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Article

A Secure Energy-Aware IoT Solution for Remote Health Monitoring and Patient Localization

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Abstract: An Internet of Things (IoT) based healthcare system is extremely beneficial for continuous patient observation beyond hospital settings. The patients recovering from surgery are helpful with this cutting-edge technology. In recent days most of the existing approaches primarily focus on real-time health surveillance without providing alert notifications for abundant value readings. The shortcoming of the current study is live location tracking that prolongs rescue times. The system latency is quite high in terms of power utilization, and the data security is inadequate due to traditional security mechanisms. The proposed methodology examines ambient environmental parameters along with vital health signs. Through an automatic notification, the system responds efficiently for quick medical support. Each piece of data is individually stored inside a cloud database in an encrypted fashion to ensure confidentiality. The system creates a dynamic link for real-time GPS location tracking to provide immediate assistance. The long-term sustainability is measured by evaluating an individual device's maximum power consumption under ideal conditions. Additionally, the performance of the system in terms of data fetching perfection is calculated with an accuracy of 98.1%.
Keywords: IoT, health observation, smart healthcare, location tracking, cloud security

1. INTRODUCTION

Nowadays, one of the most significant challenges facing the healthcare industry is improving patient outcomes. Patients with cardiovascular disorders appreciate IoT-based healthcare system for regular check-ups through remote monitoring. Real-time location tracking and quick rescue facilities are beneficial for psychiatric patients. Patients might face some problems to get emergency assistance as they are typically restricted to hospital settings. The ambient environmental factors such as air quality, loud noises, and high humidity may affect respiratory problems, stress, and sleep disorders. In this context, the suggested approach is advantageous through continuous surveillance of the immediate surroundings. The deployment of such a system can be replicated throughout smart cities. It might suggest community-wide health monitoring for preventing pandemic outbreaks in the future. Several advanced technologies, including IoT and artificial intelligence, Blockchain have significantly improved patient care facilities. IoT-based revolutionary invention that has transformed healthcare by facilitating data-driven decision-making [1, 2], automatic notifications [3], real-time patient monitoring [4, 5], and patient location tracking [6, 7]. Recently IoT-based remote health monitoring systems have improved patient outcomes [8, 9]. This area of interest enhances healthcare services in various ways during the COVID-19 pandemic [10]. This advanced technology improves the medical facilities for chronic heart patients by reducing the risk of heart failure [11, 12, 13]. Traditional healthcare systems are limited to hospital boundaries, but patients recovering from surgery need continuous medical attention [14].

This research contribution introduced a secured low-latency IoT-based healthcare solution for continuous patient monitoring. Vital health indicators such as body temperature, pulse rate, SpO2, and electrocardiogram (ECG) signals are thoroughly examined. Another crucial aspect of this study is the observation of the immediate surroundings, including indoor light intensity, humidity, temperature, sound levels, air quality, and patient movement. The suggested approach computes the load of individual devices to measure overall energy efficiency. An AWS Lambda security mechanism is employed for both environmental and biomedical data during storage in DynomoDB. The system delivered an automated notification for abnormal value readings. Additionally, the device sent a live GPS link to the nearest medical authority for immediate support. Finally, the performance of 98.1% is evaluated and compared with other existing techniques in terms of functionalities. **Fig. 1** depicted the overall architecture of the proposed system.

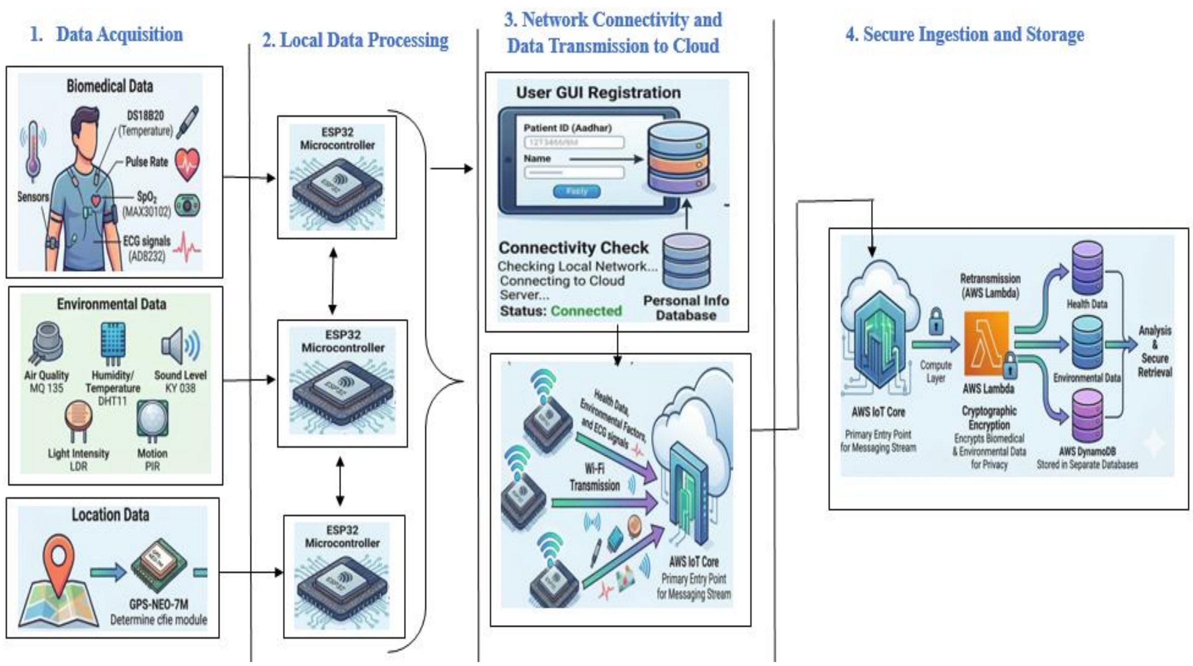

Fig. 1. Proposed System Architecture

2. LITERATURE REVIEW

Numerous researchers have demonstrated remote health surveillance and location tracking challenges in their successful studies. The methods of several IoT-based patient observation systems and their limitations are discussed in this section.

A cloud-based remote patient health monitoring system was introduced by G. Jaya Lakshmi et al. [15]. The drawback of this study was the fact it collected a wide range of diverse health data via IoT sensors that had been attached to large objects. These days, data security in IoT frameworks is challenging since sensitive data resides on clouds. In this regard, Omprakash Dewangan et al. [16] published a review study that employed a machine learning strategy to protect confidential data on cloud platforms. The unstructured biological data was formulated using a cloud-based platform that made the system more complex. During the COVID-19 pandemic, IoT-based remote patient monitoring became more popular. In this context Vaneeta Bhardwaj et al. [17] suggested a technique that measured the maximum relative error of 3.30%, 1.05%, and 2.89% separately against temperature, SPO2 and heart rate. The technique required high-speed internet that was difficult to economically execute. In another approach, Rajeesh Kumar N.V. et al. [18] developed a system for ongoing monitoring of critical COVID-19 symptoms such as fever, breathing rate, and lung condition of a patient. This research study's biggest problem was implementation infrastructure. In smart healthcare, M.K. Das et al. [19] developed an IoT-based surrounding environment monitoring system. This study's primary drawback was that the authors just examined environmental factors without observing relevant health data. Mariana Peyroteo et al. [20] conducted a systematic literature review (SLR), where 123 papers were thoroughly examined. The researchers highlighted the importance of equivalence technology for remote patient observation. The primary healthcare features such as diabetes and cardiovascular disorder were the only objective of this study without offering any emergency support solutions. Indoor environmental factors are crucial for improving a patient's health outcomes. In this context, Jun Ho Jo et al. [21] developed an air quality monitoring device. In this study every piece of information was collected from Hanyang University of Korea on time series basis and stored in web server for further analysis. The method only restricted to monitor the presence of numerous harmful gases, such as CO_2, CO, and aerosol, within an indoor environment. Bikash Pradhan et al. [22] published a review paper on IoT applications in healthcare. The primary objective of the researcher was to demonstrate various technologies and problems associated with IoT healthcare services but does not offer any comprehensive solution. Pooyan Shams Farahsari et al. [23] created an indoor positioning system that adopted a panoramic view of the interior for future data analysis. The system used a GPS module and sensors to gather environmental data for delivering location-based services. This study was primarily concerned with indoor positioning systems. Herfandi Herfandi et al. [24] introduced a novel method for real-time health monitoring and indoor position tracking based on the Internet of Medical Things (IoMT). Patient movement tracking and vital health signs monitoring were the key components of this research study. The environmental factors that are crucial for enhancing patient outcomes were not considered by the researchers. K. Saritha et al. [25] designed a hospital medical equipment tracking system to ensure smooth operations. The tracking of hospital medical equipment management was the sole restriction of the system. Nouf Abdullah Almujally et al. [26] created a tracking and localization system for human physical activity, including walking, running, and jumping in this research activity a GPS module and various IoT sensors were essential for feature tracking. The K-fold cross-validation technique was used to predict the accuracy of 96%.

3. MATERIALS AND METHODS

3.1 Process flow diagram

A comprehensive methodology from data gathering to data representation is shown in the process flow diagram (**Fig. 2**). It illustrates the data flow mechanism from sensor devices to cloud storage, anomaly detection, alert notification, and data visualization.

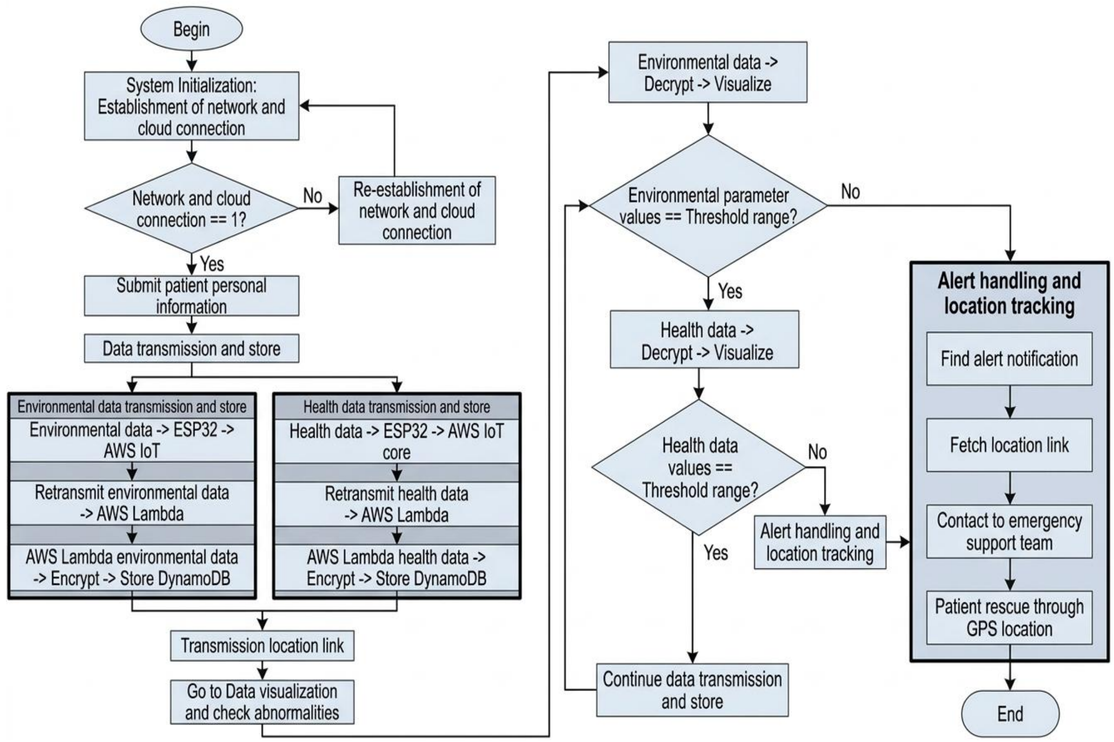

Fig. 2. Process Flow Diagram

3.2 Proposed algorithm

The system examines the network status prior to sending the data. Various heterogeneous data are sent to the cloud server via a local microcontroller. The AWS Lambda mechanism is employed to secure the information in DynamoDB. The data are decrypted before being visualized. The system delivered a notification for an abundant value reading and sent a GPS link. **Algorithm 1** illustrated the sequence of the overall framework.

Algorithm 1: Patient Observation and Alert System

Require: Network Status (S net), Environmental Data (D env), Health Data (D health), Environmental Threshold (T env), Health Threshold (T health), Location Link (L link).

Ensure: Data Visualization and Notification

```
function SystemOperation (S net, D env, D health)
    SystemInitialization ()
    S netEstablishConnection ()
    if S net = = 1 then
        SubmitPatientInfo ()
        DataTransmissionAndStore (D env, D health)
        DataVisualizationAndCheck (D env, D health)
    else
        ReestablishConnection ()
    end if
```

```
end function
function DataTransmissionAndStore (D env, D health)
    AWS IoTTransmit (D env, ESP32)
    AWS LambdaRetransmit (AWS IoT)
    Store (Encrypt (AWS Lambda), DynamoDB)
    AWS IoTcore Transmit (D health, ESP32)
    AWS Lambda Retransmit (AWS IoTcore)
    Store (Encrypt (AWS Lambda), DynamoDB)
    TransmitLocationLink ()
end function
function DataVisualizationAndCheck (D env, D health)
    if D env ϵ T env then
        Visualize (Decrypt (D env))
        if D health ϵ T health then
            Visualize (Decrypt (D health))
            ContinueTransmissionAndStore ()
        else
            AlertHandlingAndLocationTracking ()
        end if
    else
        AlertHandlingAndLocationTracking ()
    end if
end function
function AlertHandlingAndLocationTracking ()
    FindAlertNotification ()
    L linkFetchLocationLink ()
    ContactEmergencySupport ()
    RescuePatient (L link)
end function
```

3.3 Module descriptions

The proposed system is the integration of five distinct modules, including data acquisition, cloud-based encryption, data visualization, location tracking, and power management.

I) Data acquisition module: A range of high-speed biomedical data, including body temperature, pulse rate, SpO2, and ECG signal, are acquired from the patient's body utilizing ESP32 microcontrollers. Various ambient parameters such as air quality, humidity, temperature, sound levels, light intensity, and patient movement are gathered via another microcontroller using a parallel mechanism. The system is additionally linked with a GPS-NEO-7M and a GSM module for live location tracking. **Fig. 3** depicted the health data acquisition process via a local microcontroller.

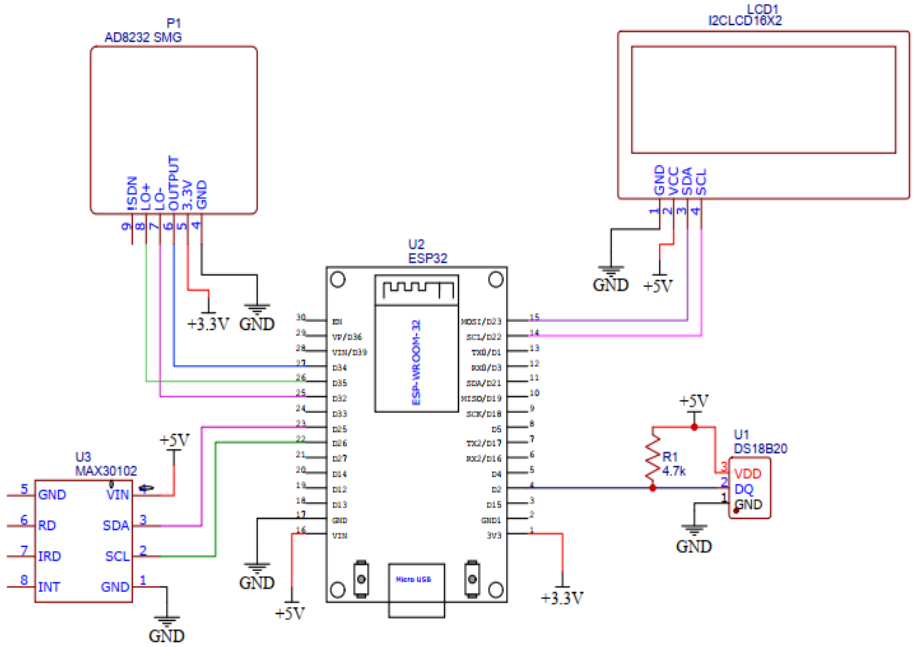

Fig. 3. Health Data Acquisition via ESP32 (Design by EasyEDA)

II) Cloud storage and security module: Data privacy is one of the primary challenges of this study. In this regard, Amazon Web Services (AWS) is utilized to handle private information with security mechanisms. The data are transmitted via WiFi to AWS IoT Core and then to AWS Lambda. Lambda functions are utilized to encrypt the sensitive information for privacy concerns. Patient personal information, health data, and environmental variables are stored in separate database. **Fig. 4**. Illustrated the encrypted health data in the cloud server.

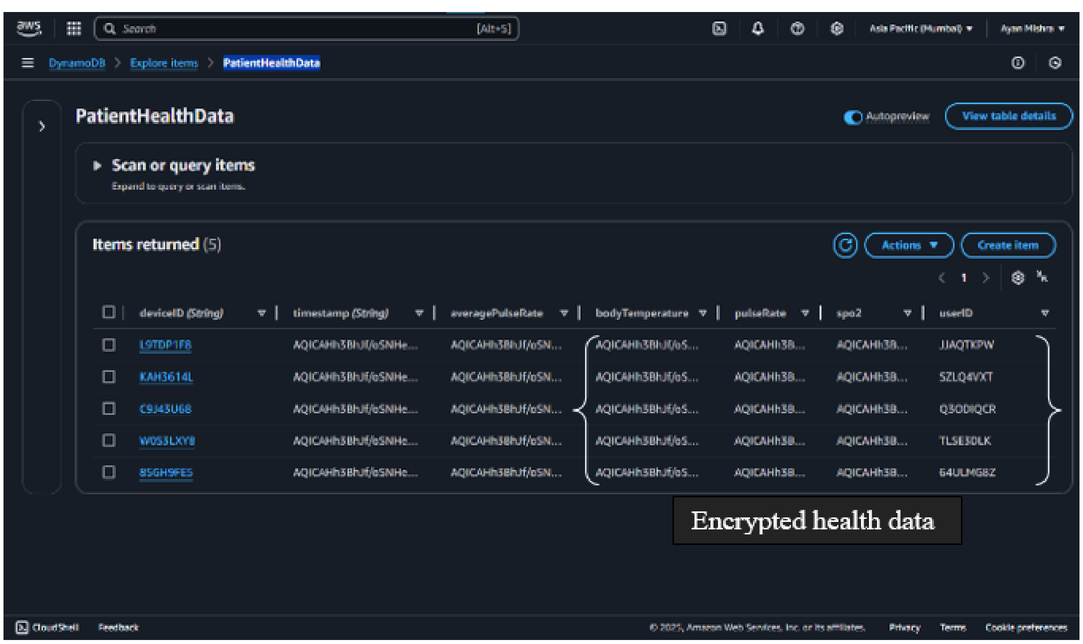

Fig. 4. Encrypted Health Data in AWS

III) Data visualization and notification module: Authorized users can create a request for data access through this module, followed by decryption for real-time visualization (**Fig. 5**). The device instantly notifies the investigator through a GUI bell icon whenever a parameter exceeds a predetermined critical threshold. Instance communication with the closest healthcare authority is rendered feasible by the GUI assistance menu that subsequently sends a GPS link.

Fig. 5. Data Visualization GUI

` ***IV) Location tracking module:*** The location tracking module is helpful for a medical rescue team to determine the exact position of a patient. The system sends a GPS link (with latitude and longitude) to the medical authority for prompt rescue. The location tracking mechanism is shown in **Fig. 6**.

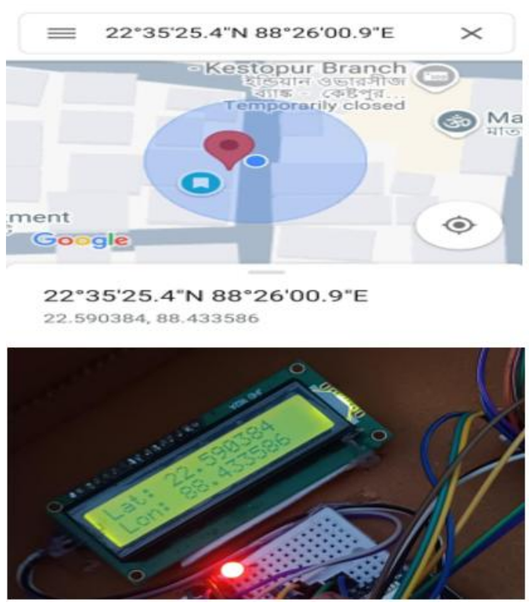

Fig. 6. Patient Location Tracking

V) Power management module: Energy efficiency measurement is another aim of this study. Power requirements depend on the active and idle states of individual components. A 5V input power supply is required to active the proposed system. The GSM module is the most power-intensive component, consuming up to 2000mA (10,000mW) during active transmission. The PIR motion detector is extremely efficient with ~0.75 mW.

The required power for the operational activity of the various devices is provided in **Table 1**. This study considered the maximum value from the Active State Range (mA) column for each component to calculate the maximum power consumption in the active state.

Table 1: Individual device power consumption

Device Name	**Max Active Current (Imax) (mA)**	**Voltage (V) (Volts)**	**Power (P=V×I) (mW)**
ESP32-1	260	5	1300
ESP32-2	260	5	1300
ESP32-3	260	5	1300
16 x 2 Display	20	5	100
MQ 135	200	5	1000
DHT11 (Temp/Hum.)	2.5	5	12.5
KY 038	<5 (use 5 for max)	5	25
LDR Module (Light)	1	5	5
PIR (Motion)	0.15 (Approx)	5	0.75
Buzzer	30	5	150
GPS NEO – 7M	40	5	200
MAX30102 (HR/SpO2)	1	5	5
DS18B20 (Temp.)	1.5	5	7.5
AD8232 (ECG)	0.5	5	2.5
GSM 800L V2 (GSM)	2000	5	10000
Total	**3080.15**	**-**	**15410.25**

The system runs on a 5-volt input power supply. The power consumption for the GSM module is significantly higher than other components. Here requiring an additional 2 Amp for efficient work (4 Amps total for the three ESP-32s and 2 Amps for GSM). Although the table lists 500-2000 mA for the GSM in an active state, we use the 2000 mA (2 A) from the table for max consumption in this calculation.

3.4 Experimental setup and testing condition

Three (3) independent ESP32 microcontrollers are employed to enhance the efficiency of the system (**Fig. 7**). ESP32-1 is linked to various health sensors, including body temperature, heart rate, and SpO2. The connection diagram between the ESP32-2 and ECG sensor is depicted in the latter section of the image. The final part of the **Fig. 7** represents how several environmental sensors, including temperature, humidity, light intensity, noise, and GSM module are connected to ESP32-3.

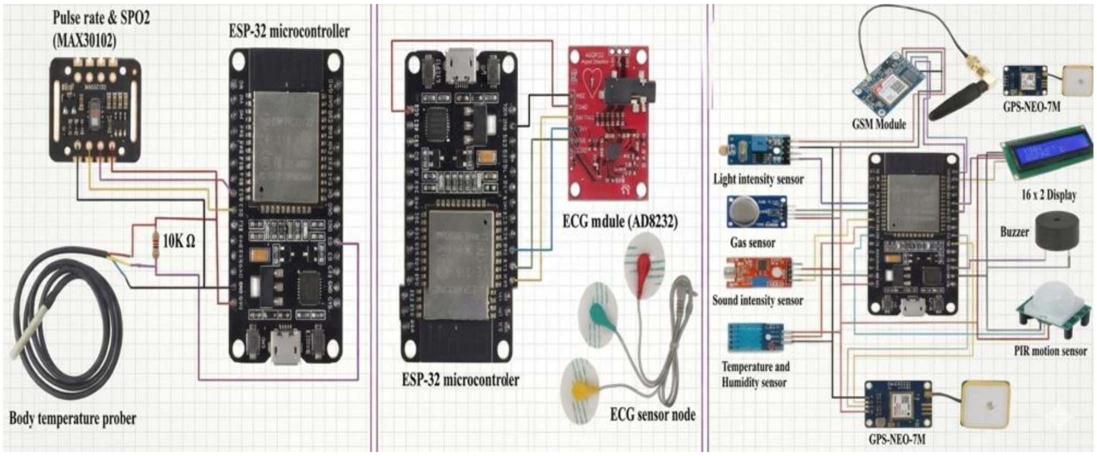

Fig. 7. Experimental Setup

Testing condition:

A predetermined number of trial runs are employed to evaluate the performance of the suggested healthcare system. Forty observations are employed to calculate the accuracy. Verifying the system's "data fetching perfection" and "exact location tracking" are the primary components of the test criteria. The "True" and "False" value readings from each sensor are utilized to evaluate the accuracy of data retrieval. This 40-observation limit is also applied to assess the GPS module's performance for live location tracking. The system estimates an overall accuracy of 98.1% by comparing the true and false value readings of individual sensors.

3.5 Data security

The crucial step of this study is patient verification with unique identification prior to sending health data. Confidential data is deliberately stored in separate cloud databases. Critical health indicators are securely stored on cloud servers via the AWS Lambda encryption method (**Algorithm 2**). Vital health parameters can be accessed by authorized medical personnel using a predetermined decryption key.

Algorithm 2: Data Encryption using AWS Lambda

Require: Sensor Data (D *senso*r)

Ensure: Encrypted Data in cloud database (D *enc*), integrity hash (H *data*)

procedure SecureDataTransmission (D *senso*r)

Verify AWS service availability for data transmission

Extract D *senso*r from IoT device

Secure connection setup to AWS IoT Core via Transport Layer Security (TLS)

Transmit AWS IoT Core D *senso*r

Execute AWS Lambda function after data arrival

Call ProcessAndEncrypt (D *senso*r)

function ProcessAndEncrypt (D *senso*r)

if Device Certificate is valid

H *data* HA256 (D *senso*r)

K GenerateKey (AWS KMS)

```
                D enc AES256 (D sensor)
                Commit the tuple (D enc, H data) to the Cloud Database
                return success
            else
                Reject connection and drop payload
                return failure
            end if
    end function
end procedure
```

The D *senso*r denoted the raw payload of health and environmental sensor data. H *data* is the raw sensor data with a 256-bit cryptographic hash. K represents the symmetric encryption key. The final ciphertext generated by the AES-256 algorithm is denoted by D *enc*.

4. RESULTS AND DISCUSSION

The results and discussion section illustrate the findings of a research effort. The performance, effectiveness, and energy consumption of the suggested method are discussed in this section.

4.1 Patient registration and profile management

At the initial step, the patient must sign up using the application's GUI by submitting basic details along with unique identification such as Aadhaar number. The user can change any fields, including name, age, photograph, gender, email, and Aadhar number, through profile settings. Additional modifications will be made to the AWS cloud in accordance with this modification. **Fig. 8** shows the user registration, sign in, and profile management process. This application has been developed by the React Native (with Expo) framework. It has an extensive library for locations and notifications for Android.

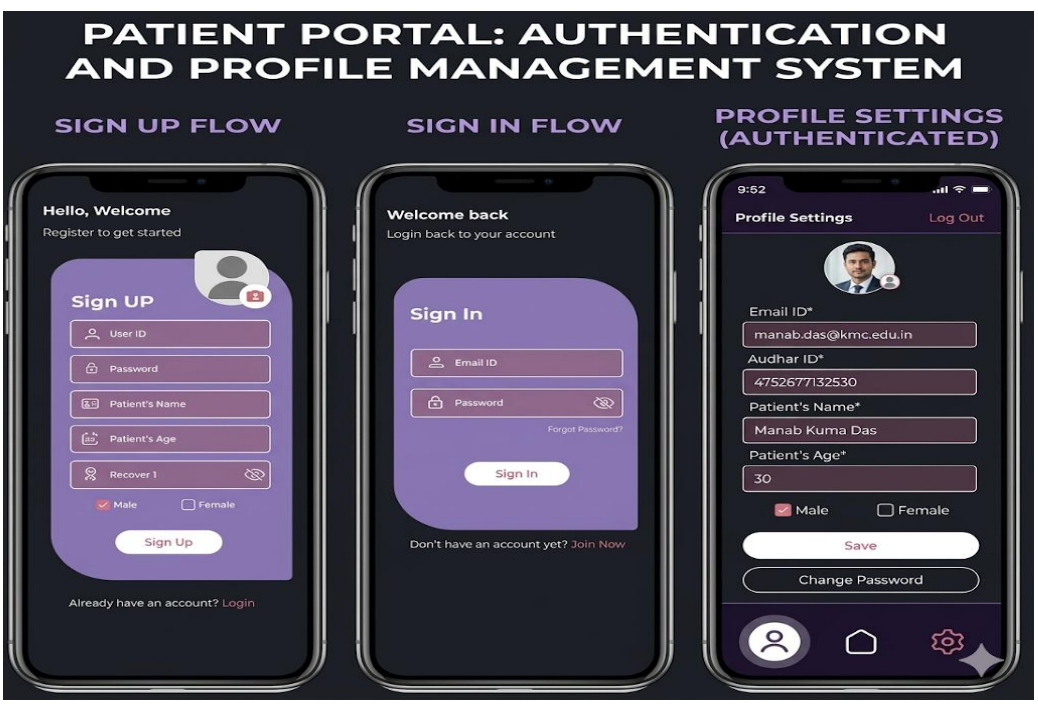

Fig. 8. User Registration, sign in, and Profile Setting GUI

4.2 Accuracy metric

The essential part of this study is performance evaluation with adequate measurement. Therefore, in this investigation, we consider 40 observations to verify the performance of the system. True and false values are used to evaluate the data fetching accuracy. **Table 2** shows the performance evaluation for environmental data fetching. Health data and the live location link retrieval procedure are depicted in **Tables 3** and **4**.

Table 2. Environmental data observation

Sensor (*ESi*)	**No. of Observation** (NEo)	**True value** ($TEVi$)	**False value** ($FEVi$)
Room Temperature	40	40	00
Humidity	40	39	01
Air Quality	40	38	02
Sound Level	40	37	03
Light Intensity	40	38	02
Motion	40	40	00

$$Environmental\ Data\ Accuracy\ (EDacc) = \sum_{i=1}^{6} \left(\frac{TEVi}{NEo}\right)/i \quad \text{--------(1)}$$

i represent the no. of environment sensors that are used to read environmental factors, $TEVi$ = True environmental value for sensor i, $FEVi$ = False value for environmental sensor i, and NEo= Number of environmental data observations. We derive the environmental accuracy value ($EDacc$) of 0.97 from Equation 1.

Table 3. Health data observation

Sensor (*HSj*)	**No. of Observation** (NHo)	**True value** ($THVj$)	**False value** ($FHVj$)
Body Temperature	40	40	00
Pulse Rate	40	39	01
SPO_2	40	39	01
ECG Signal	40	38	02

$$Health\ Data\ Accuracy\ (HDacc) = \sum_{j=1}^{4} \left(\frac{THVj}{NHo}\right)/j \quad \text{------------------------(2)}$$

j represents the no. of health sensors, $THVj$ = True value for health sensor j, $FHVj$ = False value for health sensor j, and NHo= Number of health data observations. The accuracy value for the health data $(HDacc)$, as determined by Equation 2, is 0.975.

Table 4. GPS location tracking

GPS	**No. of Observation** ($GPSo$)	**True GPS value (TGPS)**	**False GPS value(FGPS)**
GPS Location	40	40	00

$$Location\ Tracking\ Accuracy\ (GPSacc) = TGPS\ /\ GPSo \quad \text{------ (3)}$$

GPSO indicate the total no of observation for location tracking, whereas TGPS and FGPS represents true and false location tracking accordingly. Equation 3 produces a GPS location tracking accuracy (*GPSacc)* of 1.00 for this suggested system.

Finally, the system accuracy is measured through the following equation:

$$System\ Accuracy = \left[\sum_{k=1}^{3} (EDacc + HDacc + GPSacc)/k\right] * 100 \quad \text{---- (4)}$$

Where k represents the number of individual accuracy measurement process such as $EDacc, HDacc, and\ GPSacc$. In the final analysis, we measured 98.1% system accuracy from Equation 4.

4.3 Energy consumption analysis

The graph below (**Fig. 9**) illustrates the maximum power consumption for the main components, highlighting the high-power draw of the microcontrollers and the GSM module.

Table. 5. Power consumption by major components (mW)

Device	Power (mW)
GSM 800L V2	10000
ESP32-1	1300
ESP32-2	1300
ESP32-3	1300
MQ 135 (Gas Sensor)	1000
Others (Combined)	500 (Approx)

The GSM module is the least energy-efficient component, dominating the power budget in the active state due to its communication requirements. [31] The ESP32 microcontrollers also represent a significant portion of the power draw, primarily during data transmission. [32] The system's energy efficiency relies on minimizing the active time, particularly for the GSM and ESP32s, and maximizing the use of the low-power idle state for all components to conserve battery life.

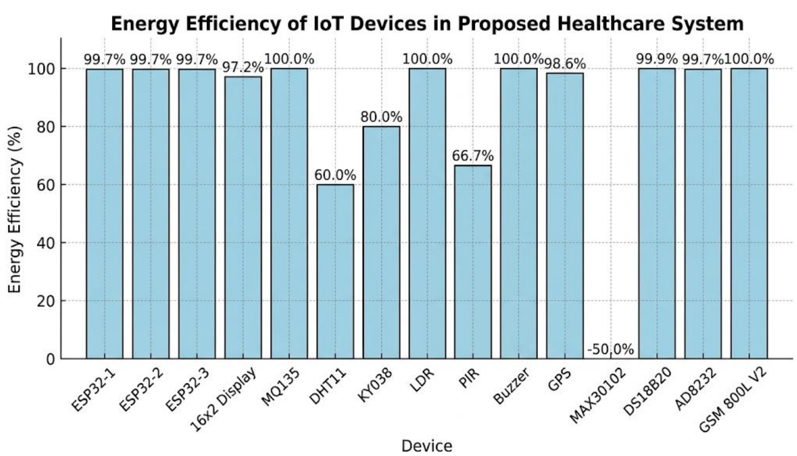

Fig. 9. Energy Efficiency Graph (Maximum Active Power)

5. COMPARATIVE ANALYSIS

Table 6 shows a thorough comparison between our suggested system and other existing methods in terms of accuracy and functionalities such as vital health signs monitoring, location tracking, and notification sending.

Table 6. A comparison of the proposed system with other existing methods

Ref.	Year of Publication	Purpose	Accuracy (%)
[27]	2023	Vital health sign monitoring and alert notification	97.7
[28]	2025	Real-time tracking of vital health signs	95

[29]	2025	Healthcare monitoring and tracking	94
[30]	2025	Patient tracking using wearable tags	92
Proposed	-----	Health and environment parameter monitoring, alert notification, patient location tracking	98.1 (Data fetching)

The outcomes of this research finding in terms of functionalities, including health and ambient parameter observation, live location tracking, energy efficiency, and cloud security are significantly remarkable. [33] Furthermore, the system's flawless data retrieval mechanism enhances its adoption in contemporary healthcare services.

6. CONCLUSION

The suggested approach demonstrates critical health indicator monitoring for post-surgery and chronic care patients who needed immediate medical attention. Environmental factors that influence sleep disorders or respiratory issues are also considered. An automatic alert notification is sent by the system whenever ambiance factors or health indicators cross a critical threshold to improve patient outcomes. GPS location tracking significantly speeds up response times. The approach might be advantageous by encrypting health data for later examination. The power consumption assessment verified the system's long-term viability.

A limited number of observations are used to evaluate the accuracy in terms of data-fetching perfection. Only authorized people may locally decrypt the data with a pre-shared decryption key. The recommended method does not employ any standard encryption algorithm during data transfer. The system's energy efficiency depends on optimizing the low-power idle state and reducing the GSM module's active duration. The system is not focused on machine learning-based predictive analysis. In this study AI-driven virtual assistants are not being employed to improve health outcomes.

Future advancements in edge computing and artificial intelligence will enhance the performance of IoT-based healthcare systems. Machine learning-based predictive analysis can expand its effectiveness, affordability, and accessibility globally. Implementation of nanotechnology and wearable biosensors may also improve the accuracy of health tracking in the future. Blockchain technology can ensure that medical records are safe by enhancing the data security. AI-powered virtual assistants are also providing prior medical emergency services based on health data analysis. The technology can also be extended for smart cities, where pandemic outbreaks could be controlled by implementing community-wide health monitoring.

7. ACKNOWLEDGMENTS

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