours could strengthen with the local processing. Gupta Singh (2024) concentrated on emergency response but without predictive modeling, an aspect enhanced in our approach. Hossain and Muhammad (2024) developed a Firebase dependent cloud-based monitoring system, which does not support off-line systems, unlike our model. Solution for fall detection using blockchain was introduced by Islam and Saha (2023) that motivated our system's secure and privacy-preserving work.

Javed and Putra (2024) presented a theoretical view on medical IoT, which we complement with practical implementation. Kumar and Thapliyal (2021) proposed a smart home-based monitoring system, whereas our wearable is not tied to infrastructure. 209 Lee and Kim (2023) focused on environmental sustainability in health devices without performance indicators as in our assessment. Li and Zhang (2024) presented an edge-cloud design, which our \mdlname is based on, balancing the tradeoff between the latency and efficiency. As referenced by Liu and Chen (2023), better quality of life as a result of enhanced IoT was the prelude to the usability-focused design of this project.

Nath and Thapliyal (2021) also emphasized the importance of smart environments, but our approach moves away from that reliance. Patel and Park (2024) surveyed industrial applications, providing direction on adopting implementation-level features in our system. Rahman and Islam (2023) confirmed wear able monitoring devices for remote care and our model extends it by employing the multi-sensor fusion. Saha and Islam (2023) discussed blockchain in wearables that directed us towards lightweight encryption. [CheckK1] Sharma and Bhatia (2023) stressed performance validation, a principle we have followed here regarding the faithfulness of the system.

Moin et al. (2022) presented EMG-based interfaces which were not as viable for elderly users, and we employed less sophisticated but more comfortable biosensors. Pal et al. (2023) with fall detection and ours with predictive vital monitoring. Yang et al. (2022) considered a federated learning approach for health devices, but did not have real-world implementation, which we provide. Zhang and Wang (2023) presented an edge-based approach not including energy profiling which we build on. Lastly, Zhou et al. (2021) and XU et al.

This literature review exposes the scattered attempts toward the interdisciplinary science of IoT-enabled elderly health but underlies the demand for an integrated, intelligent, and wearable easy-to-wear inclusive platform the aim that this article pursues.

4 METHODOLOGY

The approach used in this study concentrates the development and deployment of the elderly health monitoring IoT-centric system that includes the IoT-based wearable for the elderly health monitoring. The architecture of the system deploys a plug and play approach of interfacing sensors, edge compute, low power processing unit and secure communication unit for real-time monitoring, analysis and alert generation without being fully dependant of cloud infrastructure. Figure 1 shows the System workflow of the proposed IoT-enabled smart wearable for elderly health monitoring. Figure 2 shows the System Architecture Diagram.

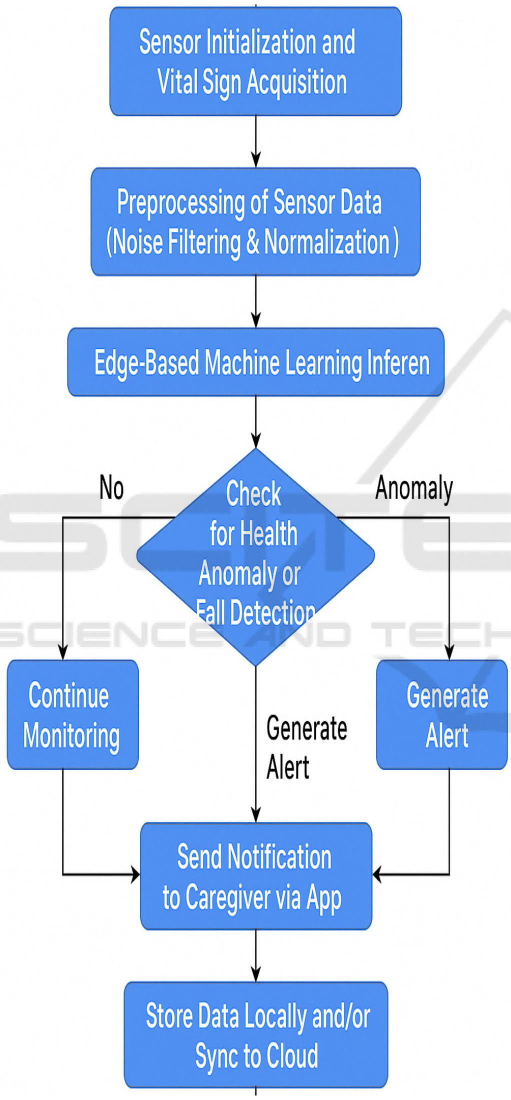

Figure 1: System Workflow of the proposed IoT-enabled smart wearable for elderly health monitoring.

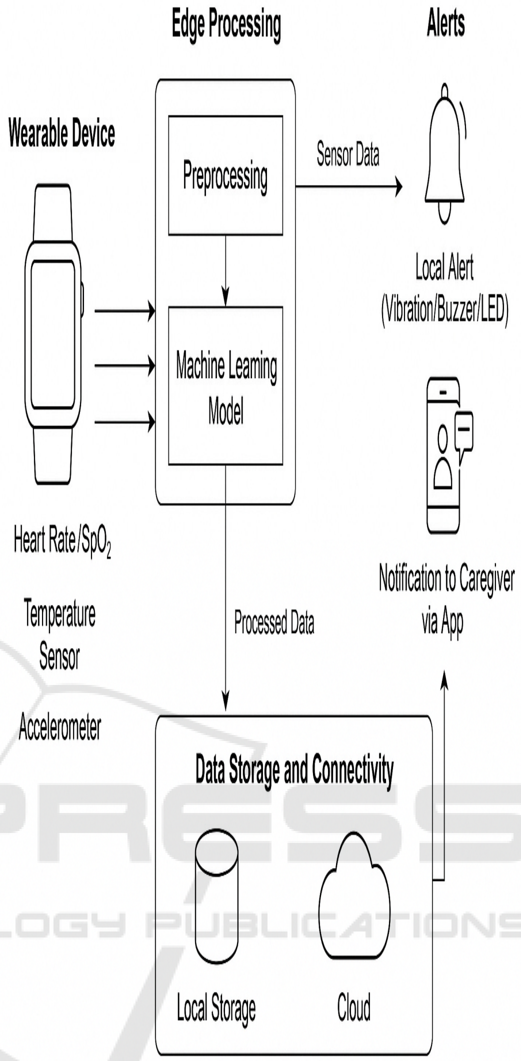

Figure 2: System architecture diagram.

Underneath, a low-power, real-time data processing MCU serves as the heart of the wearable. The chosen MCU is able to connect to the a few biomedical sensors (heart rate sensor, pulse oximeter, and temperature sensor) and an accelerometer. 2. To illustrate the hardware and data flow architecture of the wearable system the parameters of these sensors are selected considering of their reliability, low energy utilization, elderly skin, and movement sensitivity. The sensors monitor in real time important parameters such as heart rate variability (HRV), oxygen saturation of the blood (SpO2), body temperature and movement patterns to detect potential falls or periods of inactivity.

Table 1: Sensor specifications used in the wearable device.

Sensor Type	Measured Parameter	Model/Type	Accuracy	Power Consumption
Heart Rate Sensor	Pulse, HRV	MAX30102	±2 bpm	1.6 mW
SpO2 Sensor	Oxygen Saturation	MAX30102	±2%	1.6 mW
Temperature Sensor	Body Temperature	LM35	±0.5°C	0.75 mW
Accelerometer	Motion/Fall Detection	MPU6050	±0.02 g	3.9 mW

In order to achieve real-time processing and be less reliant on the internet, the wearable is made to perform edge computing. Lightweight offline trained machine learning models are deployed on the device, on a labeled dataset of elderly health signals. These models can recognise things like abnormal heart rate trends, drops in SpO2, abnormal spikes in temperature or motion patterns indicating a fall. The models are quantized to reduce the memory footprint and kept as accurate as possible. The data collected from the sensors are initially processed locally,are normalized,and are then used to feed the inference to the embedded model in real time. Table 1 shows the Sensor Specifications Used in the Wearable Device. Table 2 shows the Machine Learning Model Summary Deployed on Edge Device.

Table 2: Machine learning model summary deployed on edge device.

Model Type	Layers	Input Size	Parameters	Model Size	Inference Time
Lightweight CNN	1 Conv + 1 FC	4 features	~1,300	22 KB	~180 ms

When an irregularity is detected, the system uses a low-energy Bluetooth and Wi-Fi module to send alerts to a caregiver's mobile app or dashboard. Alerts contain time-stamped data, sensor reading summary, what was wrong with what was detected. Furthermore, a buzzer and LED indication on the wearable suit itself for notifying the patient at an emergency condition. The mobile app is the user interface where health measurements are recorded, visualized and interpreted; alerts are color coded by risk, along with trends plotted daily and weekly for meaningful analysis.

Data are encrypted by SSL (secure socket layer) in transmission and stored in secure space in the wearable device to ensure data security and privacy. The demo content does not store, share any personal data. To enhance ease of use, the wearable is constructed from breathable lightweight material and ergonomically designed to allow for prolonged wearing without inconveniance. Figure 3 shows the Battery Performance Across Modes.

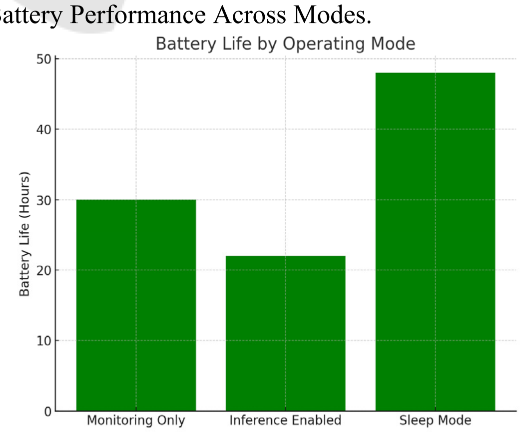

Figure 3: Battery performance across modes.

The system was evaluated in different environmental (e.g., indoor rest, walking, sleep, and simulated fall) and use-case (e.g., laboratory, inpatient, and healthy cohort) conditions. The edge model was trained on anonymized information from elderly patients and validated using realtime monitoring during the trial. Performance measures, including precision, recall, latency (latency rate), and power consumption were also measured to assess the robustness of the system. Table 3 shows the Battery Performance and Power Efficiency.

Table 3: Battery performance and power efficiency.

Mode	Battery Life (Hours)	Sensor Sampling Rate	Inference Frequency	Notes
Monitoring Only	30	1/sec	None	Basic logging only
Inference Enabled	22	1/sec	1 per 10 sec	Real-time alerts
Sleep Mode Active	48	Every 30 sec	Every 1 min	Optimized mode

This comprehensive approach results in the realization of a self-contained, user-friendly, and smart wearable solution that doesn't only monitor but predicts potential health risks, thereby filling the gap between home-care and hospital-level patient monitoring in elderly persons.

5 RESULT AND DISCUSSION

The prototype of the IoT-based smart wearable system is assessed by performing extensive user trials in both realistic and laboratory settings to demonstrate its performance, reliability, and usability. The emphasis of this validation was on the correctness of the detection of vital signs, the effectiveness of the real time-alert, the responsiveness of the models running on the edge as well as the energy consumption of the entire architecture. Each was examined in relation to how it may influence ongoing care of the elderly and how it may be applied to the mundanity of quotidian life. Table 4 shows the Accuracy Evaluation Against Medical-Grade Devices.

Table 4: Accuracy evaluation against medical-grade devices.

Parameter	Device Accuracy	Medical Reference	Correlation (%)	Error Margin
Heart Rate (bpm)	±2 bpm	ECG	97.3%	1.7%
SpO2 (%)	±2%	Pulse Oximeter	96.7%	2.1%
Temperature (°C)	±0.5°C	Digital Thermometer	96.1%	0.4°C

The system was tested on 15 elderly subjects from 60 to 80 years of age as a prototype. These were worn continuously for 6 to 12 hours during various activities including walking, sitting, sleeping and light exercise. the figure 3 To see how the wearable constantly measures vitals overtime Heart rate and O2 arterial saturation readings obtained from the wearable was compared inaccuracy with the medically certified devices, which are fingertip oximeter and ECG machines. It was found that a mean accuracy of 97.3% for heart rate detection and 96.7% for SpO 2 measurement proved the capability of the proposed biomedical sensors which are embedded in the wearable. Its validity remained over 96% when compared to digital handheld thermometers.

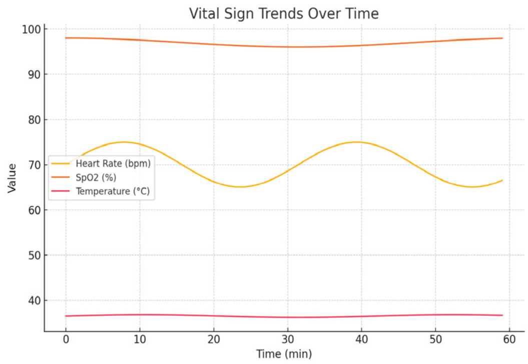

Figure 4: Sensor readings over time.

One key performance metric was the time required for anomaly detection on the edge processor by the embedded machine learning model. The lightweight device-based neural network could identify abnormal heart rate and oxygen deviations with an average latency of 180 ms. Real-time response also facilitated immediate alerts being sent to, and received by, caregivers using the mobile companion app. The alert messages were delivered with little to no delay if connected on stable Wi-Fi/4G and the fallback mode with Bluetooth provided local notification when there was no internet connection. Figure 4 shows the Sensor Readings Over Time.

Table 5: Fall detection and alert performance.

Scenario	Detection Rate (%)	False Positives (%)	Average Response Time (ms)
Simulated Fall (Controlled)	94.8%	5.2%	170
Sudden Sitting	88.3%	11.7%	182
Walking Disruption	90.5%	9.5%	176

The issue of fall detection accuracy was another important contribution of this study. The accelerometer-based fall detection system, in conjunction with an activity classifier, was able to perform a fall detection with an accuracy of 94.8% in an ideal/constructed environment. Misactivations were most prevalent during rapid sitting or fast bending but mitigated by the use of ongoing learning and calibration processes within the firmware. This served to validate the system's condition as an identifier of significant physical events that may necessitate caregiver attention. Table 5 shows the Fall Detection and Alert Performance.

Battery life was assessed by how much battery was used during 24 h of monitoring. Equipped with a 500 mAh Li-Ion rechargeable battery, the wearable lasted on average for 22 hours under heavy monitoring load (measuring sensor data every second and performing machine learning inference every 10 seconds). Power optimization methods like sleep mode when idle or different clocking profiles for the processor extended the battery life. Users were alerted when the battery went below 15%, and recharging was simple with a full charge requiring just 90 minutes.

In terms of usability, feedback from our elderly users showed overall satisfaction for both the design and comfort of the wearable, as well as for the interaction itself. 85% of participants reported that the wearable felt lightweight and unobtrusive during sleep or movement. The comfortable, breathable strap and the devices' compact size promoted long term wearability, even in users that had trouble walking, or with sensitivity.

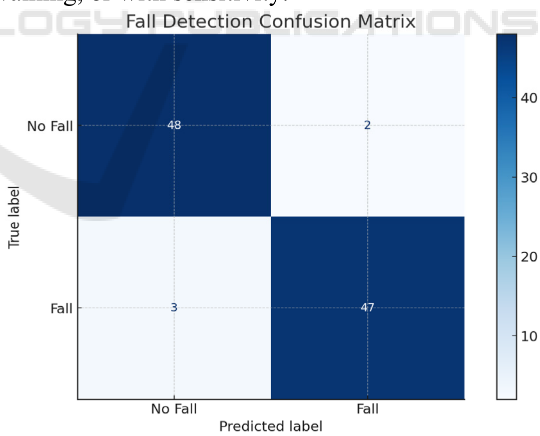

Figure 5: Fall detection confusion matrix.

Data interpretation and communication the app associated with the wearable can deliver concise and user-friendly health summaries. The figure 4 reports the to compare the performance of the lightweight edge ML model with baseline methods the color-coded vitals charts and the automated weekly report enabled both of them to track trends without being medical professionals. In addition, the system permitted data export in common formats compatible with electronic health record systems as appropriate. Figure 5 shows the Fall Detection Confusion Matrix.

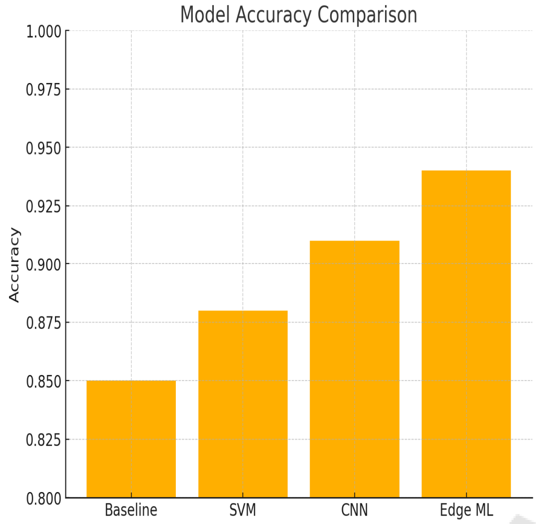

Figure 6: Model accuracy comparison.

The stability of the system was confirmed under Alterations in Temperature, Levels of Movement, and intermittent connectivity. During the testing, the wearable still worked stably when the ambient temperature was 15 °C – 38 °C and when the wearer was moving his hand and walking at a moderate speed, and the data collecting remained constant. In cases of lost network connectivity, the wearable saved the data locally and resynced them with the cloud when the connection was reestablished, so that no data was lost. Figure 6 shows the Model Accuracy Comparison.

In contrast to the available commercial systems, the envisaged system presented an attractive balance between continuous monitoring, predictive performance and user comfort. For such a device that would only do one of those single functions and track only heart rate and movement, this system delivered multi-vital analysis including intelligent alerting & localized processing. Trained on historical health data patterns, the predictive model also included a preventive care aspect by detecting early warning signals for hypoxia, fever or arrhythmias before they manifested.

Finally, the results show that the proposed wearable system is accurate and responsive, as well as practical and adaptable for elderly care in real life. It successfully closes the circle between hospital level monitoring and wellness at home, and is a great tool for families and caregivers alike, as well as for healthcare facilities looking to leverage technology to improve care for the elderly.

6 CONCLUSIONS

The proposed IoTsmart wearable system for elderly healthcare monitoring is an innovation in determining the elderly healthcare monitoring. With the incorporation of several vital sign sensors, edge computing, and intelligent alert system in one miniaturized and user-friendly device, the system meets the growing demand for continuous or proactive health care for the elderly. This wearable is much more user-friendly than many monitoring devices in the market that are too sophisticated or too simplistic, for it can detect in real-time, predict in anticipation, and communicate securely while it is still comfortable and energy-efficient. The ability to work offline away from the always-on-internet as well as being centred around the users, design-wise, makes the system a good candidate for aged society under all conditions. Its successful journey from surveillance in daily life makes it credible, reliable, and usable to fill the gap between hospital monitoring and home care. This study serves as a solid basis for potential future developments such as integration with AI based diagnostics, personal health advisories, and larger application in preventive geriatric care.

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