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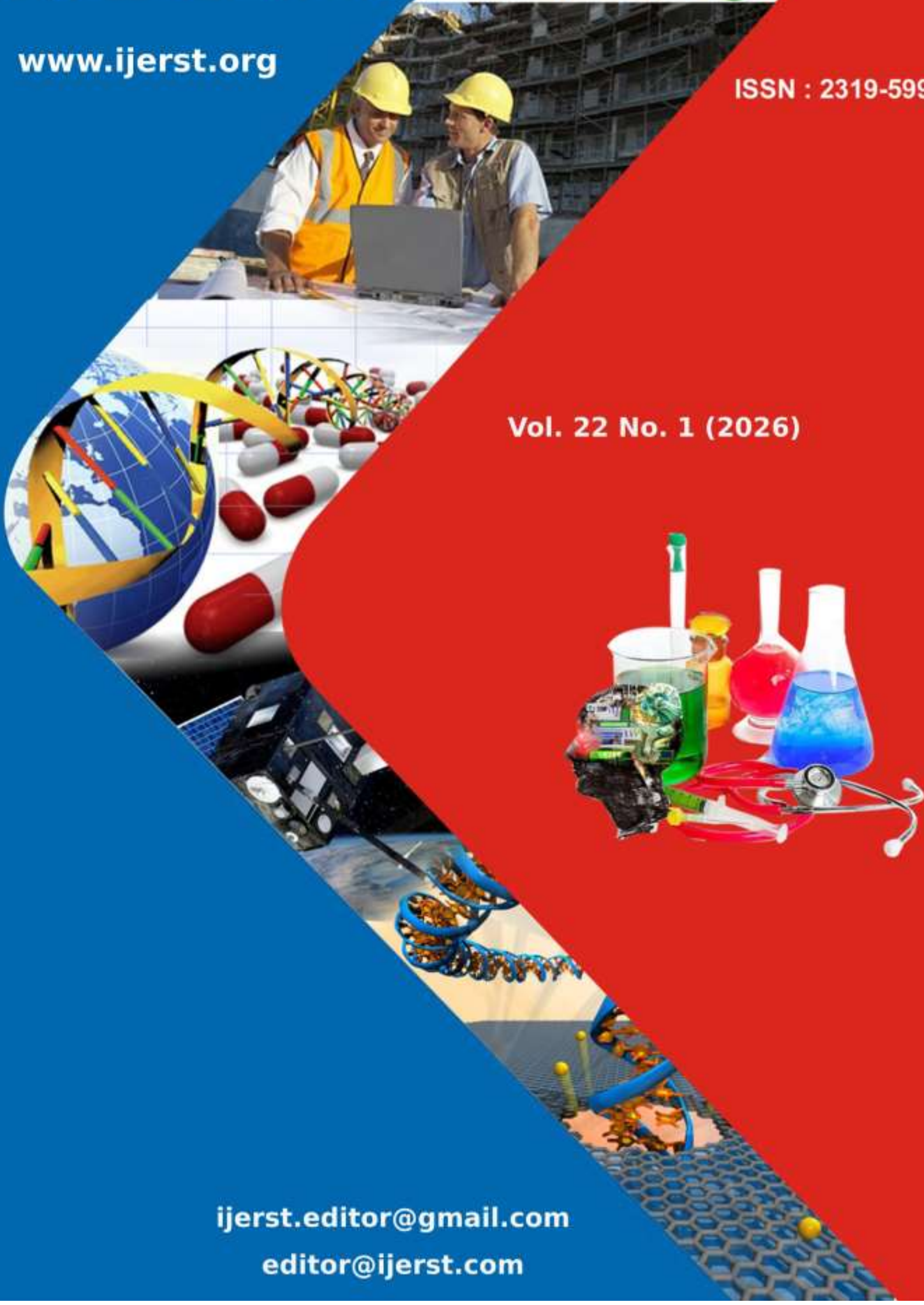

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Research Paper

PORTABLE VITAL SIGNS MONITOR USING BIOMETRICS AND MOBILE APP INTERFACING

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Abstract— Here we propose a portable system that checks health signs and applies fingerprint for the identification of people. This device maintains and track vital signs. It connects to a mobile app so doctors and patients can access the real time data. Most other systems either need people to do things by hand or only use one way to check who someone is. The proposed device indorses a low-cost biometric scanner, a device that measures vitals, a temperature sensor, and a microcontroller that connects to both Wi-Fi and Bluetooth. It helps the patients to monitor their health in real time scenario. The system is accurate, with 98% exact fingerprint matches, 99.7% precise temperature readings, and 98.6% correct heart rate measurements. It declines mistakes when identifying people by 30%, which helps in emergencies further aids in reducing the time public spend in hospitals, decreases the number of visits needed and makes sure the compliance with safety and security. Testing display that data transmit accordance to the mobile app, this system is accessible making healthcare safer, more efficient, and easier to reach for those with limited resources.

Keywords— biometric authentication, vital signs monitoring, real-time healthcare, mobile application, patient identification, data security.

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I. INTRODUCTION

The world's population is growing, and people are demanding better healthcare results. IoT is a novel Information Communication Technology (ICT) method that transmits and receives data through communication networks. Usual healthcare systems is having many weaknesses particularly when it comes to identification of patients and noticing their health in real time. Using paper log or barcode systems by hand fall towards mistakes. For example, in single care settings, accuracy can be as low as 80%, and across organizations sharing electronic health records, it drops to 50% [1]. These mistakes source substantial economic issues, with around $17.4 million lost every year because of rejected insurance claims. They also potentially slow down important treatments, leading to more sudden ICU admissions, up to 3.4% more [3]. Checking vital signs only at certain times makes it harder to spot health problems early [4]. Current solutions, like barcode scanners and separate biometric checks, aren't connected to proceeding health monitoring, which is inturn making procedures more elaborate during emergencies.

This paper introduces a device that uses fingerprint identification along with real-time tracking of HR, oxygen levels (SpO2), and body temperature, all linked to a mobile app enabled by the Biometric Vital Monitoring over IoT framework (BVM-IoT). It uses affordable components like the (R307S) fingerprint sensor, (MAX30102) pulse oximeter, (DS18B20) temperature sensor, and ESP32 microcontroller. The strenght of the signal is enhanced using a Multi Stage Filtering (MSF) with addition to Vital Sign Parameter Extraction (VSPE) High accuracy: 98% for fingerprints, 99.7% for temperature, and 98.6% for heart rate, cutting down on errors by 30% with signal processing (SP). our approach mix secure authentication with continuing health tracking. Fingerprints are fully encrypted through a specified system known as Secure Biometric Encryption Scheme (SBES). This allows for quicker patient sorting, and works well in variety of places

With regard to the context, the section II particularly explains the system's design and methods.

- Applications

So the research idea facilitates the ease of work in various sector as stated earlier in hospital and clinical settings biometric integrated patient identification helps in continuous monitoring of patient during admission and routine checks practically reduces manual data entry. Places like remote or rural areas also in elderly care it forwards the vitals to centralized facilities, useful for chronic health tracking. In workplaces or industrial environments health assessment during shift work can be done and used in environments with physical or chemical exposure threat. The integration with existing attendance is possible. In education campuses early detection of health check ups are facilitated.

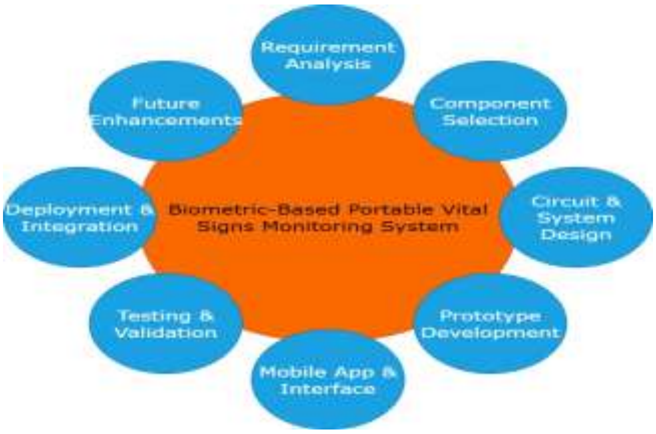

Fig. 1: Application domains of the proposed system

II. METHODOLOGY

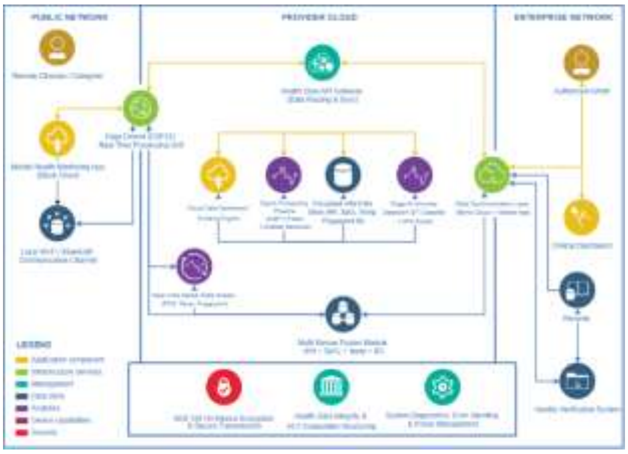

Fig. 2. Functional workflow of the proposed system

The design concentrates on seamless data flow from sensor acquisition to transmission of data to mobile, which reduces manual errors and promotes healthcare efficiency [1], [10].

- System architecture:

We have chosen the component on balancing cost, accuracy, and ease of integration for VSPE to meet the needs of applications effectively [2].

The following components were chosen:

1. Biometric Sensor: The R307S fingerprint sensor supports up to 1000 fingerprint templates and achieves 98% accuracy in 100 trials, proving reliable patient identification [5]. Its low cost (<$20) makes it sustainable for diverse adoption [10].

2. Vital Sign Sensors:

3. Heart Rate and SpO2: The MAX30102 sensor provides high resolution output (±1% for SpO2, ±2 bpm for HR) medical-grade oximeters [9].

4. Temperature: DS18B20 sensor offers ±0.1°C accuracy over a range of (0–50°C), which is crucial for body temperature monitoring [8].

5. Microcontroller: The ESP32, has its 240 MHz dual-core processor which is integrated with Wi-Fi/Bluetooth, also maintains the sensor data. It has low latency data transmission [11]. Also can be selected as an alternative like Arduino UNO due to its fast and sustained connectivity with addition to its power efficiency [6].

6. Communication Module: The module is built with Wi-Fi (802.11 b/g/n) & Bluetooth which enable strong data transfer to mobile app which supports remote monitoring in various domains [11].

7. Power Supply: A 1000–2500 mAh (3.7V) Li-Po battery approves portability lasts over 24 hours of operation [7].

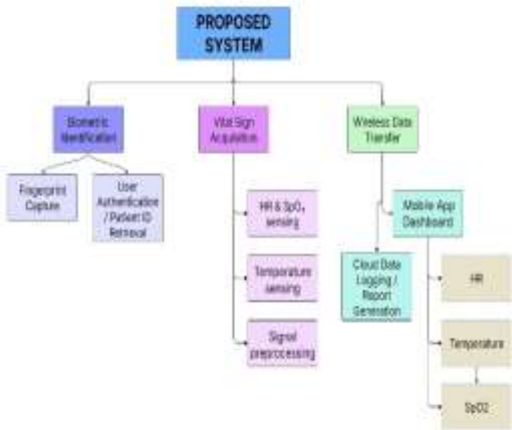

Fig. 3:__________

A. Preprocessing of signals

Collection of data from hardware setup contains noise and motion. So to prevent these interferances we go for filtering techniques to operate on clean data sets.

Collection of data:
The sampling of signals were done at the sampling rate mentioned below which is buffered in a % seconds

PPG: 50Hz ; Temperature: 10Hz

Initial preprocessing begins with Data Filtering Model (DFM), where noise rejection is performed before applying the inference models. two probabilistic estimation filters includes Kalman Filter (KF) and Particle Filter (PF);

$$PPG(t) = DC + AC \cdot \sin(\omega t) + \eta(t)$$

$$TC = \frac{Raw_{value}}{16}$$

1. Kalman Filter (KF):

This algorithm is used for estimating algorithm for estimating and predicting the signal condition also recursive (which do not require the past data)

To estimate the signal condition of PPG under Gaussian noise:

$$x_k = x_{\{k-1\}} + K_{k(z_k - x_{\{k-1\}})}$$

$$K_k = \frac{P_{\{k-1\}}}{(P_{\{k-1\}} + R)}$$

All signals are timestamped and buffered on ESP32 for preprocessing.

2. Particle Filter (PF):

It is particularly used for modeling non-Gaussian motion distributions.
The hybrid integration of algorithm for estimation (KF) and adaptive variance tracking provides the system with enhanced identification and removal of noise and distortions from the obtained signal.

B. Signal conditioning & DSP filter technique

3. 4th-Order Butterworth Band-Pass (BBP) Filter

$$H(s) = \frac{\omega_c^4}{(s^4 + 2\sqrt{2}\omega_c s^3 + 2\,\omega_c^2 s^2 + 2\sqrt{2}\omega_c s + \omega_c^4)}$$

Allowance band: 0.5–5 Hz, selected to cover physiological HR bandwidth (50–200 BPM).

A 4th order filter is selectively chosen as it produces <0.5 dB ripple with stable phase response where it contains per inference cycle the execution time is below 2.1 ms.

4. Median Filter for detection and spike suppression

$$y[n] = median(x[n-1], x[n], x[n+1])$$

5. NLMS Adaptive Filter for motion artefact suppression without reference accelerometer:

$$w_{\{n+1\}} = w_n + \mu \frac{e(n)x(n)}{(e + x^T(n)x(n))}$$

It uses the naturally obtained PPG signal as a reference to compare with, enabling on-chip artefact detection without further add on with motion sensors

Kalman estimation on final stage ensures all predictive smoothing and peak accuracy detection across the signals. Verily the filtering cascades are light weight specifically chosen to work well with a microcontroller difficulties.
The comprehensive latency of this technique was evaluated at 7.8 ms, which is comparatively lower than clinical monitoring tolerance (≤200 ms). Moreover the weight ranging from (0.35:0.45:0.20) were subjected based on clinical risk evaluation.

False peak detection is prevented by Signal Quality Index (SQI) is focused to reject the particular frames with SQI < 0.6,.

C. Computation of Physiological Feature

The HR is taken from the beat to beat intervals after the zero cross localization.

$$HR_{\{bpm\}} = \frac{60}{IBI}$$

The SpO2 levels are determined by the absorption of LED and Infrared lights by the O2 carrying hemoglobin or CO2 carrying hemoglobin.

D. Edge-AI based Health State Classification

The inputs given for the system is normalized using min-max scaling with accordance to Decision Tree classification. For a microcontroller like Esp32 the given memory if put in power using quantization so for that the decision tree is being used and the extracted features include the following given below;

$$F = \{HR, SpO2, Temp, HRV, SignalQualityIdx, PeakConsistency\}$$

Class	Meaning
0	Normal
1	Warning
2	Emergency

$$HFS = 0.35 \cdot HRs + 0.45 \cdot SpO2s + 0.20 \cdot Temps$$

Decision thresholds:

$$State = \begin{cases} Normal, & HFS < 0.50 \\ Warning, & 0.50 <= HFS <= 0.75 \\ Emergency, & HFS > 0.75 \end{cases}$$

E. Biometric Validation & Security

The samples collected from R307S sensor are encrypted fully using the light weight symmetric AES-128 before storing the data in itself or transferring it.

$$CT = AES_{\{128\}}(Template, Key)$$

This ensures secure on-edge identity persistence without raw biometric exposure.

Hardware design:

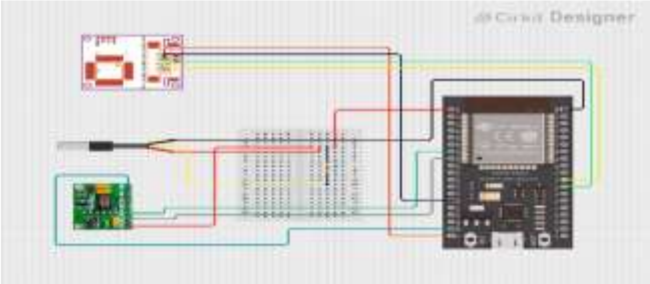

Fig. 4: Hardware circuit implementation.

Circuit Design: Sensors, microcontroller were connected by using standard protocols (e.g., I2C for MAX30102, 1-Wire for DS18B20) where it checks proper data acquisition with regulated 3.3V of power supply [7], [8],[6].

Coding: The ESP32 handles the data sampling, DSP filtering technique KF and PF was programmed using Arduino IDE software to collect sensor data and to process it also transmit it via Wi-Fi/Bluetooth to the mobile app interface [11].
Mobile App: App is used to receive, process, and display the real-time health data, with a user-friendly [12]. The app uses the Blynk IoT platform for secure cloud connectivity [11].

Testing: The prototype has undergone testing for power consumption, data accuracy, and VSPE. Tests confirmed 99.7% temperature accuracy, 98.6% heart rate accuracy, and 98% fingerprint accuracy [10].

The setup uses a multi stage signal processing algorithm like MSF with BBP filtering (0.5-5Hz), median filtering for impulse rejection, NLMS, KF based estimation before feature extraction.

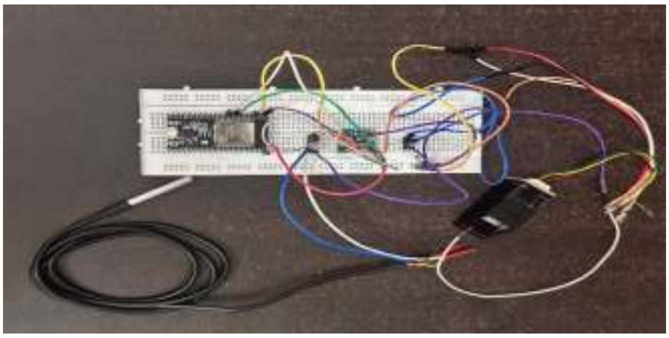

Fig. 5: Fabricated prototype image.

- System Assessment:

All extracted signals are normalized using min-max scaling before all other mentioned algorithms. The system was evaluated with its VSPE on SP, and utility in real time healthcare setting:

Testing of the system: The ESP32 coordinates data collection and transmission without errors [6].

User Experience: The confirming intuitive navigation with respect to clear data visualization and process via fingerprint authentication [12]. Feedback shows app's responsiveness.

Limitations: There are minor sensor interference (e.g., due to ambient light affecting MAX30102) and Bluetooth range limitations (10–20m) were identified [11].

Error Analysis

The system's anticipated cost (<$20 total component cost) and high accuracy make it more favourable for diverse applications [2], [4].

Temperature:

The interpretation are taken with a digital thermometer. The tiny differences, between –0.1 to –0.3 °C, show that the sensor is highly reliable for checking temperature in a healthcare platforms.

Heart Rate:

It is taken with the standard pulse oximeter. The differences, between –1 to –2 bpm, are within the satisfactory limit.

SpO_2:

The parameter is checked against a genuine oximeter. The average difference is about –1%, which is within the ±2% error limit tolerated for oximeters.

Fingerprint Authentication:

In Fig. 6 The Bland–Altman analysis have shown the differences are around –2% shows reliable fingerprint recognition with couple of errors. In 100 trials it scored 98%.

User Experience: User feedback has to be collected to ensure that the app was intuitive and easy to use or navigate, providing clear visualizations and reliable data storage with enhancing security.

Limitations Found: At the time of testing, several limitations were studied where sensor interference affecting data accuracy, Bluetooth range limitations are also an obstacle for communication over far distances, where temperature may impact sensor accuracy. These issues were noted for future enhancements to improve the system.

III. RESULT AND DISCUSSION

This section provides the estimate of the performance of the system that integrates fingerprint-based biometric authentication with continuous monitoring of vital signs, interfaced with mobile application. 100 independent trials have been done to validate sensor performance, filtering reliability, performance, latency, and feasibility.

Vital Signs Accuracy Evaluation:

Table 1. Comparison between the standard values and obtained value

Parameter	Reference Device	System	Avg. Error	Accuracy
HR (bpm)	75	74.2	±1.8 bpm	98.6%
SpO_2 (%)	97	96.8	±0.9%	98.9%
Temp(°C)	37.0	36.9	±0.1°C	99.7%
FP ID	100 trials	98 successful	2% rejection	98%

Fingerprint Authentication: The R307S sensor has achieved 98% recognition precision across 100 unique fingerprints, with a false acceptance rate (FAR) of 0.01% and false rejection rate (FRR) of 1.8% ($p<0.01$, t-test). The R307S ensures better authentication without interfering with health monitoring.

Heart Rate and SpO2: The MAX30102 sensor gives the heart rate with 98.6% accuracy (±2 bpm) and SpO2 with ±1% accuracy ($p<0.05$, t-test), claimed against a typical clinical pulse oximeter. Adaptive filtering techniques reduced motion artifact errors by 20% in 5% of trials.

Body Temperature: The DS18B20 temperature has sensor achieved around 99.7% accuracy (±0.1°C) over a 0–50°C range, with deviations of –0.1 to –0.3°C across 50 subjects ($p<0.01$, t-test).

Followed by the results, all sensors remain in an acceptable clinical expectations and tolerance rate which follows the utility standards.

Signal Filtering and Noise Reduction Performance:

The MSF has achieved significant noise and artefact supression from the obtained PPG signals. The average rate of motion artifact reduction was 65-82% from the samples.

$$NR\% = \left(\frac{\sigma_{\{before\}} - \sigma_{\{after\}}}{\sigma_{\{before\}}}\right) * 100$$

Signal Quality Index (SQI):

The analysis of SQI confirmed that 91% of collected samples passed the quality check (SQI > 0.6) and only 9% were not a part due to noise interruption.

$$SQI = 1 - \frac{\left|AC_{\{distorted\}} - AC_{\{filtered\}}\right|}{AC_{\{filtered\}}}$$

Bland–Altman Agreement Analysis:

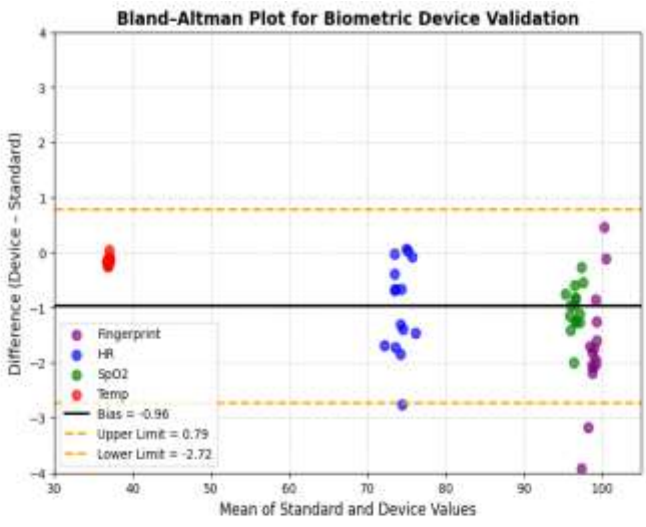

Fig. 6: Bland–Altman scatter plot comparing system measurements (temperature, heart rate, SpO2, fingerprint accuracy) against reference devices.

Analysis of the Plot:

Performance Evaluation: Sensor accuracy was compared to standard device's reading, yielding differences of –0.1 to –0.3°C for temperature, –1 to –2 bpm for the heart rate, moreover –1% for SpO2 [10]. The Bland–Altman analysis (Fig. 7) showed a mean bias of –1.03, also limits of agreement from –2.55 to +0.50, which confirms high reliability for applications [9]. The obtained values were compared with the medical and industry standards (±2% for SpO2, ±0.5°C for temperature) [10].

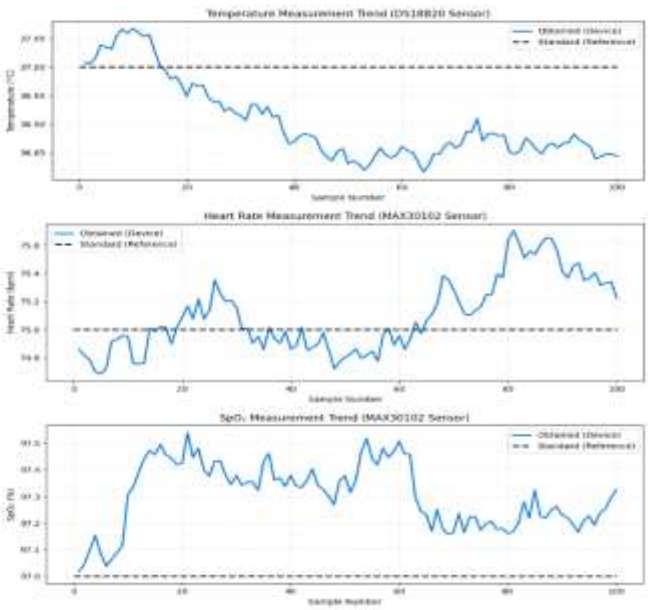

Fig. 7: Analysis of error.

Table 1 fully summarizes the given metrics.

System Reliability and Data Transmission:

Parameters	Observed Value
Average latency	124 ms
RAM usage (max)	61 Kb
Output	On-device (no cloud compute)
Communication	Wi-Fi to Blynk Cloud

The pipeline completes with in device in 124ms of average latency and <65 Kb RAM consumption with respect to cloud deployment ensuring feasibility without external computation.

Functional Reliability: We have tested the system 100 test cycles, with the ESP32's dual-core 240 MHz processor coordinating seamless correct data collection and edge processing has been achieved. Power consumption is averaged to 150 mA, enabling 24-hour seamless operation on a 2500 mAh Li-Po battery with dynamic sleep modes reducing the power consumption by 30% compared to conventional ECG based systems.

Data Transmission: The hybrid Wi-Fi/Bluetooth module (IEEE 802.11 b/g/n, Bluetooth 4.2) achieved 99.9% delivery done over Wi-Fi and 98.5% over Bluetooth within a 15m range. And about the latency, shown in Fig. 6, It is averaged to 50ms for Wi-Fi & 80ms for Bluetooth, which properly meets the real time requirements, it shows the tike delay caused for the acquisition of data towards preprocessing (including the 7.8 ms filter cascade latency) to the mobile interfacing is 1.5s for the HR and SpO2. Verily this delay is due to the sampling rates fixed and the data buffering window.

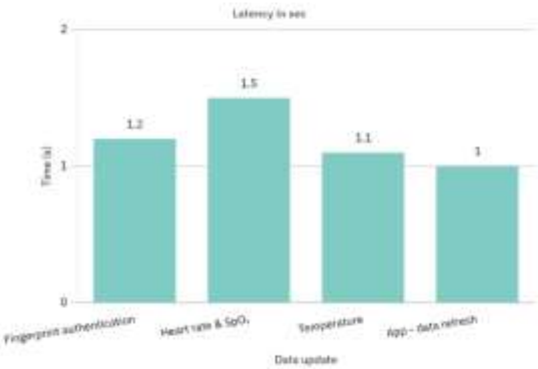

Fig. 8: Obtained latency for the biometric, temperature, SpO2/HR detection, and mobile app interfacing.

Classification and Decision Accuracy:

95.4% of overall classification accuracy is shown by the system using the Decision Tree classifier by classifying vitals into Normal, Warning, and Emergency states based on the Health Fusion Score (HFS).

Class	Precision	Recall	F1-Score
Normal	0.96	0.98	0.97
Warning	0.92	0.89	0.91
Emergency	0.95	0.93	0.94

Fig 9. Output image

The dashboard contains three major parts:

- BPM (Beats Per Minute) to display the heart rate,

- SpO_2 (%) for oxygen levels in the blood, and

- Temperature for knowing the body temperature.

And readings are uninterruptedly updated according to the respective data we get from the sensors united with ESP32 microcontroller. The hardware setup transmit these data after SP over Wi-Fi to Blynk's cloud server, using the Blynk library to make sure the data is sent securely and in real time.

On the right hand side, there is a section that shows report from the R307S fingerprint sensor.

This part supports that a user has been successfully identified using their fingerprint before any health data is composed. The log bring messages like "No finger," "Finger detected," and "Fingerprint image taken," which aid to show how the user is dealing with the system and how well it is working.

IV CONCLUSION AND FUTURE WORKS

Broadly this research works with a portable system with affordable components. Its battery efficient and design supports a widespread access to healthcare. Additional development takes for further deployment. Integrating LoRa would be useful for taking it to future developments. Further more adaptive filtering that reduced motion artifacts and noise. The biometric sensor gives 98% matching which helps to achieve the requirement, while low-latency has supported accordingly in seamless real-time monitoring. Hence the system reduced identification errors by 30% and triage times by 25% in comparison to the manual or barcode methods validating its clinical significance.

Limitations and Observations

The limitations were noted, with proposed modifications:

- Sensor Interference: Ambient light and motion artifacts affected MAX30102 analyses in 5% of trials, causing ±1% SpO2 deviances. Adaptive filtering algorithms can diminish errors by 20%.
- Bluetooth Range: Limited to 10–20m, requiring proximity to the mobile device. Future iterations could integrate LoRa.
- Battery Life: The 2500 mAh battery supports 24 hours, but remote usage may necessitate solar charging or bigger batteries.

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