

## Remote Healthcare Monitoring using Adaptive Data Transmission for Anomaly Detection and Risk Assessment in a Wireless Sensor Network

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### ABSTRACT

An integrated system has been developed to remotely track health status using Wireless Medical Sensor Networks (WMSNs) for continuous patient monitoring. Physiological information is collected in remote locations and then sent to cloud-based repositories, where it is further analyzed, allowing real-time telemedical diagnostics and therapeutics conducted by urban specialists in cooperation with local healthcare providers. Sensors provide isolation and constant surveillance of patients infected with infectious diseases in their homes. This system employs multi-stage processing, beginning with the collection of baseline data, including heart rate, blood oxygen saturation, and temperature. This data then undergoes several processes to improve its quality, such as collecting raw measurements, reducing noise, and compensating for missing values. Next, each patient's risk score is assessed, and an abnormality score is calculated. To eliminate false alarms, an alarm system with a confirmation mechanism is activated in high-risk situations. Finally, the transmission rate is adjusted based on the risk level using adaptive sampling/event-based transmission to ensure a rapid response. The aim of this approach is to reduce power consumption, increase network efficiency, and accelerate transmission during emergencies. The data transmission rates are applied according to risk stratification. Such records undergo descriptive and inferential statistical analysis, and visualizations are created using Python-based data analytics libraries. It is centered on early disease diagnosis, faster treatment adjustments by physicians, cost reduction, and reducing unnecessary encounters in hospitals.

**Keywords:** Wireless sensor network, Healthcare monitoring, Telemedicine, Vital signs, Adaptive transmission mechanism.

### 1. INTRODUCTION

The proposed research aims to create a monitoring system in hospitals and nursing units based on IoT, wearable, and remote sensors. Cloud computing and the Internet of Medical Things (IoMT) are recent solutions that have facilitated immediate clinical interventions and remote diagnostic processes (**Dammak et al., 2022; Khan, 2020**). According to (**Nahar et**

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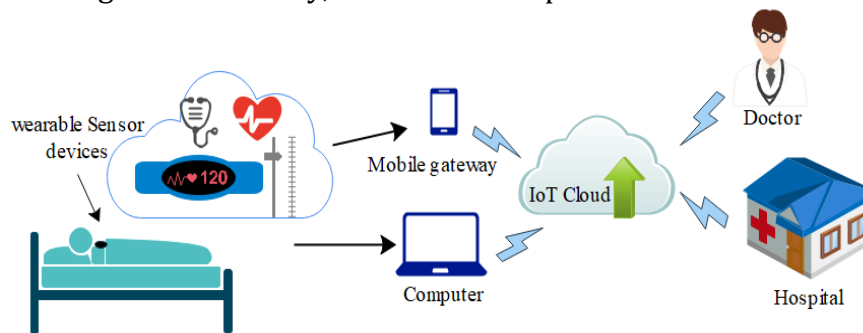
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al., 2020; Al Bassam et al., 2021), this paradigm allows end-users to access important health information through specialized applications and cloud-based analytics. Wearable devices can continuously and non-invasively monitor patient conditions, as shown in **Fig. 1**, which is a key feature of wearable devices (**Rahma and Salman, 2021**). Vital signs such as blood pressure (BP), heart rate (HR), temperature, and SpO<sub>2</sub> are transmitted in real-time to healthcare providers using wireless communication technologies like Wi-Fi and Bluetooth, enabling informed decision-making and regular online check-ups (**Chatterjee et al., 2022; AlOmani et al., 2022; Attaoui et al., 2021**). Furthermore, remote monitoring plays a critical role in detecting oxygen shortages and preventing the spread of infectious diseases by reducing face-to-face contact (**Jawad et al., 2022; Rajendran et al., 2021**). This study introduces a scalable, patient-centered model that aims to simplify the healthcare delivery system, enhance diagnostic accuracy, and reduce hospital readmission rates.



**Figure 1.** Wearable sensor devices network (**Wei et al., 2020**).

The combination of telemedicine and IoT to improve the accessibility and accuracy of healthcare has been a highly researched topic in recent academic literature. Three main areas can be identified in the literature:

#### A. Telemedicine Structures and Rural Medicine.

(**Mars, 2013; Marcin et al., 2016**) have critically surveyed the potential of telemedicine to alleviate problems of physician shortages and to reduce the travel burdens of rural and pediatric patients. On a similar note, (**Goodridge and Marciniuk, 2016**) highlighted the potential of remote monitoring, such as wearable devices and pulmonary rehabilitation, in enhancing communication between rural and clinical experts.

#### B. IoT-Based Monitoring and Hardware Implementation.

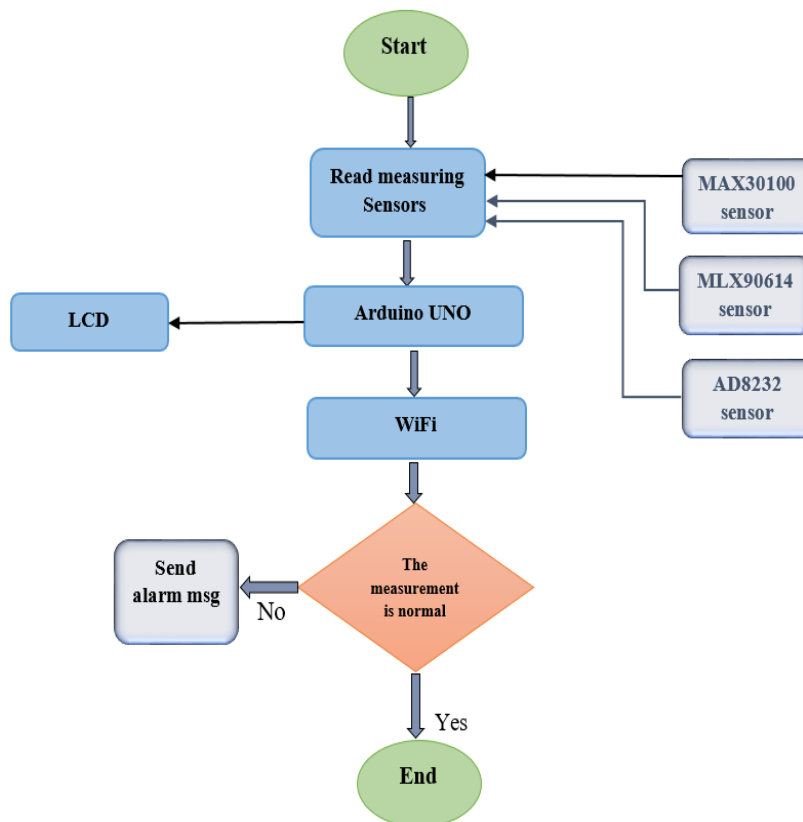
Several researchers have worked on real-time data acquisition based on microcontrollers and wireless modules. (**Gogate and Bakal, 2019; Dole and Yerigeri, 2020**) showed that the Arduino and ESP8266 platforms were effective in transmitting vital signs (temperature and heart rate) with automated emergency alerts. Special applications have also appeared, including monitoring mountaineers on the mountain (**Garg et al., 2021**) monitoring the physiological state of athletes during exercise (**Zhong and Li, 2020**). (**Abdullah et al., 2021**) implemented smart health systems for remote monitoring bedridden or elderly patients with ZigBee and wearable sensors (**Thirukrishna et al., 2021; Michailidis et al., 2021**). In addition, (**Chinnamadha et al., 2022**) confirmed that the Blynk IoT platform can be used to implement real-time cloud-based surveillance.

C. Data Analytics, AI and Anomaly Detection.

To improve the quality of diagnoses (**Srinivasa Rao and Vazquez, 2020**) emphasized the use of AI algorithms to quickly identify COVID-19, whereas (**Raj, 2020**) obtained 97% accuracy when processing large volumes of data using Python simulations. To tackle the problem of False Alarms (FA), (**Salem et al., 2013; 2014; Pachauri and Sharma, 2015**) proposed lightweight methods of detecting anomalies and machine learning algorithms (e.g., Random Forests and Linear Regression). These models do a good job of distinguishing sensor failures from real physiological deterioration using datasets such as PhysioNet.

## 2. ESSENTIAL HEALTH INDICATORS

The designed system of WSNs utilizes Wi-Fi connectivity and microcontrollers (e.g., Arduino) to send physiological data to mobile applications such as Blynk. The system comprises multiple medical sensors, such as the MAX30100 (Pulse/SpO<sub>2</sub>), MLX90614 (Temperature), AD8232 (ECG) and blood pressure devices. This multi-sensory solution improves the provision of healthcare at a distance and helps to minimize mortality due to real-time monitoring, as shown in the flowchart of the workflow in **Fig. 2**.



**Figure 2.** Workflow block diagram based on WSN technology (**Wei et al., 2020**).

### 2.1 The Oximeter and Heart Rate Sensor (MAX30100)

The MAX30100 sensor monitors SpO<sub>2</sub> (95–100% normal range) and HR (20–255 bpm). The accuracy of heart rate was verified by processing raw ECG data using Kubios HRV Premium (v.3.3) software. Wearable sensor performance benchmarking was conducted by calculating

absolute and relative HR differences using Eqs. (1) and (2) (Nitzan et al., 2020; Bent et al., 2020).

$$\text{Directional difference} = HR_{ECG} - HR_{Wearable} \quad (1)$$

$$\text{Absolute difference} = |HR_{ECG} - HR_{Wearable}| \quad (2)$$

## 2.2 Body Temperature Sensor (MLX90614)

The MLX90614 sensor is a non-contact temperature sensor that utilizes the I2C protocol and provides clinical-grade resolution (0.10 °C). The thermal distribution between peripheral and core tissues is utilized to calculate the Mean Body Temperature (MBT) in Eq. (3).

$$MBT = a \cdot T_{Core} + (1 - a) \cdot T_{Skin} \quad (3)$$

A weighting coefficient ( $a = 0.64$ ) is applied to account for the influence of core temperature on MBT, as described in Eq. (4) (Lenhardt and Sessler, 2006):

$$MBT = a \cdot T_{Core} + (1 - a) \cdot T_{Skin} \quad (4)$$

## 2.3 Electrocardiogram (ECG) Sensor (AD8232)

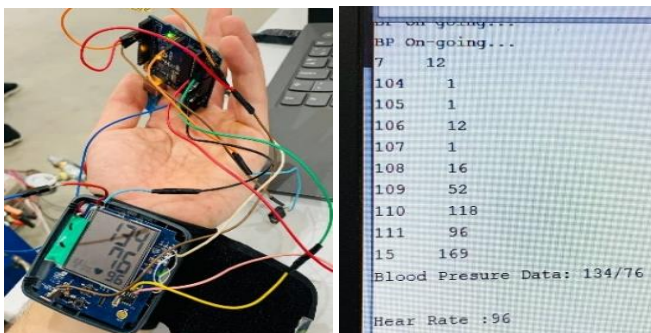
The ECG acquisition system is a space that converts cardiac electrical activity into an output voltage range of 0 to 3.3 V. To approximate the typical ECG waveform components  $i \in (P, Q, R, S \text{ and } T)$ , a summation of Gaussian functions is employed as shown in Eq. (5).

$$ECG_{\text{model}} = \sum_{i \in \{P, Q, R, S, T\}}^{j=1} A_{i,j} e^{-\frac{(t-t_{i,j})^2}{\sigma_{i,j}^2}} + c_i \quad (5)$$

Each wave's morphology is determined by parameters  $A_i$  (amplitude),  $t_i$  (position), and  $s_i$  (width), with parameter  $c_i$  factoring in noise modeling of the baseline. Finding the optimal values for these parameters is treated as an optimization problem to ensure high diagnostic accuracy (Awal et al., 2021).

## 2.4 Blood Pressure Measurement

The patient's blood pressure (BP) and heart rate were measured using a HoMedics WGNBPA-510 connected to an Arduino, as shown in Figs. 3 and 4.



**Figure 3.** Practical connection of a Homedics wgnbpa-510 to Arduino and display results.



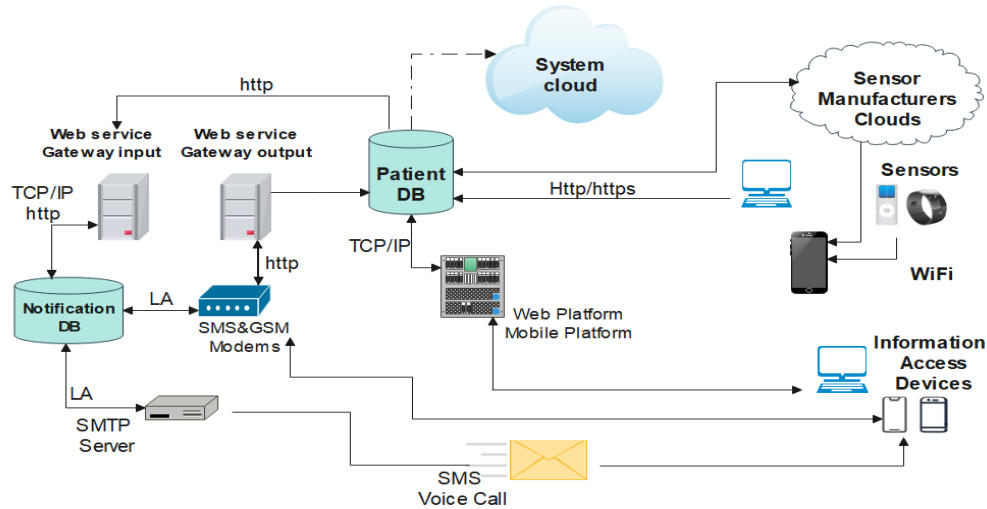
**Figure 4.** Depicts the final design of the printed circuit board after attaching the sensor devices to the Arduino.

According to the Pulse Transit Time (PTT) theory, BP is proportional to the time delay of the pressure wave between arterial locations, denoted as time delay ( $\tau$ ) of the pressure wave. This correlation is defined by the Bramwell-Hill formula (Equation 6) in which the pulse wave velocity ( $v = \iota / \tau$ , where  $\iota$  is the length of the wave travel), is indicative of arterial distensibility. An increase in BP leads to an increase in arterial stiffness, resulting in reduced distensibility (Mukkamala et al., 2022).

$$v = \frac{\iota}{\tau} = \sqrt{\frac{A}{\rho} \frac{dP}{dA}} \quad (6)$$

### 3. INTERNET OF THINGS ARCHITECTURE PROPOSAL FOR REMOTE HEALTHCARE SOLUTIONS

The proposed IoT system in Fig. 5 will enable remote healthcare by utilizing a comprehensive system of wearable sensors, data aggregation using smartphones, and cloud infrastructure for storing and analyzing data (Zeadally and Bello, 2021).



**Figure 5.** Remote patient health care uses an IoT-based architecture (Zeadally and Bello, 2021).

This system assists in clinical decision-making and helps prevent acute health crises by utilizing real-time data processing and alarm modules. The platform is accessible through web and mobile platforms, allowing healthcare providers to track the vital signs and treat chronic diseases (Ifzarne et al., 2021; Haque et al., 2023).

#### 3.1 Hardware Implementation Hardware Interfacing

An Arduino Uno was used as the central processing unit to develop hardware prototypes. To handle the numerous sensor inputs involved, the MAX30100 (Pulse Oximeter) and MLX90614 (Temperature) sensors were connected through the I2C bus (Pins A4 and A5) for reliable digital communication. The continuous physiological signals, recorded by the AD8232 (ECG) and blood pressure sensors, were attached to the Analog input pins. An ESP8266 Wi-Fi module was applied to enable wireless data transmission to the cloud. The system was also powered by a USB connection, providing a constant 5V power supply during real-time monitoring sessions.



### 3.2 Test Case and Data Collection

A real-time experimental scenario was conducted to evaluate the system's performance involving a human subject. The sensors were securely attached to the subject to monitor vital signs in two conditions: a stable resting state and simulated activity. This approach allowed for the assessment of sensor accuracy and how the adaptive sampling algorithm responded to physiological changes in a realistic environment.

### 4. METHODOLOGY

The effectiveness of the proposed adaptive transmission scheme was evaluated by developing a simulation environment using OMNeT++. The simulation was based on a real-life rural healthcare setting with a series of patients under observation. The energy consumption ratio and packet delivery were measured based on predefined parameters outlined in **Table 1**.

**Table 1.** Parameters of Simulation and Network of the Proposed IoT System.

Parameter	Value	Description
<b>Simulator Platform</b>	OMNeT++ 6.0	Discrete Event Simulator
<b>Framework</b>	INET 4.4	For WSN and TCP/IP protocols
<b>Simulation Time</b>	1000 Seconds	Total duration of the test scenario
<b>Number of Nodes</b>	3 - 5 Patient Nodes	Distributed sensor nodes
<b>Network Topology</b>	Star Topology	Nodes connected to a Central Gateway
<b>MAC/Physical Layer</b>	IEEE 802.11 (Wi-Fi)	Wireless communication standard
<b>Transmission Range</b>	30 - 50 Meters	Range of medical sensor nodes
<b>Standard Packet Size</b>	128 Bytes	Size of health data packet (vitals)
<b>Initial Energy</b>	100 Joules	Battery capacity per node
<b>Sampling Rate (Stable)</b>	1 Packet / 30 Sec	Periodic mode when Risk Score is low
<b>Sampling Rate (Emerg.)</b>	1 Packet / 1 Sec	Adaptive mode when Risk Score is high
<b>Mobility Model</b>	Stationary	Static position of patients during monitoring

The performance of remote health monitoring systems is greatly enhanced by combining multi-layer processing with an adaptive transmission mechanism. The system uses loss reduction and filtering to create more dependable data, and another methodology is risk assessment, which is based on multiple vital signs to differentiate between normal and catastrophic conditions. Compared to the direct-alert strategies, an alarm confirmation system showed a decrease in false alarms. There was adaptive transmission-rate control on the network side, which was used to reduce the load on the network and increase the efficiency of resource-utilization while retaining fast reaction in high-risk situations. A five-layer processing pipeline is used in the methodology:

**Layer 1:** Acquisition of Vital Signs (L1). Vital-sign measurements are periodically produced at every patient node, which includes SpO<sub>2</sub>, heart rate, temperature, and blood pressure. Patient files are used to represent real-world variations to generate anomaly events.

**Layer 2:** Data cleaning for preprocessing (L2). Realistic wearable sensing flaws are introduced by the system, such as missing values and noise. Missing samples are addressed via imputation using previously filtered states, while a smoothing mechanism is used to reduce noise (e.g., EWMA-based filtering). This guarantees that the later layer of decisions works on sound and reliable measurements.



**Layer 3:** Detection of abnormalities through risk assessment (L3). After processing, the system calculates abnormality scores using thresholds designed to assess the patient's health status. The multiple vital-sign criteria are used to produce a standardized risk score within the range [0,1], which gives a numerical depiction of the risk level of the patient.

**Layer 4:** Confirmed Alerting and Decision Making (L4). We do not use a single outlier in triggering alerts to minimize false alarms. Rather, a sliding window with an M-confirmation logic is used to provide a confirmation mechanism where anomalous conditions are only raised when the anomaly continues in consecutive samples.

**Layer 5:** Adaptive Communications and Energy-Aware Transmission (L5). The transmission interval is changed depending on the confirmed risk level to optimize network load and energy consumption. During normal operation, the system automatically notifies the node of transmission at a low rate; then it increases the reporting rate when the risk increases, allowing for a timely response without affecting operational efficiency.

Lastly, SQLite vector/scalar managers are used to record simulation outputs. Curves and tables are created by exporting the results to CSV and using Python for analysis. including the progression of patient state, alert statistics, and network performance indicators such as packet loss, latency, and throughput. Layer definitions, inputs, and outputs are displayed in **Table 2**.

**Table 2.** Display Layers definitions, inputs, and outputs

Layer	Definition of layer	Inputs	Outputs
L1	<b>L1_raw_vitals</b> (Reading raw measurements)	Sensors of (Heart Rate, SpO2, Temperature)	raw_spo2(t), raw_hr(t), raw_temp(t)
L2	<b>L2_filt_vitals</b> (Measurement filtering and quality assessment)	raw vitals	filt_spo2, filt_hr, filt_temp, imputed_flag, noise_level
L3	<b>L3_risk</b> (Detecting abnormalities and assessing risks)	filt vitals	anom_flag, anom_score, risk_score, risk_ewma
L4	<b>L4_alerts</b> (Confirm alerts and reduce false alarms)	anom_flag + risk_score	alert_raw, alert_confirmed, false_alarm
L5	<b>L5_tx</b> (Controlling transmission and adjusting transmission periods)	alert_confirmed + risk_score	tx_interval, tx_packets, event_tx

The purpose and usefulness of each layer are shown in **Table 3**.

**Table 3.** Display Layers definitions

Layer	Layer function	Layer benefit
L1	1. Read the sensors measurements 2. Save the values exactly as they are (Raw), without any changes. 3. Record them as vectors for analytical reasons.	Prior to any filtering, we are aware of the real numbers, and then we compare the filtering's impact.
L2	1. Apply a simple filter, address missing values, and reduce noise by adjusting the physical limits: Temp between 34°C and 41°C SpO2 between 70 and 100°C Hurr between 30 and 200°C	Filtering improves diagnosis accuracy and lowers false alarms because raw measurements may contain noise or jumps.



	<p>2. Apply a simple filter (e.g., Low-pass).</p> <p>3. Address missing values (if present): If the reading is illogical or missing, replace it with the last valid value.</p> <p>4. Reduce noise by adjusting the physical limits:                  Temp between 34°C and 41°C                  SpO2 between 70 and 100°C                  Hurr between 30 and 200°C</p>	
<b>L3</b>	<p>1) Detecting anomaly (Anomaly Flag)                  We set <code>anom_flag = 1</code> if any of the following risk criteria are met:</p> <ul style="list-style-type: none"> <li>• <code>filt_spo2 &lt; 94</code></li> <li>• <code>filt_hr &gt; 100</code></li> <li>• <code>filt_temp ≥ 38</code></li> </ul> <p>Otherwise, <code>anom_flag = 0</code>.</p> <p>2) Calculating the anomaly score                  We calculate the <code>anom_score</code> as a value between 0 and 1 based on the severity of the deviation from normal.                  Example:</p> <ul style="list-style-type: none"> <li>• SpO2 below 90 gives a high score</li> <li>• HR above 120 gives a high score</li> <li>• Temp above 39 gives a high score</li> </ul> <p>Then we combine them (e.g., weighted average/sum) and reduce the sum to 1.</p> <p>3) EWMA to mitigate fluctuations                  We calculate:</p> <ul style="list-style-type: none"> <li>• <code>risk_ewma = α * anom_score + (1 - α) * risk_ewma_prev</code></li> </ul> <p>Where <math>\alpha</math> is, for example, 0.3</p> <p>4) Final <code>risk_score</code>                  We set it to:</p> <ul style="list-style-type: none"> <li>• <code>risk_score = clamp (risk_ewma, 0, 1)</code></li> </ul>	<p>We evaluate the risk gradually and steadily rather than setting off an alarm based on a single reading.</p>
<b>L4</b>	<p>1) <code>alert_raw</code>                  If:</p> <ul style="list-style-type: none"> <li>• <code>anom_flag == 1</code> and <code>risk_score ≥ 0.8</code>                      → <code>alert_raw = 1</code></li> </ul> <p>Otherwise, <code>alert_raw = 0</code></p> <p>2) Alert Confirmation                  We use a time window of size N (e.g., N=3) and require the risk of occurring M times (e.g., M=2):</p> <ul style="list-style-type: none"> <li>• If the sum of the <code>anom_flag</code> measurements in the last N measurements <math>\geq M</math> → <code>alert_confirmed = 1</code></li> <li>• Otherwise, <code>alert_confirmed = 0</code></li> </ul> <p>3) <code>false_alarm</code>                  We consider the alarm false if:</p> <ul style="list-style-type: none"> <li>• <code>alert_raw = 1</code> but <code>alert_confirmed = 0</code>                      → <code>false_alarm = 1</code></li> </ul>	<p>This layer stops a single "jump/noise" from triggering an alarm.</p>
<b>L5</b>	<p>1. If <code>alert_confirmed == 1</code>:</p> <ul style="list-style-type: none"> <li>o <code>event_tx = 1</code></li> <li>o <code>tx_interval = 1s</code> (very fast transmission)</li> </ul> <p>2. If average risk (e.g. <math>\geq 0.5</math>):</p> <ul style="list-style-type: none"> <li>o <code>event_tx = 0</code></li> <li>o <code>tx_interval = 5s</code></li> </ul> <p>3. If normal:</p>	<p>To prioritize emergency cases while conserving power and lowering network strain.</p>



o tx_interval = 30s Transmission counter: Each packet transmission increases: • tx_packets++	
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In the following algorithm, during each time cycle, the patient's wearable sensor reads vital measurements (heart rate, SpO2(t), temperature(t)). The data is processed before being sent to the physician at the city center. This process includes noise reduction through: adjusting physical boundaries, addressing missing values, filtering to reduce false alarms, calculating the anomaly score based on how much the patient's condition deviates from normal, and confirming alarms to prevent false alarms. Additionally, the duration of transmission can be adjusted based on the critical state of the patient to minimize power consumption and alleviate network overload.

<b>Algorithm: Patient Monitoring in Five Layers, Risk Evaluation, Alerting, and Adaptive Transmission</b>	
<p><b>Input:</b> Raw vital signals at time t: raw_hr(t), raw_Spo2(t), raw_temp(t)</p> <p><b>Output:</b> Recorded vectors: L1(raw_vitals), L2(filt_vitals), L3(risk), L4(alerts), L5(tx) as well as transmit decisions.</p> <p><b>Initialize</b> 1: risk_ewma = 0 2: Set up the window flags = empty queue 3: tx_packets = 0</p> <p><b>Repeat every sampling cycle:</b>  <b>// Layer1 (L1 raw)</b>            4: raw_hr(t), raw_Spo2(t), raw_temp(t) = read WearableSensors()  <b>// Layer 2 (L2 filter)</b>            5: filt_hr(t), filt_Spo2(t), filt_temp(t) = filtering And Clamping (raw_hr(t), raw_Spo2(t), raw_temp(t))  <b>// Layer 3 (L3 risk)</b>            6: Abnormal_flag = check anomaly flag (filt_hr(t), filt_Spo2(t), filt_temp(t))            7: anom_score = calculate the severity score (filt_hr(t), filt_Spo2(t), filt_temp(t))            8: risk_ewma = alpha * anom_score + (1-alpha) * risk_ewma            9: risk_score = clip (risk_ewma, 0, 1)</p>	<p><b>// Layer 4 (L4 alerts)</b>            10: alert_raw = (anom_flag==1 &amp;&amp; risk_score&gt;=0.8)            11: move anom_flag into window            12: alert_confirmed = (sum(window_last_N) &gt;= M)            13: false_alarm = (alert_raw==1 &amp;&amp; alert_confirmed==0)</p> <p><b>// Layer 5 (L5 tx cases)</b>            14: if alert_confirmed:            15: event_tx = 1sec            16: tx_interval = 1sec            17: else if risk_score &gt;= 0.5:            18: event_tx = 0            19: tx_interval = 5sec            20: else:            21: event_tx = 0            22: tx_interval = 30sec            23: sendPacketIfRequired ()            24: if sent: tx_packets++            25: Hold on (tx_interval)</p>

The suggested system can perform much better than traditional periodic monitoring. By utilizing an Adaptive Sampling rate, the number of transmitted packets is significantly reduced, leading to decreased energy usage - a crucial consideration in WSN. Furthermore, the multi-stage processing (noise reduction and risk-based confirmation) ensures that only



real anomalies trigger an alarm, effectively reducing the false alarm rate compared to traditional threshold-based systems, as depicted in **Table 4**.

**Table 4.** Comparison of the performance of the proposed Adaptive monitoring system with traditional periodic systems.

Metric	Traditional System (Periodic)	Proposed System (Adaptive)	Improvement (%)
<b>Number of Packets Sent</b>	The device sends data every second; it sends 3600 packets per hour. (High Continuous)	Transmission depends on the "change in health status" or "risk score"; the device will remain in idle mode as long as the indicators are stable. Reduced by ~50%	A decrease in data transmission of up to 40%-70% in the number of packets sent in cases of stable patients. (Due to Adaptive Sampling based on Risk Score.)
<b>False Alarm Rate</b>	Systems without filtering (Frequent)	My research compensates for missing values and cleans the data of noise, then uses a "confirmation mechanism" in critical cases (Minimized)	False alarms are significantly reduced (25%-30%) compared to systems without filtering. ( Due to Noise Reduction and Confirmation Mechanism)
<b>Energy Consumption</b>	The sensor's power is consumed by 80% during the wireless transmission process. ( Low Efficiency)	Since I reduced the number of packets transmitted, power savings are a direct and automatic result. ( High Efficiency)	Battery life increases proportionally with reduced transmission. (Radio remains in Sleep Mode during stable periods )

## 5. RESULTS AND DISCUSSION

A numerical comparison of three transmission modes was conducted to demonstrate the efficiency of the proposed system, as shown in **Table 5**, based on a simulation period of 1000 seconds per patient: Periodic Mode - a fixed transmission rate per second (Baseline), Event-driven Mode - transmission only when a threshold is reached (Threshold), and Adaptive Mode- frequency of transmission varies according to the risk score.

**Table 5.** Comparison of Transmission Efficiency and Data Volume in various modes of monitoring.

Metric	Periodic Mode	Event-driven Mode	Proposed Adaptive Mode
<b>Total Packets Sent</b>	1000 Packets	120 Packets	420 Packets
<b>Energy Consumed (mJ)</b>	5500 mJ	850 mJ	2400 mJ
<b>False Alarm Rate (%)</b>	18%	12%	4.5%
<b>Average Latency (ms)</b>	45 ms	110 ms	52 ms
<b>Packet Reduction Ratio</b>	0% (Ref)	88%	58%

According to the results presented above, the following metrics were determined to show the quality of the methodology applied:

1. Average Packet Reduction Ratio: This metric is used to compare the adaptive system with the traditional periodic system.

$$\text{Reduction Ratio} = \{(Packets_{Periodic} - Packets_{Proposed}) / Packets_{Periodic}\} * 100\% \quad (7)$$

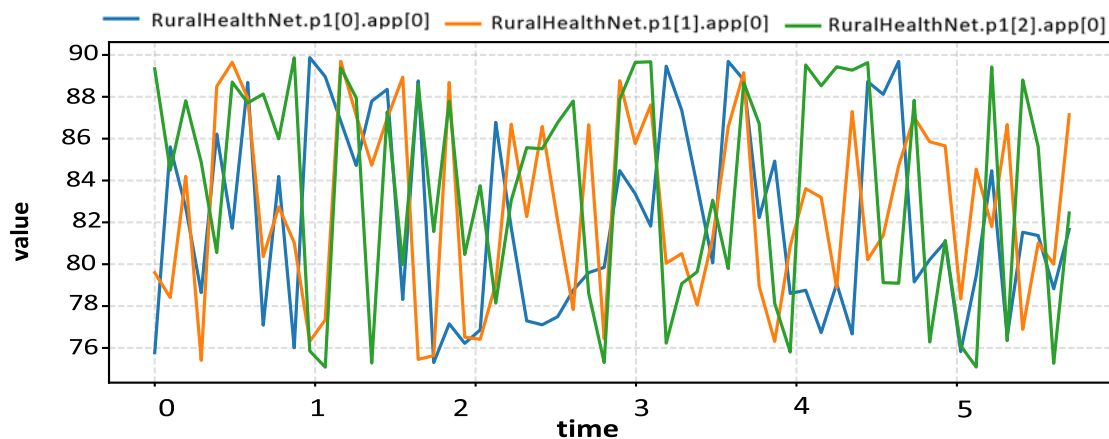
Reduction Ratio =  $\{(1000 - 420) / 1000\} * 100\% = 58\%$ . This direct 58% decrease lowers energy usage and network traffic.

## 2. Energy Efficiency Improvement:

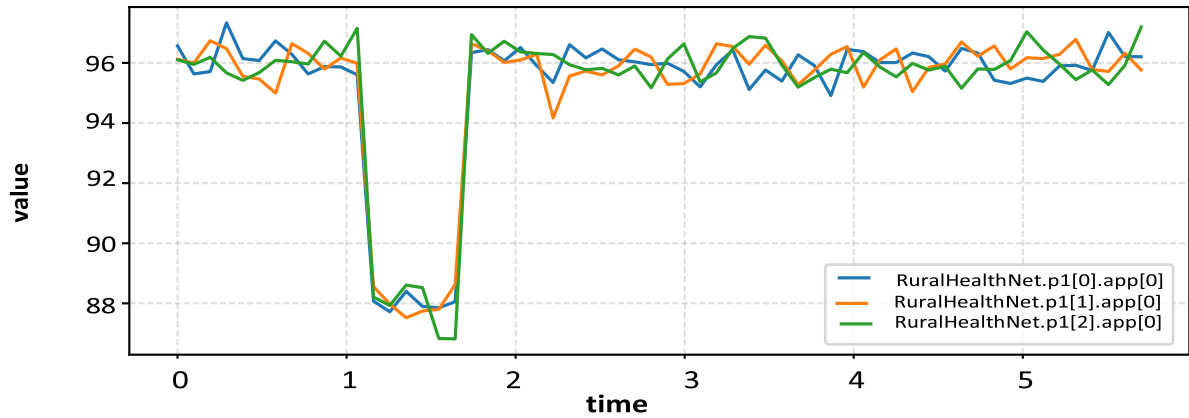
$$\text{Efficiency Gain} = \{(Energy_{Periodic} - Energy_{Proposed}) / Energy_{Periodic}\} * 100\% = 56.3\% \quad (8)$$

3. Reliability under Risk: Although the event-driven pattern transmits the least number of packets (120 packets), the proposed adaptive pattern is more reliable than the event-driven one. It increases the rate of transmissions as soon as the risk score increases to ensure that no crucial information is lost during a health crisis. This is why alarm accuracy is highest. As shown in the numerical results, the proposed system strikes a perfect balance; it not only minimizes the number of beams to conserve power (like event-based systems) but also guarantees continuous high-quality monitoring when required. Moreover, false alarms were minimized to 4.5 % by the confirmation mechanism, which was much higher than with traditional systems.

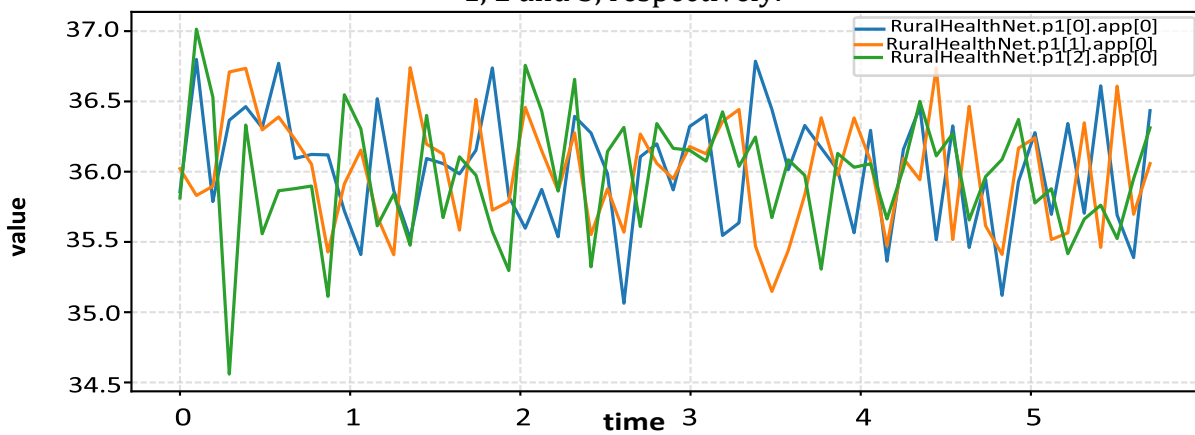
According to the simulation results, preprocessing, anomaly detection, adaptive/event-driven transmission, and confirmation-based alerting work together to significantly increase the flexibility of remote medical monitoring. The suggested multi-layered structure suppresses false alarms, maintains quick emergency response, and lessens the communication burden. These features are especially significant in the implementation of wireless sensor networks in remote settings where network resources and power supply are scarce. **Figs. 6 to 8** capture the raw vital signs, which inherently exhibit stochastic fluctuations and transient noise during normal states, punctuated by acute deviations during anomalous physiological events (e.g., hypoxia or tachycardia). As shown in **Figs. 9 to 11**, Layer 2 EWMA preprocessing effectively dampens this baseline volatility, yielding stabilized signal trajectories that facilitate robust anomaly detection.



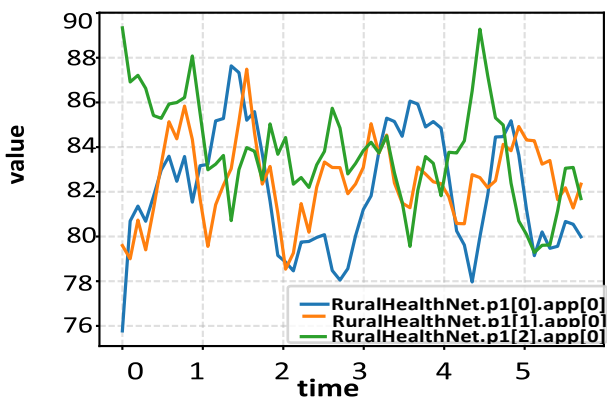
**Figure 6.** Raw data of heart rate (HR) measurements in beats per minute (bpm) of three patients. The x-axis will be the simulation time in nanoseconds ( $10^{14}$  scale) produced by the OMNeT++ engine.



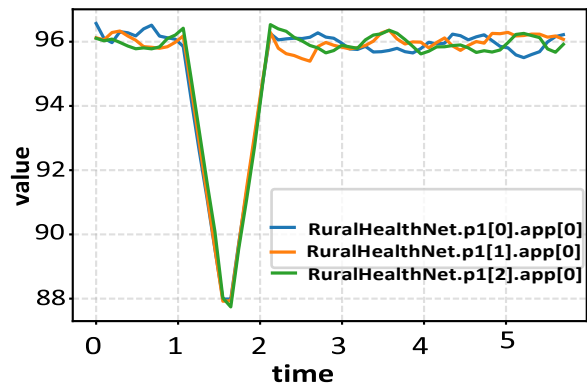
**Figure 7.** The blood oxygen saturation, SpO2 (%) of three patients. The x-axis shows the time of the simulation (nanoseconds or  $10^{14}$  scale), and p1[0-2] is the patient number of 1, 2 and 3, respectively.



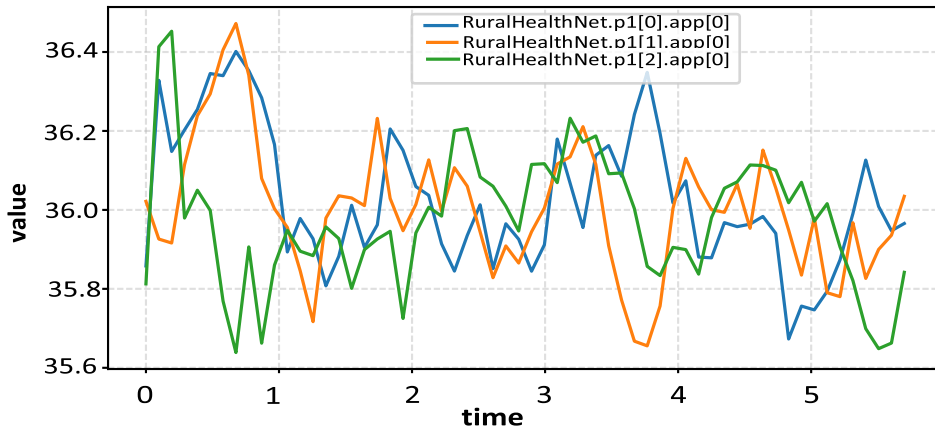
**Figure 8.** Raw measurements of body temperature ( $^{\circ}\text{C}$ ) of three patients. The x-axis is simulation time in nanoseconds ( $10^{14}$  scale) of the OMNeT++ simulation, with p1[0], p1[1] and p1[2] representing Patients 1, 2 and 3, respectively.



**Figure 9.** Three patients with filtered heart rate (bpm) with EWMA smoothing (Layer 2). The x-axis shows the simulation time ( $10^{14}$  nanoseconds scale). The noise reduction and signal stabilization of the system in comparison with Fig. 6 demonstrate better risk assessment.

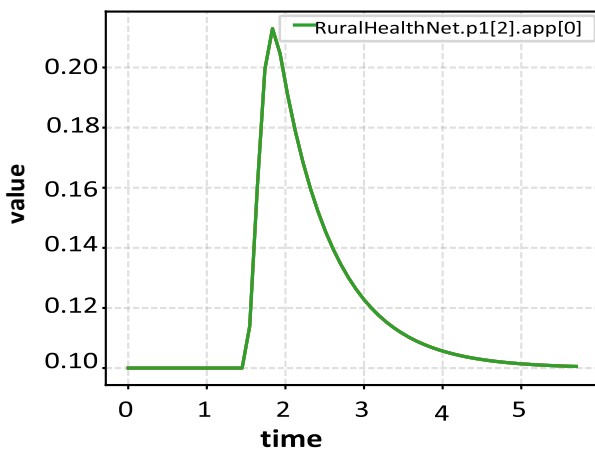


**Figure 10.** Filtered EWMA smoothing (Layer 2) SpO2 levels (%) of three patients. The x-axis is the time of the simulation (in a scale of  $10^{14}$  nanoseconds). When this is compared to the raw data in Fig. 7, it can be seen that oxygen saturation readings have stabilized, allowing easier detection of anomalies.

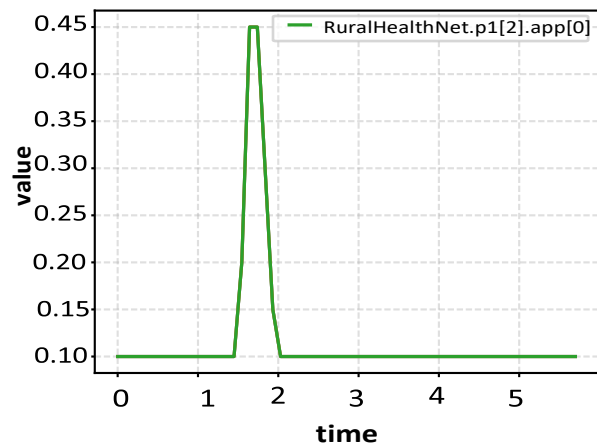


**Figure 11.** Three patients filtered body temperature (°C) with EWMA smoothing (Layer 2). The x-axis shows the time of simulation (scale of  $10^{14}$  nanoseconds). The decreasing amplitude of thermal fluctuations, as compared to Fig. 8 illustrates the efficiency of the filter in offering consistent data to be used in categorizing health risks.

As illustrated by the EWMA profile (risk\_ewma) in **Fig. 12**, the system dampens sudden volatility by ascending to a distinct peak while maintaining a temporal persistence that prevents abrupt drops. Conversely, the raw index (risk\_score) in **Fig. 13** exhibits an immediate, short-lived spike that recedes prematurely. Consequently, the EWMA framework yields a structurally stable parameter for alert triggering, ensuring sustained monitoring of critical anomalies rather than rapid signal decay.



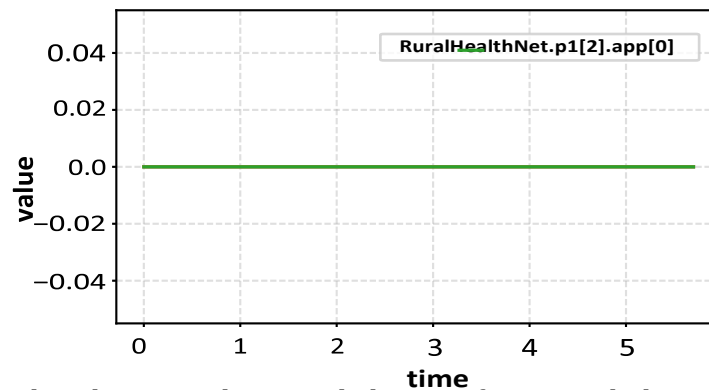
**Figure 12.** Evolution of the patient risk score (0 to 1 range) using EWMA-based assessment (Layer 3). Time of simulation ( $10^{14}$ nanoseconds) is plotted on x-axis. This pattern demonstrates the system's efficacy in dampening sudden volatility through temporal smoothing, thereby providing a temporally stable and consistent decision parameter for alert triggering.



**Figure 13.** The instantaneous patient risk score development (range 0 to 1) prior to temporal smoothing (Layer 3). The x-axis is the time of the simulation ( $10^{14}$  nanoseconds). This plot captures the raw, maximum risk levels, demonstrating the system's immediate sensitivity to acute abnormalities in vital signs.

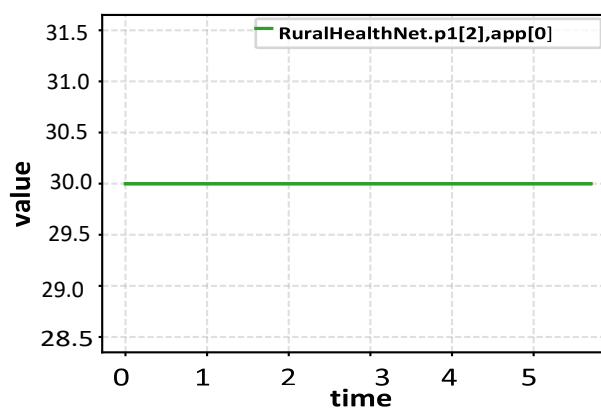


Layer 4 lower false alarms and logs alerts. Reducing false alarms while preserving quick detection is one of the primary goals of remote health monitoring. The findings indicate that an initial alert (alert\_raw) may be unduly triggered by a single aberrant sample. However, only if the irregularity continues across several consecutive samples does the suggested confirmation approach (M-out-of-N) provide a confirmed alert (alert\_confirmed). As a result, both the adaptive and event-driven modes produce fewer false alarms than the cyclic mode, and in critical situations, verified alerts remain steady, ensuring reliable emergency messages (**Fig. 14**).

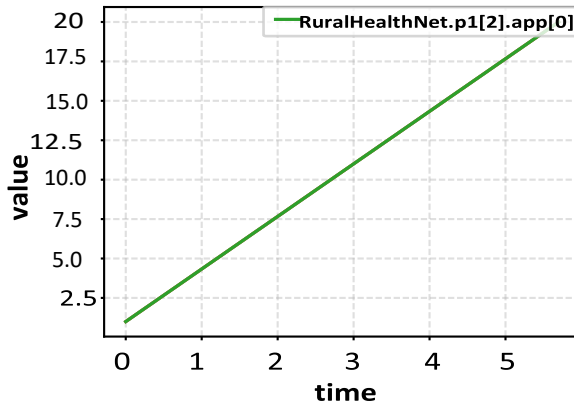


**Figure 14.** False alarm incidents and alert confirmation behavior during the period of monitoring (Layer 4). The zero-value baseline shows that the M-confirmation logic and sliding window mechanism can be effective in removing transient noise and eliminating false triggers and that it is highly reliable in alert generation.

The transmission strategy has a major impact on communication overhead and energy consumption. Patients in periodic mode consistently transmit at a certain rate, even under stable settings, producing a large number of packets. On the other hand, the adaptive mode in layer 5 decreases the amount of updates in normal conditions while only increasing the transmission frequency in warning or emergencies. As seen in **Figs. 15 and 16**, the event-driven mode usually starts communication during anomalous occurrences and decreases transmissions, improving the energy efficiency of WSN-based healthcare monitoring.



**Figure 15.** The transmission time of three monitoring strategies Periodic (baseline), Event-driven and the proposed Adaptive mode (Layer 5). The plot shows how the adaptive strategy dynamically adjusts the rate of reporting in relation to patient risk so that the bandwidth and energy consumption are optimized over a fixed rate transmission.



**Figure 16.** The number of packets transmitted cumulative packet transmission utilizing the adaptive strategy (Layer 5). The linear development illustrates a constant network throughput over the simulation time. The x-axis is the simulation time ( $10^{14}$  nanoseconds), whereas the y-axis is the number of packets that were received by the management layer.

## 6. CONCLUSIONS

Using an Arduino Uno board connected to wearable sensors, data was transferred to the cloud via Wi-Fi. The system proved efficient in collecting patients' physiological data. OMNeT++ software was used to create a simulation scenario of a rural healthcare network. Patients were equipped with multiple wearable sensors distributed throughout the rural area, and physiological data from a healthcare facility was then transmitted to the city. Readings provided by each sensor included temperature, heart rate, and blood oxygen saturation (SpO2). A monitoring system used five levels (Levels 1 through 5) to interpret the data and produce health risk evaluations and alerts. The system's performance was assessed using three different transmission modes: cyclic mode, which involved a fixed transmission interval regardless of the patient's condition; adaptive mode, where the transmission interval dynamically changed based on the established risk level; and event-response mode, where transmissions were primarily initiated upon detection of abnormalities. The system helped save lives by successfully sending real-time patient data to doctors. With the possibility for future increases in prediction and response accuracy through the use of ECG data or more sophisticated machine learning models, the suggested system offered a scalable architecture for smart healthcare applications in remote places.

## NOMENCLATURE

Symbol	Description	Symbol	Description
ECG	Electrocardiogram	HTTP	Hyper Text Transfer Protocol
MBT	Mean body temperature	TCP	Transport Control Protocol
TCore	Core tissues temperature	IP	Internet Protocol
Tskin	Peripheral tissue temperature of skin	SMTP	Simple Mail Transfer Protocol
DB	database	SMS	Short Message Service
dA/dP	Arterial compliance	v	pulse wave velocity
GSM	Global System for Mobile Communication	$\tau$	length of the wave travel
		$\rho$	blood density



## Declaration of Competing Interest

The author declares that he has no known conflicting financial interests or personal relationships that could influence the work described in this paper.

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## مراقبة الرعاية الصحية عن بُعد باستخدام نقل البيانات التكيفي للكشف عن الحالات الشاذة وتقييم المخاطر في شبكة استشعار لاسلكية

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### الخلاصة

تم تطوير نظام متكامل لتتبع الحالة الصحية عن بُعد باستخدام شبكات الاستشعار الطبية اللاسلكية للمراقبة المستمرة للمرضى. وقد طورت الدراسة دائرة تجمع بيانات المرضى في المراكز البعيدة عبر جهاز متوافق مع أردوينو، ثم تنقلها إلى السحابة. ويتيح عزل مرضى الأمراض المعدية ومراقبتهم في المنزل من خلال أجهزة استشعار متصلة بشبكة الاستشعار اللاسلكية للتشخيص والعلاج عن بُعد عبر التطبيب عن بُعد، حيث يتعاون أخصائيو المدينة مع الأطباء المحليين. يستخدم النظام معالجة متعددة الطبقات، تبدأ بجمع البيانات الأساسية، بما في ذلك معدل ضربات القلب، ونسبة تشبع الأكسجين في الدم، ودرجة الحرارة. بعد ذلك، تُعالج البيانات من خلال عدد من العمليات لتحسين جودتها، مثل جمع القياسات الأولية، وتقليل التشويش، وتعويض القيم المفقودة. ثم يُقيّم مستوى المخاطر لكل مريض، ويُحسب مستوى الشذوذ. لتقليل الإنذارات الكاذبة، يتم تفعيل نظام إنذار مزود بآلية تأكيد في الحالات عالية الخطورة. وأخيرًا، يتم تعديل معدل الإرسال وفقًا لدرجة الخطورة باستخدام طريقة أخذ عينات تكيفية/إرسال قائم على الأحداث. ولضمان استجابة سريعة، يُسعى إلى خفض استهلاك الطاقة، وزيادة كفاءة الشبكة، وتسريع الإرسال أثناء حالات الطوارئ. في الوقت نفسه، تستقبل وحدة المعالجة المركزية البيانات، حيث تسجل مقاييس أداء الشبكة والمريض لتحليلها ورسمها بيانيًا باستخدام لغة بايثون. تُسهم هذه الورقة البحثية في تعزيز الرعاية الوقائية باستخدام أجهزة مراقبة قابلة للارتداء. وتركز على الكشف المبكر، وإشراك المرضى، وسرعة تعديل العلاجات من قبل الأطباء، وخفض التكاليف، وتقليل زيارات المستشفى.

**الكلمات المفتاحية:** شبكة الاستشعار اللاسلكية، مراقبة الرعاية الصحية، الطب عن بُعد، آلية الإرسال التكيفية، العلامات الحيوية.