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RESEARCH ARTICLE

From Technical Prerequisites to Improved Care: Distributed Edge AI for Tomographic Imaging

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ABSTRACT Recent years have seen a surge in AI-driven medical image processing, leading to significant improvements in diagnostic performance. However, medical imaging technologies tend to create staggering volumes of medical data, necessitating high-performance computing. Cloud systems with robust GPUs and resource capacity are optimal choices for DL-based medical image processing. However, transferring data to the cloud for processing strains communication links, introduces high communication latency, and raises privacy and security concerns. Consequently, despite the undisputed benefits of cloud computing, dedicated standalone local computers are still used for image reconstruction in today's systems. This localized strategy uses expensive hardware inefficiently and falls short of scalability and maintainability. Edge computing emerges as an innovative concept by bringing cloud processing capabilities closer to data sources. A continuum of computing including local, edge, and cloud tiers would offer a promising solution for medical image processing. According to literature survey, there are no significant works on utilizing edge cloud continuum for CBCT imaging. To fill this gap, we introduce novel 3-TECC architectural concept, specifically designed for CBCT data reconstruction in medical imaging. This article explores the evolving synergy among medical imaging, distributed AI, containerized solutions, and edge-cloud continuum technologies, highlighting their clinical implications and illuminating the potential for transformative patient care. We uncover challenges and opportunities this convergence provides with the CBCT image reconstruction use case, while aligning with regulatory compliance. The proposed 3-TECC architecture advocates a decentralized data processing paradigm, reducing reliance on the centralized approach and emphasizing the role of local-edge computing.

INDEX TERMS CBCT, distributed AI, edge computing, edge cloud continuum, GDPR, medical imaging.

I. INTRODUCTION

Enhancing the medical imaging workflow is crucial as it plays a significant role in modern medicine's capacity for diagnosis and treatment of diseases [1]. Effective medical diagnostics requires the utilization of medical imaging techniques in a wide range of medical scenarios that involve various technologies such as Computed Tomography (CT), Cone-Beam Computed Tomography (CBCT), ultrasonography (US), X-ray, mammography, Magnetic Resonance Imaging (MRI), and nuclear medicine. Diagnostic imaging techniques are critical to confirm, evaluate, and record the progression of various diseases and improve treatment efficacy. Advanced medical imaging techniques produce more data volumes than ever to provide high-resolution images and better image quality [2]. CBCT imaging plays an important role

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in medical fields, e.g. dental imaging, as it is extensively utilized to visualize anatomical details, aiding in diagnosing and treating various conditions [3]. Nevertheless, the vast volume of data produced by CBCT scanners and the complexity of reconstructing 3D images present considerable implementation challenges. Hence, addressing key aspects and critical perspectives is essential when considering CBCT image reconstruction on distributed systems such as the three-tier edge-cloud continuum (3-TECC) architecture. The proposed computing architecture serves the medical imaging CBCT use case in health care, emphasizing the importance of current diagnostic radiology and DL-based CBCT image reconstruction processing [4]. The proposed edge-cloud computing architecture lowers the latency of transmitting and processing medical imaging reconstruction. Managing the large volume of CBCT-generated data poses a significant challenge for developing efficient and effective medical imaging-aided diagnostics. Currently, no existing studies address the distinct challenges associated with this specific use case in distributed computing. The other side of the coin is that the key legislation based on the highest European values has stringent regulation implications on the business and innovation processes, namely the European General Data Protection Regulation (GDPR) and Medical Device Regulation (MDR). First, GDPR compliance is a prerequisite for MDR compliance. Second, both regulations drive compliance and trust across the healthcare value chain for patient privacy and the security of medical devices. Furthermore, the EU Artificial Intelligence Act (AIA) was published in April 2024 to address ethical questions and harmonize implementation challenges among AI applications in healthcare [5], [6].

A. OBJECTIVES OF THIS PAPER

In the following subsections, we discuss our proposed medical imaging use case, highlighting the increasing importance of DL-based image analysis and computer-aided diagnosis in modern diagnostic radiology. A particular focus will be given for the application of DL for CT and CBCT as these modalities often produce largest image matrices, and thus are often the most computationally demanding use-cases. We then provide an overview of cloud computing and its benefits along with the challenges it poses for medical imaging. In the edge computing section, we detail the role and advantages of edge computing in addressing the challenges of cloud computing, focusing specifically on the medical imaging use case. We also explore the importance of distributed computing, based on edge-cloud integration, for digital healthcare applications. In this part of the paper, we highlight the operational gaps in solutions that rely solely on cloud or localized strategies. We propose a collaborative computing architecture for CBCT medical imaging, that primarily leverages local edge computing resources while utilizing cloud computing solutions as needed.

B. RADIOLOGICAL IMAGING ALGORITHMS

The Internet of Medical Things (IoMT) encompasses sensors, actuators, processing capabilities, and communication features, enabling interaction with the outside world through various communication protocols [7]. Radiological medical imaging techniques generate image data that need to be processed to extract useful information for diagnostic purposes. Based on classical Machine Learning (ML) and Deep Learning (DL), image processing algorithms are increasingly used in computer-aided diagnostics. These methods help physicians analyze vast amounts of medical imaging data by providing inferences from images [8]. Since the last decade, DL-based convolutional neural networks (CNNs) have obtained state-of-the-art performances for image classification and recognition in the field of computer vision [9], [10], [11], including disease diagnosis and classification in radiology imaging data [12], [13], [14]. Overall, using DL algorithms for medical image processing is computationally expensive, and, in general, requires high-performance hardware systems when the neural network size increases [15]. Furthermore, to obtain better performances from the DL algorithms, utilizing images in better quality and high resolution has a constructive impact on the overall AI model's performance [16].

CT imaging is one of the most widely used sensor modalities for diagnostic imaging in the radiology department of medical facilities. In a typical today's CT (including CBCT) imaging scenario, the raw data generated by a medical imaging device is processed or reconstructed locally on a standalone PC to produce diagnostic images, which are subsequently sent to the Picture Archiving and Communication System (PACS) and cloud data centers for data analysis and diagnostics [17].

C. CLOUD COMPUTING

Cloud computing provides global access to the services and rich resources for these services in terms of being a scalable infrastructure for massive data, hosting computationally heavy AI algorithms, and needed computational capabilities. The cloud-based operation provides a pay-as-you-go strategy, eliminating the requirement for massive initial costs on hardware and its maintenance on site and the required facilities. Cloud-based operation enables healthcare service providers to control expenditures more efficiently, especially concerning IT infrastructure [18]. In the healthcare domain, a cloud-based operation can also help simplify different hospital activities, such as administrative work and patient monitoring. Since cloud data centers have high computational capability, they are an optimal choice to host large DL models, e.g. medical imaging [19].

However, when considering medical image reconstruction, local processing is more optimal from the viewpoint of network resource efficiency, since transferring raw data to the cloud would inflict a high burden on the network links between the data source(s) and the processing unit(s) [20].

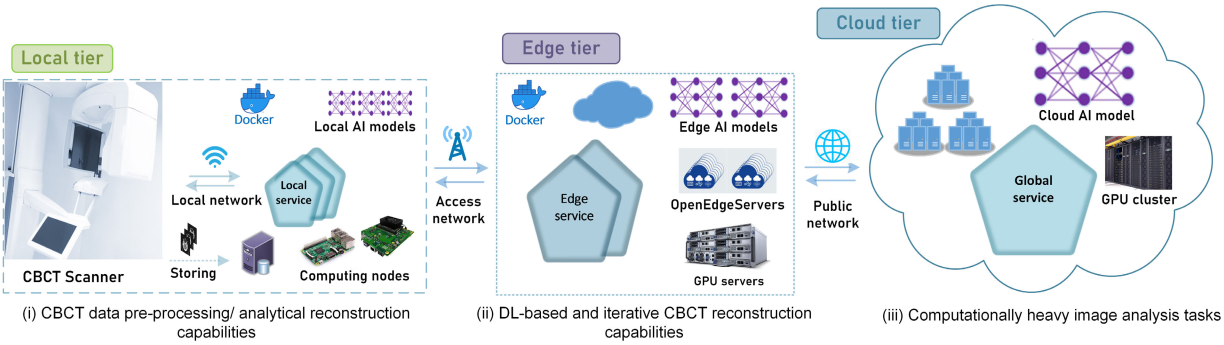

FIGURE 1. **3-TECC architecture for medical imaging and CBCT image reconstruction. The figure introduces tiers in the three-tier computing architecture: (i) CBCT scanner and its interaction with a cluster of IoMT nodes; (ii) edge tier connected via Access network, where more powerful algorithms can take place for CBCT reconstruction and DL-based approaches; (iii) cloud tier which is accessible through the Public network, capable of hosting computationally demanding tasks.**

Furthermore, relying on cloud computing service providers can pose risks, particularly in instances of service interruptions or communication, also, e.g., European facilities may want to limit the transfer of data to the cloud located in different continents. Downtime can cause disturbances in access to essential medical data, possibly compromising the treatment of patients and medical facilities [21], [22], [23]. Accessing cloud-based resources can be challenging in areas with poor network connectivity, limiting the benefits of cloud computing for medical professionals and patients in these regions [24], [25], [26].

D. EDGE COMPUTING

Edge computing (EC) has been introduced to bring cloud computing capabilities close to the end devices and data sources [27]. EC has many advantages compared to traditional cloud systems, particularly in terms of providing a high Quality of Service (QoS) and low latency. It also helps to reduce network burden in cases of data-intensive IoMT use, such as CT imaging, as well as unnecessary propagation of medical data outside of the local site [28]. EC can help ensure medical data's privacy by keeping data within hospital premises [29], [30]. Furthermore, in the case of mobile imaging scenarios with potentially low uplink capacity to data centers, the reliability and failure tolerance of the EC approach is much higher. In general, the continuum of edge and cloud computing is a promising approach to CBCT image reconstruction, as it provides the benefits of cloud computing while allowing local processing as needed to improve resource efficiency, privacy and reliability [27], [31]. Medical imaging is among the domains in healthcare that leverage EC to meet the challenges as mentioned earlier when processing medical data inside and outside of hospitals. The use cases of digital healthcare using distributed 3-TECC have been discussed in [32], where the authors focus on the deployment of virtualized docker-based dynamic services in distributed edge-cloud computing systems. Research articles in [32], [33], and [34], summarize the challenges of future digital healthcare and discuss local and edge-based service architecture in addition to cloud-based solutions to improve the efficiency and effectiveness of future smart hospitals by leveraging the role of novel Internet of Things (IoT), edge-cloud computing, virtualization, and wireless communication technologies.

Some examples of recent work including medical imaging, CBCT, GPU-based computing, edge computing, and DL-based approaches, within the main focus of these studies are presented in Table 1. The toolboxes Astra [35] and TIGRE [36] both provide strong solutions for CBCT image reconstruction, whereas Astra is more flexible and supports a wider range of algorithms. At the same time, TIGRE offers high-caliber specialized solutions that are optimized for CBCT. The choice between these toolboxes depends on the specific needs, including the coding environment, flexibility, and CBCT image quality. The study described in [37] leverages cloud computing and GPU acceleration [38], which offers high speed and high accuracy for efficient clinical workflows in medical imaging modalities. Rieke et al. [29], provide the crucial role of the FL distributed learning approach in digital healthcare. A detailed dental imaging and CBCT review are given in [3]. The open-source framework, PriMIA (privacy-preserving medical image analysis) framework, described in [39], enables encrypted inference and secure federated learning on medical data without transferring it. The framework offers robust privacy safeguards against data reconstruction attacks and achieves classification performance comparable to locally trained models. Although the DL technique has proven effective for reconstructing CT, its application to CBCT reconstruction is hindered by memory constraints due to the complexity of the 3D reconstruction process from large volumetric datasets. The authors in [40] introduce a geometry-guided DL technique (GDL) that requires less than previous networks, while also reconstructing CBCT images quickly and accurately. Another application of the DL technique, Generative Adversarial Networks (GAN) was used in [41] to improve the image quality of the reconstructed CBCT images. Reducing patient radiation exposure, minimizing costs, and increasing accessibility is crucial in CT and CBCT modalities. The study in [42] presents various solutions for obtaining 3D anatomical structures from X-ray images.

E. CONTRIBUTIONS OF THIS PAPER

This paper presents a taxonomy for understanding the technological needs of radiological medical image processing when considering the use of the distributed 3-TECC architecture, emphasizing the CBCT imaging modality. We discuss the technical requirements for CBCT image reconstruction, considering the large volumes of data from medical imaging scanners and the need for efficient processing. This involves exploring the diverse computing capabilities of the 3-TECC architecture. To achieve this, we introduce state-of-the-art technologies, such as advanced communication and computational systems, containerized solutions, and distributed ML approaches for AI-driven applications. Additionally, we cover the structure of CBCT imaging, from raw data to diagnostic formats, and address data regulation aspects, including GDPR and MDR compliance.

Our taxonomy provides an organized framework for classifying the various technical aspects of distributed platforms. The main contributions of this paper are as follows.

- Defining the technical requirements of the 3-TECC architecture, in general for medical imaging, and specifically for the CBCT imaging modality. We provide potential state-of-the-art solutions from literature to address the requirements for architecture to achieve efficient tomographic imaging and CBCT.
- Identifying the characteristics of each tier in the 3-TECC architecture and emphasizing their role in the CBCT imaging workflow, considering the management and regulatory aspects of confidential patient data.
- Bringing together scientists and physicians from both engineering and medical fields, integrating multidisciplinary efforts to tackle challenges in imaging technology, thereby aiming to achieve efficient healthcare systems.

This paper examines the latest trends in academic literature related to data-intensive medical imaging and CBCT image reconstruction using distributed computing architectures. It identifies several technical requirements that need to be addressed to enhance the efficiency of healthcare systems. The data collection involved searching online literature using edge computing and distributed learning for medical imaging as well as, on IoMT, edge computing, medical imaging and CBCT image reconstruction, and distributed learning approaches from Google Scholar, PUBMED, Science Direct, and the IEEE Library. We prioritize including research papers published in recent years.

In the following section, we discuss the computing tiers of the 3-TECC architecture in detail, including the local, edge, and cloud tiers. We cover the role of each tier and its capabilities in hosting the CBCT imaging use case. Section III outlines the main phases of the CBCT medical imaging workflow, including data collection, communication, computation, and data storage. In this section, we explain the workflow of CBCT data from the CBCT scanner through the steps required to obtain diagnostic reformats and prints, encompassing both medical imaging data and raw data. Section IV presents our defined technical requirements to enable efficient CBCT image reconstruction within the proposed computing architecture, providing a detailed overview of each requirement such as efficient medical data management, deployment of AI algorithms and functional services, and optimized CBCT image reconstruction alongside privacy and regulatory aspects. The discussion and future scope of the paper are covered in Section V, where we also address identified challenges, limitations of our study, and outline the future work. Finally, Section VI summarizes the main points and concludes the article.

II. 3-TECC ARCHITECTURE FOR CBCT MEDICAL IMAGING

The distributed 3-TECC architecture for CBCT, as illustrated in Fig. 1, includes (i) local edge nodes in the proximity of the medical equipment/CBCT scanner, capable of running lightweight computational tasks, (ii) edge servers placed in, e.g., hospital facilities or at the nearest mobile base stations for heavier computing tasks with real-time requirements, and (iii) cloud data centers available through the Internet for heavy-duty computing tasks. Furthermore, using radiofrequency technologies and different communication protocols is important for efficient intra-device and inter-tier communication in 3-TECC, particularly in managing the massive volumes of medical imaging data. The communication section in III-B provides a more detailed overview of communication techniques. Brief details of each of the tiers in 3-TECC are described below.

A. LOCAL TIER

In CBCT imaging workflow, data pre-processing and compression are the first and, at the same time, the computationally least-demanding operations. By default, in the 3-TECC architecture, these operations are run on a swarm of local edge nodes for data reduction [34]. More complex operations requiring higher computational capacity, such as AI-based CBCT image reconstruction and image analysis are left to be executed on higher tiers, the exact tier depending on which gives better end-to-end execution time considering the available capacity and load. Optionally, also lightweight reconstruction algorithms giving rough images for the physicist, e.g. assessing the patient's correct position in the scanner, could be run on the local tier.

Physically, the local edge node swarm could consist of specialized lightweight GPU computing nodes, available PCs, etc., but it could also include the GPU units of the CBCT scanners or similar integrated computational units. The benefits of this kind of swarm include resource efficiency (one swarm can serve multiple CT scanners, bringing economies of scale) and scalability (the swarm's capacity can be modified straightforwardly by adding or removing computational nodes based on the current need).

TABLE 1. A List of Studies on Medical Imaging, CBCT, 5G, Edge Computing, and AI.These papers provide detailed information on the mentioned technologies, including integrating multiple fields such as AI for medical imaging or CBCT, and the role of 5G & edge computing in AI and medical imaging.

Publication & Year	Technologies/Methods	Main Focus
Aarle *et al.* [35], 2015	Medical imaging, ASTRA toolbox	The paper presents an open platform toolbox for 3D image reconstruction that allows rapid and adaptable building blocks to create advanced 3D reconstruction algorithms.
Pauwels *et al.* [43], 2015	CBCT imaging	This review includes a thorough discussion of the technical aspects of all phases in the CBCT imaging process from imaging hardware to visualizing the images.
Biguri *et al.* [36], 2016	CBCT, FDK reconstruction [44]	The paper describes the problems of CBCT reconstruction and solutions for them, also presenting the MATLAB / CUDA toolbox (TIGRE) for fast and accurate 3D reconstruction.
Zaki *et al.* [37], 2016	CBCT, Cloud computing & GPU	This article aims to illustrate how GPUs and cloud computing can be used to improve image processing effectiveness and improve data analysis throughput.
Després *et al.* [38], 2017	Medical imaging, GPU computing	The paper focuses the novel developments for medical image reconstruction and acceleration of reconstruction tasks with GPU-based hardware.
Rieke *et al.* [29], 2020	Digital healthcare, AI	Data-driven AI/ML models for digital healthcare by leveraging the FL paradigm to train different parties of data collaboratively without centralizing data sets.
Kaasalainen *et al.* [3], 2021	Dental CBCT, 3D imaging	The paper presents the dental CBCT imaging specializations by exploring the comparison technical characteristics of currently used CBCT scanners and exploring the difficulties associated with CBCT reconstruction and image quality.
Kaissis *et al.* [39], 2021	Medical imaging, AI	This paper proposes a privacy-preserving medical image analysis framework (PriMIA), which enables privacy-preserving FL and end-to-end encrypted inference on medical imaging data.
Lu *et al.* [40], 2021	CBCT imaging, AI	Proposes geometry-guided DL (GDL) technique that addresses the memory limitations of CBCT image reconstruction.
Zhang *et al.* [41], 2021	Medical imaging, AI	The article presents the use of one of the DL techniques, generative adversarial networks (GAN) to efficiently increase the image quality of CBCT at the CT level.
Isosalo *et al.* [34], 2023	Medical imaging, AI & EC	AI-driven medical data evaluation at the network edge on GPU-enabled local computing nodes to perform CBCT reconstruction on Astra [35], and DL-based disease detection.
Maken *et al.* [42], 2023	Medical imaging, 3D reconstruction	This article comprehensively analyzes the different approaches and procedures for 3D image reconstruction from 2D X-ray data.
Putra *et al.* [45], 2024	Medical imaging, AI & 5G	Deals with managing medical data in 5G, collected from IoMT devices, considering security, privacy, and computing constraints. It investigates cloud-edge AI architecture and Edge FL (EFL) for safe and effective diagnostics based on large-scale IoMT data, and also outlines future research in IoMT-AI integration.

B. EDGE TIER

The Edge tier provides computational resources for more demanding computing tasks with real-time requirements. The edge tier contains some of the capabilities of the cloud to host processing, analysis, and decision-making near data sources. Due to its proximity to data sources and users, the network latency from local nodes to edge nodes is typically very low, just a few milliseconds, compared to hundreds of milliseconds typical to cloud connections. Furthermore, core network resources can be saved by eliminating the need for sending data for processing at the cloud data center. In the CBCT use case, this tier can provide a computationally capable environment for image reconstruction between local and cloud tiers. Edge servers can be deployed, e.g. at the hospital facilities in the case of the hospital's local area network, or the hospital's private Radio Access Network (RAN), or alternatively, the nearest base station of a public 5G RAN.

Another important aspect of this tier is the introduction of the edge AI perspective. The relatively powerful hardware at the network edge enables the deployment of DL algorithms capable of analyzing large volumes of data and providing real-time medical data processing. This tier of the 3-TECC architecture can host computationally intensive CBCT reconstruction algorithms, as well as DL-based CBCT image reconstruction and medical image analysis.

Edge computing also reduces the possibility of information being compromised throughout transmission by performing data processing locally instead of transmitting it to a central cloud. This improves patient data confidentiality and information security, which is critical in the medical field [46]. One of the key benefits of edge computing is its ability to function even when network connections are outside the RAN. This guarantees that key healthcare services, such as response to emergencies and surveillance of patient's systems, continue to function properly [47]. Healthcare institutions that have limited internet access can benefit from this optimization as it can result in considerable cost reduction and more effective use of network bandwidth [48].

Although edge computing can effectively compute data locally, heavier computing is typically more efficient to run on cloud data centers [19].

C. CLOUD TIER

Cloud tier is the highest of the 3-TECC architecture tiers, available at the core of the Internet to provide global access to various services and rich resources to provide these services in terms of massive data storage, hosting computationally heavy AI algorithms, and the needed computational capabilities. The Cloud tier is optimal for the heaviest computational tasks, requiring vast amounts of CPU, GPU, and storage resources, and exchanging data with third-party services over the Internet. In medical imaging, this tier can be considered as the default tier for medical image analysis. It enables the assessment of massive data sets using big data analytics and the execution of data modeling to analyze signs of various diseases based on large medical image databases. This ability enables physicians to effortlessly discover significant changes in a patient's medical images over time and trends in the results of treatment, hence increasing the value of treatment for complicated disease conditions.

III. CBCT MEDICAL IMAGING WORKFLOW PHASES

Reconstruction algorithms and their components can be optimally deployed in the proposed architecture as shown in Fig. 1, depending on functional service, regulatory requirements, and hardware capacity of the underlying computational and network architecture. In the following, we present the phases of the implementation of CBCT image reconstruction in detail, from data collection to data storage, including communication and computational aspects, as shown in Fig. 2.

A. DATA COLLECTION

Medical imaging involves a wide variety of imaging data, and as such, we differentiate three sub-classes: raw data, medical image data, and diagnostic reformats and prints. **Raw data** encompasses the proprietary *measurement data* from the imaging scanner. In the context of CT and CBCT, this refers to the photon flux measured by the X-ray detector. The panel electronics encompass either a field-programmable gate array (FPGA) or an application-specific integrated circuit (ASIC), which collects, localizes, and digitizes the analog signal from the scintillation or direct conversion layer of the panel. This raw data will be transferred, *e.g.,* via a category 6 ethernet cable, to a manufacturer-provided *Image Reconstruction System (IRS)*. IRS is a PC equipped with a powerful GPU that will perform further corrections to the raw data such as dead pixel correction, lag correction, dark field correction, and flat-field correction [49], [50]. The *pre-processed raw data* is then typically stored in a proprietary format, for instance as a .raw-file. Its underlying file structure often contains a header or a separate text file with information on the scanning parameters (tube current, kilovoltage, imaging geometry, etc.), and the image data itself, typically stored in 16-bit unsigned integer arrays format.

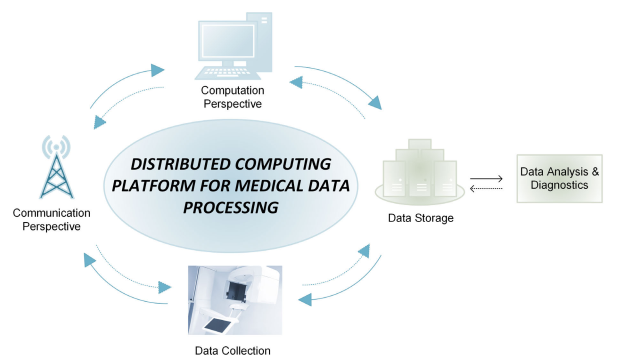

FIGURE 2. CBCT workflow phases in distributed 3-TECC architecture. This figure depicts the steps involved in the medical imaging modality. The process begins with collecting raw data from the medical device, followed by using various communication techniques to transfer the data to the appropriate component. Next, the computing nodes process the data into a diagnostic format, which can then be stored in a medical database accessible to physicians.

After the raw data has been preprocessed, the IRS will reconstruct the **medical image data** containing the slices that are visualized for the operator of the imaging device (radiographer) and the diagnostician (radiologist). The reconstruction process is a computationally demanding task and may involve solving hundreds of millions of unknown pixel values. Consequently, graphics processing units are utilized for diagnostically feasible computation times [34]. The reconstructed image slices and the metainformation associated with the study are stored in the Digital Imaging and Communications in Medicine (DICOM) format that offers a standard for communication and management of medical imaging information.

B. COMMUNICATION

In most of today's IoT systems, centralized cloud servers often handle all service functions including the processing of data. As a result, the involved end devices' computational load and requirements are reduced, but network connections are heavily utilized causing high requirements for network performance, efficiency, and reliability. Furthermore, long network delay makes real-time scenarios impossible with cloud-based IoT systems. For this, the next generation of communication systems has been designed to support delay-sensitive applications requiring high reliability, among other requirements. EC can occur either in local nodes with sufficient computational capacity – called local EC – or as a capability provided by network operator – called as multi-access EC (MEC). MEC, defined by the European Telecommunications Standards Institute (ETSI), is a network architecture specifically designed for mobile networks that brings compute, storage, and networking resources closer to the edge of the network, enabling low-latency, high-bandwidth applications, and services.

Medical imaging equipment, such as CBCT scanners, are connected to the rest of the system components through a case-specific setup consisting of access network and backbone network elements. These can be broadly classified into two categories: medium- and short-range communication technologies [51]. The former can facilitate long-distance communication, and in our 3-TECC setup, the short-range technology is used for connecting local IoT nodes while the latter is used for connecting the edge and cloud tiers. In order to communicate with nearby edge nodes and medical imaging equipment [52], the following communication protocols exist on different layers of the protocol stack:

- **Wired connections:** On physical and data-link layers, Ethernet or USB are supported by a large number of medical equipment. In medical imaging scenarios, a wired connection could be the option to link the local edge node directly to the CBCT scanner. The edge node and scanner can exchange imaging and other related data through this connection. The connections between the MEC and Cloud tiers are typically based on optical fibers. Wired communication protocols are inherently more secure because intercepting or tampering with data requires physical access to the wire. Furthermore, wired connections are less prone to interference and jamming, while wireless signals are easier to intercept and rely heavily on strong encryption and authentication.

- **Wireless connections:** Short-range wireless communication possibilities include Wi-Fi and Bluetooth on certain modern medical equipment. Furthermore, long-range wireless communication protocols, such as 4G/5G mobile networks are available for medical use. Along with 5G, private mobile networks have better support on the system level, making private RANs, managed in-house, as a viable option e.g. hospitals to take care of their wireless communications. Such setups benefit healthcare providers since the network and data management policies can be managed in-house. Furthermore, as discussed above, wireless signals are easier to intercept and more prone to interference and jamming than wired connections, making strong encryption and authentication methods a necessity. The appropriate wireless protocol to connect imaging components with the rest of the system depends on the technical, security and regulatory requirements of specific use cases.
- **Higher-layer IoT protocols:** In the IoT and machine-to-machine (M2M) communications, lightweight messaging protocols, such as CoAP (Constrained Application Protocol) and MQTT (Message Queuing Telemetry Transport) are often used. As a lightweight version of HTTP, CoAP similarly uses a request-response structure where clients send out queries and servers respond with the necessary resources. The Quality of Service (QoS) components of MQTT allow effective communications between devices and control the amount of message delivery assurance. Both protocols can be used to transmit medical imaging data, like the CBCT scanner machine in our case, and they both offer reliable and efficient communication between medical equipment and systems.
- **Application programming interfaces (API):** APIs are provided by some medical devices to enable programmatic interaction with other systems, such as nearby edge nodes. The edge node can be the option to communicate with the CBCT scanner by sending instructions, requesting data, and using the given API. The API may employ common protocols like SOAP (Simple Object Access Protocol) or APIs.

Moreover, the communication technique may vary depending on the architecture, network configuration, and compatibility of the edge node and CBCT scanner requirements. The optimal communication strategy between local edge nodes and medical equipment depends on integration requirements, security concerns, latency and regulatory constraints [53], [54]. With the option to place compute and storage capabilities closer to the edge of the network, 3-TECC architecture minimizes the need for data transmission over long distances to data centers, resulting in reduced network congestion, lower latency, and faster processing of data [55]. From the perspective of dealing with the placement of the CBCT computation, 3-TECC helps optimize network utilization to achieve efficient data transfer between sensors and processing tasks. Distributed healthcare services are important 5G application scenarios. Whereas IoT technologies have been extensively used in the healthcare industry [56], they cannot achieve their performance requirements without EC technology services like MEC [57], [58]. The huge volume of data generated by radiology, CBCT scanners, and medical imaging requires a high-bandwidth continuous communication network infrastructure. The integration of 5G and medical IoT can be enhanced by refining resource management by network slicing methods and edge-cloud computing three-tier architecture, acknowledging the more efficient, low-latency connectivity for IoT applications of edge devices [59]. However, embedding AI algorithms and ML methods at the edge tier in a three-tier architecture can improve real-time decision-making processes and predictive analytics of the system, and improve IoT performance and scalability

TABLE 2. CBCT data sizes from raw data stage to diagnostics reformats from Planmeca Viso G7 scanner. The volume of data is crucial as data transfers can cause extra burden to networks (end-to-end execution time and network overload) when moving data over different tiers of the 3-TECC architecture.

Data class	Image data size (pixels)	File size (MB)
Pre-processed raw data	0.5×10^9 - 2×10^9	40-740
Medical image data	0.1×10^9 - 3×10^9	20-700
Diagnostic reformats and prints	855×10^3 - 3×10^9	0.1-1000

C. COMPUTATION

High-resolution clinical image analytic services, including our use case CBCT image reconstruction, often require GPU-based or TPU (Tensor Processing Unit) based systems. After data acquisition from the CBCT scanner, various pre-processing tasks such as dead pixel and flat field correction are applied to raw data before moving to the image reconstruction phase. The preprocessing methods are typically computationally inexpensive operations, such as pixel-wise subtraction, summation, division, and multiplication. However, hundreds of millions of unknown pixel values may need to be solved during the computationally demanding reconstruction process. In addition to the computing capabilities of the scanner and reconstruction PC, a cluster of local nodes in the local tier can be utilized in case of more workloads/examinations for the scanners. This service can also be applied in the edge/MEC server in the edge tier upon demand. Furthermore, the edge tier could assist with image reconstruction and other image data analysis tasks such as image enhancement and 3D visualization.

Deep learning-based image processing is computationally demanding, therefore, the cloud tier can host such tasks. However, to process the data closer to the data sources, a collaboration between the computing nodes including local and edge tiers in the computing architecture can provide a scalable environment for decentralized image data processing. In this regard, distributed ML frameworks like federated and split learning could provide this environment; refer to more details in Section IV-B. In [34], the authors implemented a CBCT image reconstruction task using the Astra toolbox algorithm [35] on the NVIDIA Jetson Xavier NX device in a local configuration. However, in a context-aware deployment framework, depending on the capacity and capability of computational nodes, tasks also can be offloaded to the upper tier when needed and reloaded to the previous tier when not required. In such a framework, computation resources could be confined to a threshold for a certain number of incoming requests for the successful execution of tasks on each tier. For instance, CBCT algorithms could be deployed in GPU-enabled hardware (e.g., NVIDIA's Clara AGX) locally. At the same time, powerful computing nodes in edge and cloud can be utilized to develop an efficient and effective system. Based on the predefined threshold, a task could be offloaded from the local computing node to the edge and even from the edge to a cloud server.

In the context of medical imaging applications, the issue of optimal task placement, three-tier communication, and dealing with latency-limited and critical computing tasks is still considered an open challenge [60]. The aim is to deploy an incoming job to an appropriate serving node in the 3-TECC architecture based on the task requirements that can be, e.g. achieving sufficient end-to-end execution time while at the same time minimizing the network and processing resource consumption or energy consumption. For instance, IRS pre-processing could be optimally placed on local edge nodes while the more demanding IRS reconstruction algorithms could be deployed on a MEC server. CBCT and radiology use cases are highly data intensive and require sufficient processing capacity to ensure low execution time. EC delivers part of the cloud's processing power to where medical imaging panels or CBCT scanners are situated. Therefore, the edge-cloud continuum paradigm and the 3-TECC architecture emerge as promising approaches to manage medical imaging and the CBCT image processing workflow [61].

D. DATA STORAGE

Once the reconstruction has been processed, the output images are stored in the DICOM format and the data is sent to the PACS; the radiologist can view the images from the PACS with dedicated viewing software. If necessary, further DICOM-compatible **diagnostic reformats and prints** can be made to aid the diagnostics, e.g., by indicating critical pathologies and their dimensions in the medical image data. An Electronic Medical Record (EMR) is a digital version of a patient's medical record that is created and maintained within a healthcare organization, such as a hospital or a physician's practice. The primary goal of an EMR is to ensure that patient information is easily accessible to healthcare providers within the organization. Ideally, EMRs should also allow the sharing of patient information between different healthcare providers and settings, providing a comprehensive history of an individual's interactions with the healthcare system across multiple organizations [62].

The GDPR imposes restrictions on the purposes for which healthcare organizations can use the personal information they collect on individuals, known as the purpose limitation of data protection. It has two key aspects: (i) Personal data must be collected for specific, explicit, and legitimate purposes, (ii) and it must not be processed in a way incompatible with those purposes. However, this principle does not completely prohibit data collected for one purpose from being used for another one, as long as it is not incompatible with the original purpose. The purpose limitation principle aims to protect the reasonable expectations of individuals regarding the processing of personal data and to enable further use of such data within certain limits [63].

TABLE 3. A list of requirements for hardware specifications in 3-TECC.

Local Tier	Specification
CPUs	Intel (x64), AMD64 (x64), ARM64 (aarch64)
GPUs	NVIDIA(e.g., Jetson NX, RTX 6000), AI accelerators
Memory	Variety of options (4/8/16GB RAM)
Connectivity	High-speed Ethernet ports, Wi-Fi 6, 5G modem support
Imaging Hardware	High-resolution X-ray detectors and sensors, DICOM-compliant CBCT scanners
Edge Tier	
Processing Units	High-performance CPUs & GPUs (e.g., NVIDIA RTX 6000, AMD MI250x), NVMe SSDs, AI accelerators
Memory	32/64/128GB RAM or higher, NVMe SSDs
Connectivity	Multiple high-speed Ethernet ports, Fiber optics support
Cloud Tier	
Processing Units	Data center-grade processors, High-end GPUs, TPU
Memory	128GB RAM or higher, NVMe SSDs
Storage	Large-scale distributed storage solutions, Backup and redundancy support
Connectivity	High-speed internet backbone connections, Redundant network paths

The **raw data** collected by the scanner and the corresponding reconstructed **medical image data** are stored locally in the IRS. The types of medical image data with estimated file sizes from a collection of 700 scans from a Planmeca Viso G7 scanner are given in Table 2. The availability of the original raw data is critical because the data may sometimes need to be reconstructed. For example, the presence of metal artifacts or the use of incorrect reconstruction parameters

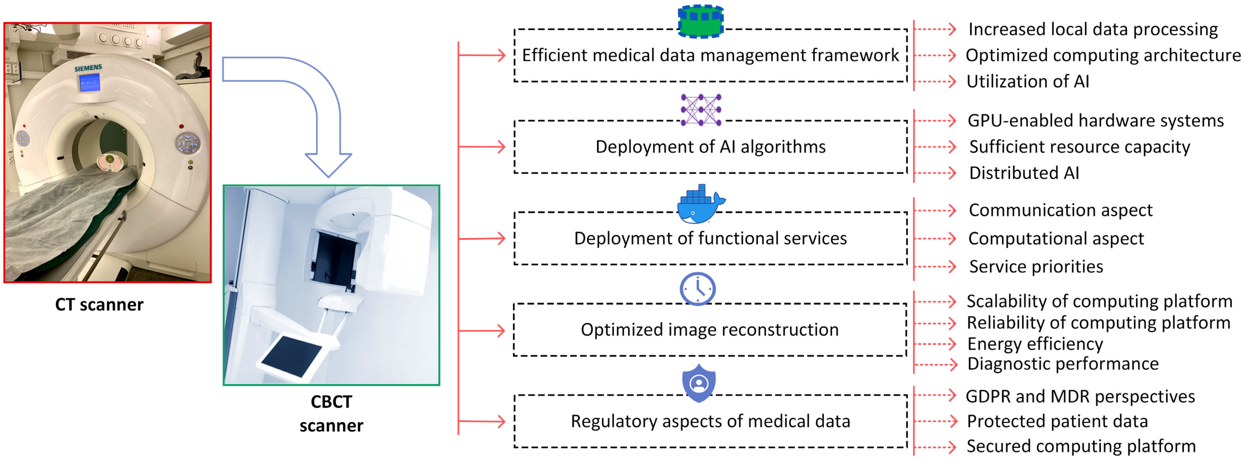

FIGURE 3. Technical requirements for distributed 3-TECC architecture for CBCT computing. This figure illustrates the steps that we cover in this research paper for the efficient realization of data-intensive medical imaging use cases on the distributed 3-TECC architecture. Research articles on the aspects mentioned here are presented in Table 11.

may necessitate redoing the reconstruction using a different algorithm or kernel [64]. As this need may arise days after the original study, the raw data has to be preserved for a sufficient duration. The IRS runs a systematic clean-up routine that may (i) remove sufficiently old data (e.g., two weeks), depending on the number of scans/storage with the system. (ii) Remove the oldest raw data to keep the available storage constant.

The **Radiology Information System (RIS)** shows a list (and times) of the imaging studies for the upcoming and past days, and their status (to-be scanned, currently being imaged, imaging done, report finished). There are also fields for further information (instructions for performing the scan in non-routine imaging cases and the potential need for special arrangements to ensure correctly answering the diagnostic question). RIS also communicates the imaging request to the radiology department and stores the radiologist's interpretation (report) of the images and activities of the imaging technicians (radiographers). Both imaging requests and radiologist's reports are finally available in the **EMR**. Additionally, it contains the medications of the patient, possible daily follow-up ward reports, diagnoses, and patient summaries.

IV. REQUIREMENTS FOR CBCT MEDICAL IMAGING IN 3-TECC ARCHITECTURE

Compared to traditional CT scanners, CBCT scanners are more lightweight and can be easily moved to different locations inside the hospitals, and in some scenarios, CBCT scanners could be moved outside of the hospitals (if neglect the need for device re-calibration), e.g. in a mobile ambulance. However, despite the advantages of the CBCT, it has some limitations such as generating low-contrast and more artifact-prone images. Furthermore, owing to the three-dimensional nature of data collection, CBCT reconstruction should be treated as a three-dimensional problem. This is in contrast to routine CT reconstruction, in which the reconstruction problem can usually be treated as a 2D reconstruction problem. Consequently, CBCT may struggle with efficient data management due to challenges in distributed computing, while potential mobility requires the use of wireless communications that require high flexibility and fault tolerance from the computational architecture. Therefore, in the following, we will define and describe the potential technical requirements, and propose potential solutions in literature to address these requirements. Fig. 3 and Fig. 4 illustrate the technical requirements for the distributed 3-TECC architecture for CBCT computing. In addition to the following requirements subsections, we have included tables alongside the list of requirements, including hardware specifications in Table 3, software tools in Table 4, and network infrastructure in Table 5.

A. EFFICIENT MEDICAL DATA MANAGEMENT IN 3-TECC

1) EFFICIENT USE OF NETWORK RESOURCES

Network resource optimization in 3-TECC architecture requires improving the efficiency of application deployment and the use of network resources throughout the architecture. Reconstruction algorithms use computationally heavy algorithms to generate medical images from huge amounts of raw scanner data. Furthermore, images should be generated and analyzed in an acceptable time frame to ensure high clinical efficiency. Dealing with these requirements is highly demanding for the networks that connect different parts of the system. The authors in [65], propose a framework that deals with the delay challenges of the Internet of Health Things.

Delivering raw data from the scanner to the unit dealing with IRS pre-processing can be considered the most data-intensive part of the process. If the IRS pre-processing is made outside the network scanner, this requires a robust network connection in the whole imaging system. Transferring the pre-processed data to IRS reconstruction algorithms could be the second most demanding connection. Therefore, it necessitates a highly capable communication link between pre-processing and reconstruction units. After

TABLE 4. A list of requirements for software tools.

Local tier	Specification
Operating Systems	Linux-based OS, Containerization platforms
Imaging Software	DICOM viewers and processors, Proprietary CBCT imaging software
AI/ML Frameworks	PyTorch Distributed [66], PySyft [67], NVFLARE [68], OpenCV, TensorFlow Lite
Edge tier	
Operating Systems	Linux-based OS, Containerization platforms, VMs
Middleware	Edge computing frameworks, Data orchestration tools (Docker swarm, Kubernetes, etc.)
AI/ML Frameworks	PyTorch, TensorFlow, PySyft, NVFLARE, OpenCV
Cloud tier	
Operating Systems	Linux-based OS, VMs
Cloud Platforms	AWS, Microsoft Azure, CSC Finland
Storage Solutions	Distributed file systems, Object storage

IRS reconstruction, the data sets delivered over the networks are comparably smaller in volume. An effective and discrete provisioning system, in which the allotted resources are elastically scalable, allows for the flexibility of network resources. As a result, elasticity ensures that different system parts receive the Service Level Agreements (SLA) needed for efficient operation, regardless of their physical location [69].

TABLE 5. A list of requirements for network infrastructure.

Local to Edge Nodes	Specification
Network Connectivity	High-speed Ethernet, Wi-Fi, 5G Radio
Protocols	HTTPS, SSH, SSL, FTP (File transfer protocol)
Advanced Security	Differential Privacy, Homomorphic Encryption (distributed ML frameworks)
Edge to Cloud Servers	
Network Connectivity	5G Core, Fiber optic connections
Protocols	HTTPS, HTTP/2, gRPC
Security	IPsec, End-to-end encryption

To deploy the task and applications to the network of physical resources at the edge, authors in [70] proposed the Autonomous- Particle Swarm Optimization (A-PSO) algorithm and hybrid swarm intelligence in [18]. The A-PSO algorithm is a practical method for load balancing and task scheduling in the constrained resources at the edge that also lowers deployment costs of the network. However, the automated orchestrator assigns IoT applications a priority, based on their requirements (latency, storage, and CPU) and deploys them to the edge node with the highest resource capacity.

Radiological image reconstruction in edge computing inflicts a significant demand on network bandwidth. The overall effectiveness of the reconstruction process may be affected by network congestion, increased latency, and limited scalability caused by transferring image data from edge devices to the remote server. The suggested framework in [71] reduces the network resource usage like transmission bandwidth and computational load, on the remote server by utilizing EC infrastructure for pre-processing and analysis. Another approach is presented in [72] to accelerate the Parallel Multithreaded Gridrec algorithm (developed in Matlab) for CT image reconstruction using GPUs in EC environments. Authors in [72], provide a resourceful solution for accelerating the CT image reconstruction process, addressing the computational requirements of edge computing. The proposed approach enables significant reductions in image reconstruction time by applying GPUs' parallel processing capabilities, which is crucial for real-time applications in resource-constrained networks.

By establishing a remote medical network using EC, hospitals may provide patients with online and real-time physician assistance regardless of location. EC is essential to minimize data transfer, such as CT images, and to increase efficiency as the amount of patient diagnosis data in the medical sector increases. Physicians may access data instantly by utilizing the EC architecture rather than depending on distant centralized servers. Physicians may access a more streamlined and quicker network environment through EC infrastructure, enabling quick response to their patient data and adaptable healthcare services [73]. Another example of a medical imaging scenario for edge computing is a case of telepathology use case presented in [74]. This work proposes LiveMicro to enable real-time pathology and remote collaboration that enables data-driven image processing and enables pathologists to perform remote consultations.

2) EFFICIENT USE OF COMPUTATIONAL RESOURCES

In CBCT, a massive amount of raw data is projected by the scanner within seconds. Transferring all data to data centers for analysis could be an expensive process in terms of efficient data management. As previously mentioned, the concept of EC [27] aims to provide computing power to the edge of the network, facilitating resource-efficient and low-latency data processing.

Although edge computing is powered by parallel computing and GPU-enabled computed hardware, there are still some capacity limitations in edge nodes when compared to cloud data centers. Thus, the distributed 3-TECC architecture can host the different portions of data collaboratively, which results in an efficient and effective resource-managed computing architecture. An intelligent resource orchestration system is required to optimize the use of all computational nodes in the computing architecture. For instance, local computing nodes have lower capacity in terms of computation and storage compared to edge and cloud servers, thus, the manager node should be able to know about the device capabilities in the architecture and deploy tasks based on the nodes' capacity and storage.

An example of such an optimization problem is visible in [71], where a multi-stage feature extraction generative adversarial network (MF-GAN) denoising algorithm and trilinear interpolation (RGT-MC) algorithms are proposed for the 3D reconstruction process at the remote edge servers by sending all the high-resolution images from the scanner to

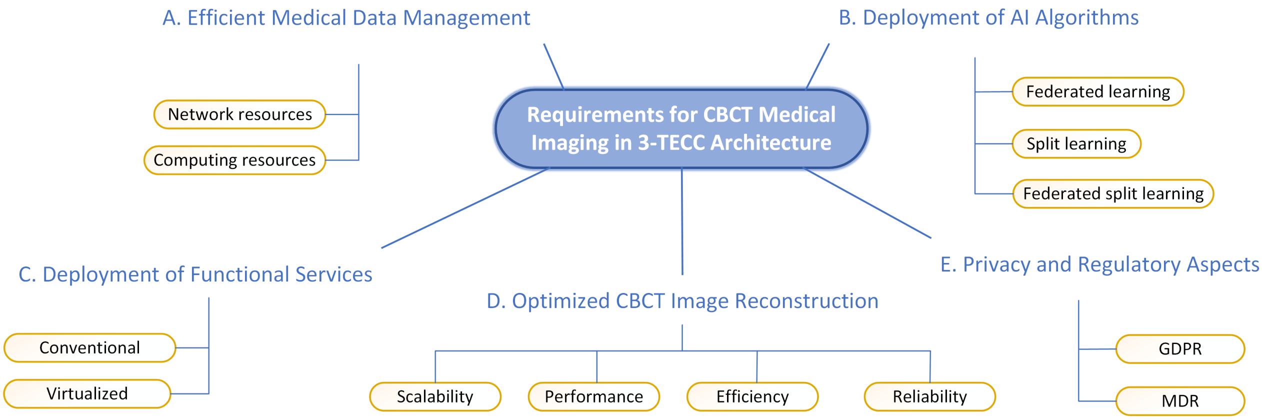

FIGURE 4. Requirements for CBCT Medical Imaging in 3-TECC architecture. This figure visualizes the main components of the requirements in Section IV, which is the skeleton of this study.

the remote edge server. This approach essentially increased the network load/traffic in the whole communication process. Another experiment conducted in [72] shows how the parallel multi-threaded algorithm outperforms traditional CPU-based implementations for CT image reconstruction in EC environments. To optimize the usage of computational and communication resources, in some cases, low-capacity GPU-enabled local computational nodes could host the necessary algorithm in the hospital premises (by enabling local computing) and contribute to the reconstruction process that would reduce image transmission to edge/cloud servers [34], [75]. To ensure the optimal usage of the resources, the task can be offloaded to the edge nodes and cloud when more computation resources are needed.

In 3-TECC, task offloading is a key focus of future work. The article in [19] offers valuable information on intensive medical data computing, addressing challenges related to large-scale medical data while integrating edge computing, cloud solutions, and AI technologies. The topics covered are closely related to what we discuss in our article. The research introduces algorithms aimed at minimizing system-wide costs and highlights the critical role of edge computing in healthcare. A similar approach could be applied in 3-TECC to enhance resource utilization effectively. A list of more recent research articles for efficient medical data management, including advanced communication (5G networks) and computing (edge, cloud) technologies for IoMT, is presented in Table 6.

B. DEPLOYMENT OF AI ALGORITHMS IN 3-TECC

The idea of mimicking mammalian features in machines and objects that we interact daily has led to labeling these technologies as "smart" or "intelligent". For future smart hospital appliances, building such edge-intelligent architectures that can deal with the high volumes of medical data and other complexities, in terms of heterogeneity of medical IoT, has a significant role in achieving better efficiency and systems. From the point of view of radiological medical image data processing, particularly CBCT image reconstruction, distributed GPU-enabled local-edge nodes can provide a computational platform for the deployment of the *Local AI* and *Edge AI* models in the local and edge tier [34], where devices can share intensive data loads for the reconstruction task. *Cloud AI* models can be applied for dental CBCT image analysis [82], [83]. In order to improve performance in smart healthcare, [84] suggests an intelligent end-edge-cloud architecture for visual IoT-assisted healthcare systems (V-HIoT). It involves defining end intelligence, assessing human-machine interactions, and developing an efficiency evaluation model for dynamic edge node management. Experiments show that V-HIoT maximizes intelligence in various devices and emergency scenarios by improving data processing and node deployment efficiency over traditional methods.

1) EDGE AI IN HEALTHCARE

Recent developments in AI, the growing adoption of medical IoT devices, and the power of edge computing have combined to accelerate the potential of edge AI, and considering the vast amount of data flowing from the healthcare sector, it is important to gather and acquire AI-based solutions in real-time to support the much faster clinical decision-making process. The survey study in [85] focuses on recent scientific papers in the field, discussing smart healthcare applications using cutting-edge technologies including modern edge-cloud computing, IoMT, next-generation wireless networks, and AI. The authors in [34] discuss the role of state-of-the-art technologies in the transformation of modern smart hospitals and presents experimental results of AI-driven diagnostics for medical imaging including breast cancer detection, as well as CBCT image reconstruction using GPU-enabled local computational nodes.

As presented in Fig. 1, the distributed 3-TECC architecture comprises the local, edge, and cloud tiers. Cloud servers can generally host heavy AI algorithms for data analytics, since they are equipped with state-of-the-art hardware resources. In contrast to cloud and edge servers, resource-constraint local IoT devices have lower computational capacities.

TABLE 6. Recent Research Articles on Efficient Usage of Communication and Computing Resources for Medical Data Management: Section IV-A.

Publication & Year	Main Focus
Lin *et al.* [76], 2018	This study introduces a novel algorithm named FOTO (Fruit Fly Optimization based Task Offloading) designed to enhance energy efficiency in edge computing. FOTO aims to offload tasks from resource-constrained devices to a nearby cloudlet, taking into account factors such as speed, cost, and existing limitations.
Dong *et al.* [77], 2020	The research paper handles resource allocation in the IoMT system overloaded with medical devices, and provides a solution for resource usage by leveraging edge computing and game theory technologies for improved healthcare.
Sun *et al.* [19], 2020	This research discusses the challenges of big medical data in IoMT and how to deal with them using cloud computing, edge computing, and AI, with a focus on improving access to high-quality medical IoT.
Abdellatif *et al.* [78], 2021	The paper proposes MEdge-Chain, a framework that combines edge computing and blockchain for secure and efficient exchange of medical data in large healthcare systems. It improves response times, critical event management, and healthcare quality.
Wang *et al.* [79], 2021	This research addresses the problem of slow and vulnerable resource allocation for massive health devices in a 5G. The authors propose a new strategy that allocates tasks between local devices, edge servers, and the cloud while considering privacy protection. This approach prioritizes tasks, reduces delay and energy consumption, and improves security compared to existing solutions.
Alatoun *et al.* [80], 2022	For real-time healthcare applications, this paper proposes an energy-efficient IoMT to Fog Interoperability of Task Scheduling (EEIoMT) framework. ECG analysis and other essential tasks are prioritized and the energy used on other tasks is minimal. In comparison to other ways, this improves latency and boosts overall efficiency.
Isosalo *et al.* [34], 2023	This paper proposes using virtualized local GPU computing capabilities (local edge) for medical image reconstruction and breast data analysis leveraging transfer learning. The work shows the feasibility of medical data processing close to data sources, which can help mitigate the use of communication resources for data-intensive healthcare applications.
Saranya *et al.* [81], 2024	This study provides a novel optimization method called DRL-LOA for improving medical data classification in cloud networks. By taking both network structure and traffic patterns into account, DRL-LOA enhances current techniques and results in notable decreases in latency and power consumption.

However, using deep networks in medical imaging, for example, CBCT image reconstruction, requires high-performance hardware [40]. At this point, local nodes are facing challenges in deploying the DL algorithms due to resource constraints native. However, GPU-enabled local devices can host local AI models by collaborating with other nodes in the computing platform to achieve performance close to centralized computing systems [86]. Moving the scenario from the local cluster to the edge servers in the edge tier will expand the capacity of computation resources, leading to the deployment of edge AI algorithms for data analytics. These edge servers include both 5G-integrated cloud-run servers and MEC servers [87] supported by GPU-enabled hardware systems.

2) SUPERVISED AND UNSUPERVISED DL FOR MEDICAL IMAGING

In literature, both approaches of DL including supervised [88] and unsupervised learning [89] have been developed for reconstruction tasks [41]. When considering clinically available products, despite extensive research on DL reconstruction [90], [91], and multiple released commercial products for CT reconstruction using DL (TrueFidelity, GE Healthcare; AiCE, Canon Medical Systems; Precise, Philips Healthcare), no commercial DL reconstruction product has been yet released for diagnostic CBCT. The currently available DL products are most commonly trained in a supervised manner, and are often based on the U-Net or unrolled variational network structures [92]. Some products, such as synthetic CT from MRI data [93], have also utilized generative adversarial network architecture.

Supervised DL algorithms are data-hungry and require large amounts of data to generalize the model well on unseen data [94]. Data are collected in data centers from multiple sources. DL models are subsequently trained using these centralized data, which contain a substantial volume of information, enabling the DL models to achieve state-of-the-art model performances. However, edge technology struggles with the challenge that the data generated at the network edge might not be sufficient to obtain reliable model performances, and training data from a single institution are often not generalizable on data from other institutions [95], [96]. To address this problem, the authors in [97] argued the concept of distributed learning in which decentralized data is used in an ML pipeline. The capacity of distributed learning to divide heavy computational tasks into smaller portions, allowing parallel computing and result aggregation to produce more accurate and efficient models, has attracted a lot of attention for resource constraint IoT in the field of AI [98]. Therefore, this plays an important role in the medical domain for intensive radiological image data, which requires more communication resources to transfer the data. It can increase collaboration between computing nodes, improve resource utilization, and preserve data privacy, which is crucial in digital healthcare. In the following paragraph, popular distributed learning methods will be presented.

3) DISTRIBUTED LEARNING IN 3-TECC

The federated learning paradigm is a promising distributed AI algorithm for collaborative learning on decentralized data [99], [100]. Although FL applications vary in many fields, digital health and medical imaging are among the main fields in which FL attracts more, due to challenges as mentioned above [29], [101], [102], [103]. In the 3-TECC architecture for CBCT, FL helps in eliminating the necessity of transferring large medical data across networks to centralized data centers, instead of only sharing the trained AI model's parameters. Data processing near data sources also ensures privacy concerns for sensitive medical data. In [104], a benchmark is provided for naturally partitioned cross-silo FL, targeted at healthcare applications, called FLamby, to bridge FL theory and practice with actual healthcare data. It is designed to work with different FL frameworks and comprises multiple data modalities.

The article in [105], studies the background of FL and examines the set-up of experiments of the centralized and FL approach with different client configurations for the use case of chest X-ray image classification. In [106], the article emphasizes the role of FL in medical applications. It covers topics such as digital health, dataset characterization, learning algorithms, communication efficiency, security concerns and attacks, and corresponding defenses. These aspects could be important for the implementation of FL in a medical context. The important aspects of FL covered in [102], such as addressing system and statistical challenges and privacy concerns in an FL setup. It highlights the significant role of FL in health.

Split Learning (SL) is another distributed AI/ML approach in which the neural network model is partitioned into submodels [107], [108]. Healthcare is among the fields that leverage the SL paradigm for collaborative learning and data privacy [101], [108], [109]. The combination of FL and SL, the Federated Split Learning (FSL) approach could perform better from both perspectives, including the efficiency of the DL model training and the improvement of the privacy of the data sets [101], [110]. The article [109] discusses key topics in distributed ML for medical use cases. It provides context on various distributed ML approaches and different medical imaging scenarios. Authors in [101] present popular distributed ML approaches such as FL, SL and FSL for healthcare context, discuss the distributed learning challenges such as system heterogeneity, and other important aspects of these approaches. A comprehensive list of similar research articles on distributed ML approaches in digital healthcare is presented in detail in Table 7.

TABLE 7. A list of Recent Research Articles of Distributed AI. These approaches mainly include FL, SL and distributed learning frameworks for medical imaging and CBCT use case: Section IV-B.

Year & Study/Relation	Main Focus
Kirienko *et al.* [109], 2021	This research assesses the effectiveness of distributed AI compared to centralized approaches in multi-institutional research and practice, highlighting privacy in healthcare applications. It discusses distributed ML performance alongside experiments, emphasizing its reliability and potential applications in health while addressing technical constraints, ethical concerns, and future research directions.
Pfitzner *et al.* [106], 2021	A systematic review paper of FL in digital healthcare, by addressing research questions regarding the use of and benefit of FL for medical purposes.
Xu *et al.* [102], 2021	The review paper provides an overview of FL in healthcare by discussing statistical challenges from data distribution and communication efficiency. It also covers distributed ML frameworks and addresses open questions for FL implementation in healthcare.
Díaz *et al.* [105], 2022	The role of FL in chest X-ray image analysis. The paper compares the FL with the centralized approach regarding privacy, training accuracy, and execution time while addressing issues related to irregular clients.
Gupta *et al.* [95], 2023	The authors provide an overview of collaborative DL training, deployment aspects, FL frameworks, and real-world examples to inform clinicians about the implications of using distributed ML.
Shiranthika *et al.* [101], 2023	This survey comprehensively examines contemporary FL, SL and federated split learning approaches in healthcare, statistical and system heterogeneity challenges, privacy preservation, and communication efficiency, proposes strategies to address challenges, and provides future directions, such as personalized model development and bias reduction in health.
Chang *et al.* [86], 2024	The paper compares DL performance between two distributed learning approaches: cluster computing and FL. It also compares the centralized approach with distributed AI frameworks, Spark on Hadoop for cluster computing, and PySyft [68] for FL, and tests these frameworks on publicly available data sets considering data distribution.
Guan *et al.* [111], 2024	This article reviews recent developments in FL for medical image analysis by addressing small sample size issues. These developments allow for collaborative model training without requiring cross-site data sharing. In addition to reviewing benchmark data sets and software platforms, it classifies methods according to the client end, the server end, and communication approaches.
Rauniyar *et al.* [96], 2024	A review on the integration of FL with emerging technologies for the medical domain, exploring its synergy with emerging technologies to address challenges, including recent advances in computer-aided diagnosis tools, and offering an overview and comparison of existing open-source FL software frameworks while identifying key challenges.

C. DEPLOYMENT OF FUNCTIONAL SERVICES IN 3-TECC

1) CONVENTIONAL SERVICE DEPLOYMENT

Traditionally, functional components of highly demanding computing medical services, e.g. CBCT analytical services, are being deployed at remote centralized cloud data centers in the form of Software as a Service (SaaS), Platform as a Service (PaaS) or Infrastructure as a Service (IaaS) [112], depending on the scale and granularity of the service deployment. Medical SaaS providers offer comprehensive, ready-to-use software solutions to analyze CBCT images. In contrast, PaaS providers offer a pre-built platform for deploying CBCT applications needed by medical institutions.

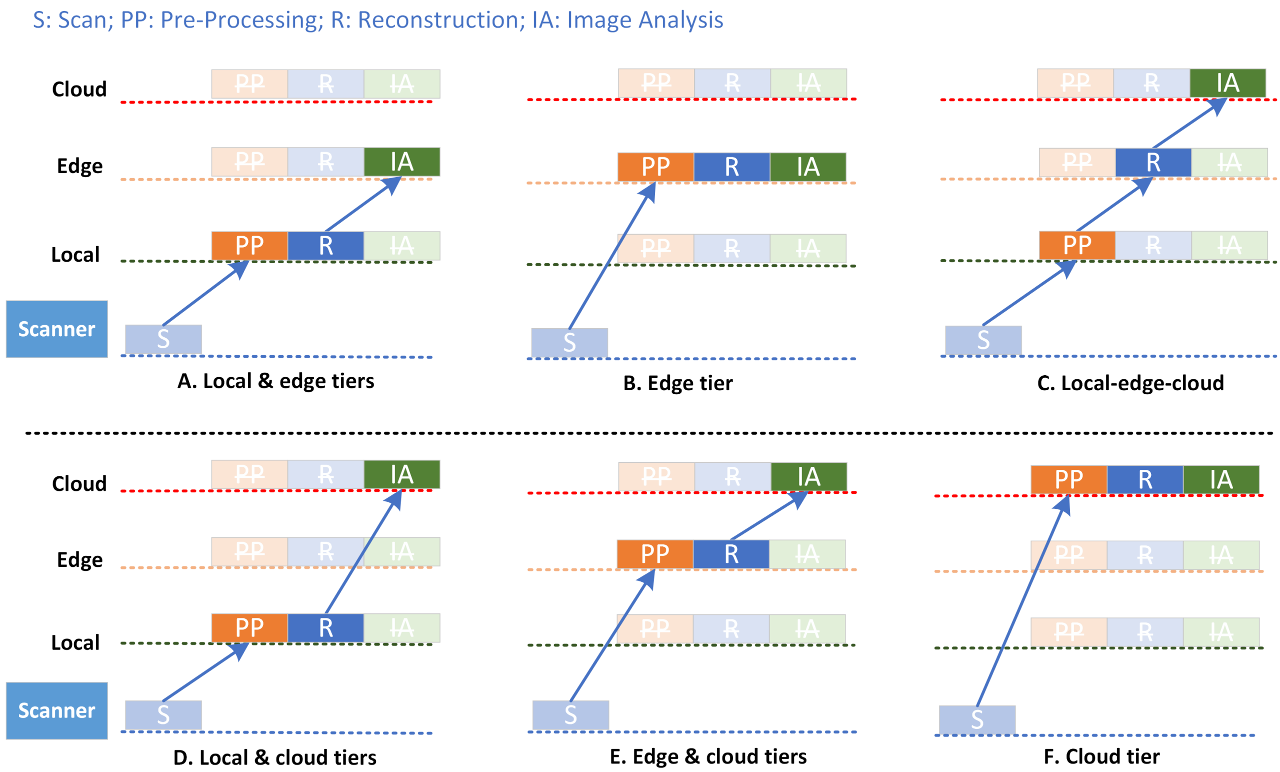

FIGURE 5. Example CBCT data processing workflows. Different scenarios for medical imaging and CBCT data processing in the 3-TECC architecture are discussed in Section II, which includes distributed tiers of the architecture. These scenarios can vary based on the computing capabilities of each tier. The main goal is to achieve data analysis relative to the data source. In scenario (A), a cluster of local computing nodes can collaboratively host pre-processing and lightweight reconstruction algorithms in the local tier and perform image analysis in the edge tier. In scenario (B), 5G-enabled MEC servers can host three data/image processing steps in the edge tier. In scenario (C), different phases of CBCT are distributed across the tiers: data preprocessing occurs in the local tier, while reconstruction and data analysis occurs in the edge and cloud tiers, respectively. Additional scenarios (D, E, and F) are also provided. These scenarios can be selected based on specific requirements and the computing capabilities of the local and edge tiers. For example, if data cannot be taken outside the hospital premises, scenarios excluding the cloud tier would be prioritized.

Furthermore, IaaS providers offer the infrastructure with essential computation resources such as CPU, GPU, memory, storage, and networking resources. The advantages of these models include scalability, flexibility, reduced downtime, and minimized hardware maintenance. However, network performance can affect the overall CBCT analysis during data transmission, such as when sending reconstructed images to GPU-enabled remote SaaS, PaaS, or IaaS servers, particularly when real-time CBCT analysis is required. Alternatively, several standalone local applications on hospital premises can also improve the performance of CBCT analysis, particularly in situations where network capacity is, for some reason, low. However, standalone CBCT applications will increase the overall installation cost. As a result, neither option is optimal from the scalability, resource efficiency, and reliability viewpoints, particularly in mobile imaging scenarios.

2) VIRTUALIZED SERVICE DEPLOYMENT

Virtualized services essentially reduce overall operational costs, especially by avoiding the purchase of new hardware resources. Virtualized CBCT analytical services can be deployed in two major forms, through either virtual machines (VMs) or containers. Generally, a VM requires a full-fledged OS to deploy a service whereas a container requires only run-time libraries required by that service. A VM acts like a guest OS on top of the host OS whereas a container acts like a single granular process. Therefore, provisioning of services through a container performs better than in a virtual machine [114] in terms of resource utilization. VMs, however, could run with a hypervisor such as VMware, Oracle VirtualBox, etc. on top of a physical host machine. A system administrator (SysAdmin) must explicitly write a routing logic to distribute incoming requests among VMs according to their capacity to ensure the overall system load.

On the other hand, orchestration engines like Kubernetes, Docker Swarm, and Apache Mesos distribute requests among lightweight containers, reducing errors that can occur with explicit routing logic written by system administrators. To ensure a resource-efficient system, an orchestrator should also consider the efficient use of the available resources in a cluster and deploy the required IRS among the capable nodes [116]. To ensure optimal utilization of resources, the authors in [118], [119] proposed a two-tier deployment approach in their studies. According to their proof of concept

TABLE 8. A list of Recent Research Articles on Deployment of Functional Services on Edge-Cloud Continuum: Section IV-C.The articles in this table cover topics including distributed computing, edge-cloud computing, and functional service deployment.

Publication & Year	Main Focus/Relation to This Manuscript
Tran *et al*. [58], 2017	This article investigates using MEC at the edge of mobile networks to provide faster and more accessible 5G service deployment. The framework for collaboration of MEC servers and devices is suggested, and its advantages for data processing and mobile network management are examined. The paper also addresses challenges that must be tackled to integrate MEC into 5G successfully. The article highlights the pivotal role of the MEC paradigm in executing time-critical applications and addresses aspects such as heterogeneity, which we also considered in our manuscript.
Porambage *et al*. [55], 2018	The survey studies how MEC facilitates the proliferation of the IoT. Real-time applications in fields like healthcare and smart cities have become accessible by MEC, which brings the capability of cloud computing closer to devices. The survey examines how MEC and IoT might cooperate to improve service quality and response times that includes important contents for efficient 3-TECC architecture for IoMT.
Harjula *et al*. [113], 2019	This article introduces a decentralized IoT edge architecture for deploying ultra-lightweight nanoservices, that are miniature versions of microservices deployable to constrained-capacity local computing nodes. The architecture improves edge-cloud performance by leveraging local nodes for reliable deployment of services that require low latency, enhanced privacy, and high resilience to network problems. In our manuscript, we emphasize the importance of processing data at the source, especially for sensitive health data. The referenced study highlights the crucial role of local resources in service deployments.
Leppänen *et al*. [7], 2019	The authors propose the use of mobile agents for data processing in the network in resources-constrained IoT devices where these mobile agents can collaborate and share information locally, reducing data transmission and improving energy efficiency, particularly for large amounts of data. The article correlates our study with respect to energy efficiency and collaboration between computing nodes in 3-TECC architecture.
Potdar *et al*. [114], 2020	This research paper compares Docker containers, a less complex solution that shares the host machine's operating system, with virtual machines, which build isolated environments on a single machine. It evaluates how well they perform in tasks like CPU and memory utilization using benchmark tools. The article emphasizes the containerized solutions for task processing, which we discussed in Section IV.
Saraswat *et al*. [112], 2020	This article describes how cloud computing gives consumers online access to computer resources like storage and services. Platform as a Service (PaaS), Software as a Service (SaaS), and Infrastructure as a Service (IaaS) are among the several service models provided by Cloud Service Providers (CSPs) that are the focus of the paper. The market share and expansion of different service models are also examined in the study. This study gives insights into cloud tier in 3-TECC architecture.
Islam *et al*. [32], 2021	This research proposes the use of decentralized service management architecture at local edge to automate the deployment and management of miniature microservices called nanoservices on local devices to manage jobs such as remote health monitoring efficiently and reliably. The strategy proposed by the authors prioritizes data privacy and uses less resources while adjusting to changing situations like challenges with the quality of network connectivity. In our previous study, we studied the use of containerized approach for improving resource efficiency, which can be an important aspect for different computing nodes in 3-TECC architecture.
Malazi *et al*. [115], 2022	The research article focuses on the placement of dynamic services for the MEC by including a systematic literature review. Among other parts, the paper also discusses different use cases and examines concerns regarding task planning and management of the resources for the use cases in the MEC environment. The article comprehensively explains MEC, representing the middle tier of the 3-TECC architecture.
Rajkovic *et al*. [116], 2022	This study emphasizes how crucial it is to take into account resource constraints (memory, processing speed, etc.) while developing medical information systems. Skipping these constraints can lead to issues at every stage of the system's lifecycle, from initial design to maintenance and upgrades. The authors convey several requirements to support resource awareness as a crucial component of medical information system design. The article raises awareness about medical systems' resources and use cases, which provides insights into the computing and networking resources within the 3-TECC architecture.

(PoC), the three-tier virtualized nanoservices deployment model [113] on-premises could be a potential solution to existing native cloud (SaaS, PaaS and IaaS) and local standalone applications especially when resource-efficient and real-time data processing is taken into account. A list of recent research articles on deploying functional services is presented in Table 8.

D. OPTIMIZED CBCT IMAGE RECONSTRUCTION IN 3-TECC

1) SCALABILITY

Each tier in the 3-TECC architecture has various characteristics regarding software and hardware specifications. A scalable distributed 3-TECC architecture should accommodate the increasing amount of medical imaging with increasing computational needs without sacrificing overall performance. Scalability becomes a balancing act when dealing with medical data processing, given the continuous growth in volume and complexity of medical imaging data, which requires substantial processing capacity and storage [26]. The authors in [120] address the challenge of processing large amounts of sensor data by proposing a scalable three-tier architecture for efficient storage and processing. Stakeholders in healthcare require a distributed computing platform that can scale smoothly to meet growing requests for healthcare applications and data analysis of radiological medical imaging.

The 3-TECC architecture can host various phases of CBCT data processing. The concept involves deploying a cluster of local nodes near the scanners, supported by slightly more powerful MEC servers at the edge, along with 5G connectivity, and accessible cloud resources via the internet. As illustrated in Fig. 5, different CBCT data processing scenarios can be accommodated according to specific requirements and use cases. The setup can be tailored according to the workload intensity. For example, if data from multiple scanners needs to be processed, a sufficient number of local computing nodes, aided by nearby MEC servers, can handle the task. This flexibility allows the architecture to be implemented in small healthcare facilities and scaled up for larger hospitals. In larger hospitals, there may be a need for a greater number of processing units to handle, e.g., the higher number of concurrent CBCT scans and possible other tasks.

2) PERFORMANCE

Minimizing the end-to-end execution time of a CBCT-related computing task is crucial in enhancing the diagnostics performance [36], [38]. The two major factors contributing to the end-to-end execution time are the processing time at the computing node [37] and the throughput and latency of the networks in between. As a rule of thumb, processing times tend to grow when tasks are deployed closer to the data due to constrained CPU/GPU resources, while network latency tends to reduce due to shorter data paths. The network throughput depends on the lowest performance link on the data path, which can be reduced by e.g. poor radio network conditions if wireless connections are used, or congestion in core networks. The edge computing environment and new-generation mobile communication (5G and beyond) enable latency-sensitive medical imaging use cases in wireless settings [31]. The performance of centralized learning exceeds the distributed performance in terms of distributed learning algorithms depending on the various conditions.

The performance of an AI model is critical for ensuring its reliability and robustness. Due to the challenges inherent in distributed systems, centralized AI models outperform their distributed counterparts. In [86], Chang et al. examine two distributed learning frameworks: cluster computing and federated learning. For the FL experiments, PySyft distributed learning framework [67] was utilized. The experiments' findings demonstrate a decrease in AI model performance with multiple distributed nodes under IID data distribution compared to centralized results. This performance degradation is even more pronounced with non-IID data distribution, which is more representative of real-world scenarios. Consequently, achieving performance close to centralized solutions in distributed settings requires extensive fine-tuning and robust network designs. Therefore, data heterogeneity and network overloads are among important practical challenges in deploying distributed learning paradigms. A comparative analysis of the performance of distributed learning frameworks including NVFlare and PySyft is given in [121].

3) EFFICIENCY

Recently, energy efficiency has been emphasized as a future goal in practically every aspect in our societies, as it is crucial for sustainable development to avoid climate change with a reduced carbon footprint, in addition to more traditional motivators, such as cost efficiency. Awareness of energy consumption also applies to the healthcare sector, medical imaging, and radiology [122]. When considering billions of medical IoT devices worldwide, having smart orchestration and efficient optimization algorithms that led to utilizing the computational nodes based on the task specification has a greater impact on effective resource utilization. Furthermore, in order to cope with the deterioration of dependency ratios, the cost efficiency of healthcare systems will be emphasized in the future. In Radiology, medical imaging techniques consume high energy that adds to the climate footprint, and based on this, Woolen et al. in [123] studied to reduce the carbon footprint of different MRI scanners for energy savings and found that radiology departments are more energy-efficient when powering down MRI scanners. Energy and resource efficiency are important contributors to cost efficiency, which tends to emphasize these factors even more.

In 3-TECC architecture, different tiers can host different portions of medical data processing, which can optimally leverage the strengths of different types and locations of computing nodes in the computing architecture, which has a high potential to increase energy, resources and cost efficiency. The allocation of tasks according to energy availability is a crucial component of resource-aware task orchestration [124]. To do this, a source of power-based measuring framework must be put in place to carry out activities, including task classifications. Time-critical healthcare applications and tasks can dynamically assign power supplies and balance loads of networked computing nodes in a three-tier edge cloud architecture [125], to reduce energy costs and increase efficiency by utilizing real-time data on power market pricing [126].

Split learning can be crucial for constrained computing nodes within the 3-TECC architecture. DL models contain layers that require high-performance computing. Thus, with the help of SL, the first couple of DL model's layers reside in the constraint device, and the remaining part of the model resides in the slightly powerful computing nodes. With this, we can improve the efficiency of the resources by leveraging various computing hardware in the architecture.

4) RELIABILITY

Utilizing local and edge tiers to process data near the data source mitigates the reliance on accessing cloud centers via the Internet. This approach offers a more reliable computing architecture to address network bottlenecks and failures effectively [45], [127]. However, it is worth noting that local-edge nodes may encounter occasional failures or performance hindrances, particularly for service deployment and other node-related issues like their mobility and potential concurrent utilization for different purposes, since they may be shared resources with other tasks. Nevertheless, the entire edge-cloud continuum system provides a flexible environment for distributed data processing and management.

In the event of network bottlenecks or technical difficulties at certain levels in 3-TECC and computational nodes, the remaining nodes within the collaborative framework can collaboratively host tasks, thus contributing to the system's overall performance. Consequently, decentralized CBCT data harnesses distributed computing, while centralized cloud centers are more susceptible to the abovementioned challenges. In [128], the authors proposed a system architecture that

TABLE 9. A list of Recent Research Articles on Optimized CBCT Image Reconstruction: Section IV-D. These research articles are mostly related to reliability, performance, efficiency, and scalability, which are important parameters in this setup.

Publication & Year	Main Focus/Relation to This Study
Grover *et al*. [128], 2018	This paper addresses reliability challenges in edge-cloud IoT systems. It proposes a new architecture with a distributed cloud (cloud-fog-mist-dew) and data replication for fault tolerance. Mobile agents are designed to immediately redeploy applications in the case of an edge server failure, ensuring minimal latency and uninterrupted operation. The article emphasizes reliability and fault tolerance for distributed computing architectures, providing insights into an efficient 3-TECC architecture.
Yang *et al*. [131], 2018	This research examines a wearable mask to measure pain via facial muscle activity, to help disabled patients to communicate the pain. It works wirelessly within an IoT system for remote monitoring and prioritizes comfort for long wear. Real-time data is sent to a cloud for processing and displayed on a mobile app that offers a scalable automatic pain assessment solution. The work discusses medical applications using cloud technology, which is related to the topics covered in our study.
Kumar *et al*. [120], 2018	The paper addresses the challenge of processing large amounts of sensor data by proposing a scalable three-tier architecture for efficient storage and processing by leveraging cloud storage (Apache HBase) and ML (Apache Mahout) for heart disease prediction and analysis. The paper discusses managing large amounts of medical sensor data to support cloud computing and ML-based diagnostics. Similarly, our study focuses on handling extensive medical imaging and CBCT data, and ML-driven data analysis.
Heye *et al*. [122], 2020	This study focuses on the energy use of CT and MRI scanners in a university radiology department to find ways to reduce costs and adopt greener procedures. The paper examines the energy aspects of CT and MRI imaging techniques. From a 3-TECC perspective, it can provide insights on improving energy efficiency.
Ejaz *et al*. [132], 2021	This paper proposes a scalable architecture including local, access and core levels for remote healthcare that treats elderly patients at home as a use case. It leverages edge computing and blockchain technologies for long operation times, affordability, security, and resilience in dynamic networks. The authors evaluate the effectiveness of the framework compared to a non-blockchain approach. The article highlights the role of edge computing and blockchain in distributed computing architecture.
Bishoyi *et al*. [133], 2022	This research uses MEC for wearables wireless body area network (WBAN) to address energy usage in healthcare. It suggests a negotiation strategy for WBAN and MEC servers. Instead of offloading everything, the wearable's server promotes partial data processing, which lowers server load and energy consumption without compromising user experience. The proposed approach demonstrates how to improve the efficiency of the MEC server (edge tier in 3-TECC) compared to traditional methods.
Hartmann *et al*. [31], 2022	This article reviews current and future edge computing architectures for smart healthcare, focusing on device requirements and challenges across different applications by highlighting edge computing with 5G for real-time analysis such as the need for faster healthcare data processing to meet patient demands. The article includes various aspects for the edge computing in healthcare, compared cloud-based solutions alongside with low-latency applications. Therefore, it provides insights for edge and cloud tiers in 3-TECC.
Shah *et al*. [26], 2022	This work investigates the potential benefits, risks and regulatory issues related to adopting cloud computing in healthcare. It explores the advantages of cloud computing such as flexibility and scalability, including integration with current IT infrastructure, data security, privacy, and regulatory compliance. The article discusses the pros and cons of cloud based solutions for healthcare, which provides knowledge for the cloud tier in 3-TECC architecture.
Izhar *et al*. [130], 2023	This study uses state-of-the-art technology to propose an innovative healthcare framework. Prioritizing patient privacy, it integrates edge computing for real-time processing, AI for threat detection, and blockchain (DLT) for secure data storage. The article focuses on the seamless connectivity of IoT by leveraging ML, distributed ledger technology and edge computing technologies for health, providing insights for our 3-TECC architecture.
Woolen *et al*. [123], 2023	This paper studies to reduce the carbon footprint of different MRI scanners for energy savings and emphasized that the radiology departments can be more energy-efficient in case of powering down MRI scanners. This work can be adapted to various medical imaging modalities, such as CBCT scanners in 3-TECC, to help reduce the carbon footprint.

deals with faults at some level of the distributed computing architecture and emphasizes improving fault tolerance and reliability. Heterogeneity is one of the notable challenges of novel technologies including 5G/6G, AI, and IoMT which adds more complexity to the existing systems. Authors in [129] discuss AI-based methods to provide more reliable resource management and address heterogeneity issues in distributed 3-TECC architecture.

In 3-TECC architecture, seamless intra-tier and inter-tier connectivity is essential for efficient data processing. The authors in [128] provide insights into potential failures and propose their solutions. The role of AI-driven edge computing in enabling real-time medical data processing is discussed in [130]. In addition, the article proposes an ML-based model for detecting security threats to improve the system efficiency. Table 9 lists more recent research articles focused on optimized CBCT image reconstruction, covering aspects such as reliability, performance, efficiency, and scalability.

E. PRIVACY AND REGULATORY ASPECTS OF MEDICAL DATA IN 3-TECC

In addition to the functional and technical requirements described in the sections above, medical systems must conform to national and international regulations and legislation to fulfill strict requirements for the privacy, security, and confidentiality of medical data.

The EU's GDPR is the key legislation governing the processing of personal data, applying to companies and businesses operating in EU markets. This law stipulates important prerequisites for all manufacturers of medical devices regulated under the EU's MDR. In this section, we survey the main privacy implications, still, it should be noted that the detailed requirements specification for eurozone healthcare market approval of CBCT tied to the above 3-TECC architecture is essential. The successful market entry requires a sound regulatory strategy initially and following the project development phase, data-driven clinical evaluation takes place to meet safety, security, and performance criteria to obtain EU-market approval. This is followed by post-market audit throughout the product life cycle [134].

However, national data protection and special sector provisions may also be applicable depending on the context. For example, a unique law in Finland has been established on the secondary use of health and social data complementary to the GDPR legislation. A special tooling for publicly operated data space in the health and social sectors is a Finnish Act of ''Secondary use of health and social data (552/2019)'', where the secondary uses include scientific research, statistics, development and innovation activities, steering and supervision of authorities, planning and reporting duties by authorities, teaching, knowledge management [135]. GDPR Article 4 defines ''personal data'' as any information related to an identified or identifiable natural person (''patient as data subject''), identifiability refers to e.g., a name, identification number, location data, online identifier, or other specific factors related to their identity particularly tied to medical imaging e.g., patient data on anatomical, physical, physiological, and genetic factors [63].

As a default to protecting and complying with patient privacy, effective data anonymization consists of the irreversibility and impracticability of identifying the data subject. However, it should be noted that pseudonymized data qualify as personal data under the GDPR. Hence, the distinction between these two concepts should be firmly fixed and embedded in new edge-cloud continuum healthcare system designs. Furthermore, GDPR Article 83 should be addressed on business ramifications since it lays down implications for non-compliance of implementation, recovery, and damage related to patient privacy protection exposing potential financial risks. The legal penalties are ruled from less severe violations up to fines capped at 20 million euros of annual global business revenues [136]. Following Article 5, an important organizational capability is to demonstrate full-fledged compliance at all times and ensure that privacy protection is professionally managed, building valuable trust and providing competitive advantage across the healthcare value chain, while neglecting data protection may become very expensive.

Hence, a driving value from regulation-compliant and dependable end-to-end communication path for connected future healthcare should encompass also the main important provisions of GDPR tied to regulation of the technical requirements. These are stipulated in Articles 24, 25, 30, and 32. The responsibility and liability of the healthcare organization as a data controller specify the measures that must be taken to ensure compliance when processing personal data, as described in Article 24. The provision imposes an obligation to do due diligence and to demonstrate the steps taken to ensure compliance with the law, for example, in the case of an audit. Article 25 emphasizes the importance of data security to protect patient privacy, and sensitive EMRs, the need to incorporate it by default and by design into all stages of the 3-TECC architecture, from the initial planning phase to the end of the data lifecycle. The requirement for the preservation of a record of personal data processing activities, which must be available to supervisory authorities upon request is presented in Article 30. Finally, Article 32 provides specific provisions on data security for the obligatory implementation of fit-for-purpose technical measures and organizational capabilities to ensure appropriate cybersecurity performance to risks [63].

The main challenge anticipated in the future is navigating the current regulations and the stipulations of the new EU's Artificial Intelligence Act (AIA) [6]. Currently, healthcare operates as a closed system, but the novel concept proposed by the authors aims to break this silo. Therefore, future implications for MDR and ISO 13485:2016 manufacturing best practices must be carefully monitored. However, as highlighted in a recent article, we must be cautious of excessive regulatory measures. Big data techniques need to balance social advantages with patient privacy to create value in healthcare. According to Paul et al. [137], big data requires significant changes to database usage, access, sharing, privacy, and sustainability procedures and regulations.

The EU's AIA will significantly impact distributed 3-TECC architectures through its transparency and documentation requirements, particularly in healthcare applications where it puts patients in a stronger position compared to US and Asian frameworks.

While these regulations enhance patient rights and data protection, they create two significant challenges: first, EU-based companies may face competitive disadvantages due to increased compliance costs and slower innovation cycles compared to non-EU competitors; and second, hospitals' day-to-day operations may experience new bottlenecks due to additional documentation requirements, mandatory human oversight procedures, and compliance checks that could slow down clinical workflows and decision-making processes. These practical implications will require careful consideration in both system architecture design and operational planning. The focal point is the system-level integration of digital healthcare powered by a distributed 3-TECC architecture.

A list of recent research articles on medical data's privacy and regulatory aspects is presented in Table 10.

V. DISCUSSION AND FUTURE SCOPE

As we have covered in this article, medical imaging technologies, including CBCT, produce vast amounts of data, which is neither optimal to be solely processed in centralized cloud locations nor optimal to be processed in local dedicated computers. The traditional centralized cloud approach is sub-optimal due to the high dependency on the correct functionality of the communication links between the scanner and the cloud-based processing units and the high burden inflicted on these links by high data volumes. Long communication routes can also introduce performance

TABLE 10. A list of Recent Research Articles on Privacy & Regulatory Aspects of Medical Data: Section IV-E.

Publication & Year	Main Focus/Relation to This Study
Kanwal *et al.* [138], 2021	This paper investigates the ways to integrate privacy models and strategies to achieve a compromise between privacy and utility. Specifically, it examines privacy concerns in cloud-based Electronic Health Records (EHRs). It addresses evolving privacy legislation and rules by identifying the most relevant privacy strategies that can be modified to protect the privacy of EHRs in the cloud. This article is important from a regulatory perspective for the cloud tier of 3-TECC, especially when data processing is conducted in a remote cloud.
Mayer *et al.* [139], 2021	This work gives a general review of MDRs in Europe, Australia, and the United States with a particular emphasis on vascular aging evaluation. It highlights how crucial interdisciplinary cooperation is between government agencies, business, academia, and medical professionals to improve the social and ethical implications to foster innovation. To scale up our proposed 3-TECC architecture for CBCT, this study provides important context regarding MDR for different continents.
Sahi *et al.* [140], 2021	This paper highlights the advantages and disadvantages of current technologies and methodologies while reviewing recent research on security and privacy in eHealth clouds through an analysis of relevant studies. It attempts to inform academics and stakeholders in eHealth about the latest developments and data security specifications. The paper explores health data's privacy and security considerations within eHealth clouds and introduces potential security algorithms for data protection. In 3-TECC, we address CBCT medical imaging use cases. Therefore, this research offers valuable insights into data protection strategies, particularly for cloud tiers and other remote servers where data is processed away from its source.
Bianchini *et al.* [134], 2022	The significance of the new EU MDR is emphasized in this study, along with its consequences for stakeholders at every stage of the lifetime of a medical device and its function to guarantee user safety. It makes the case that being aware of these legal obligations can foster innovation, providing new opportunities in the medical industry as well as social and ethical advantages. Regarding the MDR aspects of 3-TECC, the reference paper highlights key elements of the new EU medical device regulations and other significant considerations related to MDR compliance.
Vegesna *et al.* [141], 2022	In this study, the usage of blockchain technology is proposed as a solution to security and privacy problems in IoT systems that depend on central servers. This article delves into how distributed ledger-based blockchain (DL-BC) technology enhances security and privacy in the IoT. It also describes how DL-BC is applied in different industries and discusses the unique difficulties surrounding blockchain integration with IoT. The paper focuses on security-related threats, which serve as critical points of consideration for the local and other tiers within the 3-TECC architecture.
Abbas *et al.* [142], 2023	In the context of IoT services and applications, this article discusses Deep FL (DFL) and its advantages by addressing existing obstacles. It also outlines potential future research avenues to integrate DFL into IoT, examines the effects of DFL on security and privacy, and presents a DFL-based framework compliant with GDPR. The key topics covered in the paper, including federated learning, privacy, security, and GDPR aspects, are central to the areas we are examining in our study.
Nowrozy *et al.* [143], 2024	This study explores the role of distinguishing between privacy, confidentiality, and security when creating secure EHR systems. It lists popular privacy-preserving methods, including cryptography, cloud-based solutions, blockchain, and access control, and suggests combining these methods to improve the privacy, confidentiality, and security of EHRs. The article places greater emphasis on the healthcare perspective, addressing the aspects mentioned above and paving the way for potential technologies to support a secure EHR system.
Tettey *et al.* [144], 2024	In this article, hardware and software advancements such as AI and IoT are highlighted with an overview of Food and Drug Administration (FDA) classifications and regulatory procedures for biomedical devices. It explores cybersecurity concerns, laws for AI/ML and IoT devices, and the advantages of human factors engineering in lowering user error and recalls. In this Review, the first FDA-approved AI treatment for diabetic retinopathy and upcoming developments in biomedical device development are also covered. The study provides an overview of FDA regulatory procedures in the United States, while our discussions primarily focus on MDR compliance in Europe. As such, this work highlights regulatory compliance from a transcontinental perspective.

bottlenecks for latency-critical medical imaging scenarios. Furthermore, confidentiality requirements of medical data cause restrictions for centralized processing scenarios. On the other extreme, the traditional dedicated local reconstruction computer approach is suboptimal due to the inherently high hardware costs and poor scalability. Furthermore, the traditional medical image processing workflow is being challenged by novel mobile imaging scenarios that require using wireless networks for data communication.

Based on this rationale, this article focused on a three-tier computational continuum architecture, in short 3-TECC, which provides a dynamic and flexible placement of medical data processing in an optimal computational tier of the computing continuum spanning from local virtual computational units through edge servers co-located with access networks to remote cloud servers. While the concept of a three-tier architecture is well-established, its application to medical imaging, especially CBCT imaging, is an unexplored idea. CBCT imaging generates a large volume of data, and there is currently no existing work that addresses the unique challenges of this specific use case on distributed edge cloud computing. Our proposed solutions, grounded in state-of-the-art literature, are not only applicable to CBCT but can also be extended to other data-intensive medical imaging modalities. To deal with data-intensive medical imaging applications, particularly CBCT image reconstruction, the distributed 3-TECC architecture, through its different levels, provides a flexible platform to prevent network bottlenecks and the propagation of medical data outside the hospital premises for better protection against privacy and security threats.

First, we detail the phases of CBCT imaging data, their properties, and the data flow from the imaging device to the diagnostic format. When implementing a distributed computing platform, it is essential to understand the types of data and the requirements for processing and communication in order to build a system that meets its specifications. Moreover, we identified the characteristics of the various tiers and emphasized their role in computing architecture by including data management across these tiers, and also draw attention to the importance of medical data processing in terms of privacy and security concerns, with a focus on data regulations. Furthermore, to achieve privacy-preserving, secure, reliable, resource-efficient, and high-performance computing architecture, we discussed the most related technical, functional, performance, and regulation-related requirements and challenges, as well as provided a glance at potential solutions for optimal utilization of each tier of the computing architecture.

Primarily, this research aimed to outline the technical requirements for executing medical imaging use cases in 3-TECC, with a specific focus on the CBCT image reconstruction use case. The workflow phases for CBCT reconstruction span from collecting data on medical imaging devices to transferring the data to be processed in appropriate nodes at appropriate tiers in the computing architecture. Potential privacy-preserving distributed AI techniques for implementation, functional service deployment among nodes, computational hardware, and communication tools were discussed alongside related work from the literature to achieve efficient future digital healthcare systems. The results of this study show the wider implications for medical imaging and healthcare technologies in addition to providing technical details and a workflow for the CBCT imaging modality. This work offers a comprehensive framework that can improve the efficiency of CBCT by outlining the steps involved in data gathering and processing.

We also elucidate the technical specifications of tiers in the distributed 3-TECC, highlighting the importance of their characteristics during the image reconstruction process. Our proposal leverages local scalable swarms of GPU-enabled computational nodes in the local tier, MEC servers co-located, e.g., with the nearest cellular base stations in the edge tier, and GPU clusters from data centers in cloud tier. The results highlight how important each tier is to the distributed 3-TECC system. The architecture ensures efficient data processing close to the data source by utilizing local GPU-enabled nodes. For example, distributed AI methods, such as FL, aim to leverage data at its source. By keeping the large volumes of CBCT data localized, the demand on network resources can be significantly reduced, offering a cost-effective solution while maintaining efficiency. This approach is crucial for enhancing real-time processing capabilities. In addition, it helps address privacy and security concerns associated with medical data by keeping the data local. The cloud tier's strong GPU clusters perform the computationally demanding operations for image data analysis, while the edge tier's MEC servers provide effective intermediate processing and data transport, further streamlining the workflow.

Data regulatory aspects, including GDPR and MDR, were also discussed in the survey, in addition to the technical requirements. The study contributes to creating a legal framework for medical imaging by considering factors when implementing the distributed computing architecture. This architecture can accelerate and enhance the accuracy of diagnostic operations, which would benefit patients and lead to significant improvements in clinical practice. This article serves as a paradigm for further developments because it combines cutting-edge computational and communication methods with regulatory compliance into a unified distributed architecture.

A. IDENTIFIED CHALLENGES

- **Heterogeneity:** There is heterogeneity in (i) hardware capacity, both computational and communication; (ii) software: various APIs, data formats, etc.; (iii) virtualization systems, orchestration mechanisms; (iv) service providers' security policies; (v) application/use case requirements; (vi) regulations across countries and continents. Centralized cloud centers provide a uniform platform for data processing. In contrast, in distributed systems, heterogeneity is a fundamental challenge [145]. Within the framework of the 3-TECC architecture, device providers in terms of computing architecture and manufacturers' equipment in the context of medical imaging techniques [146] play an important role in ensuring heterogeneity paradigm through computing hardware, network connectivity, and medical imaging techniques. Due to the distributed nature of the system, the technologies mentioned above can vary among the different tiers. Thus, the implementation of the 3-TECC architecture requires dealing with computing nodes with different technical specifications in hardware and software, different medical imaging vendors, and the dissimilarity of the networking technologies [19]. Deploying tasks uniformly across distributed computing nodes would streamline task processing compared to using devices from different vendors. For instance, in containerized solutions, Docker containers built for AMD hardware architecture may fail on aarch64-based hardware processors.
- **Medical data volume:** In general, transferring and processing raw data from medical imaging devices and CBCT scanners to remote processing units is challenging. These challenges are emphasized due to the considerably fast growth of medical imaging data due to higher-quality imaging devices producing e.g. higher-resolution and/or 3D image data from CT and MRI scanners, which also requires more storage in addition to the growing burden on networks [147]. This requires more efficient algorithms to perform well on large, noisy and complex datasets, powerful computing hardware, robust/seamless network services, data integration, and adequate storage infrastructure.
- **Computational capacity:** The deployment of data processing among the computing nodes is a crucial step of the 3-TECC architecture. The capability of the computing node can be seen from a use case viewpoint, such as a device that is capable of processing classic IoT data might have challenges when facing the data-intensive medical imaging processing task, whereas the volume of images can grow at gigantic scales.

- **Network capacity:** To process medical data from scanners, data must be transferred to the processing unit. This requires a well-managed fiber/ethernet-based transfer or advanced cellular networks like 5G and beyond. High data volumes necessitate a fast network connection to ensure efficient data transfer, significantly impacting diagnostics. In addition to delays [65], a 5G-enabled MEC server in the hospital may be needed to handle slightly heavier tasks.
  Physical barriers within the unit can hinder communication between the medical imaging unit and the base station, affecting the propagation of high frequencies during examinations. Hence, a well-covered connection is essential for efficient healthcare systems. Furthermore, in mobile imaging scenarios, mobility-related challenges may significantly affect the performance and capacity of local computing. Due to potentially poor access network connections, it may not be feasible to use cloud or even MEC servers for data processing. Therefore, it is essential to implement mechanisms to handle reconstruction and analysis tasks with limited data connections. For example, maximizing local computation and utilizing only the most critical external resources can help conserve the limited capacity of the Internet connection. A rough CBCT image could be reconstructed locally for quick analysis. When the imaging vehicle, such as a truck or ambulance, reaches a location with better connectivity, higher-capacity cloud servers can be used to reconstruct higher-quality images. These servers offer superior computational capacity and access to external databases necessary for tasks like artifact reduction.
- **Medical data/device regulation:** Medical data processing whether inside or outside of health centers requires adherence to strict regulations. MDR and GDPR emphasize the importance of proper medical data handling [63], [134], [139], [144]. The use of public cellular networks in medical centers is particularly affected by the need for a secure environment, especially for patient data confidentiality and device integrity. Third-party vendors operate these networks with their security regulations that may not completely comply with the strict guidelines required by healthcare providers. Furthermore, sensitive patient data may be accessible through public networks due to various risks, such as non-authorization access and data breaches.
- **Data privacy:** A big part of the regulation comes from data privacy, private 5G networks owned and managed by hospitals can be provided to avoid these risks. These private networks give healthcare providers a complete understanding of security guidelines, guaranteeing strong defense against potential attacks. Health centers can customize their defenses to fit certain regulatory standards and clinical needs by managing the network architecture and security procedures. This makes the environment more safe for the functioning of medical devices and data. By removing the need for third-party suppliers and reducing the possibility of incompatible security protocols, this autonomy improves overall data integrity and patient safety in healthcare facilities.

B. LIMITATIONS

The limitations of our work include a focus on the CBCT imaging modality. We selected CBCT image reconstruction as a use case because it typically generates significantly more image slices per examination compared to other radiological imaging techniques. Thus, we selected the imaging modality with the most stringent requirements for the 3-TECC architecture including computational and communications aspects. However, the computational workflow varies between different medical imaging technologies, and therefore further focused studies are needed for various imaging modalities, such as mammography, MRI and US.

Furthermore, although this article covered the privacy and regulatory aspects of medical data in 3-TECC architecture, including aspects of privacy, GDPR, and MDR in Europe in Section IV-E. The data regulatory aspect for other geographic areas was not covered within this article. Therefore, we can see a clear need for a dedicated article to cover these topics in more detail. Security represents another limitation of this article. Further work is needed to cover and mitigate potential security threats at different tiers of the 3-TECC architecture.

Finally, we have approached this research paper from an edge AI perspective, where different computing nodes in the platform can host various phases of medical imaging and CBCT reconstruction. However, efficient optimization of the AI algorithm among the 3-TECC computing nodes is necessary to improve the utilization and efficiency of the system resources. Conventional and AI-based optimization techniques can be employed to optimize the resources of the computing nodes in the dynamic environment of 3-TECC architecture.

C. FUTURE WORK

The future work focuses on the implementation of a real-world platform based on the proposed distributed 3-TECC architecture for CBCT image reconstruction. The following research questions (RQ) would be important to be assessed as the future work. *RQ-1: What are the potential challenges for the real-world implementation of 3-TECC architecture, considering the distributed systems, huge volume of medical imaging data, data privacy and security, the role and performance of distributed AI methods in realizing the architecture?* As computing resources, we plan to use GPU-enabled hardware in the local tier, MEC servers with GPUs at the edge tier, and cloud platforms as cloud tier in realizing the 3-TECC architecture. *RQ-2: How can centralized AI model performance be achieved in a decentralized manner? RQ-3: How can robust communication among computing nodes on distributed tiers be ensured? RQ-4 How to effectively utilize resource-constrained computing nodes in 3-TECC architecture?*

TABLE 11. Related research papers for the requirements in Section IV including the objective and required/expected outcome from the requirement.

Objective	Key components	Source
Efficient Medical Data Management	Increased local data processing	[19], [34], [72], [77], [78], [113]
	Optimized computational nodes	[76], [79]–[81], [148]
	Utilization of AI	[34], [41], [45], [120], [149]–[151]
Deployment of AI Algorithms	GPU-enabled hardware systems	[34], [37], [152]–[154]
	Sufficient resource capacity	[40], [155]–[157]
	Distributed AI	[29], [30], [86], [96], [99]–[101], [105], [106], [109]
Deployment of Functional Services	Communication aspect	[7], [52], [55], [58], [115], [128]
	Computational aspect	[32], [112]–[114], [116], [118]
	Service priorities	[31], [115], [158], [159]
Optimized Image Reconstruction	Scalability of computing platform	[26], [32], [120], [131], [132]
	Diagnostic performance	[34], [36], [37], [86], [130]
	Energy efficiency	[31], [76], [122], [123], [133]
	Computing platform reliability	[32], [45], [127]–[129]
Privacy & Regulatory Aspects	Secured computing platform	[134], [139], [144], [154], [160], [161]
	Protected patient data	[6], [63], [138], [162]

In addition to the CBCT use case, it would be relevant to extend the computing architecture to accommodate various imaging modalities and medical use cases, as well as to conduct more detailed testing, as mentioned in Section V-B, including, e.g., digital mammography and MRI. *RQ-5: How to scale 3-TECC to adopt various imaging modalities efficiently? RQ-6: What parts in 3-TECC architecture must be modified to host different medical imaging use cases?* Our implementation approach will emphasize distributed AI, particularly federated and split learning techniques.

In addition, our research will further investigate AI optimization techniques to improve the performance and efficiency of medical imaging processes. *RQ-7: How can computing and networking resources be efficiently utilized to meet the dynamic needs of devices in the 3-TECC platform, enhancing system performance and efficiency?* Moreover, we recognize the importance of mobile imaging-related work, particularly in addressing network-related issues under the Section V-A. Future studies will include these aspects to ensure comprehensive solutions for mobile medical imaging applications. In addition, we will explore adaptive security measures to ensure robust protection for our computing architecture.

VI. CONCLUSION

This article investigated the technical prerequisites for improved care using a three-tier edge-cloud continuum (3-TECC) architecture, a conceptual framework designed to host radiological medical imaging data, focusing on the CBCT image reconstruction use case. We presented the key aspects of collecting and processing CBCT data within this architecture, detailing the technical requirements for the implementation of the computing architecture by utilizing the latest technologies. These technologies serve as a foundation or one of the modalities for data-intensive medical imaging use cases on distributed edge cloud computing. The findings suggest that the 3-TECC architecture can significantly improve the processing and management of CBCT data, potentially improving the overall quality and efficiency of radiological imaging. This could lead to better diagnostic capabilities and patient outcomes in medical imaging.

In addition, the review includes an overview of the technical specifications of computing devices of different tiers and emphasizes both existing and novel wired/wireless communication technologies for communication. Specifically, we examined the technical requirements for CBCT image reconstruction from various perspectives. We proposed solutions for achieving efficient CBCT data management, using and deploying distributed AI algorithms, deploying functional services, and the necessary optimal performance metrics. We also highlighted GDPR-compliant approaches to ensure the privacy and confidentiality of medical data. These contributions provide a comprehensive understanding of the technological landscape necessary for effective CBCT image reconstruction and management. The proposed solutions and highlighted approaches can significantly enhance the efficiency, security, and privacy of medical imaging data management, potentially leading to advancements in improved patient outcomes in medical imaging.

Finally, the proposed distributed AI-based 3-TECC approach can reduce the need to transmit large volumes of medical imaging data to centralized centers. This approach alleviates network bottlenecks, privacy concerns and integrates novel technologies such as distributed ML that preserves privacy, advanced communication and computational tools, virtual deployment services, and data regulatory standards. The IoMT leverages interconnected distributed nodes and tiers in the 3-TECC architecture, combined with distributed ML, to transform the industry. These advancements can play an important role in future digital healthcare. The 3-TECC approach can significantly improve diagnostic capabilities and patient outcomes in medical imaging by reducing transmission needs and integrating state-of-the-art technologies.

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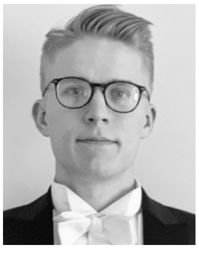

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