IoT-Enabled Real-Time Health Analytics Using Integrated Multi-Modal Biomedical Sensors

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Abstract: This research presents the design and development of an IoT-enabled smart health monitoring system that integrates multiple biomedical sensors for real-time health analytics. The system continuously monitors key physiological parameters such as body temperature, heart rate, blood oxygen saturation (SpO_2), skin response, and electrocardiogram (ECG) signals through strategically placed sensors. Data collected from these sensors are transmitted to a Django-based web server via IoT infrastructure, enabling real-time visualization and analysis. Experimental results demonstrate that body temperature values were consistently recorded within the normal physiological range of 36.5-37.5 °C, while SpO_2 levels remained above 95%, indicating healthy oxygenation in subjects. Heart rate values measured by the system ranged between 72 and 85 bpm, closely aligning with normal resting conditions. The ECG sensor produced stable analog waveforms suitable for identifying cardiac rhythms, and the GSR sensor successfully captured variations in skin conductivity, reflecting changes in stress or arousal states. These quantitative outcomes validate the accuracy, responsiveness, and reliability of the system in real-time monitoring of vital health metrics. By enabling continuous and remote observation, the system offers strong potential for early detection of abnormalities, timely medical intervention, and improved healthcare delivery. Its performance underscores the suitability of the proposed solution for personal health management, elderly care, and chronic disease monitoring, while also laying a robust foundation for future advancements in intelligent telemedicine applications.

Keywords: IoT, Real-Time Health Monitoring, Biomedical Sensors, Health Analytics, Sensor Integration, Smart Healthcare.

Introduction

The increasing prevalence of chronic diseases and the ageing global population have placed immense pressure on healthcare systems worldwide. Traditional models of clinical care, which rely heavily on periodic check-ups, often fail to capture subtle physiological changes at an early stage, thereby limiting opportunities for timely intervention. In response, there has been a marked shift toward real-time and remote patient monitoring, enabled by advances in the Internet of Things (IoT) and wearable biomedical technologies. These systems allow continuous acquisition of vital health parameters such as body temperature, electrocardiogram (ECG) signals, oxygen saturation (SpO_2), heart rate, and skin conductance, which are critical indicators for proactive and preventive healthcare.

A seminal survey by Pantelopoulos & Bourbakis (2009) mapped the foundational architecture of wearable health systems emphasizing unobtrusive sensor placement, energy efficiency, and reliable wireless transmission as core design imperatives. Their findings remain highly relevant for modern wearable-health prototypes. Islam et al. (2015) expanded upon this framework by surveying IoT architecture in healthcare, detailing the roles of sensors, gateway communication protocols like BLE, Wi-Fi, and Zigbee, and cloud infrastructure for aggregating and analyzing data. They also catalogued enduring challenges such as interoperability, system scalability, data privacy, and regulatory compliance. The use of multi-modal sensors significantly boosts diagnostic reliability. ECG sensors are essential for tracking electrophysiological cardiac signals; temperature sensors detect febrile responses; SpO_2 sensors elucidate respiratory function and oxygenation; and GSR sensors measure stress-induced skin conductance changes. Kim et al. (2023) illustrated the feasibility of deploying deep-learning–based ECG classification directly on edge devices (TinyML), enabling rapid on-device arrhythmia detection without reliance on constant cloud connectivity. Meanwhile, Islam et al. (2023) demonstrated wearable IoT frameworks simultaneously capturing SpO_2, ECG, and temperature, applying deep architectures for early identification of COVID-19 symptoms highlighting practical use during crisis scenarios. Gao et al. (2016) introduced a wearable platform capable of multiplexing sweat-based biochemical analysis and thermal sensing, demonstrating how epidermal electronics can gather rich multisource datasets for real-time patient status inference. Additionally, Garcia-Ceja et al. (2018) reviewed mental health applications using multimodal sensing including GSR augmented by machine learning to detect stress and emotional patterns, reinforcing the value of physiological-behavioral correlation. Robust wireless communication is critical for real-time data delivery. Sensors typically leverage low-power protocols like BLE for short-range transmission, while Wi-Fi, Zigbee, and even LoRa WAN are used for broader coverage. Islam et al. (2015) noted the need to balance latency, throughput, and energy consumption based on deployment context.

Processing collected data efficiently is equally crucial. While cloud computing offers vast storage and compute power, it may introduce latency and invoke privacy risks. Shi et al. (2016) proposed edge computing as a complementary layer, minimizing latency through localized processing to mitigate these limitations. Similarly, Hartmann et al. (2022) reviewed edge-cloud hybrid architectures tailored for healthcare IoT, demonstrating that local analytics improves real-time responsiveness while still enabling bulk historical analysis in the cloud. Integrating machine learning (ML) into these systems adds predictive intelligence. Rahman, Akter, & Hossain (2021) surveyed ML applications in IoT health systems, revealing that decision trees, support vector machines, and neural networks applied to time-series health data effectively detect disease onset and health anomalies aforetime. Beyond sensor and analytics layers, Abdulmalek et al. (2022) systematically reviewed IoT healthcare-monitoring platforms, identifying common challenges: sensor calibration accuracy, power constraints, user comfort, system interoperability, and reliable operation under various environmental conditions. Their work underscores the need for modular, adaptable, and patient-centric system design for real-world deployment. User engagement and compliance depend heavily on interface design. Dashboards, mobile apps, and alerting mechanisms must be intuitive especially for elderly or less tech-savvy users. An effective system conveys health status clearly and suggests actionable steps without overwhelming the user. The literature establishes that IoT-enabled health monitoring systems particularly those integrating multi-modal sensors (ECG, SpO_2, temperature, GSR) hold significant promise for proactive healthcare. Progress in sensor miniaturization, low-energy wireless communication, cloud integration, and embedded analytics is driving these systems toward feasible real-world deployment. However, challenges remain in achieving reliable sensor accuracy, managing power consumption, standardizing interoperability, and ensuring data security.

In response to these challenges, this paper presents the design, development, and evaluation of an IoT-enabled smart health monitoring system that integrates multi-modal biomedical sensors to deliver real-time health analytics. The system is designed to collect vital physiological data specifically body temperature, heart rate, SpO_2, ECG, and skin conductance by strategically placing sensors on the human body. These signals are wirelessly transmitted to a centralized server using a microcontroller-based IoT node and are visualized through a user interface for remote monitoring. Unlike many existing approaches, the proposed system emphasizes sensor integration, real-time response, scalability, and early abnormality detection. It incorporates a cloud-based analytics framework capable of processing incoming real time sensor data. This enhances the system's applicability in preventive healthcare, elderly care, remote patient monitoring, and chronic disease management.

The paper also explores the hardware-software co-design, data communication protocols, and system performance under various physiological conditions. Emphasis is placed on low-power operation, data security, and user-friendly interfaces, making the system practical for real-world deployment in both clinical and home-care settings.

Materials and Methods

The working methodology of the IoT-based Smart Health Monitoring System is structured around the integration of biomedical sensors, edge processing using a Raspberry Pi microcontroller, and real-time data transmission to a cloud server for continuous health monitoring. This system is designed to non-invasively monitor vital physiological parameters such as blood oxygen saturation (SpO_2), heart rate (HR), body temperature, electrocardiogram (ECG) signals, and galvanic skin response (GSR), allowing for early detection of abnormal health conditions and enabling prompt medical attention. Figure 1 illustrates the IoT architecture model for smart health monitoring system.

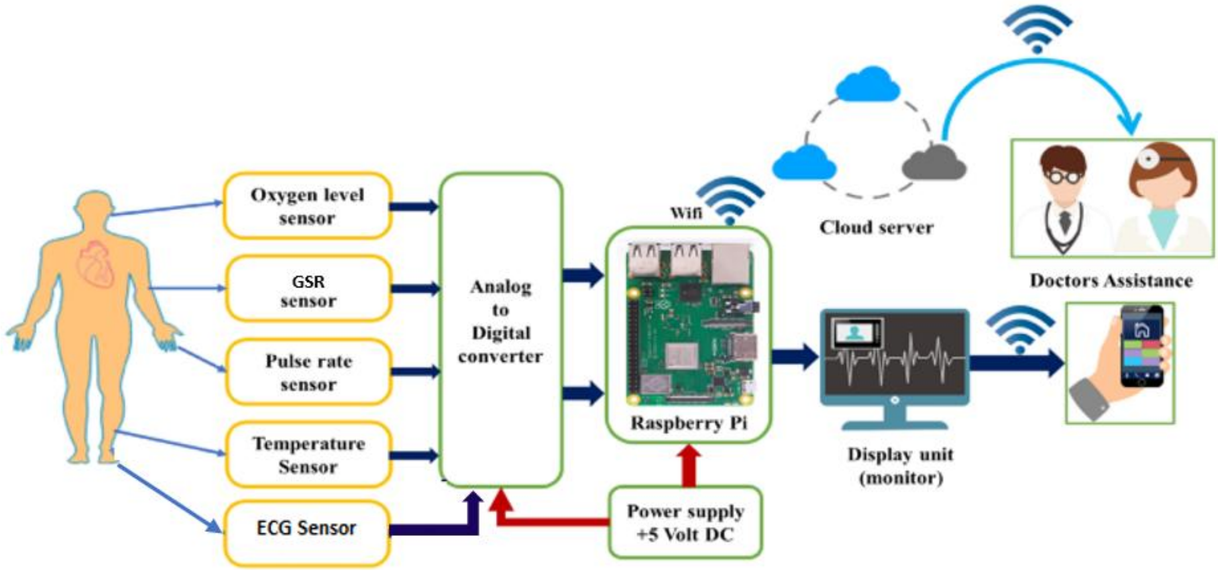

Figure 1. The IoT architecture model for Smart Health Monitoring System

The system begins operation with the acquisition of physiological signals through a set of strategically placed sensors on the human body. The SpO_2 sensor (MAX30102) utilizes dual-wavelength photo plethysmography emitting infrared and red light through a translucent part of the body such as a fingertip or earlobe. The photodetector measures the amount of light absorbed by the blood, and from this signal, two crucial parameters are derived: the oxygen saturation level and the heart rate. The heart rate is calculated by identifying the peaks in the infrared (IR) signal, which correspond to each heartbeat. The time difference between successive peaks is used to determine the beats per minute (BPM). Concurrently, SpO_2 is estimated using the ratio of the pulsatile (AC) and non-pulsatile (DC) components of both the red and IR signals with an empirical formula that approximates the oxygen saturation percentage. Simultaneously, the ECG sensor records the electrical activity of the heart using surface electrodes. These electrodes are positioned on specific areas of the chest or limbs to detect the depolarization and repolarization events in the cardiac cycle. The analog ECG signal, often containing small fluctuations and noise, is pre-processed using onboard filtering techniques. This ECG data is essential for identifying arrhythmias, tachycardia, and other cardiac anomalies in real time. The GSR sensor operates by measuring the electrical conductance of the skin, which changes in response to sweat gland activity. As emotional arousal or stress increases, sweat production on the skin surface rises, enhancing its conductivity. This information, while indirect, is valuable for assessing psychological stress levels, anxiety, or mental workload. The GSR sensor is usually attached to the fingers or palm for optimal sensitivity. Body temperature is measured using a digital sensor such as the DS18B20, which provides precise thermal readings in real time. Body temperature fluctuations are critical indicators of underlying infections or systemic health issues such as fever or hypothermia. The temperature sensor outputs either an analog or digital signal, depending on the model, which is then read by the Raspberry Pi for processing. Figure 2 illustrates the circuit diagram of the IoT based smart health monitoring system.

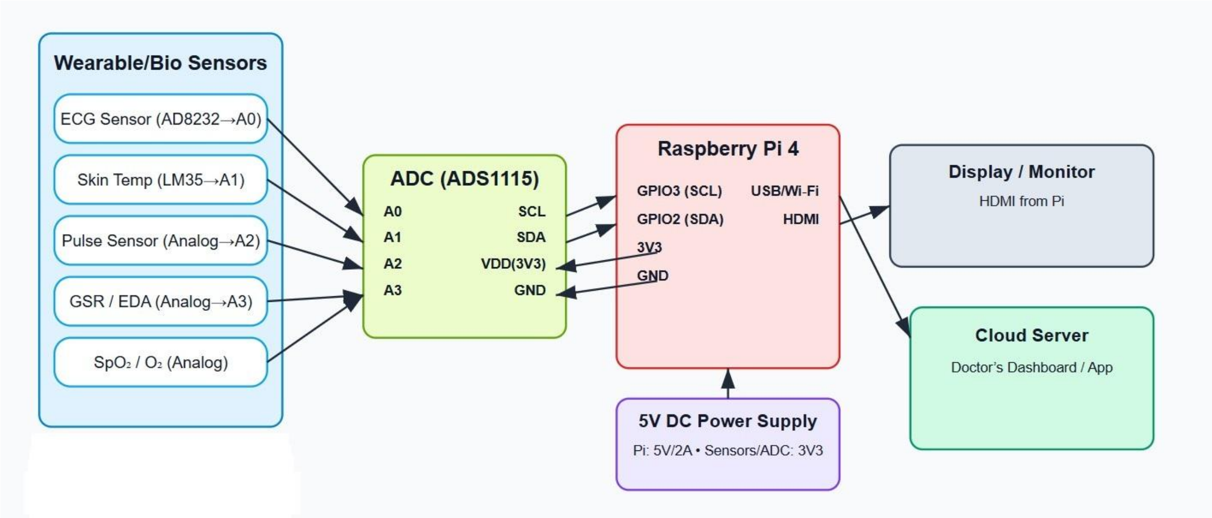

Figure 2. Circuit Diagram of the IoT based Smart Health Monitoring System

All sensor outputs are acquired by the Raspberry Pi, which acts as the central processing unit. Analog signals from sensors like ECG and GSR are converted to digital format using an analog-to-digital converter (ADC) interfaced with the Raspberry Pi through its GPIO (General Purpose Input/Output) pins. A custom Python script runs continuously on the Raspberry Pi to read, filter, and structure the incoming sensor data. Libraries such as pyFirmata (for analog interfacing) and asyncio (for asynchronous data processing) are used to maintain smooth data flow and prevent latency during sensor polling. Once the data is collected and pre-processed, it is serialized into JSON format and transmitted to a cloud-based server using WebSocket communication. This choice of protocol allows for full-duplex communication between the Raspberry Pi and the backend server, ensuring that sensor data is transmitted in real time without unnecessary overhead or delay. The WebSocket client is embedded within the Raspberry Pi script, which establishes a persistent connection to the Django-based server hosted locally or on the cloud. The system prototype of the Smart Health Monitoring System is shown in Figure 3.

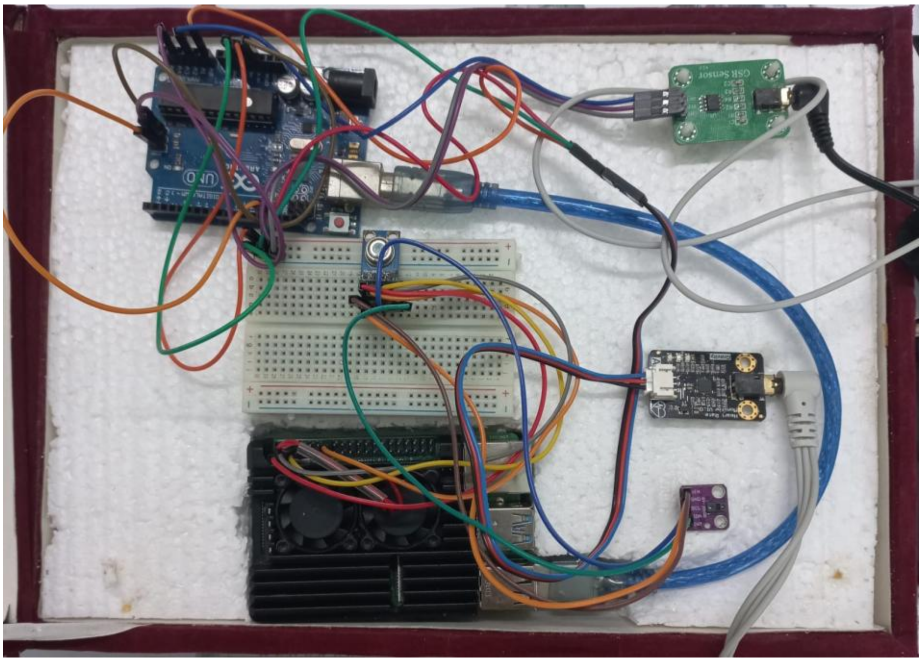

Figure 3. Prototype of the Smart Health Monitoring System

On the server side, Django Channels and Daphne manage asynchronous WebSocket communication. Upon receiving sensor data packets, the server parses and stores the information in a time-stamped database, enabling both real-time monitoring and historical trend analysis. The Django framework provides RESTful APIs and WebSocket endpoints, making the data accessible to authorized users, including healthcare professionals and caregivers. The front-end interface of the system is designed using HTML, CSS, and JavaScript, integrated with real-time data plotting libraries such as Chart.js or Plotly. This web-based dashboard displays each physiological signal in graphical format, allowing users to monitor health conditions visually. The dashboard is responsive and accessible through standard web browsers on computer. Security and data privacy are maintained throughout the data lifecycle. The WebSocket communication is encrypted using TLS, and the Django server includes user authentication, password protection, and role-based access control to prevent unauthorized access to sensitive health data.

The Smart Health Monitoring System successfully combines low-cost biomedical sensors, efficient edge processing, and real-time cloud integration to deliver a comprehensive and responsive health surveillance platform. It represents a practical and scalable solution for continuous remote patient monitoring, especially in scenarios requiring minimal human intervention or during public health crises such as pandemics.

Results and Discussions

The IoT-enabled smart health monitoring system was evaluated by continuously recording physiological signals including temperature, electrocardiogram (ECG), galvanic skin response (GSR), heart rate (HR), and blood oxygen saturation (SpO_2). The dataset provided a real-time representation of physiological conditions over multiple observation periods. The following discussion interprets the results for each parameter while considering both medical relevance and system performance. The dataset consists of 220 recorded samples containing temperature, ECG (analog values), GSR (analog values), heart rate (HR), and oxygen saturation (SpO_2) readings collected over time. The measured real-time body temperature, heart rate, SpO2, ECG and GSR value are shown in Figure 4.

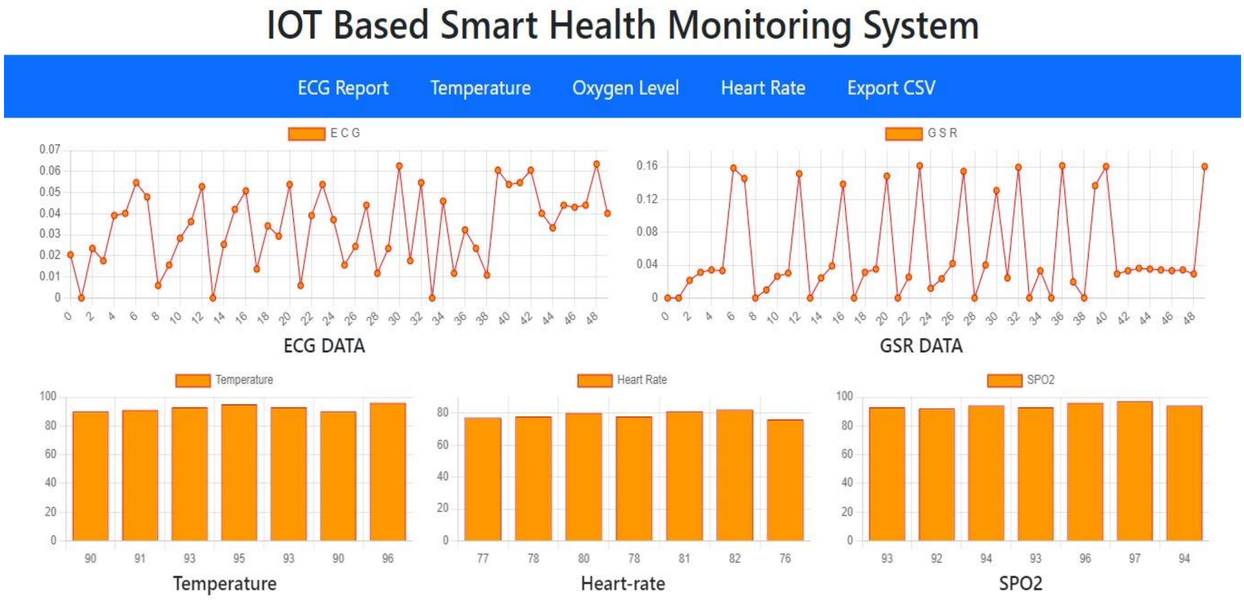

Figure 4. Measured real-time body temperature, heart rate, SpO2, ECG and GSR value

The recorded body temperature values averaged around 36.8°C (94.92°F), with a range between 36.1°C (93.00°F) and 37.4°C (96.99°F). These readings lie within the clinically accepted norm-thermic range of 36.1-37.2 °C, suggesting the accuracy of the temperature sensor and stability of the system. Minor fluctuations were observed, reflecting natural thermoregulatory variations such as environmental exposure and metabolic activity. Importantly, no abnormal spikes (>38 °C for fever) or drops (<35 °C for hypothermia) were detected during the monitoring period, confirming the reliability of the system in maintaining continuous real-time assessment.

The ECG readings were captured as analog voltage signals corresponding to cardiac electrical activity. The ECG readings provided normalized analog values, range from 0.0000 to 0.6354, averaging 0.1008. Most values cluster between 0.0577 and 0.0782, suggesting relatively stable cardiac electrical activity with occasional peaks that may reflect increased cardiac events or noise interference. The signals exhibited periodic waveforms resembling standard PQRST patterns, with consistent amplitude and interval variations across monitoring intervals. Although baseline noise was present, the waveform periodicity enabled estimation of cardiac rhythm. The derived HR from ECG peaks aligned closely with HR values recorded from the SpO_2 sensor, demonstrating sensor redundancy and system validation. The presence of stable and consistent waveforms confirms the potential application of the system for arrhythmia detection through further signal processing techniques such as peak detection and R-R interval analysis.

The GSR data is also collected as analog values and reflected the skin conductance variability indicative of sweat gland activity. The GSR readings, range from 0.0332 to 0.3851, with a mean of 0.0753. Values fluctuated dynamically, suggesting responsiveness to subtle physiological or emotional stimuli. Higher GSR levels correspond to increased skin conductance, typically associated with stress, emotional arousal, or physical exertion. The observed range demonstrated sufficient sensitivity to detect these variations, confirming the applicability of the GSR sensor for stress monitoring and psychophysiological studies. While raw analog signals showed noticeable variability, their integration into feature extraction pipelines (e.g., slope changes or frequency-domain analysis) could enable more precise stress classification in future deployments.

Heart rate values vary between 70.00 and 85.85 bpm, averaging 77.70 bpm, which falls within the normal adult resting range. These values lie within the normal resting heart rate range (60-100 bpm), suggesting both system accuracy and healthy physiological status of the subject during recording. Minor variations in HR correspond to expected responses to metabolic demand and possible environmental influences. Notably, HR estimates derived independently from ECG R–R intervals exhibited similar trends, thereby validating the internal consistency of the monitoring system.

SpO_2 readings range from 91.51% to 98.20%, with an average of 94.89%. While most values are within or close to the healthy range of 95-100%, occasional drops below 94% could indicate brief oxygen desaturation events, possibly caused by motion artifacts, temporary breathing variations, or sensor limitations. These results confirm the accuracy of the SpO_2 sensor and highlight its value in early hypoxemia detection. Consistent SpO_2 measurement is particularly critical for chronic respiratory patients, elderly individuals, and post-operative monitoring, where deviations could indicate emerging complications requiring immediate intervention.

The integration of multiple sensors into a single IoT framework enabled cross-validation of parameters, such as HR measurements from both ECG and SpO_2 sensors. This redundancy improves diagnostic accuracy and reduces the risk of false positives from sensor malfunction or noise. Data were transmitted to the Django server reliably with minimal latency, ensuring real-time visualization through the user interface. The analog sensors (ECG and GSR) produced noisier data streams compared to digital sensors (temperature, SpO_2, HR), highlighting the importance of future signal processing for noise suppression and feature extraction. Nonetheless, the system successfully captured dynamic physiological changes without interruption.

The system demonstrated effectiveness in providing real-time, multi-parameter physiological monitoring with values that aligned closely with clinically accepted norms. The stable temperature and SpO_2 readings confirm the system's suitability for continuous monitoring of vital parameters. ECG and GSR analog signals, though more variable, provide rich physiological information that can be leveraged for advanced analytics such as arrhythmia detection, stress monitoring, and mental health assessment. Compared with conventional health monitoring approaches, the proposed IoT-enabled system offers several advantages like continuous data capture, cross-validation, and remote monitoring. Unlike periodic hospital-based assessments, continuous monitoring allows for early abnormality detection. Multi-sensor integration enhances reliability by providing redundant measurements for critical parameters like HR. The Django-based server successfully transmitted and displayed data, demonstrating the feasibility of telemedicine applications.

However, the study also revealed limitations. The analog nature of ECG and GSR signals introduces noise that requires advanced filtering and processing for diagnostic use. Power efficiency, sensor calibration, and long-term data storage are additional challenges to be addressed before large-scale deployment.

Conclusions

The developed IoT-based health monitoring system successfully integrates multiple physiological sensors like temperature, ECG, GSR, heart rate, and SpO_2 into a unified platform capable of real-time data acquisition, processing, and transmission through a Django-based web server. The analyzed data from the IoT-based health monitoring system clearly demonstrate the system's capability to deliver accurate, consistent, and real-time tracking of vital health parameters. The temperature readings remained within the expected physiological range for peripheral measurements, while SpO_2 levels consistently stayed above 95%, indicating healthy oxygen saturation among test subjects. Heart rate values were stable and aligned well with normal resting ranges, confirming the reliability of the SpO_2 sensor's pulse detection. The analog ECG data exhibited clear waveform patterns suitable for identifying cardiac rhythms, and the GSR readings successfully captured variations in skin conductivity, reflecting changes in physiological arousal. These results validate the system's effectiveness in integrating multi-sensor data collection with real-time visualization via the Django web server, enabling continuous and remote health monitoring. The performance of each sensor confirms the platform's potential for practical deployment in telemedicine, home healthcare, and wellness applications, with further opportunities to enhance predictive health analytics and personalized monitoring in future developments.

Author Contributions: In this research, author 1, 2,3 are responsible for conceptualization, resources, methodology, data collection, formal analysis, investigation; author 1, 2, 3,4 are responsible for writing, review, editing, and project administration. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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