

AI AND IOT HEALTH CARE MONITORING SYSTEM

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ABSTRACT

Continuous monitoring of vital signs is essential for patients with chronic illnesses, elderly people living alone, and patients recovering at home after discharge from hospital. In most cases these patients are checked only during occasional visits to a clinic, and a sudden deterioration may go unnoticed until it becomes serious. Hospitals also face a shortage of nursing staff, which makes frequent manual checks on every patient difficult. This paper presents an AI and IoT health care monitoring system that measures vital signs continuously, sends them to a cloud platform, and uses machine learning to identify patients whose condition is becoming abnormal.

The patient unit is built around an ESP32 microcontroller connected to a MAX30102 sensor for heart rate and blood oxygen saturation, a DS18B20 sensor for body temperature, an AD8232 module for a single-lead electrocardiogram, and an accelerometer for fall detection. A small display on the unit shows the current readings to the patient, and a buzzer gives a local warning when a reading goes beyond safe limits. The unit is powered by a rechargeable battery so that it can be worn at home or in a hospital ward without restricting movement.

Readings are sent over Wi-Fi to a cloud server using the MQTT protocol at regular intervals. The server stores the data in a time series database and applies two levels of analysis. The first level checks each reading against clinical thresholds for immediate danger. The second level uses a trained machine learning model that considers several vital signs together, along with recent trends, to estimate a risk score and to identify early signs of deterioration that simple thresholds would miss. An anomaly detector also looks for irregular heart rhythm patterns in the ECG signal.

Doctors and caregivers access the information through a web dashboard and a mobile application. The dashboard lists all monitored patients sorted by risk score and shows graphs of their recent readings. When a critical condition or fall is detected, the system sends push notifications and SMS alerts to the assigned doctor and family members, including the patient's latest readings and location. Patients can also press a help button on the unit to request assistance.

I. INTRODUCTION

The burden of chronic diseases such as hypertension, diabetes, heart disease, and respiratory disorders is growing steadily, and the population of elderly people who need regular health supervision is increasing. Many of these patients live at home, sometimes alone, and visit a doctor only when they feel unwell or at scheduled intervals. Serious events such as heart rhythm abnormalities, drops in oxygen

saturation, high fever, or falls can occur between visits and may not be noticed until the patient's condition has become critical.

In hospitals, vital signs of ward patients are usually recorded by nurses a few times a day. Continuous bedside monitors are available in intensive care units, but they are expensive and cannot be provided for every bed. Studies of hospital practice show that deterioration is often preceded by gradual changes in vital signs over several hours, and that these changes are missed when readings are taken infrequently. Recording readings on paper also makes it difficult to see trends and to share information quickly with doctors.

The Internet of Things allows low-cost sensors to be connected to microcontrollers that send data over wireless networks to cloud platforms. Wearable and bedside sensors for heart rate, oxygen saturation, temperature, and ECG are now inexpensive and small enough for continuous use. At the same time, machine learning methods can analyse streams of physiological data and recognise patterns associated with deterioration that are hard to capture with single threshold rules. Combining these technologies makes continuous, intelligent monitoring affordable outside intensive care.

This paper describes an AI and IoT based health care monitoring system that collects vital signs from a wearable patient unit, transmits them to the cloud, analyses them with threshold rules and a machine learning risk model, and alerts doctors and caregivers when attention is needed. The objective is to provide continuous supervision for patients at home and in general wards, to detect deterioration earlier, and to help medical staff focus their attention on the patients who need it most. The system is intended to support clinical judgement rather than replace it, and every alert is presented with the readings that caused it.

II. LITERATURE SURVEY

Remote patient monitoring has been studied for many years under the name of telemedicine and telehealth. Early systems required patients to take their own measurements with standalone instruments and send the readings by telephone or through a computer at scheduled times. Studies of these programmes found that they improved the management of chronic conditions such as heart failure and hypertension, mainly because doctors could adjust treatment without waiting for a clinic visit. However, the reliance on patients to take and report measurements meant that data was irregular and sometimes incorrect, and elderly patients in particular found the process difficult to follow. Researchers therefore turned to automated systems in which sensors transmit readings without patient involvement. The spread of wireless technologies such as Bluetooth, ZigBee, and Wi-Fi made these automated systems practical, and many later designs adopted a structure in which body-worn sensors send data to a local gateway that forwards it to a remote server for review by clinicians.

A large number of studies describe IoT-based health monitoring prototypes built with low-cost microcontrollers and sensors. Common designs use Arduino or ESP32

boards with pulse oximetry sensors, digital temperature sensors, and ECG front-end modules, and send data to cloud services such as ThingSpeak, Firebase, or custom servers. Evaluations of these prototypes report that heart rate and temperature readings are generally close to those of reference instruments when the patient is at rest, while oxygen saturation and ECG signals are more sensitive to motion and sensor placement. Several authors recommend signal filtering, motion artefact detection, and discarding readings of poor quality before analysis. Battery life and the comfort of wearing sensors for long periods are also reported as practical concerns, and duty cycling of sensors and radios has been proposed to extend operating time.

Early warning scores are widely used in hospitals to identify patients at risk of deterioration. These scores assign points to ranges of heart rate, respiratory rate, blood pressure, temperature, oxygen saturation, and level of consciousness, and the total indicates the level of concern. Research has shown that such scores help staff recognise deterioration earlier than unstructured observation. At the same time, studies note that the scores depend on regular manual measurement and treat each vital sign independently. Automated calculation of warning scores from continuous sensor data has been proposed in several works, and results suggest that continuous scoring detects deterioration earlier than intermittent manual scoring, provided that sensor noise is handled properly to avoid excessive false alarms. Researchers have also proposed adjusting the score ranges for individual patients whose normal readings differ from population averages, such as patients with chronic lung disease whose baseline oxygen saturation is lower.

Machine learning has been applied to vital sign data for prediction of deterioration, detection of arrhythmia, and classification of patient condition. Models such as logistic regression, random forests, gradient boosting, and recurrent neural networks have been trained on intensive care and ward datasets to predict events such as cardiac arrest and transfer to intensive care several hours in advance. Reported results show that models using combinations of vital signs and their trends outperform single-parameter thresholds. For ECG analysis, convolutional neural networks have achieved high accuracy in detecting atrial fibrillation and other arrhythmias from short recordings. Authors emphasise the importance of interpretability, since clinicians must understand why a patient has been flagged, and of validation on data from the population where the system will be used.

Recent research has focused on complete platforms that integrate sensing, cloud processing, analytics, and clinical workflow. These systems provide dashboards for doctors, mobile applications for family members, and alert mechanisms that escalate notifications if they are not acknowledged. Studies highlight data security and privacy as key requirements, recommending encrypted communication, authenticated access, and compliance with health data regulations. Fall detection using accelerometers has also been incorporated in platforms aimed at elderly users, since falls are a major cause of injury in this group.

III. SYSTEM ANALYSIS

The system is analysed as a patient-side sensing unit, a communication path, a cloud analytics service, and user applications. The sensing unit consists of an ESP32 microcontroller, a MAX30102 pulse oximetry sensor, a DS18B20 temperature probe, an AD8232 ECG module with three electrodes, an MPU6050 accelerometer, an OLED display, a buzzer, a help button, and a lithium battery. The microcontroller samples the sensors, filters the signals, computes heart rate and oxygen saturation, and checks for falls using acceleration patterns. Every few seconds it publishes a data packet containing the patient identifier, vital signs, signal quality indicators, and event flags to an MQTT broker over Wi-Fi, and short ECG segments are uploaded at longer intervals. On the cloud server, a rule engine compares readings with clinical thresholds, and a machine learning service computes a risk score from recent readings and trends. Results are stored with the raw data, displayed on the doctor dashboard, and used to trigger notifications to doctors and caregivers.

Existing System

In the existing system of care, patients with chronic conditions are monitored mainly through periodic clinic visits and occasional measurements taken at home with separate instruments such as a thermometer, a pulse oximeter, or a blood pressure monitor. These readings are recorded on paper, if at all, and shared with the doctor only at the next visit. In hospital wards, nurses measure vital signs a few times each day and write them on charts, and continuous monitors are reserved for intensive care units. Deterioration that develops between measurements can go unnoticed for hours. Elderly patients living alone may fall and be unable to call for help. Where commercial remote monitoring devices are used, they often measure only one parameter, rely on proprietary platforms, and are too expensive for widespread use. Alert rules, where present, are based on fixed thresholds for single parameters, which produce many false alarms and fail to detect gradual combined changes that indicate a patient is becoming unwell.

Disadvantages of Existing System

- Vital signs are measured only occasionally, so changes between checks are missed.
- Readings are recorded on paper and are difficult to share and analyse.
- Continuous monitors are costly and limited to intensive care units.
- Nursing staff spend considerable time on routine manual measurements.
- Elderly patients living alone have no automatic fall detection.
- Commercial home devices usually measure a single parameter.
- Fixed single-parameter thresholds generate frequent false alarms.
- Gradual deterioration involving several vital signs is not recognised early.
- Doctors cannot view patient trends remotely in real time.
- Family members are not informed promptly when a problem occurs.

Proposed System

The proposed system provides continuous and intelligent monitoring of patients using wearable IoT sensors and cloud-based machine learning. A compact patient unit built

on an ESP32 measures heart rate, oxygen saturation, body temperature, and a single-lead ECG, detects falls with an accelerometer, and includes a help button. Readings are filtered on the device and sent to a cloud server over Wi-Fi using MQTT. The server applies clinical threshold rules for immediate danger, computes an automated early warning score, and runs a machine learning model that estimates the risk of deterioration from combinations of vital signs and their recent trends. A separate model examines ECG segments for irregular rhythms. Doctors see all their patients on a dashboard sorted by risk, with graphs and alert history, while caregivers use a mobile application. Critical readings, falls, and help requests trigger push notifications and SMS alerts, and unacknowledged alerts are escalated to additional contacts.

Advantages of Proposed System

- Vital signs are monitored continuously rather than at occasional intervals.
- Several parameters are measured by a single low-cost wearable unit.
- Machine learning detects gradual deterioration that thresholds miss.
- ECG analysis identifies irregular heart rhythms automatically.
- Falls and help requests raise immediate alerts to caregivers.
- Doctors can review patient trends remotely from a dashboard.
- Risk-based sorting helps staff attend first to the patients who need it most.
- Alert escalation ensures that critical events are not ignored.
- Digital records remove manual charting and support later analysis.
- Home monitoring reduces unnecessary hospital visits and readmissions.

IV. METHODOLOGY

The methodology begins with the interfacing and calibration of each sensor with the ESP32. Heart rate and oxygen saturation are computed from the red and infrared signals of the MAX30102 using peak detection and ratio calculation, with readings discarded when the signal quality index is low. Temperature is read directly from the DS18B20. The ECG signal from the AD8232 is sampled at 250 hertz, filtered to remove baseline wander and power line noise, and stored in short segments. Falls are detected when a high acceleration peak is followed by a change in orientation and a period of inactivity. The firmware publishes a JSON packet to the MQTT broker every five seconds. On the server, a Python service subscribes to the data, stores it in a time series database, and applies threshold rules and an early warning score. A gradient boosting model trained on a public vital signs dataset predicts deterioration risk from the last hour of readings, and a small convolutional network classifies ECG segments. Alerts are sent through a notification service to the dashboard and mobile application.

SYSTEM ARCHITECTURE

The architecture of the health care monitoring system is arranged in layers from the patient to the care team. The Sensing Layer includes the pulse oximetry, temperature, ECG, and motion sensors attached to the patient, together with the help button. The Patient Unit Controller Layer is the ESP32, which samples and filters signals, computes vital signs, detects falls, and drives the display and buzzer. The

Connectivity Layer transfers readings to the cloud using MQTT over Wi-Fi with secure authentication. The Cloud Storage Layer holds vital sign streams, ECG segments, and patient records. The Rule Engine Layer checks readings against clinical thresholds and computes early warning scores. The AI Analytics Layer runs the deterioration risk model and the ECG rhythm classifier. The Doctor Dashboard Layer displays patients sorted by risk with trends and history, the Caregiver Application Layer provides family members with readings and alerts on their phones, and the Alert and Escalation Layer delivers notifications and escalates those that are not acknowledged.

AI and IOT health care monitoring system

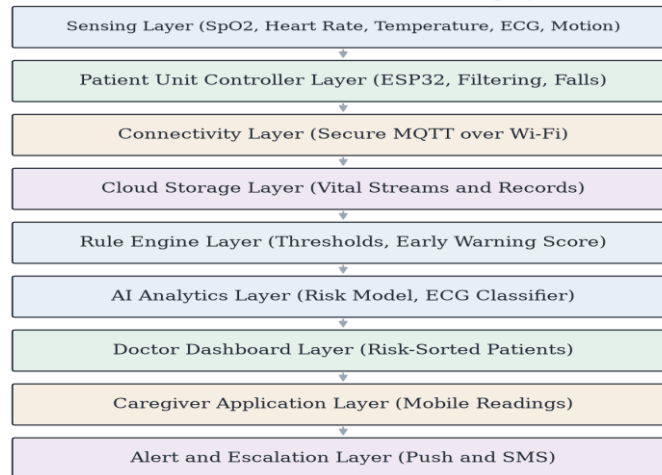


Fig. 1 System Architecture

V. RESULT AND OUTPUT



VI. CONCLUSION

This paper has presented an AI and IoT health care monitoring system that measures vital signs continuously, analyses them in the cloud, and alerts doctors and caregivers when a patient needs attention. A single wearable unit based on an ESP32 measures heart rate, oxygen saturation, temperature, and ECG, and detects falls, providing much more complete information than the occasional measurements that patients receive at present.

The combination of threshold rules and machine learning gives the system two complementary ways of recognising danger. Thresholds respond immediately to clearly dangerous readings, while the risk model identifies gradual deterioration that develops across several vital signs over time. Automatic ECG analysis adds the ability to detect irregular heart rhythms that would otherwise require a specialist to review the recording. Together these methods help detect problems earlier while keeping false alarms at a manageable level.

The doctor dashboard and caregiver application make the collected information useful in everyday care. Doctors can see which patients are at highest risk and review their trends before deciding on action, and family members receive timely notice of falls or critical readings. Alert escalation ensures that important events receive a response even if the first contact is unavailable. For hospitals, continuous monitoring in general wards can reduce the time nurses spend on routine measurements and allow them to focus on patients who are showing signs of deterioration.

Future work includes adding cuffless blood pressure estimation and respiratory rate measurement, integrating the platform with hospital information systems and electronic health records, and validating the risk model on data collected from local patient populations. Clinical trials in partnership with hospitals would be needed before the system is used for medical decisions. Improvements in sensor comfort, battery life, and data security would also make the system more suitable for long-term home use by elderly and chronically ill patients.

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