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Biosensing in the Internet of Medical Things: A System Architecture and Design-Oriented Survey

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***Abstract*—Diseases and healthcare concerns have become more prevalent in our society. As a result, more individuals are turning towards wearable technology as a way to keep track of their well-being. In addition, the introduction of the Internet of Medical Things will allow for continuous tracking of individuals' health through a distributed network of devices.**

For engineers, the design of these networks must be done carefully in order to maximize their efficiency and effectiveness; however, engineers cannot focus solely on individual sensor technologies because they must consider all aspects of an IoMT ecosystem. This paper reviews biosensing systems used in the IoMT and provides an overview of how a wide variety of medical sensors can be integrated together for maximum effectiveness, illustrating how such systems can be organized into an entire ecosystem from the end-users' perspective and how that broad Vision can be achieved through engineering design.

This paper will help researchers and practitioners in the design and development of scalable, efficient and adaptable IoMT solutions. It will also help determine direction for future research into intelligent and sustainable biosensing systems.

Keywords: Internet of Medical Things (IoMT); Biosensors; System Architecture; Edge Computing; Design-Oriented Survey; Healthcare IoT

I. Introduction

Medical Devices are integrated biomedical sensors, networks, computer intelligence, and support distributed and ongoing medical data collection on patients [1], [2]. Rapid improvements to low-power electronic devices, wireless communication networks, and embedded processors have made it technologically possible to equip environments for remote patient monitoring with wearable, mobile, and ambient sensors that capture patient data in environments away from clinics [3], [4]. However, to be successful, the IoMT system requires that the sensors that make the sensing possible, function well together, and that the heterogenicity of the sensors is constructed into an effective, scalable, reliable, and secure/platform end to end.

Sensing verses sensing means; The sensors are essentially what enables the physician to interpret clinical assessment information collected to ensure patient safety. Therefore, the sensors are foundational to the systems and change physiological, [5] biochemical or physical signals into digital data that are then available for communication between providers and for analysis, evaluation and research.

Each of the various types of sensors has a range of characteristics; thus, each sensor varies with respect to the way it senses, how it is deployed, its sampling characteristics, and the resources required for it to operate. Thus, the many characteristics of sensors introduces complexity and challenges to the overall architecture of an IoMT. The efforts to work together to solve or address issues such as energy efficiency, reliability of data, communication delays, and inter-compatibility must be addressed comprehensively from the sensing layer, network layer, and data processing layer [6], [7]. Therefore, a comprehensive system architecture-based view is necessary to understand how sensors can best be integrated or embedded into an IoMT ecosystem.

Within the literature, there are numerous research articles that review a specific sensor technology or individual sensor that may be used with a single patient type [8], [9]. While these papers add value, many fail to take into consideration how these technologies may work together within a complete IoMT system or workflow. Additionally, many of these articles combine aspects of clinical practice with sensor design and do not explicitly outline the technical trade-offs associated with designing the system. There is a need for an article that specifically reviews sensors in the context of how they fit into the IoMT ecosystem based on the architectural role they perform and how they will influence design constraints associated with IoMT systems.

The intent of this paper is to provide a survey of biosensing technologies in the context of the IoMT ecosystem from a system architecture standpoint. There are three primary contributions of this paper that will benefit the reader: First the paper presents a broad system architecture overview for the IoMT and highlights the interplay between sensing, communication, and data processing elements [1], [6]. Second it introduces a means by which to classify and compare biosensing technologies based on their mode of sensing (how), deployment strategy, method of connecting to other devices, and the nature of the data they produce. Finally it discusses several representative biosensing areas and presents the issue of design trade-offs and identifies current and future engineering challenges and research suggestions associated with IoMT design.

II. IoMT System Architecture Overview

Multi-layer cyber-physical architecture is a typical realization of IoMT systems in a single product. Therefore, IoMT systems implement various types of heterogeneous biosensing devices, their associated communication infrastructures, and platforms for intelligent data processing. An architectural perspective of IoMT systems highlights the relationships between sensing–networking–computing so that they collectively create an integrated pipeline for data acquisition, transfer, and analysis [1], [2]. Fig. 1 depicts a generic example of an IoMT system architecture illustrating these integrations across sensing, communication (edge/cloud), processing, and applications. The following describes the major layers of the IoMT system architecture and provides an engineering and design-focused perspective.

A. Sensing Layer

The sensing layer serves as the link between the anatomy of humans and IoMT (Internet of Medical Things) ecosystems. A biosensor takes advantage of physiological, biochemical or physical signals from a human body and converts them to an electrical/digital signal for communication with other devices and systems [5]. Depending on how the sensor is used, it can serve multiple functions. It can be worn, implanted, or integrated into the location from which it senses. The wearable form of a sensor is the preferred option because they are not invasive, they offer convenience for continuous monitoring and they are typically easy to set up. However, implantable sensors generally produce a significantly more refined/accurate signal than their wearable counterparts, but they often must be operated within a much stricter set of guidelines related to power, safety and reliability [8]. Since the sensing layer is impacted by strict requirements of energy consumption, form factor, and sampling rate when designing IoMT systems, the selection of the sensor and configuration must be carried out at the same time as the networking and computation since the selection of the network structure, configuration and the capabilities will dictate the manner in which sensors output and process data to later levels of the IoMT system architecture [6].

B. Communication and Gateway Layer

The Communication Layer facilitates the transfer of information between the Biosensors and Backend Processing Devices. Short-range wireless technologies (e.g., Bluetooth Low Energy (BLE), ZigBee, and IEEE 802.15.6) are used to connect Body Area Sensors with Local Gateways; long-range wireless technologies (Wi-Fi and Low Power Wide Area Networks [LPWAN]) are used to connect Body Area Sensors to Cloud Services or Data Lake [6].

Due to their ability to transmit data, the choice of a particular communication protocol affects how quickly that data is transmitted, how reliable it will be when transmitted, and how much power it will consume.

Gateways are important components of Internet of Medical Things (IoMT) systems because they provide a consolidated view of sensor data and allow for the initial processing of the sensor data before it is sent to backend processing units, as well as for converting between the protocols used by resource-constrained sensing devices and those used by high-capacity networks. Through off-loading computation, gateways increase system scalability and decrease the power requirement for using sensing devices [2].

C. Data Processing Layer: Edge and Cloud Computing

Data processing in the Internet of Medical Things (IoMT) is continuing to evolve with an ever-growing reliance on both edge computing platforms and cloud computing platforms. Edge Computing enables computation to occur close to the location of the data, which allows for the processing of data quickly (low latency), limits the amount of network traffic required to transfer the data, and provides tighter control over the privacy of the data [10]. This model is particularly useful for time-critical applications and for continuously streaming bio-signals. On the other hand, Cloud platforms support larger-scale analytics, long-term archiving of data, and allow for machine learning models to be trained; these types of services provide elastically scalable compute resources and storage resources that allow for greater scalability when developing IoMT systems. Hybrid Edge-Cloud architectures are increasingly common to achieve an optimal balance of responsiveness, scalability, and computationally efficient [11]. The manner in which processing tasks are divided between Edge and Cloud layers is a fundamental architectural design decision in IoMT systems.

D. Application and Intelligence Layer

The Application layer in Internet Of Medical Things (IoMT) is where the interfacing to enable users access to their data and for clinicians, researchers, or operators of software/hardware related applications to manage the Internet Of Medical Things (IoMT). Data from biosensors are visualized through the application layer, analyzed to create alerts and provide user assistance. Utilizing Artificial Intelligence and Machine Learning (ML), techniques such as predictive modelling or pattern recognition are being implemented to help physicians utilize useful data produced through biosensors [12].

In terms of an IoMT Architect, both ”Intelligence” could be assigned to any tier depending on the constraints of ”Latency”, ”Energy”, and ”Privacy”; therefore, Intelligent agents can execute at Remote locations for real-time use while complex analysis is conducted within the Cloud. Consequently, where

AI is located within the IoMT Architect is a major compromise in creating systems that are optimized for optimal performance, minimum utilization of system resources and performance characteristics [10],[12].

III. Taxonomy of Biosensors for IoMT Systems

IoMT (Internet of Medical Things) systems utilize a variety of heterogeneous biosensors that exist within a multi-layered architecture, as represented by the figure below. Whereas biosensors were historically categorized based on their physiological function or area of application, the architecture-based view necessitates a categorization approach that assesses how the various sensors will interact (within the IoMT system) with the communications, processing and application layers of each IoMT system [13], [14]. Such an architecture-centric approach is especially critical in IoMT environments, where there is a large diversity of devices being used, strict and limited resources available and different types of data being captured. This section places a greater emphasis on the technical aspects of engineering design, rather than on the clinical-based view of the use case for a specific biosensor. The taxonomy provided in this section gives an integrated design approach to understanding how different types of biosensors can shape the design decisions made at the system level (and therefore the architecture) within IoMT architectures.

A. Taxonomy Dimensions

The proposed taxonomy groups biosensors according to five specific but interrelated dimensions that influence IoMT system design and performance in a significant way.

1) Sensing Modality: Different biosensors use different physical or chemical methods for signal detection, e.g. electrical, optical, chemical, and mechanical sensing modalities. Each sensing modality has different requirements for signal conditioning, noise susceptibility, and sampling conditions, thus affecting how they will communicate and process [15],[16].

2) Deployment Model: Sensors can be deployed in three ways: wearable, implantable, or ambient. Wearable sensors are often preferred due to their non-invasive nature and ease of integration into IoMT systems; Implantable sensors have stricter energy, reliability, and safety requirements than wearable devices, and Ambient Sensors leverage infrastructure resources to provide greater flexibility concerning power and communications constraints [14][15].

3) Connectivity and Power Constraints: The vast majority of IoMT biosensors are resource-constrained devices that use low-power wireless communication technologies. Choosing which connectivity to use greatly affects the data rate achieved, the energy consumed, and the need to use gateway or edge devices for data aggregation and protocol translation [13].

4) Data Characteristics: Biosensors produce data with different volumes, frequencies, and latency sensitivities. Continuous high-rate biosignals require large amounts of communication bandwidth and processing resources, while periodic or event-driven data streams can be managed with more flexible data-handling approaches [10],[17].

As illustrated in Fig. 1, all biosensors can support either continuous monitoring, event detection, or periodic screening, which determines the data flow through the various communication, edge, and cloud layers of the system, and the location of analytics and intelligence within the system.

B. Biosensor Taxonomy for IoMT Architectures

The proposed system-oriented taxonomy of biosensor system design is summarized in Table I, and provides biosensors with a standardized way of referring to architecture characteristics associated with IoMT systems.

C. Architectural Implications of the Taxonomy

The Taxonomy outlines how the nature of a biosensor affects the architecture designs selected at all three-layers of the biosensor system presented in Fig. 1. For example, a continuous electrical biosignal is likely to require preprocessing on Edge Devices which will help to reduce the volume of data that needs to be transferred and latency, whereas a low sample rate chemical biosensor, will most likely rely on Cloud based analytic capability more than Edge Device based analytic capability [10], [17]. Further, Wearable biosensors typically rely on Gateway Devices for aggregation and translation of protocols, whereas Ambient biosensors may connect directly to higher volume capable networks.

By providing a systematic system-level classification of various types or classifications of biosensors, the proposed taxonomy facilitates the comparison of heterogeneous types of sensor technologies and aids in developing highly scalable, efficient and flexible IoMT systems.

IV. Representative Biosensing Domains and Design Considerations

Section 3 describes a new taxonomy of biosensors based on their architectural roles and design constraints. In this section, we review specific examples of biosensing domains to support the idea that different sensor characteristics affect architectural choices across the IoMT layers outlined in Fig. 1. We review biosensing domains that represent a variety of sensing modalities, data characteristics, and deployment methods typically encountered within the design of IoMT systems [18].

A. Cardiovascular and Vital-Sign Monitoring

The monitoring of vital signs and cardiovascular health is one of most well-established application areas for IoMT (Internet of Medical Things) systems. There is a large number of wearable physical electrical and optical biosensor devices, such as electrocardiograms (ECG) and photoplethysmography (PPG), available today that can continuously stream high volumes of data. Many of these sensors are available in wearable form factors [19], [15]. As shown in Fig. 1, the continuous nature of biological signals presents extreme demands on the throughput and latency of communications protocols. It is

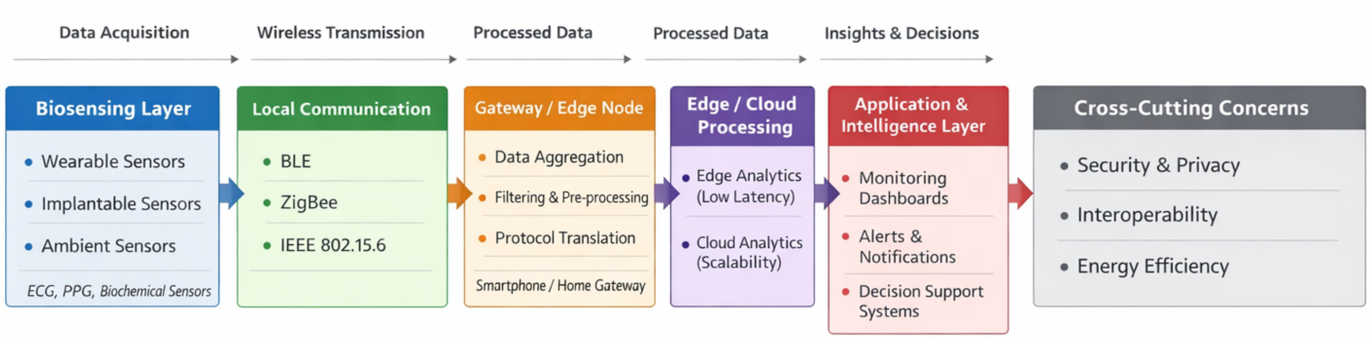

Fig. 1. Generic multi-layer system architecture of the Internet of Medical Things (IoMT), illustrating the end-to-end data flow from bio-sensing and local communication to edge/cloud processing and application-level intelligence, with cross-cutting system concerns

Dimension	Category	Description / Examples	Architectural Implications
Sensing Modality	Electrical Optical Chemical Mechanical	ECG, EEG, EMG PPG, SpO, imaging sensors Glucose, biochemical markers Motion, pressure, respiration	High sampling rate, noise-sensitive, edge filtering required Moderate data rate, sensitive to motion artifacts Low-rate, calibration and reliability critical Event-driven or continuous, low-power friendly
Deployment Model	Wearable Implantable Ambient	Smartwatches, patches Embedded physiological sensors Bed, room, or environment sensors	Energy-constrained, short-range communication High reliability, strict power and safety constraints Infrastructure-supported, relaxed energy constraints
Connectivity	Short-range Long-range	BLE, IEEE 802.15.6 Wi-Fi, LPWAN	Low power, gateway-dependent Higher energy cost, direct cloud access
Data Characteristics	Continuous Periodic Event-driven	ECG, EEG streams Temperature, glucose Fall detection, anomaly alerts	Edge analytics, latency-sensitive Batch processing, cloud-friendly Fast response, lightweight models
Architectural Role	Monitoring Event Detection Screening	Long-term observation Abnormality identification Periodic assessment	Emphasis on storage and trend analysis Edge intelligence, low latency Minimal processing, cloud-based analytics

TABLE I
SYSTEM-ORIENTED TAXONOMY OF BIOSENSORS FOR IOMT ARCHITECTURES

therefore rarely feasible to send raw signals to cloud-based storage systems due to issues related to power consumption and data volume. Therefore, many IoMT architectures implement edge level processing of the biological signal before transmitting to the cloud, which includes the removal of noise from the signal and extraction of relevant signal features from the noise, reducing the overall volume of data and permitting rapid analysis of the signals [10]. The way in which signals are processed and utilized by IoMT systems is often determined by both the types of sensor devices used to collect the signals and their respective characteristics.

B. Metabolic and Physiological Monitoring

Unlike cardiovascular monitoring, which requires low-latency data to provide precise and immediate feedback on heart conditions, applications for metabolic and physiological monitoring (such as temperature and glucose sensing) often utilize chemical or low-flow electrical sensors that produce periodic or low-frequency measurements. Wearable or minimally intrusive devices are typically used with these sensors, making them well-suited for long-term monitoring but not for immediate event detection [20].

The architectural requirements for metabolic and physiological monitoring systems differ from those of cardiovascular monitoring due to the fact that many of these applications' data characteristics and roles are not sensitive to latency. Typically, data from these devices will be collected at the gateway layer and sent to cloud service providers for storage and analysis (as illustrated in Fig. 1). The periodic nature of the data collection from metabolic and physiological monitors allows for decreased computational complexity and hence increased energy savings at the sensor(s) level [21].

C. Neurological and Brain–Computer Interface Sensing

The domain of neurosensing (e.g., EEG and BCI) is characterized by very high volume of data, high levels of noise susceptibility, and stringent requirements on the integrity of the signal. Most of these types of sensors are worn on the body and generate complex electrical biosignals that require a great deal of pre-processing [22].

In the context of IoMT as shown in Fig. 1, local or edge-based signal conditioning is critical to manage noise and reduce the dimensionality of the data before it is sent via the network. For most systems, lightweight feature extraction or inference is conducted at the edge of the network in order to provide rapid responses to users, while also keeping network congestion low [10] [23]. This example demonstrates how sensor modality and data characteristics together impact decisions regarding the location of processing in the architecture.

D. Wearable and Multi-Modal Biosensing Systems

Multi-modal, wearable systems integrate several factors of interaction together to provide a single unit of measurement. Multi-modal wearables generate various streams of data that have different sampling rates, latencies, and levels of reliability [15],[24]. As a result, the architecture for this type of system tends to stress the use of gateway and edge layers, as shown in Fig. 1, as a point of data fusion, synchronization and initial analytics. In turn, coordinating many types of data sources, along with the need for interoperability, energy management and scalable solutions to manage these types of data contributes to some of the challenges to be addressed when developing multi-modal IoMT solutions.

E. Cross-Domain Design Trade-offs

Across the Representative Domains described above, a number of common design trade-offs arise. High-frequency and latency-sensitive biosignals promote local preprocessing and Edge Intelligence, whereas those that are low-rate and periodic are more reliant on Cloud-based Analytics. Wearable and Implantable implementations favour Energy Efficiency and Short-range Communications, whereas Ambient Sensing benefits from infrastructure-based connectivity [10],[21],[15].

By creating a mapping of Biosensor Domains to the Taxonomy Dimensions shown in Section 3 and Architecture Layers represented in Fig.1, several examples of how system-level considerations will support the integration of Biosensors into scalable and efficient IoMT Architecture will be provided.

V. System-Level Challenges and Design Trade-offs

Designing IoMT systems, as seen in Fig. 1, involves a combination of objectives that may compete with each other across the architecture's layers. In sections 3 and 4, we show how the taxonomies developed here suggest frequent challenges at the system level affecting the design of all four components: sensing, communications, computing and intelligence placement. This Section looks at some of the most common engineering trade-offs that face engineers creating IoMT systems.

A. Energy Efficiency vs. Data Fidelity

Energy efficiency continues to be a significant limiting factor for IoMT devices, especially for biosensors that are in the form of wearables and implants. In order to achieve high fidelity for sensors, a high sampling rate will typically require continuous information transmission that results in high amounts of energy use. Using alternative methods such as adaptive sampling, duty cycling or local compression can increase the lifespan of the device but may result in decreased temporal resolution and signal quality [25]. This architectural feature provides motivation for edge level preprocessing (see Fig. 1) through filtering and feature extraction that reduce the size of the data before sending over the network for processing. The use of edge level preprocessing reduces the amount of energy and bandwidth consumed by the sensor; however, it may also limit the possibility of analytics that require the use of raw signal data. The selection of the appropriate balance between filtering or feature extraction, and raw signal processing at the edge, is determined by the role of the sensor (e.g., continuous monitoring and event detection), which is identified in the taxonomy.

B. Latency vs. Scalability

The processing of latency-sensitive applications, like anomaly detection or event detection, is best suited for close to the data source so that the application can respond quickly. Edge computing meets this need by minimizing round-trip times to the cloud. However, processing a great deal of data at the edge can add complexity to management and restrict scalability as the number of devices will be increased [26]. Meanwhile, cloud-based architectures provide additional resources and easy-to-implement updates, but incur greater latencies and therefore, are more dependent on the network. As illustrated in Fig. 1, hybrid approaches to edge/cloud computing integrate all these advantages. However, finding the right balance between cloud and edge processing is still an area of active research in IoMT systems [11].

C. Data Reliability vs. Resource Constraints

The quality of biosensor data can be greatly affected by a number of factors including noise, motion artifacts, and environmental conditions, especially with wearables. To improve reliability often requires additional sensing, calibration or signal processing which increases computational load and energy consumption. Lightweight inference models may work under strict resource limitations but will typically have lower robustness to variability in signals [31]. This issue illustrates the need for evaluating the way the sensing modality and the characteristics of data relate to the implemented processing methods at the gateway or edge layer. System designers must determine if reliability-type improvements should take place locally (with an associated energy cost) or occur centrally (with an associated latency and bandwidth cost).

D. Privacy and Security vs. System Complexity

IoMT architecture processes sensitive health-data. Since privacy and security are critical cross-functional issues in this framework, the IoMT security framework supports securing sensitive health-related data using encryption, supporting authentication, and supporting access control. The added benefits of these types of security implementations include increasing security; however, there are now additional computing and communication overhead for users associated with these security implementations [4]. The ability of Edge Computing to enhance individual device privacy through decreased raw data transmission to the cloud, allows IoMT deployments to also increase overall cyber-attack surface due to their increased intelligence distributed across potentially many devices. Cybersecurity in large scale IoMT Deployment is a balancing act between achieving adequate levels of security, and also maintaining the overall complexity and performance of the IoMT deployment as a whole [4].

E. Interoperability vs. Optimization

IoMT ecosystems are a collection of devices integrated from various manufacturers and connected via disparate protocols and data formats. Using standardized interfaces to create interoperability and extensibility within an ecosystem can limit the ability to implement highly optimized, application-specific solutions. Conversely, implementing highly optimized designs may provide the potential for optimal performance; however, the trade-off will be portability and long-term sustainability [6],[31].

The decision of how to balance these conflicting priorities from an architectural perspective is critical to the design of gateways, data models, and application interface architectures. Thus, the architectural design of an IoMT ecosystem necessitates a system-level design methodology rather than merely optimizing an individual component.

VI. Future Research Directions

Although much has been done to improve IoMT systems, researchers still have many areas to explore when working with these systems. Using the Fig. 1 example of an IoMT architecture and the Section 3 taxonomy of IoMT system components, as well as information in Section 5 about IOT systems, we have identified several technology-based avenues where further research can be conducted by engineers.

A. Edge Intelligence and Adaptive Processing

It is likely that in the future IoMT systems will be able to incorporate more edge intelligence for low latency analytics and reduced network loads. The next step in research will be to develop mechanisms that adjust sensing, preprocessing and inference in an adaptive manner depending on context, energy availability and data quality. Approaches to accomplish this will be through adaptive sampling, on-device learning and collaborative edge-cloud intelligence balancing between the energy efficiency and analytical accuracy of IoMT systems [28][29].

B. Multi-Modal Data Fusion and Context Awareness

Wearables and ambient systems will benefit from multiple sensing methods; therefore, multivariate data fusing is essential. Future research will advance the creation of scalable fusion frameworks to permit heterogeneous data streams exhibiting different time scales and levels of trustworthy information. Additionally, context-aware fusing techniques that utilize environmental factors and user-specific characteristics will enhance both the robustness and the clarity of IoMT applications [30].

C. Privacy-Preserving and Trustworthy IoMT Architectures

The ongoing struggle of protecting sensitive health data continues as a major challenge. Emerging research is being conducted in creating privacy-preserving analytics, such as federated learning and secure multi-party computation, which are focused on how to perform collaborative intelligence while limiting the visibility of raw data. The design of architectures that incorporate these types of privacy-preserving analytics across the layers of sensing/edge and cloud while minimizing excessive overhead is still an open question [31].

D. Energy-Aware and Sustainable Biosensing Systems

To achieve sustainable use of IoMT devices for longer periods of time, future innovation must include advancements in the area of energy aware design for IoMT systems, such as ultra-low-power sensing technologies, energy harvesting solutions, and smart power management systems. To improve the sustainability and lifespan of IoMT devices, future research should focus on optimizing their cross-layer performance through integrated consideration of the sensing methods used, the communication protocol applied and the method of processing placement [32].

E. Interoperability and Standardized System Integration

Variety among IoMT devices and platforms points to a need for better interoperability and standardization. Future research efforts must focus on creating common data models, developing open interfaces, and establishing middleware solutions for successful integration of diverse biosensor applications into large-scale IoMT ecosystems. These parts of the IoMT system will be critical in ensuring that the government can support future development of these devices and systems without adding unnecessary complexity [33].

VII. Conclusion

The purpose of this paper was to present an architecturally focused (rather than an application-oriented or clinically focused) state-of-the-art survey of biosensing in the Internet of Medical Things (IoMT). This paper is presented as a system architecture-based survey that reflects on the engineering aspects of the integration of biosensors within IoMT systems, rather than from the clinical or application perspectives.

An architecture-driven approach allows the reader to understand the interaction between the multiple types of biosensors that may be employed and the communication architecture, the edge and cloud processing platforms, and the application layers, associated with each of these sensors within the overall architecture of an IoMT solution.

The authors present a structured and systematic taxonomy to allow the classification of biosensor technologies based on five different categories (sensing modality, deployment model, connectivity constraints, data characteristics, and architectural role) that provide a unified framework for the comparison of various technologies and their implications for design choices of the system.

The authors provide a discussion of typical biosensing applications to demonstrate the effect of the taxonomy categories on the architecture and technology employed and the resultant effect of the two factors collectively on data processing location, communication methods, and resource management.

The system-level challenges and design trade-offs serve to demonstrate that an effective design of an IoMT system requires consideration and agreement among the many engineering factors of the sensors across all of the architecture layers (such as energy efficiency, latency, scalability, data reliability, and security). A holistic approach to system architecture, rather than an approach that only works to optimize each individual component in isolation, is also supported through this paper.

This paper will aid researchers and practitioners in the design and development of scalable, efficient and adaptable IoMT solutions as well as aid in determining direction for future research into intelligent and sustainable biosensing systems, by providing an integrated perspective of biosensor technologies and IoMT architectures.

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