SmartLife Guardian: An AI-Driven Multimodal Health Monitoring System for Elderly Care

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Abstract. Many elderly people require constant monitoring of their vital signs. Every day, going to hospitals for checkups or being admitted for monitoring of vital signs is tiring; therefore, there is a high demand for smart health monitoring systems. To support elderly healthcare, this paper introduces the SmartLife Guardian, a glove-based wearable system that helps monitor vital signs. This glove integrates multiple sensors, Edge AI (artificial intelligence that processes data on edge devices), and cloud-assisted monitoring. Heart rate, SpO_2, body temperature, respiration, and activity patterns are vital parameters monitored by this wearable system. Tiny ML models are integrated with the hardware that helps in spotting odd patterns of the vital signs and customized health assessments. TinyML enables low-latency and also brings data privacy into play, as evidenced by an alert response time of less than three seconds in our experiments, and it reduces network dependency since all necessary pathology analysis was performed on the ESP32 microcontroller, without the cloud being present for inference. The overview of the health insights and alerts is sent to the cloud so that the caregiver and family members can access and visualize the patient records. It employs a voice assistant to remind the patient to take medication, drink water or rest if they show early signs of instability in vital signs. The proposed system has been tested against experimental dataset, and the obtained results indicate that our system was able to achieve 87%-93% accuracy for vital sign monitoring, a TinyML anomaly classification success rate of 75–85%, an alert response time in below three seconds and less false alarm rates due to personalized baseline learning approach; thus making the system suitable for prolonged continuous health tracking of aged population.

Keywords: Edge AI, TinyML, IoT-based elderly monitoring, Wearable healthcare systems, Embedded sensors, Medical Reminder System, Real-time health prediction, Intelligent alerting.

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1 Introduction

As reported by the World Health Organization, the population aged 60 and over is expected to double from 1 billion in 2020 to more than 2.1 billion in 2050, underscoring the immediate need for innovative, continuous health monitoring services [7]. Indeed, older individuals are at higher risk of suffering from several medical disorders like cardiovascular diseases, respiratory issues and even acute medical emergencies if they do not have immediate access to their medication or a healthcare facility [18][7]. The traditional health care system relies on regular medical check-ups and observations, which are inadequate for detecting abnormalities in health status that may occur between checks [18]. People need continuous health monitoring, but the traditional healthcare system cannot meet this demand. Health monitoring beyond the clinical environment has become a reality in recent years due to improved wearable sensor technology, the Internet of Things (IoT), and artificial intelligence [1][2][15].
Wearable monitoring devices that incorporate recent technologies remain reliant on cloud computing for inference and continue to use standard threshold-based alert systems [6][7][15]. Reliance on cloud computing can pose several challenges, including potential delays during emergencies due to real-time processing, questions about patient data privacy, and increased power consumption. All of these challenges are particularly problematic when considering the routine monitoring of older patients. Also, fixed thresholds do not capture variations in individual patient physiology, resulting in numerous false alerts that can diminish caregiver trust in the monitors. Current solutions are reactive and monitor only a limited number of vital signs; as a result, caregivers are unable to intervene proactively. They can only react to problems that have already occurred. We present SmartLife Guardian, a multimodal wearable designed for real-time personal healthcare for the elderly. This proposed system is a wearable glove with various physiological sensors. It uses Edge AI and Tiny ML models, which run on an ESP32 microcontroller for health analysis. The system has a low-latency response, maintains user privacy, and does not require a network connection to operate. Also, it has a cloud back-end access, which we have used via Firebase. Also included in the system is a voice-based reminder that sends alerts for medication, hydration, and sleep based on early signs of physiological instability.

Our put forth system includes:

- We present a smart glove that puts together various physio sensors, including PPG, temperature, IMU, and respiration.
- We have a wearable device that uses Edge AI and Tiny ML models in an ESP32 microcontroller for real-time health analysis, which does away with the cloud. The system provides low-latency responses while preserving user privacy.
- We have a learning feature that determines the user's physiological baseline, which is adaptive to each individual and which, in turn, reduces false alarms.
- A proactive voice-based reminder system that reacts early to vital sign instability and, in turn, provides for preventive care before an emergency.

- A Firebase-based caregiver dashboard that allows for the visualisation of vital signs, health risk scores, and emergencies from anywhere.

2 Literature Review

A large number of studies focus on the use of wearable health-monitoring devices, especially for elderly patients. These devices can be useful for monitoring the patient by physicians and nurses at any location. Wearable health sensors were first addressed by Pantelopoulos and Bourbakis [18] in their survey of devices that track heart rate, oxygen level, ECG, and body temperature. They state that these devices must consume low power, be comfortable, operate dependably, and keep user data safe. In [3], Delmastro et al have shown the usefulness of automated health alerts using a machine learning algorithm applied to multi-sensor wearable data. The algorithm used was for the purpose of recognizing cognitive stress and abnormal physiological changes in frail elderly, and they obtained a reliable detection in real time without clinician intervention. Detection of stress signals and unusual physiological changes in older people is achieved using a machine learning algorithm, with data collected from multiple wearable sensors. Various IoT systems have been designed to monitor the health of elderly people. These systems make healthcare readily available and also make fast decisions based on real-time health data. Study [10]. Dzacky et al. use an IoT system with a heart rate and oxygen level monitor by using the MAX30102 and temperature sensors. The research paper [10] also mentions that wearable sensors in IoT are used to monitor heart rate and oxygen levels. The health information is sent to the cloud server, and the doctor or caregiver can access it from anywhere in the world. In [4], H. Calderón-Gómez et al proposed an advanced remote health monitoring system. The advanced system utilises smart, connected devices for real-time health monitoring and analysis of health information to assess the risk of infections in the elderly. IoT has proven very helpful in remote health monitoring. It provides real-time health information to the patients and caregivers. Another contribution to the literature concerned fall detection technology. Falls in the elderly are very common, and LIDAR-based fall detection [5] technology uses depth sensing for precise fall detection. This study was done by Lakhdari et al [11]. In their paper entitled "IoT-based fall detection systems". Three key issues have been discussed in the studies referred to as follows: load distribution of tasks within the system, protection of users' privacy, and instant fall notification. In their study, Khojasteh et al. showed that fall detection by wearable devices using a machine learning algorithm is more accurate than fall detection based on threshold values [13]. Thus, they increased the accuracy of fall detection by using accelerometer data from falling individuals and smart methods.

An interesting paper titled "A TinyML-Based IoT Wearable Device for Real-Time Health Monitoring and Anomaly Detection" used a smart wearable device based on an ESP32 board and implemented Edge Machine Learning (TinyML)for health monitoring [17]. The device can track various health parameters. If there is any rapid rise or fall in heart rate, blood oxygen level, or body temperature, the patient is notified via the app. This research demonstrated that a small deep learning model can be implemented and executed on a low-power microcontroller. An article titled “Edge machine learning for AI-enabled IoT devices” published by Merenda et al. [16] presented a survey on the current state of the edge machine learning approach for IoT systems. They concluded that Edge-based inference leads to latency reduction, bandwidth utilization decreases, and better data privacy compared to traditional cloud-based processing architectures. Edge-based Machine Learning implementation at wearable devices for elderly health care will lead to smart, low-power, real-time wearable health gadgets for continuous patient monitoring.

3 System Architecture

Our proposed solution integrates the edge and cloud together [15][16]. The smart glove will perform all the health analysis tasks at the edge. The health information collected from the various sensors in the glove, such as the heartbeat sensor, SpO2 sensor, temperature sensor, gas sensor and fall-related movement sensors, will be transmitted to the cloud for data analysis and an online health-related dashboard. In this proposed solution, the health-related information of the elderly will be continuously collected from the smart glove using the various sensors it contains [3][7][10]. The health information collected from the various sensors will be processed at the edge by the Arduino microcontroller to reduce noise using a moving-average filter and to validate the physiological validity of the data using range-checking threshold values (e.g., 32-220 bpm). The valid health information will be sent to the ESP32 module [12]. The health information will be processed at the edge using Edge AI to evaluate the health status of the elderly [8][12][17]. A TinyML model has been implemented at the edge. This model is a one-dimensional Convolutional Neural Network (1D-CNN) that is quantised from 32-bit floating-point to 8-bit integer using TensorFlow Lite Micro. The model learns the normal or baseline values of the vital signs from users' recent health-related information and also evaluates the health risk score based on deviations from these baseline values. By using Edge AI, health information can be processed at the edge, enabling a fast system response. If all the health information is sent to the cloud, it will not provide a fast response. The processed health information will be transmitted to the cloud for further processing. The health information will be stored in Firebase for further use [3]. It will be used to send alert or notification messages whenever necessary. In this proposed solution, the mobile application is very user-friendly. It displays all real-time health information for the elderly. It sends alert or notification messages to ensure timely medication administration via voice messages. Hence, caregivers and families of the elderly can stay up to date on all health-related information and take necessary actions or respond in an emergency as shown in Fig.1.

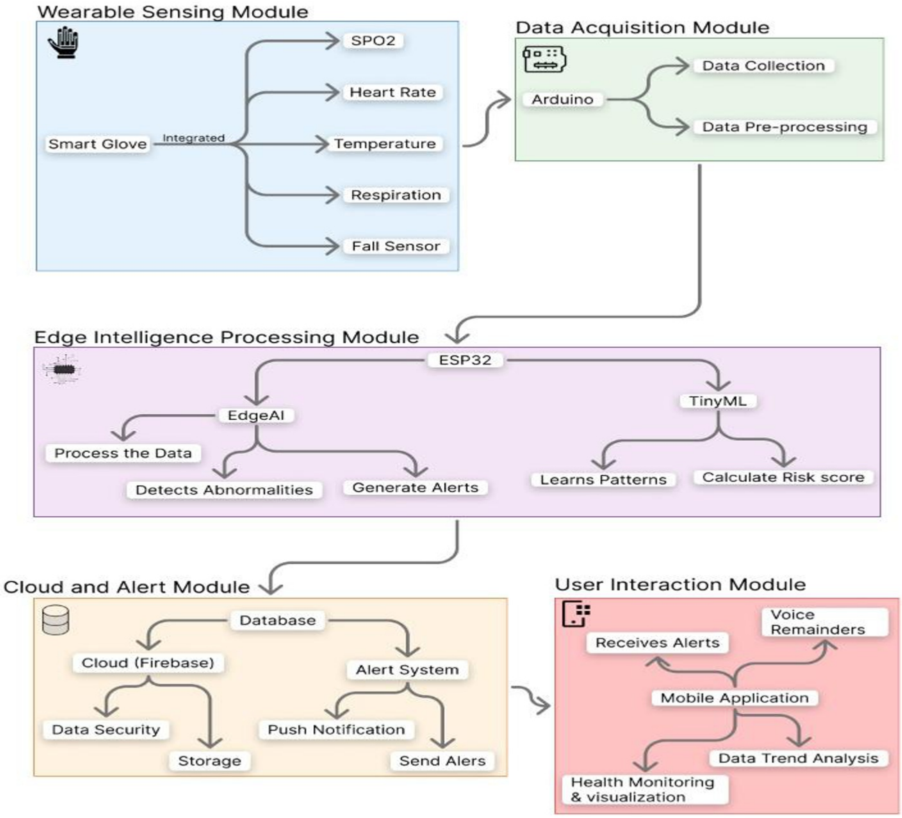

Fig. 1. Methodology of proposed system

Hardware Design

a. **Smart Glove Design**

The smart glove is one of the wearable devices in this elderly support system. It is designed for long-term comfort, with sensors fixed in place and easy operation for the elderly. To provide comfort during long-term wearing for elderly people. The smart-glove was fabricated using lightweight, breathable and stretchable fabric materials. The sensors were inserted into the smart glove lining to ensure they have a fixed position relative to the skin, while the processing and power units were mounted on a small wrist-mount enclosure, where they can be easily removed for maintenance. The sensor and processing units were first tested on a modular hardware configuration using a breadboard system. To evaluate each sensor individually, the results were compared with those of a commercially calibrated device (the pulse oximeter for MAX30102 and a digital thermometer for the temperature sensor). 50 iterations were conducted for each data parameter, and the final result was considered valid if within ±2% of the reading from the reference device. The proposed smart glove layout for implementation is shown in Figure 3.

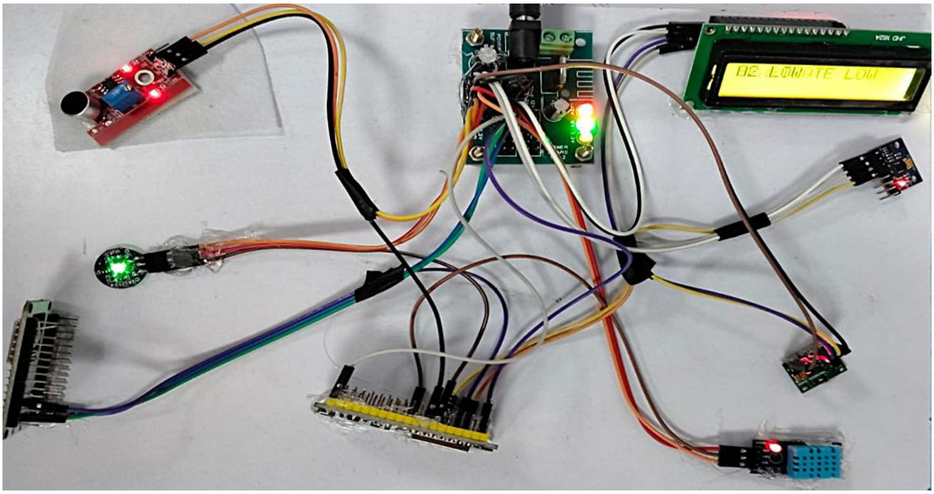

Fig. 2. Hardware prototype of the SmartLife Guardian monitoring System.

Fig. 3. Proposed smart health monitoring glove with sensor placement.

b. Sensors and Embedded Processing

The hardware is equipped with various sensors that monitor the body movements and vital signs. The patient's health can be monitored without interruption. The heart rate and blood oxygen concentration were measured using a PPG sensor at the end of the patient's fingertip [3][7][10]. The circulation of blood just under the fingertip helps measure vital signs accurately. In addition to its primary functions, the smart glove device also includes a body temperature sensor, an IMU for movement/activity tracking, and a respiration sensor. Although the Arduino microcontroller acquires and preprocesses the sensor data, the task to be carried out by the ESP32 is edge AI feature extraction and inference [8][12][17].

Microcontroller and Local Processing

Arduino and ESP32 microcontrollers are used to enhance the system. Arduino reads nearly all of the health sensors attached to the system. The Arduino also acts as the preliminary data processing unit by gathering clean data (filters noise from signals, sorts collected signals, organizes clean data for future use) [12][13]. The ESP32 acts as both a processing and communication unit in one. It collects necessary information from the Arduino and feeds it through TinyML to reach smart conclusions [8][12][17]. Cleanups are done through software. ESP32 has built-in Wi-Fi that securely transmits data to the cloud. ESP32 has many perks, such as its dual-core processor, which allows it to perform its tasks smoothly and reliably. It also has built-in machine learning capabilities.

Data Transmission using Firebase

Firebase Cloud Platform stores and receives health data from the smart glove. ESP32 then sends cleaned health data to Firebase via a secure connection as it is received. Things like heart rate, oxygen level, breathing, temperature, and risk score can be sent and received. When Firebase receives this information, it then updates the user dashboard seamlessly [3][10]. We don't need any manual support to refresh the vital signs measurement for updates. Firebase can also automatically send notifications to caregivers and family members if the health monitoring system senses that something may be wrong with a patient. The system can track vital signs, act quickly in the event of an emergency, and store secure information about the patient's well-being [3].

Power Management

Wearable devices require proper power management because they run continuously. The rechargeable lithium-ion or lithium-polymer battery in the smart glove is positioned in a secure, safe location [1]. Integrated voltage regulators ensure that system components are not subjected to sudden voltage surges by providing a stable supply to all sensors and microcontrollers. The system also uses energy-saving techniques to increase battery life, such as on-demand sensors, low-power sleep-mode microcontrollers, and data transmission to other systems only in the event of an important event, such as a sensor [12][17].

c. Sensors and Embedded Processing

The AI platform is based on the software design structure and acts as a cloud-edge. The ESP32 instantiates lightweight TinyML models that execute real-time personalized baselines, anomaly detection, and health risk assessment and scoring [12][16][17]. The cloud backend is Firebase, which is used to store, synchronize, and display data [3][10]. Moreover, Firebase is employed to deliver alerts and push notifications. Live vital signs, past trends in vital signs, health scores, visualization, and emergency notifications are available in the mobile app [3]. The software offers voice-based medical reminders. The software workflow is presented in Fig. 2. It begins by measuring all vital signs using the built-in sensors in the smart glove. Vital signs collected are then transferred to Arduino, where the data is preprocessed, such as eliminating noise, smoothing the signals, and preparing the data for efficiency. Subsequently, the information is sent to the ESP32, where the data undergoes Edge AI processing. TinyML is trained to learn the patterns of the patient's health vitals, and, according to these patterns, it creates a personal baseline for the patient. This system may have two outcomes.

- Once the system identifies any abnormal changes, TinyML compares the risk score and creates the alert, which is immediately transmitted in the form of a notification to the caregiver and the family members, and the necessary measures are taken.
- In case of normal vitals, the health vitals are saved in the cloud and can safely display the vitals of the patient at dashboard. Such information is available to caregivers and family members anytime and anywhere.

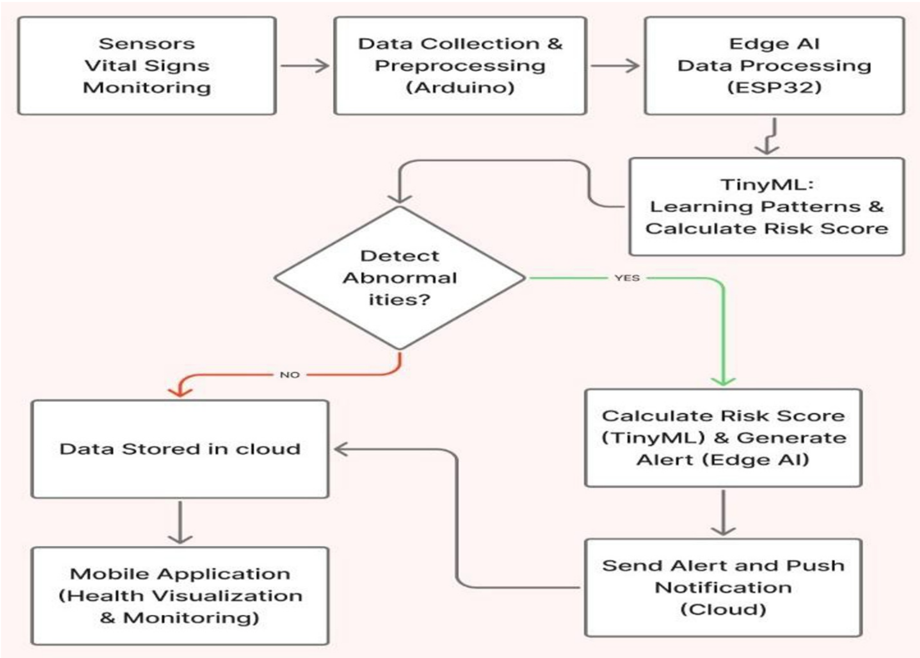

Fig. 4. Workflow of the System

4 Results and Analysis

Throughout a fourteen-and-a-half-hour monitored period, as many as 5,000 sensor records were collected every ten seconds to be analyzed during the test pool for SmartLife Guardian. Each of these records had heart rates along with the amount of oxygen in a person's body, and heat signatures, breathing patterns, motions, orientations and many additional variables associated with any combination of four recognized activities of walking, jogging, cycling or remaining still. Of the 760 total data marks made during the test, due to some form of abnormal signal occurring, the most relevant values were the accuracy of tracking the numerical value of the original record, how accurately each of the records was identified as not normal and, to an extent, the number of seconds before an alert was received, as well. Since the results indicated that tighter measurements were achieved through analysis, the noise level of any alerts would also be lower than that of historic methods based solely on hard limits. Within the fabric of the glove, sensors track a person's heartbeats, blood oxygen levels, skin temperature, and breathing pattern every second. An ESP32 chip embedded in the same fabric material operates silently, running edge-based smart behavior algorithms and other Machine Learning (ML) models that are likewise of limited size. This data collection occurs in real time on the affected part of the user's body before an abnormal value (defined as a value exceeding the normal range) is identified as a problem shown in Fig.4.

4.1 Vital Sign Monitoring Performance

The monitoring performance of the SmartLife Guardian system was evaluated using multiple physiological parameters, including heart rate, SpO2, temperature, respiration and fall detection.

Table 1. Comparison of vital signs and monitoring accuracy between the traditional health system and SmartLife Guardian.

Vital parameter	Traditional Method (Fixed Threshold)	Proposed System (Personalized)	Accuracy (Traditional Method)	Accuracy (Proposed System)
Heart Rate	60-100	Baseline ± 10 bpm (e.g. 68-88)	75-80	87-94
SpO2	>=95	Baseline ± 2% (e.g. 94-98)	78-82	85-92
Temperature	36.1-37.2	Baseline ± 0.5oC (e.g.36-37)	78-83	83-88
Respiration	12-20	Baseline ± 3 (e.g. 14-20)	70-75	80-86
Fall Detection	>2.5g	Baseline deviation + risk score > 60	72-78	80-88

It links different sensors to a small on-board computer that runs light machine learning code - this unit inspects the data on the spot. This design shortens the time required to spot unusual readings and provides older adults with a steady stream of reliable health data. Table 1 shows how the vital signs are monitored in both the traditional and proposed systems. The results show that SmartLife Guardian has achieved higher accuracy, faster detection, and fewer false alarms than traditional monitoring systems.

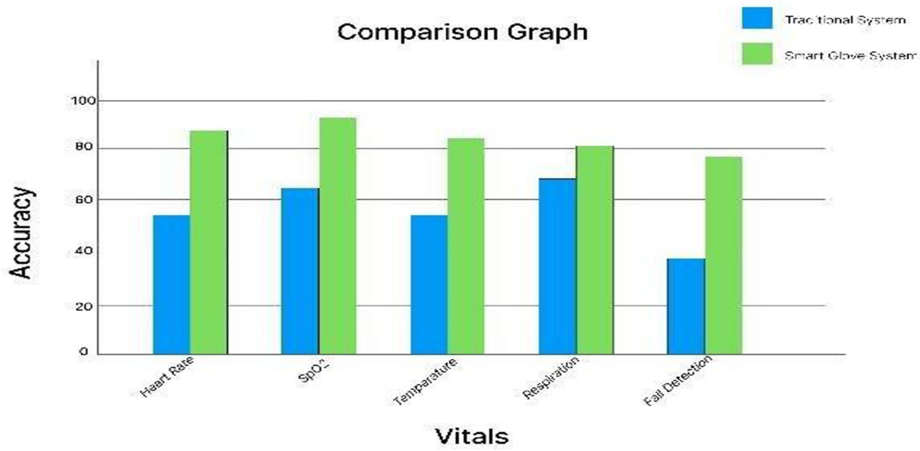

Fig. 5. Traditional health system vs SmartLife Guardian.

The personalized baseline for each user, created using TinyML, helps understand the patient's normal health patterns and monitor changes in the patient's vital signs shown in Fig.5.

4.2 Comparison with existing health monitoring systems

The SmartLife Guardian system was compared with current wearable devices that track health. It uses multiple types of sensors together with Edge AI, in addition to TinyML. Those technologies allow the device to analyze health data immediately on the device itself. This approach increases monitoring accuracy and reduces delay. It also lowers the need to send data to the cloud for processing.

Table 2 shows the differences between the SmartLife Guardian system and the health monitors that people now wear on the body. SmartLife Guardian joins Edge AI, alongside TinyML, to support multiple sensor types in a single device. This union allows the device to analyze health data at once, to raise accuracy, to cut delay and to tailor the results to each user.

Table 2. Comparison with Existing Wearable Health Monitoring Systems.

Study	Sensors Used	Processing Method	Key Features	Reported Accuracy
Abdullah et al. (2025)	Heart rate, SpO_2, temperature	TinyML on ESP32	Basic anomaly detection	82–88%
IoT Monitoring System [10]	Heart rate, SpO_2	Cloud-based processing	Remote monitoring dashboard	78–84%
Lakhdari et al. (2025)	IMU sensors	Distributed IoT processing	Fall detection alerts	80–86%
SmartLife Guardian (Proposed)	Heart rate, SpO_2, temperature, respiration, IMU	**Edge AI + TinyML**	Personalized monitoring, risk prediction, voice reminders	**80-93%**

4.3 Experimental setup and test strategy

The SmartLife Guardian prototype was developed, including the development of a working prototype consisting of a smart glove combining all the hardware components listed above, such as a MAX30102 sensor, which measures heart rate and blood oxygen levels, a temperature sensor, an IMU that measures motion and indicates falls, and a respiration sensor. The sensors were connected via wires to both an Arduino and an ESP32 microcontroller, which processed and collected the sensor data as raw data.

The TinyML model's training was done to identify and differentiate normal from abnormal vital signs; using the custom biometric wearable dataset with 5,000 time-stamped records collected every 10 seconds over the 13.9 hr. session which has six physiological and motion parameters (HR (ranging from 60-179 bpm), O2 Saturation (ranging from 90-100%), Body Temp (ranging from 36-39), Respiration (ranging from 12-24 breaths per minute), 3-Axis Accelerometer Reading, and 3-Axis Gyroscope Reading) recorded for 4 Activity Classification types Walking (1306 samples), Cycling (1248 samples), Running (1247 samples), Resting (1199 samples); 4240 of the total records are good while 760 of the total records are tampered with, giving the true positive anomaly classification for use during TinyML classification training. A Mobile Application and Firebase Cloud Service were set up, enabling continuous transmission of records to the cloud, instantaneous alerts to the caregiver(s), and remote monitoring of users.

In a controlled laboratory setting, tests were conducted to validate correct sensor readings, rapid and valid AI outputs from the on-device AI, and that alerts were triggered as specified. The operator simulated heart rate, oxygen saturation, temperature, and breathing by contacting the sensors, and simulated a fall by moving the glove in a predetermined direction. For each module, the observed behaviors were consistent with the system's expected performance (i.e., the system was considered capable of participating in human-based trial testing).

4.4 Performance Observation

According to testing, the prototype generated consistent, reliable measurements of all physiological signals of interest. The ESP32 board, utilizing a TinyML algorithm, was capable of recognizing abnormal events. The two-performance metrics reported in this paper should be defined separately.

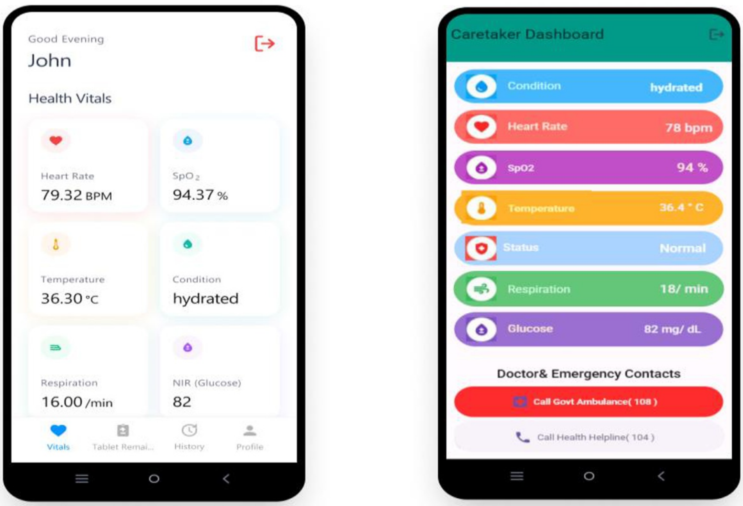

Fig. 6. SmarLife Guardian mobile application showing real-time health monitoring dashboard.

The monitoring accuracy of the vital sign sensors (the accuracy with which each of the sensors measured the physiological values compared to the references devices) ranged from 87% to 93% across all parameters listed in Table 1; and 2) The anomaly classification accuracy of the TinyML model (the accuracy with which the model classified a pattern as normal or abnormal) ranged from 75% to 85%, which reflects the challenge of classifying subtle physiological deviations using a lightweight model that is executed entirely on the device. Each of these metrics will be presented as a percentage for each signal in Table 1. In testing, the device had an average response time of less than three seconds once a dangerous value had been marked as a response. This is the time it took for the device to send a push alert via Firebase to the carer. The voice module also reminded the patient to take their medication at the exact time set for the dummy medication, and the patient did so without any failures. When the tracked data remained constant, the false alarm count remained low. This indicates that a model that learns a range for each person will have fewer false alarms than a rule-based approach. The SmartLife Guardian prototype is now functional as expected. It is ready for the next stage - actual tests on humans as shown in Fig.6.

5 Future Scope

One step ahead, tiny machine learning tools such as autoencoders and LSTM models could sharpen our forecasts of personal health risks [8][12][16]. Instead of just tracking symptoms, the setup may spot fall chances by studying walking rhythms, shaky hands, tiredness clues - patterns already linked to falling risks [6][13]. Down the line, forecasts for key body signals might come from past user records, shaping an LSTM network trained on time-linked details; splitting the present pool of 5,500 bio-readings into four-fifths for practice and one-fifth for testing helps project heart rate, oxygen levels, heat, breathing rates 12 to 36 hours out, matching trends seen in real-body behavior; mismatches between live results and earlier projections can spark warnings so helpers get notice before trouble strikes - or even stop it. That kind of foresight sits on the drawing board now, still untested in today's version. A new gesture-based signal option will let older adults call for help with simple hand motions.

6 Conclusion

This paper presents a wearable-enabled system that utilizes multimodal sensing using Edge-AI and TinyML for real-time and personalized health monitoring of the elderly through a smart glove. Through the transfer of processing to the edge, the system has improved latency and privacy while providing predictive healthcare monitoring capabilities. Therefore, this method provides a realistic, scalable, and user-centric way to enhance both safety and quality of life in elderly care.

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