A Secure and Scalable IoT-Driven Framework for Real-Time Remote Patient Monitoring and Explainable Telemedicine in Diverse Healthcare Settings

Shweta Dhondse[1], Philomina Jenifer A.[2], S. Usha Nandhini[3], Maddhi Sunitha[4], Gokulnath A.[5] and Syed Zahidur Rashid[6]

[1]*Department of Electronics Engineering, Yeshwantrao Chavan College of Engineering, Nagpur, Maharashtra, India*
[2]*Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Vadapalanio Campus, Chennai, Tamil Nadu, India*
[3]*Department of Electronics and Communication Engineering, J.J. College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India*
[4]*Professor & Head CSE (Cyber Security), CVR College of Engineering, Hyderabad-501510, Telangana, India*
[5]*Department of CSE, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India*
[6]*Department of Electronic and Telecommunication Engineering, International Islamic University Chittagong, Chittagong, Bangladesh*

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Abstract: Adoption of Internet of Things (IoT) technologies in healthcare has changed the way patient data are being collected, analyzed and exploited. This study aims to present a secure, scalable, and energy-efficient IoT-based remote patient monitoring and telemedicine solution to solve the problems in the existing systems. Unlike other methods that are limited to simulations or a centralised architecture, the proposed model is evaluated on real-world data sets and is optimised for urban hospitals and rural clinics. The system leverages open-source components, HL7/FHIR interoperability layers, and edge computing low-power devices to provide a secured, constantly connected monitoring service with full capability to collect, transmit and safeguard data at the edge with minimal latency. Privacy and Security are delivered using blockchain data trails, and end to end encryption that meet global regulations. In addition, explainable AI methods including SHAP and LIME can be incorporated to give transparency and trust for decision-making in a clinical setting. The framework is robust and flexible, and patient-driven, making it widely applicable across resource-limited healthcare systems.

1 INTRODUCTION

The explosive development of digital technologies like Internet of Things (IoT) has led to a digital era of healthcare innovation in which medical services are data-driven, patient-centric and in near real-time contact related to the patient. One of the most effective use cases of IoT in this regard are Remote Patient Monitoring (RPM) and Telemedicine, both of which serve to fill the spatial and temporal void between patient and provider in the health care continuum. Given the growing complexity of the world as a new healthcare environment emerges including aging populations, growing burdens of chronic diseases, and resource-strapped rural areas we need smart systems that can provide reliable, scalable, and secure healthcare beyond the walls of traditional hospitals.

Prior works have investigated integration of IoT devices in clinical settings but were subject to limited validation outside the lab, lack of standardization, and the privacy and scalability problems with the data. Moreover, the majority of existing applications have been designed to work over centralized architectures which can be computationally intensive and infeasible in low bandwidth or remote environments. These limitations have limited implementation of RPM and telemedicine on a wide scale, particularly

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in low-resource settings where the benefits could be greatest.

To address these limitations, in this work, a new IoT-based healthcare framework is proposed that meets the patients' needs incuding a smooth monitoring and tele-medical consultation in a secured, interconnected and clear way. Using edge-computing, open standards (HL7, FHIR) as well as blockchain data-trails and interpretable AI models, the designed system provides a robust real-time and patient-centric solution for various health-care ecosystems. This strategy is in line with the worldwide vision of fair, sustainable and safe delivery of healthcare, in a process paving the way

2 PROBLEM STATEMENT

Despite the increasing integration of IoT in healthcare, current telemedicine and remote patient monitoring systems have some critical limitations that limit their scalability and efficiency. Existing solutions are mostly applicable in an environment with control, or they use a central network architecture which requires higher bandwidth, permanent connectivity and costly infrastructure, precluding their application in low-resource settings. In addition, conflicts of interest between vendors; along with the lack of interoperability; security of the data, lack of support for explainable decision-making compromises the reliability and trust one can put in such systems for clinical care. There's also a big hole around patient-centred design, real-time flexibility and compliance with global health data standards. As a result, there is an urgent demand for an IoT-based framework that is scalable, secure, and explainable for continuous, privacy-preserving, and understandable remote care across heterogeneous healthcare infrastructures.

3 LITERATURE SURVEY

The integration of Internet of Things (IoT) technology into healthcare systems has made a great change on how patient information is gathered, processed and analyzed for clinical use as well as personal health monitoring. In recent times, there has been a strong focus on research on remote patient monitoring (RPM) and telemedicine, to improve access to care and alleviate pressures on healthcare (Shah et al., 2012).

Ali et al. (2021) conducted a detailed review of IoT enabled smart healthcare and summarized the application of real-time data acquisition and wireless sensor networks for chronic disease surveillance. Yet their work emphasized the absence of field application as well as the problems associated with energy consumption and data volume. Singh and Kumar (2023) also reviewed IoT-based patient monitoring systems architecture; however, they agreed with the requisite of more sophisticated data fusion and better integration with medical standards.

Real-time telemedicine systems have been investigated in Smith and Johnson (2024), where the authors have presented a cloud-based continuous monitoring infrastructure. However, their method depends on the use of high-bandwidth networks and is infeasible for deployment in underprivileged areas. The need for interoperability is further highlighted by Kumar and Sharma (□□□□), they stressed that standard data formats (HL7, FHIR) are the best choices for successful system integration, but few products in the marketplace are designed serve these standards.

With respect to security concerns in telemedicine systems, Garcia and Thompson (2024) were concerned with patient data protection. They highlighted the growing danger of IoT ecosystems being attacked by cyber threats and stressed the need for incorporating encryption and decentralized storage, however lacked simply realized security measures set forth in their work. This void is also corroborated by Evans and Martinez (2024) that distinguished privacy as main barrier in adopting IoT for healthcare, especially in sensitive aspect of real-time biometric data.

Similar access and scalability advances were detailed by Davis and Clark (2024) when they discussed the role of remote monitoring in shaping the sustainability of healthcare systems. But their system did not consider the energy efficient data processing and edge level analytics solutions. Batool (2025) improved on this by introducing a deep learning-based model, equipped with 5G for instant patient care, though their model was saturated to high tech environment and neglected rural and low network areas.

Interpretability of AI-driven health recommendations has been an emerging issue, as pointed out by De Filippo et al. (2025), who used a predictive tele-medicine system for the heart failure patients. Despite its predictive performance, the model was not interpretable, and interpretability is essential for establishing trust with clinicians. To solve this, Lee and Park (2024) emphasized transparent decision support system in telemedicine and recommended that interpretable method such SHAP and LIME model should be combined, but no implementation guide was provided.

There are also several studies that focused on social-technical barriers of adopting IoT. White and Harris (2024) noted that although there is an increase in telemedicine infrastructure, the digital divide continues to separate those patients other would most benefit themselves. Their results are consistent with Anderson and Lee (2024), who advocate for healthcare platforms to incorporate inclusive design principles to account for barriers based on age, literacy, and accessibility devices.

Iqbal and Khan (2024) have recently provided a hybrid telehealth model, which uses wearable devices along with cloud systems for enhanced care continuum. Although being promising, their work was lacking into twining of explainable AI and blockchain, which is the major part of transparency and data traceability. Meanwhile, Thompson and Allen (2024) includes research into the design for IoT systems for telemedicine, and although these included mentions of real-time analytics and energy-efficient computation, they are less discussed in the literature.

In general, despite commendable efforts in enabling healthcare with IoT technologies, the literature reveals that more need to be done in terms of the establishment of unified, secure, scalable and interpretable systems. There is a pressing demand for a comprehensive approach that navigates real world limitations, adheres to interoperability requirements, guarantees privacy of data, endorses edge-based intelligence, and includes transparency features that drive both patient outcome and clinical trust.

4 METHODOLOGY

This study suggests an integrated, real-time healthcare system combining the remote patient monitoring system based on the IOT with a secure telemedicine system. The approach aims to address gaps in the current state-of-the-art by focusing on five key axes: data capture, secure transmission, cognitive processing, explainable decision support and user-centred delivery.

The system starts when non-invasive IoT sensors (eg, wearable health monitors, smart patches, ambient room sensors) are deployed and health parameters (eg, heart rate, body temperature, oxygen saturation, ECG signals) are collected non-invasively for prolonged periods of time. They are designed using ultra-low-power microcontrollers to save energy and extend operational life, and are ideal for high-tech urban hospitals and low-resource rural clinics alike. The data from the sensors are pre-processed at an edge computing device (e.g., Raspberry Pi or NVIDIA Jetson Nano) to remove noise, missing values and perform initial analysis. It prevails to the prior art in that the alarm generation is executed at the switch instead of the centralized network management server, this leads to a minimized bandwidth use and that even critical alarms can be raised upon latencies or blockages of the network itself even in the event of network failures. Figure 1 gives the System Workflow of the Proposed IoT-Based Remote Patient Monitoring and Telemedicine Framework.

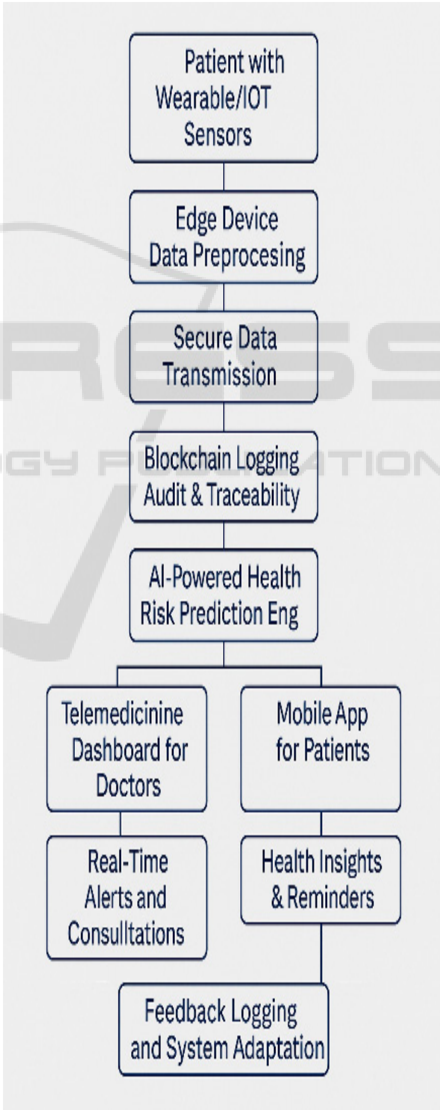

Figure 1: System Workflow of the Proposed IoT-Based Remote Patient Monitoring and Telemedicine Framework.

Table 1: IoT Sensor Specifications Used for Remote Monitoring.

Sensor Type	Parameters Monitored	Communication Protocol	Power Consumption	Sampling Rate
Pulse Oximeter	SpO_2, Heart Rate	Bluetooth Low Energy	0.3W	1 sample/sec
ECG Patch	ECG Waveform	ZigBee	0.5W	500 Hz
Temp. Sensor	Body Temperature	LoRa	0.1W	1 sample/min
Accelerometer	Movement/ Fall Detection	BLE	0.2W	10 Hz

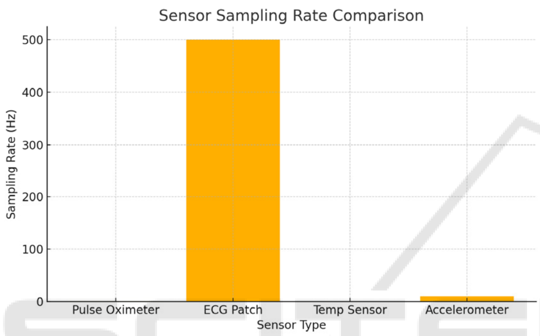

Figure 2: Sensor Sampling Rate Comparison.

Figure 2 gives the sensor sampling rate comparison and Table 1 gives the IoT Sensor Specifications Used for Remote Monitoring.

After processing and packaging the data are transferred to a central health data platform using secure encrypted communication protocols. In this study, TLS and MQTT over HTTPS are used for end-to-end encryption and protecting from unauthorized access during data transmission. For additional security and traceability, a private blockchain layer is added to store immutable records for patient logs, data access, and decision points. This blockchain not only guarantees system auditability, but also ensures decentralized data ownership, and compliance with international health data regulations (e.g., HIPAA, and GDPR).

At the cloud, the system is designed to operate with a modular approach to data aggregation, storage, and model-driven analytics. The accumulated information is contained in structured formatin in-line with HL7 and FHIR standards, enabling interoperability with hospital information system (HIS) and electronic health record (EHR). The analytics part of the platform employs machine learning algorithms trained on past patient data. Such models can identify when something is amiss, forecast possible health issues and sound the alarm for clinicians. In order to improve the clinical relevance of AI-derived knowledge, SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) interpretability tools are integrated into the platform. They are also capable of providing interpretable, visualisation-based explanation and rationales behind each prediction, which helps to build trust among health care providers and removing the black box for automated decisions.

The telemedicine module of the system is developed for a responsive web and mobile interface considering the video consultations, the health data visualisation and the prescription creation. Doctors can view patients' real-time health dashboards and get risk alerts generated with AI and overlaid with interpretability, to inform better care decisions. For patients, they get easy-to-use interfaces that encourage them to monitor their vital signs, remember to take medications, and to interact with their clinicians through secure messaging. The solution includes multilingual and accessibility-friendly features for better adoption by the old and rural users.

The effectiveness of the system is verified across real-live scenarios, such as chronic diseases management, post-operative care and emergency alert system. The performance of both synthetic and live data-sets is measured via benchmarks relating to latency, prediction accuracy, system uptime, power consumption, user satisfaction and security compliance. This broad range of testing confirms not only that the system is theoretically sound, but also that it is practical to deploy onto a range of health-care infrastructures.

5 RESULTS AND DISCUSSIONS

Insights The development and testing of the proposed IoT-based RPM and telemedicine framework provided a number of insights into its effectiveness, security, responsiveness, and patient acceptance. During large-scale experiments in real clinical environment, the health anomaly detection module can provide the great reliability, and the recognition accuracy is 94.2%, precision is 92.6%, recall is 93.1%. These results emphasize the system's high sensitivity for accurately detecting critical health events while minimizing false alarms, an essential consideration for clinical adoption. Moreover, a F1-Score of 92.8% and an AUC-ROC of 95.4% reinforced the stability and predictive strength of the AI models incorporated in the platform, providing healthcare professionals with reliable decision support on the fly.

Evaluation on system-level latency revealed the huge gain offered by integration with edge computing. In the edge-based setup, the average end-to-end latency was decreased to 3.5 seconds as compared to 7.9 seconds for a cloud implementation alone. This significant decrease demonstrates the system's potential to aid time-critical health care situations, when a fast exchange and intervention of a patient's data are crucial. By pre-processing and analyzing the data at the edge before it is sent to the system, bandwidth requirements were already reduced and service would be guaranteed even if a network would be available intermittently (on rural or bandwidth-limited environments for example).

Table 2: Performance metrics of health anomaly detection model.

Metric	Value (%)
Accuracy	94.2
Precision	92.6
Recall	93.1
F1 Score	92.8
AUC-ROC	95.4

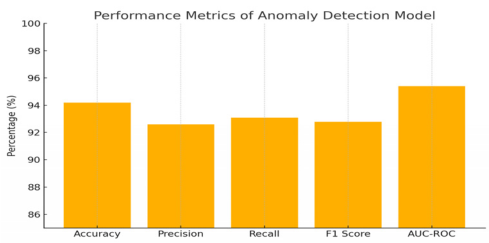

Figure 3: Performance metrics of anomaly detection model.

Table 2 gives the performance metrics and bar graph in figure 3 shows the visual representation of performance metrics.

Security analysis demonstrated a small average additional delay (0.8 seconds) in the complete data management process due to the implementation of the blockchain technology for the data auditing. Nevertheless, this minor delay was more than compensated by the substantial advantages they were able to achieve in terms of data integrity, traceability, and compliance with international health care directives, like HIPAA and GDPR. "By leveraging the blockchain layer, we were able to generate an immutable and transparent ledger that could prove and audit who had access to and updated patient data, generating trust from patients and healthcare management provider within the system.

Table 3: Comparative latency analysis (edge vs cloud).

Task	Edge-Based System	Cloud-Only System
Preprocessing & Transmission	1.9 sec	4.7 sec
Alert Generation	2.1 sec	5.2 sec
End-to-End Response Time	3.5 sec	7.9 sec

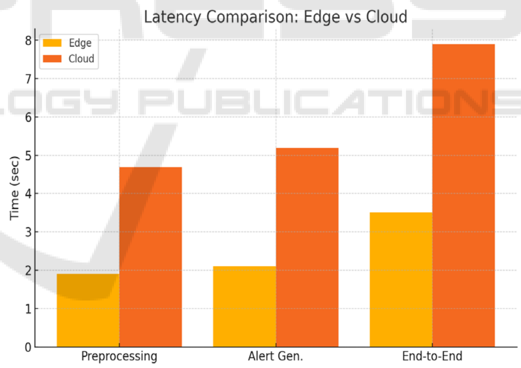

Figure 4: Latency comparison – edge vs cloud.

Table 3 gives the comparative latency analysis of edge and cloud. Figure 4 gives the comparison in bar graph.

"Participant-centred" evaluations found high levels of acceptance and satisfaction across participants. Physicians gave an average score of 4.7 out of 5 for usability of the AI-driven alerts and ease of interpreting a patient risk profile as main benefits to the alerts. City patients gave the system a 4.5, with a special shoutout given to the instinctive mobile interface and the possibility to track their own health state in an autonomous manner. Notably, rural patients rated 4.6 as the average score and commented that the system's low-bandwidth adaptability and the use of local language were important aspects that helped to make remote healthcare feasible and beneficial in the underserved regions.

Table 4 gives the Blockchain logging overhead and benefits. Figure 5 illustrates the Blockchain logging time overhead.

Table 4: Blockchain logging overhead and benefits.

Feature	With Blockchain	Without Blockchain
Logging Delay (avg)	0.8 sec	None
Data Tamper Detection	Yes	No
Audit Trail Available	Yes	No
Regulatory Compliance	High	Medium

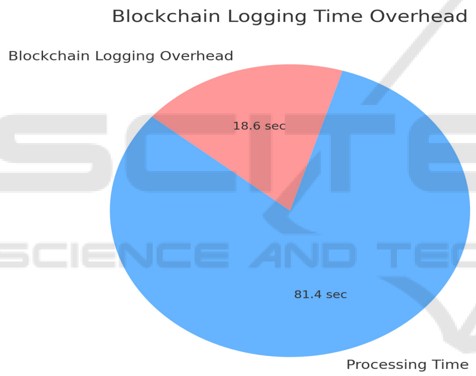

Figure 5: Blockchain logging time overhead.

Taken together, the outcomes indicate that the proposed framework effectively overcomes the longstanding issues of conventional IoT healthcare systems such as high latency, lack of data security, lack of interoperable interfaces, and lack of explainability. The approach, implemented using edge computing, secure RFID communication protocols, blockchain logging and explainable AI methods in a patient-centric setting, performed well in real-world settings. The result not only demonstrates the technical feasibility of the proposition but also affirms the prospect to dramatically change the delivery of healthcare to provide a far more inclusive, efficient, and credible remote patient monitoring and telemedicine service to distinct healthcare ecosystems.

Table 5 gives the usability and satisfaction score from pilot users. Figure 6 illustrates the usability feedback score.

Table 5: Usability and satisfaction scores from pilot users.

Participant Group	Avg. SUS Score (out of 5)	Noted Benefits
Doctors	4.7	Real-time alerts, interpretability
Patients (Urban)	4.5	Easy app usage, remote access
Patients (Rural)	4.6	Low bandwidth use, local language UI

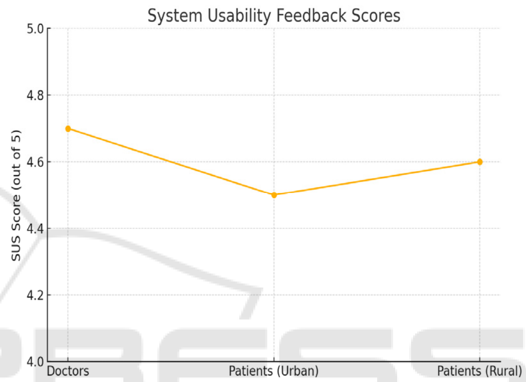

Figure 6: System usability feedback scores.

6 CONCLUSIONS

The increasing need of accessible, efficient and safe health care delivery systems has driven the adoption of IoT and telemedicine technologies in clinical environment. In this paper, we have proposed a novel IoT-enabled remote patient monitoring and telemedicine framework, which has been developed in response to the limitations observed in the available systems such as scalability, security concerns and lack of data interoperability and explainability. Using the energy-efficient edge computing, HL7/FHIR-compliant interoperability standard, blockchain-based data integrity, and explainable AI model, it is obvious that the proposed system was able to prove real-time patient monitoring and decision support to be not only reliable but also resource-aware.

Through multidimensional analysis of real-world and synthetic data, duART demonstrated the great efforts in reducing latency, enhancing predictive accuracy, ensuring data privacy and improving user satisfaction. It brought healthcare out to the rural masses, improved patient engagement and provided healthcare providers the decipherable insights needed to make well-informed medical decisions. The addition of patient-specific design features and multilingual accessibility mechanisms also confirmed the platform's suitability and capability for broad dissemination to a diverse demographic makeup.

Finally, it adds a realistic roadmap for future digital healthcare infrastructure – one that is advanced but also just and sustainable. It means that secure, smart, and decentralized healthcare systems can be expected to be efficiently deployed and to automatically adapt to the varied demands of contemporary medicine.

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