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Holistic Data Processing: Designing the Intelligent Edge-to-Cloud Pathway for IoMT

Hayat Zaydi, Zohra Bakkoury

Ecole Mohammedia d'Ingénieurs,
Mohammed V University
Ibn Sina Street
Rabat, Morocco

email: zaydi.hayat@gmail.com, bakkoury@gmail.com

Abstract

The healthcare sector is witnessing rapid transformation with the rise of the Internet of Medical Things (IoMT). This presents unparalleled opportunities for continuous, personalized health surveillance. To truly tap into the IoMT's capabilities, it's essential to employ a flexible and robust data processing framework. In this article, we introduce a comprehensive four-tiered architecture tailored for the IoMT. This model, which we foresee as a benchmark for similar platforms, spans from interconnected devices to an edge computing layer, extends through a fog computing level, and culminates in the cloud. To bolster the system's resilience and features, two cross-sectional layers - one centered on security, and the other on artificial intelligence (AI) - are integrated across the four tiers. Additionally, we outline strategies for efficient load balancing, enhancing overall system performance. This initiative marks a pivotal advancement in IoMT architectural standardization, setting the stage for broader, more effective deployment in healthcare.

1   Introduction

Recently, healthcare is undergoing a rapid transformation with the infusion of information technology, leading to the creation of smart systems. These systems aim to hasten diagnostics and accurately prescribe treatments, ultimately preempting severe health situations. Such advancements span across all sectors of healthcare, ushering in cost reductions and enhancing overall health conditions [4] .

A significant driving force behind this transformation is the Internet of Medical Things (IoMT). It radically redefines the delivery, management, anticipation, and even governance of healthcare services [5][6]. The broader Internet of Things (IoT) holds the potential to revamp healthcare by profoundly altering how hospitals, clinics, and other healthcare institutions collect and utilize data. This evolution converges the principal technological and commercial trends related to mobility, automation, and data analytics, improving patient care [7, 8, 9].

These interconnected devices produce vast amounts of data. When processed through architectures and platforms underpinned by artificial intelligence, especially ML and DL, these data can flag potentially severe health conditions, detect patterns to prevent them, and much more. This proactive approach facilitates early interventions and enhances overall health conditions [10, 11]. These data, categorized as BIG DATA, traditionally relied on Cloud Computing architectures and various models like IAAS, PaaS, SaaS, CaaS, FaaS, etc [12, 3].

Although this yielded significant performance and cost benefits for businesses, the model encountered issues related to latency, internet dependency, bandwidth, and security. Such concerns are especially pressing in healthcare, where rapid response times are often critical [13, 14] . Recent trends showcase a growing interest in hybrid architectures [12], which harness the robustness of Cloud computing for compute-intensive tasks and large storage demands. At the same time, they address latency and bandwidth challenges through Edge and Fog computing[2, 1], ensuring the distributed and reliable deployment of healthcare applications. This caters effectively to the demands of IoMT.

IoMT-based healthcare solutions rely on data storage and processing approaches that utilize clusters positioned at varying user and sensor proximities. In Edge Computing, computation occurs close to the user's physical location or data source, such as IoT devices. Positioning computational services nearer to these sources ensures faster and more reliable services,

benefiting users with enhanced experiences, and businesses by supporting latency-sensitive applications, trend identification, and better product and service offerings [15]. Conversely, Fog Computing nodes distribute across local networks, handling larger and more powerful devices like PCs, local servers, and gateways. These might be somewhat distanced from IoT devices such as sensors and actuators [16]. Both computing paradigms ensure geolocated health services with high availability and minimal latency. Generally, neither paradigm aims to replace Cloud computing but is instead integrated to offload the Cloud. This enables healthcare systems to leverage the strengths of each paradigm in a distributed, data-centric hybrid approach [12].

In this paper, we introduce a novel data processing architecture for IoMT, merging Edge, Fog, and Cloud computing into a four-tiered hybrid model. This structure aims to be versatile for all healthcare use cases and establishes a standardization benchmark for such configurations. Additionally, our proposal incorporates two cross-cutting layers: one dedicated to security and another to artificial intelligence, spanning the four tiers. We also explore various load-balancing techniques across the three data processing layers (edge, fog, cloud) to enhance the system's overall efficacy.

One of the seminal contributions of this study, besides the architecture itself, is laying groundwork towards the normalization and standardization of such architectures.

The structure of this paper is organized as follows: In the upcoming section, we revisit related works, providing context and emphasizing prior contributions in the domain. This is followed by a section elucidating the motivations behind our contribution. Subsequently, we delve into our proposed architecture, breaking it down by specific layers and implementation prerequisites. Two distinct sections follow, dedicated to detailing the security and artificial intelligence layers, emphasizing their crucial role in the comprehensive system. We then shift our attention to load-balancing approaches, illustrating how they enhance inter-layer interactions. We conclude the paper with a general discussion, summarizing key findings and offering insights for future research.

2 Related work

We start with a proposed IoT software architecture for the fields of agriculture, smart cities, and health [17]. The architecture for health is presented

in five layers in terms of functionalities: data collection, data processing, communication, security, and data presentation. In the study [18], the authors reviewed IoT in the healthcare domain, describing the technologies that provide intelligence through connected objects. They also introduced a cloud-based three-layer architecture for health IoT: the sensor perception layer, the Fog layer, and the Cloud layer. Abdelmoneem et al. [19] suggest a Cloud-Fog-based architecture for IoT health applications. Their generic architecture, suitable for various healthcare applications without being specific to a medical case, consists of four layers: the things layer, the sink layer, the fog layer, and the cloud layer. Another study [20] proposes an IoT application architecture for healthcare based on Fog Computing to address the limitations of Cloud, especially in latency terms. Their structure focuses on three layers: the IoT devices network, the Fog layer, and the Cloud layer. Paul et al. [21] discuss the use of Fog Computing for monitoring chronic disease patients. The proposed structure, in line with most reviewed architectures, includes a Sensor layer, a Fog layer, and a Cloud layer. The fog layer, comprising several fog nodes and a smart gateway, is positioned between the cloud and sensors, making it suitable for time-sensitive applications like healthcare. The research concludes that fog computing is a promising technology for efficient patient monitoring and improved health outcomes. Debauche et al. [22] offer a unique three-level distributed architecture consisting of a sensor network, a smart local gateway, and a cloud layer. This architecture stands out for its specificity, from the precise sensor environment to the cloud layer that integrates a suite of Apache Hadoop ecosystem tools built around HDFS. Verma et al. [23] delves into the use of advanced technologies like fog computing, IoT devices, and machine learning algorithms for real-time remote health monitoring in smart homes. The proposed model employs a layered architecture for data collection and analysis, which is then sent to a cloud storage layer for further processing. This architecture consists of five layers: the Data Acquisition Layer (DAL), Event Classification Layer (ECL), Information Mining Layer (IML), Decision Making Layer (DML), and Cloud Storage Layer (CSL). Another approach [24] suggests an architecture based on Mobile Edge Computing (MEC) for connected health applications. It focuses on two core functionalities: multimodal data compression and peripheral feature extraction for event detection. Addressing challenges related to energy consumption, bandwidth economy, secure transmission, and data protection, the article also highlights the potential of edge computing. In [25], a personalized healthcare support system for remote diabetic patients is presented. This system combines IoT and Cloud computing to monitor

blood glucose levels and predict diabetes risk. It comprises three main components: IoT devices, a fog layer with local data storage and interoperability, and a cloud server. A novel approach for early Covid-19 detection using IoMT, cloud computing, fog computing, deep learning, and QoS is suggested by the authors of [26]; This system is structured into three layers: a user layer capturing patient chest x-rays, a fog layer preprocessing data ensuring data confidentiality, and a cloud layer offering high computational capacity and extensive storage. This structure is specifically dedicated to diagnosing Covid-19. [27] introduces HealthFog, a smart system for automatic heart disease diagnosis. It uses cloud computing, fog computing, and IoT to manage patient data efficiently. The architecture consists of body area sensors, gateways, fog computing nodes, and cloud servers. Similar to the aforementioned architectures, this system is designed specifically for heart disease. The research in [28] proposes a three-tier architecture for IoMT systems: a first layer using wearable sensors, a second with fog nodes processing the data, and a third cloud layer storing data for health applications. This structure reiterates the typical three-tiered approach: Sensor - Fog – Cloud, with "Fog" denoting the edge. In [29], an IoT architecture is proposed for elderly monitoring. It comprises two processing layers: the "fog" layer for data collection and preprocessing and the "cloud" layer for storage, real-time analysis, and decision-making. Lastly, authors of [30] suggest a remote health monitoring architecture through two processing and computing layers: the Edge layer and the Cloud layer. Deep diving into this proposal reveals a convergence to the typical three-layer approach seen in most studied architectures, with "Edge" used synonymously with "Fog". This particular architecture focuses on video processing for remote health monitoring.

3 Motivation

This research seeks to elucidate and model a new IoT architecture for healthcare that harmoniously and complementarily employs various IT computational locations relative to the data-generating object. Several reasons drive this endeavor. Firstly, to alleviate the strain on cloud computing, which, while proven, possesses inherent limitations. Additionally, we aim to harness the benefits of intelligent data processing and analysis close to, and very close to, the source. Thus, we put forth an architecture designed to be holistic and intricately detailed—a feature glaringly absent in most architectures reviewed in our literature survey. Most of these structures are either tailored

for a very specific use case, like solutions dedicated to a particular disease or a patient category, or ones addressing a single architectural level without regard to potential limitations. As highlighted in the related work section, we observed that these architectures predominantly consist of three layers: Object, Fog, and Cloud or Object, Edge, and Cloud, with typically just one aspect detailed. Our proposed architecture comprises six layers: four primary horizontal layers and two vertical layers intersecting the first four.

4   Designing for the Future: A Holistic and Generalizable IoT Architecture as a Prelude to Healthcare Standardization

This section focuses on introducing an innovative Internet of Things (IoT) architecture for the healthcare domain. Our aim is to lay the groundwork for a robust and universal standardization that addresses the growing challenges in healthcare data monitoring and management. To achieve this goal, we have developed a holistic and adaptable approach that provides a flexible framework for IoT in healthcare. The proposed architecture not only optimizes data collection and processing but also ensures the security and confidentiality of medical information. By emphasizing standardization, we strive to promote wider adoption of IoT technologies in healthcare, paving the way for significant advancements in healthcare delivery.

4.1   Description

As depicted in Figure 1, the proposed architecture consists of four horizontal layers and two cross-cutting vertical layers. These layers collaboratively function to establish a distributed framework, wherein data is collected, processed, and harnessed effectively at various stages across the network.

In the following sections, we provide a brief overview of each layer within our holistic architecture:

The Sensors/Actuators Layer (IoMT Devices) : Bridging the digital and physical realms, this layer is comprised of tangible, interactive elements that stand at the forefront of data collection within the context of connected health. Medical sensors are specialized devices that measure vital signs such as body temperature, heart rate, blood pressure, and oxygen saturation. They meticulously capture patients' physiological information. Conversely, actuators might be pumps used to administer medications, electrodes for

electrical stimulation, or other devices that deliver specific therapies based on medical data and system-driven decisions. In the spirit of innovation, we advocate for the use of smart sensors capable of preprocessing data locally before transmission, thus conserving bandwidth and enhancing overall efficiency. We also propose the development of biomarker sensors for the early detection of diseases.

The Edge Computing layer : plays a pivotal role in the healthcare sector, facilitating near-source processing of medical data. This ensures swift and real-time processing of vital signs, which is quintessential for monitoring patient conditions and promptly detecting any irregularities. Edge Computing can also enhance privacy by minimizing the transmission of sensitive data to the cloud, while still maintaining a high responsiveness for medical decision-making. This layer may comprise smart devices located near the patients, such as IoT gateways, embedded devices, or microservers. These devices handle the preprocessing of medical data at its origin, performing tasks such as data filtering, compression, and fusion. Machine Learning (ML) algorithms or Artificial Intelligence (AI) can be deployed at the Edge for rapid anomaly detection, preliminary diagnostics, or real-time monitoring. They will also be employed to determine the location for data storage and processing based on criteria set for each use case. For more cutting-edge architectures, we suggest integrating distributed machine learning techniques, allowing various Edge nodes to learn from each other and enhance their performance over time.

The Fog Computing Layer: In the context of connected health, the Fog Computing layer extends the capabilities of Edge Computing by offering an intermediate level of data processing and storage closer to healthcare services. This facilitates the efficient handling of larger volumes of medical data, including high-resolution medical images and electronic patient records. This layer introduces a more advanced computing infrastructure and storage capabilities close to healthcare establishments, including local servers, enhanced gateways, or data centers located near health centers. This provides reduced latency and high availability, significantly enhancing the performance of critical medical applications. This distributed computational capacity ensures service continuity even when the cloud connection is lost or unstable. This layer might incorporate functionalities such as real-time processing of vast data volumes, coordination of Edge devices, and resource management. An innovative approach would be to develop orchestration algorithms that can smartly distribute resources among different Fog nodes based on their requirements and capacities.

The Cloud computing layer: At the pinnacle of the architecture is the

Cloud Computing layer, which is pivotal for the secure storage of large-scale medical data. Cloud data centers facilitate the consolidation and efficient management of health records from a vast patient population. This provides universal access to electronic records, enabling authorized healthcare professionals to swiftly retrieve pertinent information for diagnosis and treatment. Cloud Computing also streamlines the secure data sharing across different healthcare institutions and expedites medical research through big data analytics. It serves tasks ranging from large-scale data analytics, intensive computation, AI model training, to long-term data storage, and much more. We advocate for the integration of a federated cloud learning feature. This allows various cloud systems to share machine learning models and insights while safeguarding data confidentiality.

The figure below (figure 1) provides an overview of our proposed architecture, highlighting the core layers and their interactions. For clarity, only a select set of functionalities and components are showcased for each layer. In practice, the breadth of functionalities and the diversity of components can be much more extensive. This depiction offers a general snapshot and is not exhaustive, aiming to maintain simplicity while capturing the essence of our architecture as the IoMT landscape evolves.
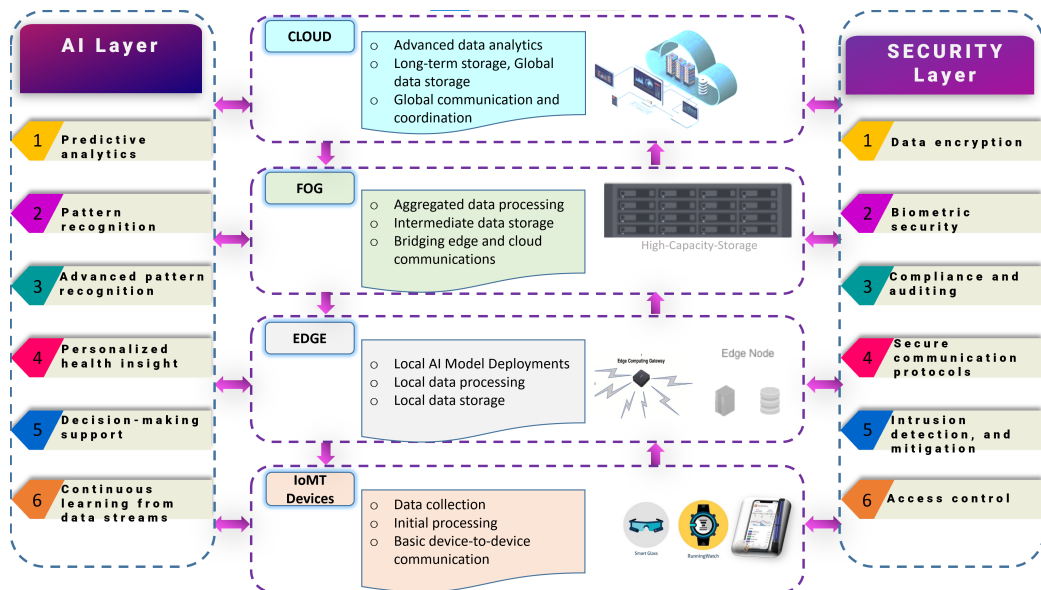

Figure 1: Schematic Overview of the Proposed Architecture

4.2 Cross-sectional Layers: Artificial Intelligence and Security

4.2.1 The AI Layer: An Intelligent Conduit for Data Stream Management

The cornerstone of our solution's optimization strategy is the AI layer, a sophisticated Deep Learning model. This layer is not just a mere computational tool; it's an adaptive, decision-making entity that's pivotal for the efficient and effective management of data streams. Herein, we enumerate the distinctive features and functionalities rendered by this AI layer :

1. Adaptive Decision Making : The AI layer is designed to evaluate data in real-time, making determinations based on metrics customized for each specific application. This adaptability ensures that it can respond appropriately to varying data types and requirements, channeling information to where it's most valuable.

2. Data Routing and Storage: A critical responsibility of the AI layer is to determine the most efficient paths for data streams. It assesses the best locations for data storage, considering factors such as accessibility, processing speed, and redundancy. By doing so, it guarantees that data is both secure and readily available for analysis when needed.

3. Advanced Analysis and Utilization: Beyond storage and routing, the AI layer is equipped to carry out advanced analytical tasks, transforming raw data into actionable insights. This capability is invaluable for extracting the maximum potential from the primary layer's data streams.

4. Selective Processing: One of the most innovative aspects of the AI layer is its ability to discern the relevance of each data stream. By evaluating the potential significance of each stream to stakeholders, it can prioritize processing for the most valuable data and bypass streams that don't provide pertinent insights. This ensures that system resources are allocated effectively and reduces unnecessary computational overhead.

4.2.2 Security Layer

One of the paramount challenges encompassing the Internet of Things (IoT) – and more specifically within the healthcare sector – is the multi-faceted nature of security. This not only pertains to unauthorized access to both data and architectural equipment but also extends to the unique aspects related to healthcare data, such as the adherence to prevailing legislation that

mandates varying degrees of health data protection. Such security considerations permeate every level of the architecture, from individual IoT devices through the gamut of Edge and Fog equipment, and extend to Cloud Computing. Depending on the criticality of the data, the specific location within our architecture, and the allocated budgetary considerations, diverse security solutions and mechanisms are implemented. To ensure the confidentiality, integrity, and availability of sensitive health data, we advocate the implementation of our solution using a 'security-first' approach. This not only emphasizes initial robust security measures but also ongoing evaluation and reinforcement throughout the system's lifecycle. This holistic strategy might encompass, but is not limited to, the following elements:

1. Authentication and Authorization: Implementing a robust authentication system to verify the identity of users and connected medical devices. Employing suitable authorization mechanisms to control data access based on roles and privileges.

2. Data Encryption: Applying encryption for data, both in-transit and at-rest, to safeguard sensitive information during transmission and storage.

3. Firewalls and Packet Filtering: Leveraging firewalls to regulate network traffic, complemented by packet filtering to prevent unauthorized device and data access.

4. API Security: If Application Programming Interfaces (APIs) facilitate communication between architectural layers, ensure they are secure, demanding suitable authentication.

5. Threat Monitoring and Detection: Employing real-time surveillance systems to pinpoint suspicious activities or intrusion attempts.

6. Physical Security: Safeguarding the physical integrity of medical IoT devices, Edge gateways, and Cloud data centers to thwart unauthorized physical access.

7. Vulnerability Management: Regular software and firmware updates for connected devices to address known security vulnerabilities.

8. Data Isolation: Mechanisms to quarantine sensitive data, clearly identifying it to prevent unauthorized access or leaks.

9. Business Continuity Plan: Establishing a contingency plan for major security incidents to minimize operational impacts.

In conclusion, it is recommended to adhere to widely-recognized cybersecurity standards and norms to ensure the foundational pillars of information security in such architectures. This approach should also consider the critical nature of health data and the legal frameworks of each respective country.

4.3   Load Balancing

In addition to establishing a foundation for potential standardization of hybrid and distributed IoT architectures for data collection, routing, storage, and analysis in healthcare, our work also offers another significant contribution. It provides insights into the load distribution among the different components of our architecture. Consequently, we propose four possible scenarios for this distribution, we will also outline potential algorithms suitable for its implementation:

1. Vertical Distribution: If we adopt this distribution scenario, sub-tasks are distributed vertically along nodes organized in a hierarchical tree structure. Tasks are divided and allocated over the three layers – Edge, Fog, and Cloud – based on their complexity.

● **Potential Algorithms and Strategies:**

o Hierarchical Partitioning Algorithms: These algorithms split tasks based on a hierarchical tree structure and assign sub-tasks to various layers as per their complexity.

o Decomposition Approach: This involves breaking tasks down into sub-tasks which are then assigned to different layers as per their complexity level.

2. Horizontal Distribution With this mode, sub-tasks are distributed horizontally amongst the Edge, Fog, and Cloud nodes. The tasks are allocated based on their geographic proximity and processing capacity. ● **Potential Algorithms and Strategies:**

o Geographic or Locality-based Algorithms: Tasks are allocated to Edge nodes that are closer to the data source [31]. o Round Robin: A straightforward algorithm that distributes each new task to the next node in sequence [32].

3. Incremental Distribution: Here, the capability and processing power of nodes dictate how and how many tasks are assigned to these nodes. The larger a node's capacity, the more tasks it receives incrementally.

● **Potential Algorithms and Strategies:**

o Capacity-based Algorithms: Tasks are distributed with more tasks allocated to nodes with higher processing capacity. o Threshold-based Algorithms: These define a threshold for each node. When a node reaches its threshold, tasks are incrementally distributed to other nodes [33].

4. Negotiated Distribution: This approach allows nodes to negotiate among themselves to distribute tasks based on their processing capacity and availability. Nodes can send task requests to other nodes, and nodes with available processing capacity can respond to these requests.

- **Potential Algorithms and Strategies:**

o Bidding Algorithms: Nodes "bid" for tasks based on their available processing capacity. The task is allocated to the node with the highest bid (i.e., the highest available processing capacity)[34].

o Contract Net Protocol (CNP): It's a negotiation technique where nodes announce tasks, and other nodes bid to undertake them. The initiating node then selects the most suitable bid.

5   Conclusion and Discussion

In this paper, we've embarked on a journey through the rapidly evolving landscape of the Internet of Medical Things (IoMT), proposing a unique, comprehensive four-tiered architecture for healthcare. This architecture, deeply rooted in the confluence of Edge, Fog, and Cloud computing, offers a promising pathway towards addressing the critical challenges and harnessing the immense potential of IoMT in healthcare. The design has been made resilient with two cross-cutting layers emphasizing security and artificial intelligence. The synergistic combination of these layers ensures not just the safe storage and processing of patient data, but also a more proactive, personalized, and efficient healthcare delivery system. Our exploration into load-balancing strategies further augments the performance capabilities of the proposed architecture. These strategies ensure optimal resource utilization and task distribution, minimizing latency and enhancing responsiveness — features that are critical in a healthcare scenario where timely interventions can significantly impact patient outcomes. With the rapid emergence and expansion of IoMT in healthcare, there exists a pressing need for standardized norms and benchmarks to ensure efficiency, security, and scalability. We ardently hope that our holistic proposal can serve as a blueprint for the normalization and standardization of such architectures, bridging the prevailing gaps in the field.

Future Work

In the aftermath of our architectural proposition, a horizon of new exploratory avenues unravels before us. Within the framework of future endeavors, several avenues present themselves due to the foundation set by our proposal. Specifically:

Refinement through Real-world Testing: While our architecture provides a robust blueprint, it's imperative to evaluate its performance in real-world conditions. Pilot implementations in select healthcare institutions will

provide insights into possible optimizations and adjustments.

Integrating Advanced AI Models: As the field of artificial intelligence continues to evolve, there will be an opportunity to integrate more advanced models that can further enhance patient care. For instance, the incorporation of federated learning could allow for collaborative model training across various IoMT devices without compromising patient data privacy.

Standards and Policy Advocacy: A significant challenge in the implementation of such advanced systems in healthcare is the development and adaptation of industry standards. Future work could involve advocacy and collaboration with stakeholders to develop standardized policies and procedures that accommodate the rapid advancements in the IoMT domain.

Interoperability with Traditional Systems: As healthcare systems worldwide are diverse, integrating the proposed architecture with traditional healthcare information systems will be crucial. This will allow for seamless data flow and enhanced patient care.

In wrapping up, the healthcare industry is on the verge of a monumental digital transformation, with the IoMT acting as a pivotal player. Through our proposed architecture, we aspire to pave the way for scalable, efficient, and patient-centric healthcare solutions for the future. Our ultimate vision is for this architectural model and accompanying strategies to become a cornerstone for next-generation healthcare systems, revolutionizing patient experiences, reducing costs, and elevating health outcomes on a global scale.

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