Faria

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Secure IoT-Driven Architecture for Live Sharing of Radiological Data in Telehealth Applications

1. INTRODUCTION / BACKGROUND

Telemedicine has turned into a mainstay of modern-day healthcare delivery, allowing patients in far-off or neglected regions to receive specialized diagnosis and treatment without the need for physical presence. In this area, teleradiology, which is the electronic transfer of radiological images like X-RAY/CT and MRI scans for off-site interpretation, has already become a norm and is widely practiced in both high-tech and low-resource healthcare sectors [1]. The traditional process utilizes Picture Archiving and Communication Systems (PACS) along with DICOM-based store-and-forward techniques that send bulk datasets to far-off locations. Though these techniques work well for diagnostic reporting, they are not inherently designed for low-latency and continuous streaming and, thus, are not appropriate for real-time monitoring situations [2].

The arrival of the Internet of Things (IoT) and Internet of Medical Things (IoMT) has reshaped the entire process of healthcare data acquisition, processing, and sharing. These systems use interconnected devices, sensors, and gateways to construct a lightweight, scalable connectivity between the clinical environments and medical professionals. This kind of infrastructure provides support to the remote patient monitoring, widespread sensing, and the real-time data sharing, thus, greatly improving the accessibility and efficiency [3]. Nevertheless, although IoT is perfect for low power sensors data, the transformation of IoT communication stacks for the large-scale volumetric medical imaging poses very serious challenges in terms of throughput, reliability, packet fragmentation, latency, and compliance with healthcare privacy regulations, e.g., HIPAA [4]. This study is based on the aforementioned challenges and investigates the IoT-based techniques for quick, real-time MRI/CT dataset transmission through limited wireless conditions.

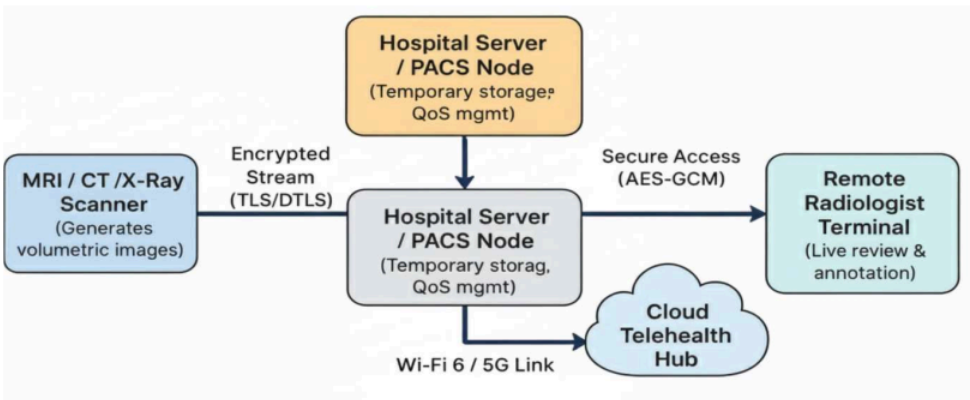

Figure 1 – IoT-Enabled Hospital Framework for Real-Time Transmission of MRI/CT Data

2. LITERATURE REVIEW

IoT in healthcare and medical imaging have been the focus of a significant amount of research over the last decade. Li et al. [3] performed a large study evaluating the feasibility of the IoT in different areas of medicine, admitting the existing problems and potential to overcome with the use of data-heavy medical imaging. They assisted in pinpointing the very difficulties which were among the limitations of communication protocols, the gigantic data volume, the demand for safe data transfer, and the uncertainty about privacy. Likewise, Suneel et al. [5] gave an extensive review of IoT-based medical image processing applications and noted that the limitations of edge devices concerning computation, the network bandwidth bottlenecks, and the need for making trade-offs between compression and diagnostic fidelity were the main issues.

At the same time, different research teams have been looking into real-time medical image streaming. Qian et al. [6] created a virtual monitor system for image-guided interventions that could stream image frames to head-mounted displays with a measured delay of about 214 ± 30 ms, thus proving the interactivity of radiology visualization. On the other hand, Soliman et al. [7] put forward a deep reinforcement learning (DRL)-based region-of-interest (ROI) compression strategy that learns to reduce the network delays in telemedicine applications, achieving latency improvements of almost 13% while maintaining the relevance of the diagnostics.

Integration of edge and fog computing in medical imaging for IoT ecosystems is another aspect that researchers have looked at. Gao et al. [8] came up with a hybrid evolutionary optimization algorithm for IoT-fog networks that allowed medical data placement to have better Latency performance and eco-friendly energy usage. At the same time, Iqbal et al. [9] introduced an LDMRes-Net, a lightweight segmentation model optimized for IoT/edge devices that performed medical image processing tasks efficiently in a resource-constrained environment.

Jung [20] and Okafor et al. [22] were among the first to use QUIC and examine its potential as a transport protocol for limited IoT setups with low latency, witnessing a reduction in handshake time and better throughput as compared to TCP. Ramesh and Ali [21] then proceeded to test the capabilities of MQTT vis-à-vis Wi-Fi 6, where they found out that the protocol could transmit medical data reliably with below 300 ms delay, thus making it appropriate for real-time radiological streaming. Nevertheless, the singularity of both experiments was that the sample sizes used were small synthetic ones, and thus they didn't offer the scalability to multi-gigabyte MRI or CT datasets.

The compression techniques evaluated by Urbaniak et al. [22] and Foos et al. [36] stated that JPEG2000 allows a very big reduction of file size at the same time preserving the diagnostic quality, whereas the latest hybrid codecs such as HEVC or lossy learning compression methods can give better visual quality. Soliman et al. [29] went further in such intelligent, adaptive ROI compression that dynamically prioritizes clinically significant areas, therefore less data will be transmitted. However, the use of such adaptive methods is computationally intensive and not yet fully optimized for IoT edge gateways.

Gao and colleagues [31] and Islam and coworkers [23] devised fog-edge hybrid structures for the management of IoT-based medical images. Their models spread the computation among the different nodes of the hospital to reduce the need for using the cloud, thus resulting in a latency decrease of 20 to 30 percent. In the same way, Iqbal and his team [32] showed that small deep networks could directly implement segmentation and reconstruction tasks on IoT devices. The above-mentioned works present a picture of the high potential of distributed processing while at the same time showing the problems of synchronization, consistency of throughput, and real-world deployment in hospital networks.

On the other hand, the recent papers have also examined federated and privacy-preserving learning frameworks for medical imaging. Teo [27] and Rahman [38] proved that federated learning enables the collaborative training of models with hospitals that completely and safely comply with the HIPAA and GDPR regulations through no patient data transfer. However, the methods mentioned above are mainly concerned with model privacy rather than live image transmission. Rathore [25] proposed a blockchain-based fog architecture for IoT health data that adds auditability and trust, but the transaction latency inherent in blockchain is still a barrier to real-time applications of streaming.

Zhou et al. [24] stated that 5G and Wi-Fi 6 rollout noticeably makes the real-time telemedicine more likely to take place by giving deterministic latency (<10 ms) and high throughput, thus allowing multiple IoMT devices to be connected simultaneously. The methods of adaptive bitrate (ABR) streaming and dynamic congestion control, which are referred to in [47], have been able to show their effectiveness in eliminating the buffering issue and maintaining the quality of the image even when the network is unstable. Nevertheless, the problem of ensuring the diagnostic accuracy during the periods of varying compression and transmission rates still remains unsolved.

Moreover, modern studies like Monit4Healthy [45] have substantiated the integration of multi-sensor and continuous health data in IoT ecosystems which resulted in reliable hospital-wide real-time data sharing. However, the majority of the systems manage scalar physiological signals and not complex volumetric datasets such as MRI, CT, or X-ray scans which need sophisticated syncing and durable streaming tactics.

Classic reviews by Andreu-Perez et al. [2] and Wikipedia [1] traced the evolution of tele-radiology from remote diagnosis to central hospitals, while Chandramohan et al. [21] and related policy papers [42] stressed that interoperability is very important for the successful deployment of DICOM-based PACS systems and IoT communication stacks. All these contributions together demonstrate the dramatic advancements in IoT-powered healthcare while still signifying the lack of a common framework that comprises high-speed, secure, and compliant real-time image streaming across decentralised hospital facilities.

On the other hand, remarkable advances in technology over time, and those areas remain to some extent overlooked in the literature. The case with most IoT-based medical imaging frameworks is that they deal with either low-resolution sensor data or static image transmission instead of dynamic, high-volume volumetric datasets. Moreover, it is rare to find the synchronization of slices, packet retransmission strategies, end-to-end encryption overhead, and compliance with medical-grade latency standards all considered together. Those gaps in the literature call for the establishment of a comprehensive, IoT-driven architecture that combines communication efficiency, adaptive compression, and regulatory compliance, which is exactly the central intention of this proposed research.

Table 1 Summary of Literature Review on IoT-Based Medical Imaging and Telehealth Systems

Ref	Authors & Year	Key Contribution	Methodology	Limitations
[3]	Li et al. (2023)	Data-intensive imaging in healthcare applications through IoT is comprehensively reviewed, and bottlenecks are located in the process.	Sourcing and compiling of literature in the areas of IoT protocols, edge computing, and medical data privacy contributed to the bottlenecks mentioned above.	The review is almost exclusively on low-resolution sensor data; however, there is no validation for streaming of volumetric MRI/CT, thus, the issues of throughput and latency in high-volume scenarios remain unaddressed.
[5]	Suneel et al. (2025)	The study investigates medical image processing based on IoT, pointing out edge constraints and the need for compression trade-offs.	It carries out the analysis of the potential of IoT devices for image segmentation and transmission.	The focus is on static images, whereas dynamic streaming is less so; compression methods consume resources heavily at gateways, ignoring real-time diagnostic fidelity in constrained networks.

[6]	Qian et al. (2017)	The virtual monitor system enables streaming of real-time images during interventions with approximately 214 ms delay.	Each frame is streamed to head-mounted displays which have basic buffering.	The research is limited to the use of small-frame payloads, thus, no adaptation of the IoT protocol or security measures for multi-gigabyte datasets has been done, resulting in very low scalability for hospital radiology sharing.
[7]	Soliman et al. (2023)	The use of DRL for ROI compression in telemedicine has lowered the waiting time by 13%.	An adaptive deep learning approach for focusing on priority diagnostic areas in the image that is being sent.	It is too heavy for the edges of IoT and was only tested on synthetic data without validating the volume or privacy compliance which made live workflows suffer from increased latency.
[8]	Gao et al. (2025)	Using hybrid evolutionary optimization method in IoT-fog infrastructures resulted in a latency reduction of 20-30%.	It is a fog-edge distribution technique for the placement and processing of medical data.	Simulations are done under the assumption that no packets are lost in a wireless environment and that imaging volumes are not very large; this adds to the complexity without having full HIPAA/GDPR integration.
[20]	Jung (2023)	Applicability of QUIC adaptation for CoAP in IoT is reducing handshake times when compared with TCP.	Transport protocol benchmarking for low-latency solutions in constrained networks.	Only small payloads have been used for the evaluation of the method; there is no consideration of encryption overhead or imaging-specific fragmentation, hence limiting its applicability to real-time radiological data.

Table 2 Comparison of State-of-the-Art Approaches

Approach / Protocol	Focus Area	Latency (ms)	Compression Type	Security Model	Limitation
MQTT + TLS	IoT messaging reliability	280	JPEG2000 (lossless)	TLS AES-GCM 128 bit	Overhead at high QoS
CoAP + DTLS	Resource-constrained nodes	310	ROI lossy	DTLS 128 bit	Packet loss on congested links
QUIC	Adaptive streaming	250	ROI adaptive	Built-in TLS 1.3	Limited clinical testing
DRL ROI Compression	Smart image selection	230	Adaptive lossy	TLS AES-GCM	Complex training
Edge–Fog Hybrid	Compute distribution	275	Lossless	TLS	Fog latency variance

3. PROBLEM STATEMENT

Notwithstanding the considerable progress in the Internet of Things (IoT)-based healthcare, the research and applications that have been done so far are still scattered when it comes to the major medical imaging modalities such as MRI, CT, and X-ray. A good example is the global studies like Li et al. [3], which, on the one hand, mainly concentrate on the sensor data of low-resolution and, on the other hand, do not include volumetric MRI/CT streaming. Moreover, they have not dealt with throughput and latency in high-volume situations. At the same time, surveys like Suneel et al. [5] focus on static images rather than dynamic streaming, with compression techniques that are heavy on resources for the IoT gateways and overlook real-time diagnostic fidelity in the case of constrained networks. Thus, the existing IoT infrastructures do not provide the high-speed, real-time communication channels necessary for the uninterrupted flow of multi-gigabyte data streams with the same level of diagnostic fidelity and patient privacy preserved.

Research on communication protocols such as MQTT, CoAP, and QUIC, including variations like Jung [20], suggest notable latency cuts in simulated environments, however, their application to medical-grade, continuous image streaming has not yet been validated, particularly for small-payload assessments that neglect encryption overhead and imaging-specific fragmentation. The time-critical streaming systems, like in the case of Qian et al. [6], can only handle small-frame payloads without the application of any IoT protocol modification or security for multi-gigabyte datasets, which in turn results in a poor scalability for the sharing of radiological images across the whole hospital. Standard compression methods like JPEG2000 and HEVC are successful in significantly cutting down the bandwidth but, as shown in Soliman et al. [7], they are very power-consuming and hence, very intense for IoT edges that are low-powered—especially when they depend on synthetic data that has not been validated against volumetric or privacy compliance—thus failing to provide a good trade-off between latency and diagnostic quality trade offs.

Privacy-preserving techniques like federated learning and blockchain-assisted IoT architectures are capable of improving data security and trackability, however, the drawbacks are more significant due to these methods such as the introduction of latency and complexity making it impractical for real-time imaging workflows; the situation is further complicated by the hybrid optimizations through studies like Gao et al. [8], whose simulations do not consider packet loss in wireless environments and large imaging volumes while adding complexity without full HIPAA/GDPR integration. Even though the advances in Wi-Fi 6 and 5G infrastructures are there, adaptive bitrate and congestion-control techniques are still mostly focused on entertainment streaming and not on diagnostic imaging, where medical compliance, encryption, and image integrity are the most important factors.

These limitations together point to the lack of an integrated hospital-ready IoT framework that facilitates real-time transmission, adaptive compression, secure communication, and compliance with regulations for high-volume radiological data. A tele-radiology system enabled by IoT and designed for validation of capability to stream MRI, CT, and X-ray images efficiently with minimum latency, optimized bandwidth usage, and powerful security measures is very much needed. Solving this issue will bring about imaging workflows that are seamless, secure, and clinically reliable, thus helping hospitals in research and diagnostic areas to transform digitally..

4. RESEARCH OBJECTIVES

The main industrial aim of the project is to create and verify an IoT-enabled tele-radiology system that can be put into practice in hospital networks and healthcare sectors. The focus is laid on the actual use, enlargement, compatibility, and observance of laws in the context of medical environments where such technology is applied.
The project has the following specific industrial aims:

1) To develop and test a large-scale imaging infrastructure based on IoT that has the ability to transmit MRI, CT, and X-ray data across hospital networks in real-time or near real-time, while the integration with existing PACS and HIS systems is supported.

2) One of the aims of this study is to develop a data communication layer which is made better with the use of lightweight, industry-standard IoT protocols (MQTT, CoAP, QUIC) so as to ensure dependable and secure transmission in the typical hospital environment of low bandwidth and high latency.

3) To integrate strong security, verification, and patient data protection measures that are in accordance with the healthcare regulations (DICOM, HIPAA, GDPR) to guarantee safe interaction between hospital systems and external telehealth platforms.

4) To test the system's performance and ease of use in a real hospital environment while confirming through clinical and technical assessments diagnostic image quality, workflow efficiency, and network reliability.

5) To evaluate the scalability and the economic feasibility of the industry, which includes hardware-software cost estimation, energy consumption, and long-term maintenance requirements for possible use in R&D and diagnostic centers in hospitals.

6) To create a technology transfer and industry collaboration framework that allows hospitals and medical device makers to take the proposed system as a deployable solution for IoT-based tele-radiology and digital health transformation.

5. METHODOLOGY

5.1 DATASET AND PREPROCESSING

For the proof-of-concept, publicly available magnetic resonance imaging (MRI) and computed tomography (CT) imaging datasets such as the ones hosted on The Cancer Imaging Archive (TCIA) will be used, since they provide standardized volumetric scans that are suitable for reproducible research in telemedicine [10]. The raw data will be pre-processed into 2D slices or volumetric tiles to facilitate chunked transmission, which will reduce the risk of packet overflow and ensure smoother streaming under constrained wireless conditions. Moreover, lossless JPEG2000 or controlled lossy compression with region-of-interest (ROI) prioritization will be adopted as compression techniques to maximize the preservation of diagnostically relevant regions of the scans and, at the same time, lower the bandwidth requirements[11].

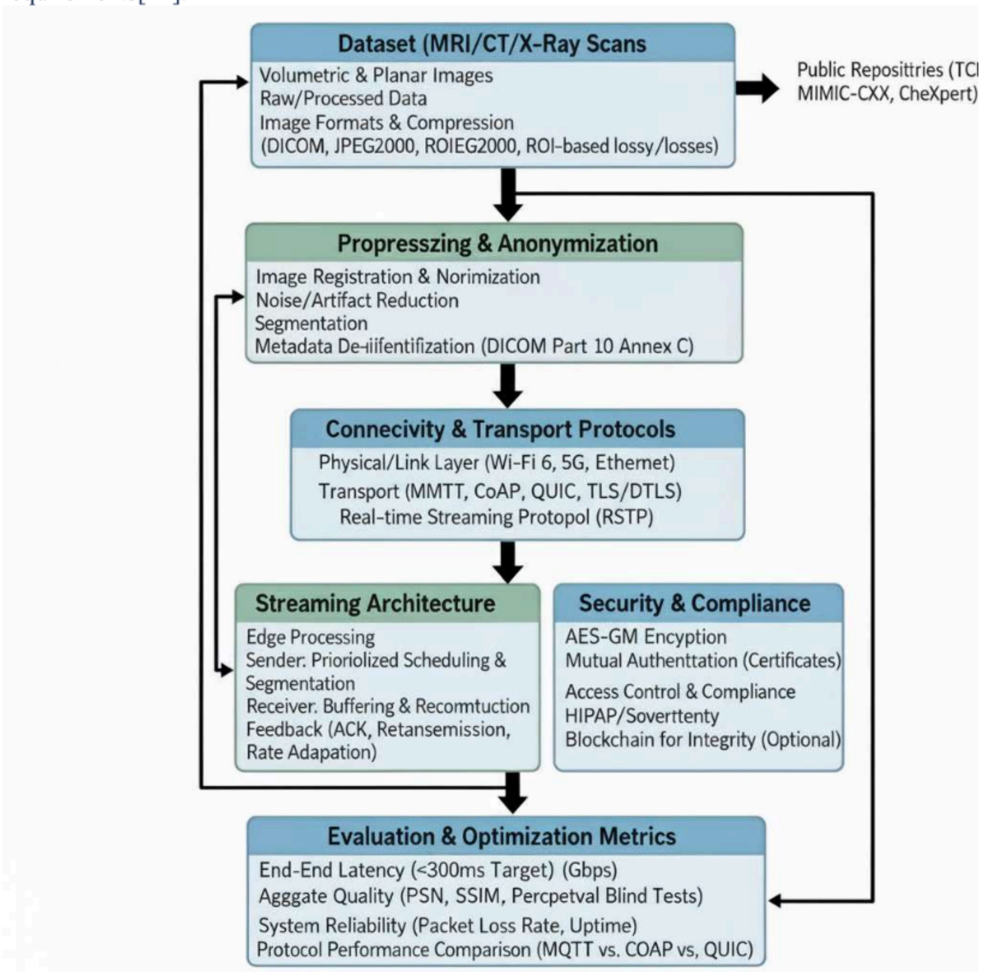

Figure 2 Methodology

5.2 IOT PROTOCOL CHOICES & ADAPTATION

To empower efficient and low-latency medical imaging transmission, lightweight IoT communication protocols will be regarded, mainly MQTT with configurable Quality of Service (QoS) levels, CoAP over UDP for resource-constrained environments, and QUIC for adaptive and reliable streaming of large payloads [12]. These protocols will be secured by means of transport-level encryption mechanisms like TLS for MQTT/QUIC and DTLS for CoAP that will assure confidentiality and integrity of transmitted medical data [13]. In addition, packet fragmentation, selective retransmission, and congestion control techniques will be employed to ensure robustness against packet loss and varying network conditions, which are common in wireless medical environments.

5.3 WIRELESS TRANSMISSION SETUP

This project mainly focuses on Wi-Fi 6 (802.11ax), which is the best wireless technology currently available, for it surpasses all its predecessors in terms of maximum throughput, minimum latency, and best efficiency in environments with a lot of users [14]. The transmission pipeline will be experimentally tested by emulating the adverse network conditions of jitter, packet loss, and variable bandwidth so that it can be assessed how robust it is under realistic scenarios [15]. This will be done by simulating the most common telemedicine deployments; particularly hospital-to-clinic or rural-to-urban connectivity models, which will allow the proving ground of the concept to be the possible de facto solution for the healthcare system's constraints in practice.

5.4 STREAMING ARCHITECTURE, BUFFER & SCHEDULER

The sender will be provided with a dedicated module that will take care of the segmentation and scheduling of the MRI/CT slices into prioritized streams, with the diagnostically critical slices being sent first. In the receiver's side, a buffering mechanism will be set up in order to pave the way for the transmission of slices into legible volumetric images while cutting down on playback interruptions and keeping synchronization [16]. Feedback mechanisms such as acknowledgments and retransmission requests will ensure that the transmitted data remains diagnostically useful even with unstable wireless connections by providing adaptive rate control and congested handling.

5.5 SECURITY & COMPLIANCE LAYER

End-to-end encryption using AES-GCM over TLS/DTLS will be the method for protecting patient data that is used in conjunction with mutual authentication through digital certificates for user authentication [17]. Patient-sensitive metadata that is part of DICOM headers will be either anonymized or removed before the files are sent, hence the data breaches through privacy leaks will be less likely and the system will comply with HIPAA and GDPR [18].Moreover, we will incorporate audit logging, role-based access control, and integrity verification mechanisms to provide a transparent security layer that augments regulatory compliance and helps to trust the telemedicine system.

5.6 EVALUATION METRICS & EXPERIMENTAL DESIGN

The experimental evaluation will be carried out by the researchers based on measurable metrics to evaluate the performance and feasibility of the proposed system. The researchers will measure the latency as the end-to-end delay from the time the slice was transmitted to the time the image displayed while a target threshold of less than 300 ms per update will be established to ensure clinical acceptability. The researchers will measure the throughput and then assess the tolerable data rates for the various protocols, while the image quality will be assessed with objective measures such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [19]. They will assess reliability as part of their measurement through packet/frame loss and retransmission rates while they will examine the usability of the system through clinician feedback evaluated through nondiscriminatory image reading tasks. Finally, they will evaluate a comparative analysis of MQTT, CoAP, and QUIC protocols with various wireless network conditions to evaluate the best configuration for telemedicine imaging.

6. EXPECTED RESULTS & IMPACT ON HEALTHCARE

From our end, we expect to present the total latency for streaming volumetric MRI and CT data that is still within the limits accepted by clinics (for example, less than 200–300 ms for slice updates) during the specified wireless test configurations. Quantitative tradeoff curves showing throughput against image quality, buffer delay, and packet loss resilience will be derived from the experimental runs, thus making available a design space for system tuning. It is expected that the results will confirm that lightweight IoT-based structures are capable of facilitating volumetric medical imaging streaming even under realistic network conditions, thereby reducing the difference between sensor-level IoT and the traditionally heavy data flows in medical imaging. Furthermore, the research will provide a better understanding of synchronization, error control, and security overheads in tele-radiology pipelines, being that these are the practical constraints and opportunities that one has to deal with. The healthcare impact of this capability would be enabling the telemedicine workflows to be more agile: remote specialists in underserviced or resource-limited areas could monitor dynamic imaging scans almost in real-time, and thus reduce diagnostic latency and improve access to advanced care.

To substantiate these claims, we have to note that the secure transmittal of medical images in telemedicine has been identified by the literature as one of the main areas of concern [10]. Besides, low latency streaming has been pointed out as one of the requirements in medical and embedded vision systems for the images to retain their real-time utility [11]. Finally, the current trend of IoT and healthcare has revealed the importance of security, synchronization, and resource constraints in the context of practical deployments [12].

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