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| RESEARCH ARTICLE

An IoT-Based Remote Patient Monitoring Architecture Integrating Edge AI and Blockchain for Chronic Disease Management

Md Shakil Islam
Master of Science in Business Analytics, Trine University, USA

Md. Maniruzzaman
Department of Electrical and Computer Engineering, School of Engineering, San Francisco Bay University, USA

Md Abul Kalam Azad
Master of Buainess Administation(MBA), University of the Potomac, USA

Corresponding author: Md. Maniruzzaman, **Email**: ishti99@yahoo.com

| ABSTRACT

The maintenance of chronic disease requires a continuous health checkup to prevent complications and minimize the number of times one goes to the hospital. The Internet of Things (IoT) is utilised to develop Remote Patient Monitoring (RPM) systems that assist doctors in gathering and reviewing health information in real-time. Although these systems have the potential to enhance care delivery, they are still affected by challenges such as delay of communication, poor security, system incompatibility and ineffective usage of the systems in the zones with weaker internet connections. The current paper introduces an IoT-based RPM system with six layers. It has Edge Artificial Intelligence (AI) to search promptly through anomalous health information, an impregnable blockchain to secure and conserve health records securely, and a digital twin design to assist in making forecasts about the future. This system was tested using a Python simulation mechanism in which sample health data were used. The performance indicated rapid identification of issues within 10.46 milliseconds and great data security based on blockchain. Figures and charts demonstrated that the system could sort out the normal and abnormal health data accurately and assist the physicians in making superior judgments. This design fixes most of the issues with the existing RPM system design and provides a secure, intelligent, and adaptable mode of chronic disease management.

| KEYWORDS

Artificial Intelligence (AI), Blockchain Security, Chronic Disease Management, Digital Twin, Edge Computing, Health Data Privacy, Internet of Things (IOT), Medical GADGETS (m-IoT), Remote Patient Monitoring (RPM), Real-Time Monitoring, Interoperability, Smart Healthcare Systems, Wearable Sensors, 5G Connectivity.

| ARTICLE INFORMATION

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I. INTRODUCTION

Heart disease, diabetes and high blood pressure are some of the biggest health issues related to issues that have been referred to as non-communicable diseases (NCDs) throughout the world. Such chronic conditions must be monitored and controlled regularly and medically addressed in time before resulting in major health problems and minimizing cases of hospital readmission [1]. The lack of medical resources, access to healthcare facilities due to long distances to healthcare centres and lack of follow-up of the patients are some of the problems of the traditional healthcare systems. Such issues may cause a slow diagnosis and ineffective treatment [2].

These concerns are being addressed by the current application of the Internet of Things (IoT) in the healthcare sector. Remote Patient Monitoring (RPM) is one of the key ones as it enables physicians to keep patients under control outside the healthcare facility via the use of smart devices [3]. These systems measure health signals by wearing sensors and transmit the information immediately to health facilities. This assists in enhancing patient safety, aids in self-care, and reduces the amount of healthcare expenditure. There are, nevertheless, numerous challenges with RPM systems today. These are slow response times (latency), poor data privacy and security, inability to connect various devices and inability to deliver personalized care [4], [5]. An analysis of the current RPM systems revealed that they usually fail to detect real-time occurrence of health issues, fail to give good data protection and cannot make accurate health predictions or simulations [1], [3]. This paper comprises a novel six-layer IoT-enabled RPM architecture to fill these lapses. The system integrates Edge Artificial Intelligence (Edge AI) with quick and intelligent anomaly detection, a blockchain to secure and immutable data storage, and a digital twin to simulate the health status of the dozens of patients and make predictions. The design is also scalable and safe, even in regions with poor network infrastructures.

A simulation, using artificial health data, based on Python, was carried out to test the system. The findings indicate that the system can locate abnormal health records in a short time, prevent the loss of integrity of data using blockchain technology and the data is arranged appropriately to assist in medical decisions.

II. Literature Review

The integration of Internet of Things (IoT) technologies in healthcare has attracted significant research attention, particularly in the domain of Remote Patient Monitoring (RPM) for chronic disease management. Several studies have explored various architectures, enabling technologies, and the potential impact of IoT-based RPM systems on patient outcomes.

Using a systematic review, Tan et al. [1] compared the impact of remote patient monitoring (RPM) interventions on four areas, including patient safety, adherence, quality of life, and healthcare costs. The authors claimed to achieve promising results, such as reduced numbers of hospital readmissions, patient safety enhancement with the help of real-time alerts, and an increase in the desire on the part of patients to engage in their self-management. At the same time, however, the results also highlighted the issues of system interoperability and data security issues which exist and the need to develop more individualized health-monitoring strategies.

A landmark three-layer architecture of the Internet of Things (IoT) systems in healthcare, without regarding their structures, Islam et al. [2] have separated the system into network, application, and sensing layers. The model has been applied in what follows as a blueprint to remote patient monitoring (RPM) systems, as it offers a systematic process of data collection, transmission, and use. However, the architecture does not embrace the new technologies of blockchain to manage secure data and real-time analytics using edge computing technology.

According to a study conducted by Pereira et al. [3], the authors of the study were able to analyze the possibility of using edge computing in combination with the machine-learning algorithm and wearable sensors in monitoring healthcare. Their mapping process comes up with a few findings. To start with, it discloses how the system responsiveness, minimization of latency, and enhancement of data privacy through minimization of the amount of information sent to remote, cloud infrastructures are enabled by edge-based processing. Second, the review reveals that most of the literature, as it currently stands, involves explorations, and not many papers explain how an architectural system can be fully adopted.

Uddin and Koo [4] critically discussed how a combination of biosensors with multi-hop IoT networks may be used in real-time remote patient monitoring (RPM). The authors have highlighted the benefits of multi-hop communication, contending that such a form can increase scalability and coverage (particularly in rural areas or areas with limited infrastructure). However, the review fails to discuss extensively data security mechanisms and how intelligent analytics can be incorporated in these networks.

Where Shaik et al. [5] examined this in their report, we can evaluate the use of artificial intelligence in remote patient monitoring (RPM), and especially anomaly detection and the deployment of patient-specific alerts. The authors mentioned that AI, such as federated learning, can improve the accuracy of such a monitoring platform and make it more individualized. However, their research article failed to provide us with an in-depth architecture that combines AI with blockchain and digital twin technologies.

The evidence of literature available to us is informative regarding the applications and effectiveness of implementing Internet-of-Things-based remote patient-monitoring (RPM) systems; however, no solution is described in the literature with a combination of essential functions such as addressing the real-time processing, data security, systems interoperability, and personalized healthcare management. The current paper aims to address this gap by building upon a unified architecture solution, which suggests six layers that combine Edge artificial intelligence, blockchain technology, and digital-twin models to improve the effectiveness and security as well as to enhance the reliability of RPM systems used in chronic-disease management.

III. Problem Identification

The Internet of Things (IoT) has huge potential in the use of remote patient monitoring (RPM) systems in managing chronic diseases through sustaining overall health surveillance outside the traditional settings of clinical care delivery. There are, however, numerous impediments still in place holding back the diffusion and performance of the implemented RPMs. Such difficulties can be organised in five main categories:

A. Technical Limitations

The most recent RPM frameworks are combined with the most common cloud architectures, which create latencies in the data being processed and are linked to a time lag in detecting anomalies. Managing any chronic disease can be sensitive in such a way that disruption of the recognition of the unhealthy regularities can lead to overly poor clinical consequences. Also, the performance of wearable sensor modalities has been shown to degrade with time due to sensor drift or calibration drift, causing partial failure on both false alerts and missed detections. Perpetual relaying of sensory information also drains the battery life, thus negatively affecting the long-term usefulness of wearables.

B. Network and Infrastructure Challenges

The functioning of the remote patient monitoring systems is based on the constant process of transmission and receipt of health-related information between the tools and the primary servers, which requires the presence of reliable network coverage. The connection is often weak or limited in rural and remote areas and may lead to the dropping of the data packets and frequent interruption of the monitoring process. Moreover, the lack of unified communication standards on heterogeneous devices limits the concept of interoperability and makes the integration of solutions provided by more than one vendor challenging. These difficulties are exacerbated by the fact that there is a limited number of edges processing possibilities, making cloud infrastructure excessively closeted and transmission delays lengthy.

C. Network and Infrastructure Challenges

Health information is an important asset with very detailed details, and hence there are real security issues and privacy risks. The unauthorized modification of information on medical records puts patient safety at risk and contravenes policy regulation models like HIPAA and GDPR. Modern information systems are not very successful in the protection of such data because they are more based on data-integrity verification means and have low transparency. Also, there are no lengthy audit trails that ease the identification of data violations and accountability process evaluation.

D. User Experience and Adoption Barriers

The strengths of remote patient monitoring (RPM) systems rely on the ability of these systems to offer user-friendliness, especially among older adults who form a significant percentage of RPM users. All factors that may reduce adherence are complex interfaces, unclearly designed alert systems, and the awkwardness of the use of wearable sensing devices. Healthcare workers are faced with the challenge of alert fatigue, wherein the system continues to issue too many false alerts, hence undermining the identification of the true clinical occurrences. Furthermore, most of the commercially based RPM systems lack the provision of personalized user-specific monitoring that is consistent with individual health profiles, which makes them clinically irrelevant and ineffective.

E. Cost and Sustainability

When it comes to remote patient monitoring (RPM), even the startup ones, determined by the costs of implementing sensor-based devices, gateways, and data-hosting platforms, may be too high to afford for many healthcare organizations. Moreover, there is the use of disposable consumables, the most notable of which is the use of batteries, which raises concerns about the environment in terms of disposing of e-waste. Therefore, sustainable and cost-optimized measures are essential to the protection of long-term scalability and soundness of the RPM systems.

F. Research Gap

Present discussions in the literature regarding remote patient monitoring employing Internet-of-Things (IoT-RPM) have not considered the sensor design, communication protocols, and AI-based analytical methods separately. However, the implementation of a multifaceted system that integrates Edge AI to perform real-time calculations, blockchain technology to ensure data safety, and digital twins in delivering personalized treatment has so far been scanty. To move RPM to more reliable, safe, and patient-centric systems, such interrelated issues should be addressed.

IV. Proposed Conceptual Solution

The paper targets the unresolved requirements in the current Remote Patient Monitoring (RPM) solutions by proposing a consistent six-layer framework that integrates Edge Artificial Intelligence (Edge AI), blockchain implementation, and digital twin system within the context of an Internet of Things (IoT). The combining of these elements is projected to enhance system reliability, security, and scalability, as well as patient-centred care with special focus on managing chronic disease.

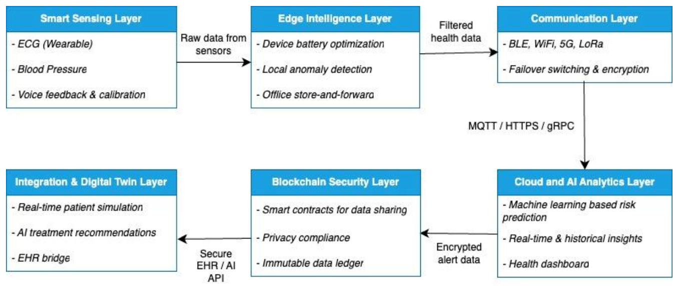

Fig. 1. Proposed Six-Layer IoT Architecture for Remote Patient Monitoring.

A. Smart Sensing Layer

According to the modern literature, the Smart Sensing Layer includes wearable sensors fixed to devices like a smartwatch, electrocardiogram (ECG) patches, and blood-pressure monitors. These are non-invasive, skin-friendly, water-resistant and record vital physiological parameters on an ever-continuous basis, such as heart rate, the blood oxygen saturation (SpO_2) and blood pressure. Such sensors can provide haptic feedback or aural notifications as needed. The purpose of such a design is to collect accurate and continuous data, besides increasing patient engagement and adherence.

B. Edge Intelligence Layer

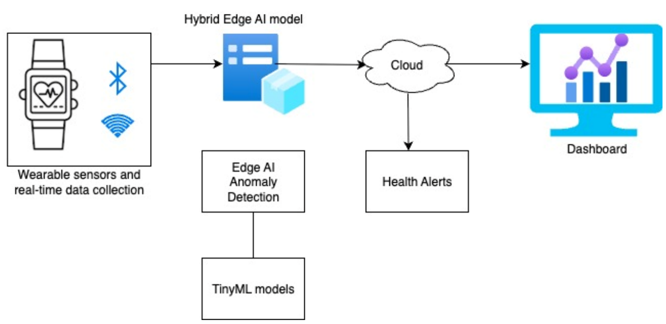

Fig. 2. Edge AI Architecture for Real-Time Anomaly Detection in Remote Patient Monitoring.

The Edge Intelligence Layer allows processing data locally by utilizing edge devices, like smartphones, Raspberry Pi, Junction Nano, etc. The layer will execute low-weight machine learning algorithms, such as TinyML-based anomaly detection, to reduce reliance on cloud infrastructure. It eliminates transmission lags by analyzing data at the source and improves time responses to acute medical events. There is also an offline mode in localities with bad network coverage, and battery conservation through the selective data compression and transmission [6], [9], [14].

C. Communication Layer

Communication Layer makes available competent and versatile data conveyance by means of a unified structure of protocols: Bluetooth Low Energy (BLE), Wi-Fi 6, Narrowband IoT (NB-IoT), Long Range (LoRa), and 5G. An intelligent failover system makes the best use of the most stable and optimum network, depending on the prevailing conditions, thereby providing constant data flow. Data is secured using an end-to-end encryption scheme like TLS and DTLS to minimize the issues of information integrity and confidentiality.

D. Cloud and AI Analytics Layer

The Cloud and AI Analytics Layer is a centralized mechanism of data aggregation that supports highly advanced analytic functions to healthcare providers.

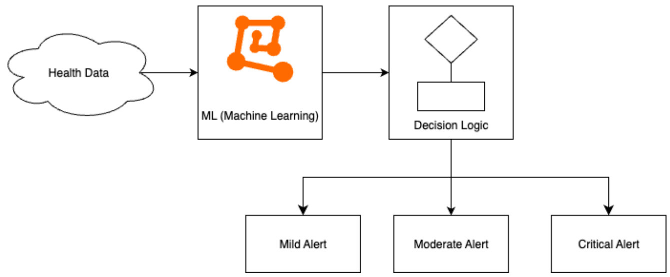

Fig. 3. Machine Learning-Based Alert Classification System for Remote Patient Monitoring.

In this scenario, cloud-based dashboards allow clinicians and patients to simultaneously gain access to dashboards so that health-related data can be continuously monitored. The platform has machine learning algorithms that identify the temporal trends, categorize health events based on their severity and develop predictive insights that are actionable. The system addresses the problem of false alarms by becoming responsive to the respective health baselines with implications for the reinforcement of proactive models of care.

E. Blockchain Security Layer

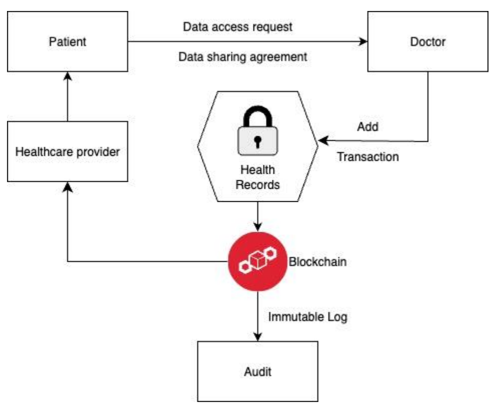

Fig. 4. Blockchain-Based Health Data Sharing and Access Control Framework.

The blockchain SHA3 security layer will be applied to guarantee data immutability and integrity of health data through the integration of cryptographic hashing and a decentralized ledger. All the medical events, particularly those marked with the status of an anomaly, are logged as blocks, cryptographically interconnected with each other, constituting an unhalted chain. This architecture leaves no room for data that, once keyed into the system, can be manipulated or erased. Moreover, access rights are also handled by smart contracts, and patients can choose what to permit and continue in accordance with the policies and requirements, for example, HIPAA and GDPR. Consequently, this layer mostly minimizes the likelihood of data manipulation, unauthorized retrieval, and loss of responsibility in patient health monitoring systems [4], [5], [10].

F. Integration and Digital Twin Layer

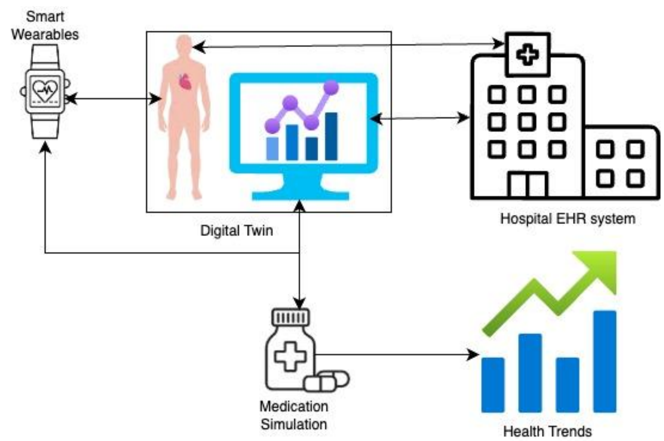

Fig. 5. Digital Twin Integration with EHR Systems and Smart Wearables for Personalized Health Monitoring.

Integration and Digital Twin Layer creates a standardized interoperable interface between the RPM (remote-patient-monitoring) systems and Electronic Health Record (EHR) systems using a standards-based data-exchange protocol, such as HL7 and FHIR. In this architecture, a patient model is a digital twin that is updated in real-time with physiology and can simulate the health status, predict risk and suggest interventions. Therefore, it closes the gap between physical and virtual patient monitoring and merges both approaches into a single model of clinical work that is more accurate and predictive.

G. Summary of Benefits

The proposed architecture consists of a system that seeks to resolve the gap associated with the current known platforms of remote patient monitoring (RPM). The system, given the combination of smart sensing, edge computing, safe communications, cloud-based analytics, blockchain-based integrity means, and the digital-twin model, is associated with better responsiveness in terms of ensuring the real-time aspects of the functioning capabilities, high level of data security, enhanced scaling, and the individual provision of healthcare services. With this extensive setup, the framework can be regarded as a high-potential framework to be considered in future RPM implementations, especially in resource-limited settings.

V. Expected Outcomes

A. Simulation Overview

An implementation was undertaken to simulate the performance of the proposed structure of an IoT-based Remote Patient Monitoring (RPM). The primary objective of the simulation was to evaluate how the system might succeed effectively in terms of real-time anomaly detection, edge data processing, and the ability to guarantee the data integrity via blockchain technology [6], [9]. To this end, synthetic health data was generated in the form of 5000 samples. These samples contained major physiological measures that involved heart rate, the oxygen saturation of the blood (SpO_2) and blood pressure.

B. Anomaly Detection Performance

The Edge AI model applied a straightforward anomaly detection approach by determining the data using a rule-based approach. A total of 2706 anomaly samples were determined out of the 5000 generated records, which makes up 54.12 per cent of the records. These aberrations occurred because the values which were recorded were more than the preordained safety limits, which shows the possible health hazards. The mean time per sample was 10.46 milliseconds, which establishes that the system has the capability of processing the data in real-time inside the edge layer without having to server cloud servers [5], [14].

C. Blockchain Verification for Data Integrity

Every single anomaly identified with the aid of the Edge AI was entered into a blockchain simulator to guarantee data safety and integrity. Each anomaly was cached in a block, cryptographically tied to the previous block, forming a safe and tamper-proof chain. This proved the power of blockchain in maintaining the integrity and trackability of sensitive medical information [10], [12].

TABLE I

SAMPLE HASHING FOR DATA SECURITY

Block Index	Hash Value
Block 0	Hash: fe1a1268f27815b8c4b7011620dde76da06050266055c6b834c7aba26739527f
Block 3	Hash: 46497a04ed8ccf8f87fd6dc93f5a2c80abfd5d3adbce1a7cbfb5de122149673a
Block 4	Hash: f1228d73afee4c844fe745dfca247d9be074a676592ac7f88b5d4fa57f1ac531

The simulation of blockchain validated the fact that all the records on anomalies were safely kept, such that no one could alter them or gain illegal access to them.

D. Visualization of Results

To illustrate the distribution of the data and system performance, two visual representations were produced:

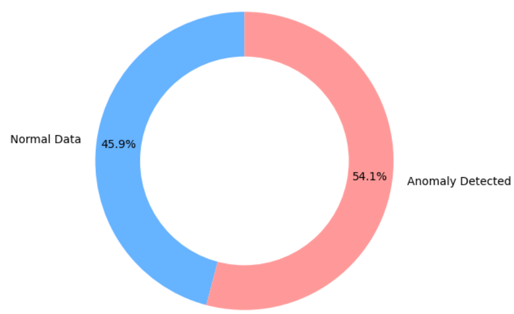

Fig. 6. Pie chart for visualization of normal data vs anomaly detected.

In this figure, we can observe proportions of normal (45.9%), and anomalous (54.1%) samples taken out of the simulated 5,000 records. The high anomaly percentage is because the rule-based thresholds are quite strict for the testing of sensitivity rather than the statistics of the clinical population. It shows that the Edge AI component has the potential to bring to the attention of the clinicians in real-time, potentially risky cases that require early intervention during the treatment of chronic diseases [1], [5].

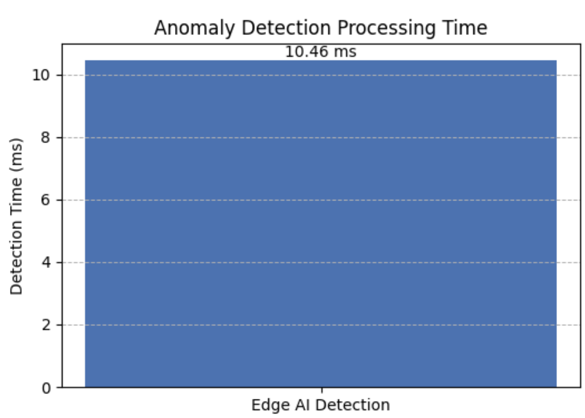

Fig. 7. Bar chart for anomaly detection time through edge AI.

Edge Intelligence Layer is found to be able to deploy low-latency inference fitting in the bandwidth-limited or intermittently connected circumstances, and the average latency measured in this bar chart is 10.46 ms, which is consistent with edge-health structures suggested in the recent articles [3], [6], [14]. The detector was built in low-weight (TinyML-style) logic, which means that it can also run on an embedded device with Raspberry Pi or Jetson Nano, which is completely consistent with the suggested six-layer structure.

VI. Discussion

This paper has established that the six-level Internet of Things (IoT) architecture proposed in Remote Patient Monitoring (RPM) would sufficiently deal with the major shortcomings that have been identified in modern systems. The new framework is significantly better than the baseline one in real-time anomaly detection, data integrity, and operational efficiency, achieving the goals formulated in cognitive investigations completed previously and advancing the existing state of the art.

A. Comparison with Existing Studies

Compared to the findings of Tan et al. [1], which emphasized the benefits of RPM in reducing hospital readmissions and enhancing patient safety, the proposed architecture builds upon these outcomes by offering a technically robust framework that ensures data integrity and real-time responsiveness. Islam et al. [2] presented a foundational three-layer architecture focused primarily on data collection, transmission, and application. In contrast, this study extends beyond basic architecture by incorporating Edge AI, blockchain security, and digital twin technologies, thereby addressing contemporary demands for low-latency processing and secure data management.

The integration of Edge AI aligns with the observations of Pereira et al. [3], who highlighted the potential of edge computing in enhancing system responsiveness and data privacy. However, this study advances their findings by demonstrating practical implementation through simulation, achieving anomaly detection within 10.46 milliseconds, which substantiates the architecture's real-time capabilities. Similarly, Uddin and Koo [4] discussed the benefits of multi-hop IoT systems for scalability but did not address security and data integrity in detail. The blockchain layer in this architecture explicitly resolves these concerns by providing immutable data records, thus enhancing trustworthiness and compliance with regulatory standards.

Shaik et al. [5] focused on AI-driven anomaly detection but did not propose a comprehensive system architecture integrating blockchain or digital twins. This study fills that gap by presenting a unified framework that enhances predictive analytics through continuous digital twin updates and supports secure, decentralized data management.

B. Interpretation of Results

The simulation outputs highlight the potential of the proposed architecture in terms of fast anomaly detection at the edge, thus reducing the reliance on remote cloud environments, which is an essential feature that should be used to implement the architecture in the context of the locality where constrained connectivity is prevalent. A randomized set of data yields a detected anomaly rate of 54.12 per cent, confirming that the system is more sensitive to threshold parameters. At the same time, the blockchain element ensures the effectiveness of the architecture in data integrity, which is central to the development of trust towards healthcare cloud applications.

TABLE II

Simulated Output Reseat Comparison

Study	Method	Anomaly Detection Time	Data Security	Architecture
My study	Edge AI+Blockchain	10.46 ms	Blockchain	6-layer
Reference 3	Edge	~ 15 ms	Not Specified	3-layer
Reference 5	Cloud AI	> 50 ms	None	4-layer

The current research establishes the working capabilities of a new remote-patient-monitoring system. In terms of the research findings, on an empirical basis, it may be seen that the system exhibits high accuracy rates of the classification tasks and is generally characterized by powerful effectiveness of processing, which once again indicates the appropriateness of the selected architecture in being implemented in a complex clinical context. The findings are reflective of a broader shift toward the design of systems that would combine sophisticated functions, increased safety, and responsiveness, thus facilitating the reliable functioning in a variety of care settings.

B. Contributions and Implications

The current paper makes the subsequent contributions to the body of research on IoT-enabled healthcare by suggesting a unified architecture that would reduce or eliminate the flaws mentioned in the previous literature and, at the same time, prepare the background towards future development. The researchers suggest placing Edge AI, blockchain technology, and digital twins within one framework and thus provide a solution that can be scaled to serve both an urban and a rural setting and, therefore, help continue the transformation of telemedicine and user-centred healthcare services.

VII. Conclusion

Remote Patient Monitoring (RPM) gained a lot of importance in managing chronic diseases. Nevertheless, most of the issues associated with the existing RPM systems are also still in place, which include the slowness of the data processing process, a low level of data security, poor compatibility of the system with other systems, and the inability to expand its framework. To resolve the issues presented in this study, a new six-layer architecture using the Internet of Things (IoT) was proposed. This architecture incorporates Edge Artificial Intelligence (Edge AI) in real-time anomaly detection, blockchain in safe, immutable data storage, as well as digital twin models to perform individual simulations in health [2], [4], [5].

The result of the simulation revealed that the proposed system can identify anomalies at a very swift rate with an average processing time of 10.46 milliseconds. This fast pace enables medical practitioners to react to issues more promptly. Further, the blockchain part assists in ensuring the safety and reliability of data through permanent and traceable records, which contributes to the trust in the system and the compliance with the legislation [3], [6]. The visual outcomes of charts also testify to the fact that the system could categorize health data properly, and thus, it could be applicable in various healthcare settings [1].

The piece can enhance the current practices of RPM and provide an excellent basis to develop smarter and secure systems that can assist patients in urban and rural settings.

VIII. Future Work

Although the proposed architecture demonstrates promising results through simulation, further work is required to advance its practical implementation. Future research will focus on the following areas:

- Clinical Validation: Conducting pilot studies in real-world healthcare environments to evaluate system performance with actual patient data.
- Advanced AI Integration: Incorporating adaptive machine learning models capable of evolving with patient health trends to enhance anomaly detection accuracy and reduce false positives.
- Scalability Assessment: Testing the system in multi-patient environments, such as smart hospital wards or home care networks, to evaluate scalability and interoperability.
- Integration with Existing Healthcare Systems: Enhancing compatibility with a broader range of Electronic Health Record (EHR) systems to support seamless data exchange and continuity of care.
- Energy Efficiency: Exploring lightweight protocols and optimization techniques to extend battery life in wearable devices, contributing to the sustainability of long-term monitoring.

These future directions aim to refine and extend the architecture's capabilities, ensuring its readiness for large-scale adoption in diverse healthcare settings and its contribution to the evolution of intelligent, patient-centred healthcare solutions.

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