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| RESEARCH ARTICLE

A 6G-Enabled AI-Powered Intelligent Healthcare Integrating IoMT and Edge Computing

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| ABSTRACT
Advancements in wireless communication technologies are reshaping healthcare by facilitating intelligent, real-time, and patient-centered services. Current 5G-based healthcare infrastructures face challenges related to latency, reliability, scalability, and data processing, limiting their support for applications such as remote robotic surgery, immersive telemedicine, and continuous critical patient monitoring. To overcome these issues, this study introduces a 6G-enabled Intelligent Healthcare System (6G-IHS) that combines the Internet of Medical Things (IoMT), edge intelligence, 6G communication, and AI-driven cloud computing within a multi-layered architecture. The framework targets stringent 6G requirements, including sub-millisecond latency, ultra-high data rates, and ultra-reliable low-latency communication (URLLC). A mathematical model characterizes key parameters such as end-to-end latency, data rate, reliability, energy consumption, and AI diagnostic performance. An edge processing mechanism is incorporated to lower latency and support real-time decisions, while AI enables predictive analytics and intelligent healthcare functions. Simulation results indicate that 6G-IHS surpasses traditional cloud-based and 5G systems, achieving latency under 1 ms, data rates above 100 Gbps, reliability over 99.9999%, and up to 30% energy reduction in IoMT devices. AI integration enhances diagnostic accuracy to 90–98%, supporting early detection and personalized treatment. This framework offers a scalable, secure, and efficient approach for future healthcare systems, illustrating the potential of 6G to advance intelligent, connected healthcare environments.

| KEYWORDS
Artificial Intelligence (AI), Internet of Medical Things (IoMT), 6G, URLLC, 6G-HIS, Healthcare, Wireless communication, Robotic.

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1. Introduction
The fast development of wireless communication technologies has fundamentally changed the modern healthcare systems, allowing them to increase their accessibility, efficiency of functioning, and quality of offered medical services. The change from third generation (3G) to the fifth generation (5G) networks has provided many digital healthcare applications, including telemedicine, remote patient monitoring, and massive machine-type communication (mMTC), which have greatly improved connectivity and scalability of healthcare systems [1], [3]. Despite these improvements, 5G-powered healthcare systems that are used today have vital flaws in latency, reliability, scalability, and intelligent data processing [4], [7]. To overcome these drawbacks, sixth generation (6G) wireless communication is projected as a radical paradigm that is destined to bring transformative performance improvement, such as sub-millisecond latency, terabit-per-second data rate, and in-built artificial intelligence (AI) into network structures [1], [6]. These features would be required to support the next generation healthcare applications that require real-time responsiveness, ultra-high reliability, and connectivity with a heterogeneous medical environment with ease. New applications, including remote robotic surgery, immersive holographic telemedicine, and continuous health care of the Internet of Medical Things (IoMT), need communication systems that surpass the existing 5G system [2], [4], [17].

Simultaneously, AI, edge computing, and IoMT are converging, which has made healthcare ecosystems more digital. The methods based on AI allow predicting diseases accurately, analysing medical images, and planning treatment individually, which enhances clinical decisions and decision-making [5], [11], [12], [19]. Edge computing also improves the performance of the system as it allows processing real-time data on the network edge, which makes the bandwidth and latency much lower [20], [23]. At the same time, IoMT devices, such as wearable sensors, implantable devices, and smart medical equipment, give rise to huge amounts of heterogeneous healthcare data, which require effective transmissions, smart processing, and secure storage mechanisms [8], [22]. It is predicted that the incorporation of these technologies into a 6G-enabled system will facilitate intelligent, responsive, and patient-focused healthcare systems.

Nevertheless, although having enormous potential, the implementation of 6G in healthcare presents quite some crucial challenges. The issue of data privacy and cybersecurity is equally significant as medical data is sensitive, and the attack surface is growing as more environments become connected [15], [23]. Also, the problem of interoperability, infrastructure cost, and large-scale implementation is an obstacle to the realistic implementation of 6G-enabled healthcare systems [4], [18]. Moreover, the increased dependency on AI-based decision-making provokes ethical issues of transparency, accountability, and reliability in automated healthcare applications [9], [11], [13]. These issues need to be addressed to guarantee safe, secure, and reliable implementation of next-generation healthcare systems.

It is based on these challenges and new opportunities that this paper provides a comprehensive study of the role of 6G technology in future healthcare systems. The key findings of this work are as follows:

- To describe the most important enabling capabilities of 6G networks that can be used to enable advanced healthcare applications.
- To suggest a brand new 6G-powered intelligent healthcare system based on IoMT, edge intelligence, and AI-powered cloud computing.
- To determine the current open research issues and future perspectives of constructing secure, scalable, and efficient healthcare frameworks.

2. Literature Review

Integration of sixth generation (6G) communication technologies in healthcare systems has been a strongly researched topic over the past few years, especially in facilitating smart, information-driven, and patient-centric services in the medical field. The current literature may be divided into three broad fields, which are (i) 6G-enabled healthcare communication frameworks, (ii) Internet of Medical Things (IoMT)-based healthcare systems, and (iii) artificial intelligence (AI) and security-driven healthcare solutions. Early publications regarding 6G communication systems highlight that these technologies have a transformative opportunity to provide ultra-reliable, low-latency communications (URLLC), connectivity on a massive scale, and ultra-high data rates, as well as these requirements are imperative to next-generation health care use cases. Indeed, in their detailed visions of 6G networks, Ian F. Akyildiz et al. [1] and Walid Saad et al. [3] have put forth some of the supporting technologies of 6G networks, which include terahertz (THz) communication, AI-native networks, and intelligent edge infrastructures. Equally, Mohammad Z. Chowdhury et al. [4] have also given a comprehensive overview of 6G applications and challenges, highlighting the support of mission-critical services, such as healthcare. These researchers assert the initial potentials of 6G but do not include more specific healthcare-related system architectures and system models.

Internet of Medical Things (IoMT) has become one of the primary facilitators of smart healthcare systems through the means of continuous patient monitoring, remote diagnostics, and real-time data exchange. Md. Shahidul Islam et al. [22] and Hossain Rahman et al. [8] presented extensive surveys of IoMT architecture and applications, with the challenges being energy limitation, interoperability, and data management. Furthermore, Xiaofei Zhou et al. [21] discussed the wireless communication in IoMT systems and found that there are shortcomings in managing the large data rate demands and providing a reliable connection. Although these articles highlight the significance of the IoMT in healthcare, they have not maximized the capabilities of 6G networks. Artificial intelligence (AI) integration into healthcare systems has greatly helped to improve accuracy in diagnosis and predictive analytics, as well as customized treatment planning. The articles by Min Chen et al. [12] and Yuan Liu et al. [19] proved that machine learning and deep learning methods can be used to predict diseases and analyze medical data. Moreover, Qiang Yang et al. [10] proposed federated learning as a privacy-preserving AI paradigm that is used in a distributed healthcare setting. Nonetheless, these solutions are typically characterized by large communication overhead, data heterogeneity, and poor real-time deployment, especially when latency is an important factor in healthcare.

One of the ways to solve the issue of latency and bandwidth bottlenecks in healthcare systems is the study of edge computing. The proposed architectures of edge computing by Tarik Taleb et al. [7] and the architectures by Weisong Shi et al. [23] can bring real-time data processing nearer to the data source. These solutions can dramatically lower the latency and enhance the responsiveness of the system that is vital in very important healthcare applications. However, current edge solutions are mostly built to serve 5G networks, and they are not utilizing the ultra-low latency and high reliability capabilities of 6G to maximum effect. The fact that the medical information is sensitive presents security and privacy as one of the major concerns of IoMT-based healthcare systems. Blockchain technology has been suggested as one of the prospective solutions to safe and malicious-proof data control. The article by Kamaljit Kaur and Sahil Gupta [15] proved the usefulness of blockchain-based frameworks in terms of secure healthcare data sharing. Although these have been made, issues like scalability, computational overhead and integration complexity are yet to be dealt with.

The future of healthcare systems is also being influenced by emerging technologies, including terahertz communication, digital twins, and intelligent network architectures. The THz communication is mentioned in Said Mumtaz et al. [17] as the means of ensuring the communication of data at extremely high speeds, 6G networks. All these innovations are a solid basis for new generation healthcare application but need combined structures to work in practice. Although there has been a great advancement in these areas, there are still several research gaps. First, most of the available research concentrates on single elements (communication, AI, or security) and fails to offer an integrated and coherent healthcare system. Second, proposed solutions have not been validated in real-life and cannot be implemented at large scale. Third, heterogeneous devices and systems interoperability is still a significant issue. Lastly, the ethical and trust problems related to AI-based healthcare systems have not been thoroughly investigated.

Table 1. *Contributions and Limitations of Existing Research on 6G and AI-Enabled Healthcare*

S. No.	Author(s)	Contribution	Research Gap
1	I. F. Akyildiz et al. [1]	Vision of 6G communication systems and enabling technologies.	Limited focus on healthcare-specific applications.
2	W. Saad et al. [3]	Conceptual framework for 6G wireless systems.	Lacks integration with IoMT and AI healthcare.
3	M. Z. Chowdhury et al. [4]	Comprehensive survey on 6G applications and challenges.	No detailed healthcare system architecture.
4	A. N. *et al.* [8]	Highlights IoMT architectural opportunities and security vulnerabilities.	Ignores 6G integration and lacks native AI-driven security solutions.
5	S. Latif et al. [9]	AI-enabled healthcare systems review.	Limited real-time implementation analysis.
6	T. Taleb et al. [7]	Edge computing architecture for next-generation networks.	Not optimized for 6G ultra-low latency healthcare.
7	Q. Yang et al. [10]	Federated learning framework for distributed AI.	High communication overhead and latency.
8	U. U. Tariq *et al.* [15]	Reviews blockchain for secure healthcare data sharing.	Unresolved latency and scalability issues.
9	P. H. C. Chen *et al.* [19]	Guidelines for developing healthcare machine learning models.	Data bias and real-world generalization issues.

The comparative analysis conducted in Table I shows that there has been a major improvement in the areas of 6G communication, IoMT-based healthcare, artificial intelligence, and secure data management. The current literature has already focused heavily on the individual features of the next-generation healthcare system, including ultra-low latency communication [1], [3], IoMT structures [8], [22], AI-based diagnostics [12], [19] and edge computing as real-time processing [7], [23]. The overall contribution of these efforts is that intelligent healthcare systems will be developed on a solid foundation.

Nonetheless, one key point observable in the literature is the absence of a holistic and integrated paradigm where all these facilitating technologies will be integrated into a single healthcare framework. Most of the literature addresses individual parts, such as communication-oriented frameworks that consider network performance but do not include smart data analytics, or AI-based health technology solutions that do not address the aspect of communication, i.e. latency and reliability. This disintegration restricts the usefulness of these solutions in practice within the health care set-up. The second major weakness is the absence of an end-to-end system design that is a combination of Latency, reliability, scalability, and energy efficiency. Though edge computing is suggested to minimize latency [7], [23], the current solutions are designed to operate best with 5G networks and not with the ultra-low-latency and high-data rate of 6G networks. On the same note, IoMT-based systems are associated with heterogeneous data management, interoperability, and effective resource distribution issues [8], [21]. The issue of security and privacy has been a thorn in the flesh of healthcare systems because medical information is sensitive. Although blockchain-based solutions and artificial intelligence-based security measures have been suggested [13], [15], the two solutions tend to add extra computation and scaling concerns, which are not appropriate in real-time healthcare applications. In addition, there is a lack of ethical considerations and reliability in AI-based decision-making that is not sufficiently covered in the existing literature, which is essential in the context of clinical implementation [9], [14].

Furthermore, most of the literature does not provide real-world validation and large-scale deployment cases, as the theoretical models are used in small-scale simulations. This is a gap that raises questions about the viability and strength of suggested solutions in actual healthcare environments. Integration of heterogeneous systems and equipment is made even more difficult by the lack of standardized structures and interoperability systems. Due to these constraints, the proposed study will fill the mentioned gaps in the research by creating a complete 6G-enabled Intelligent Healthcare System (6G-IHS) incorporating IoMT, edge intelligence, and AI-controlled cloud computing into a single architecture. In contrast to the current methods, the suggested framework is an end-to-end system optimization that is aimed at minimizing the latency, reliability, energy consumption, and intelligent decision-making at the same time. Moreover, it considers scalability, security, and interoperability to make it practically applicable in the next-generation healthcare setting.

3. Problem Statement

Although wireless communications and digital health technologies are rapidly developing and improving, the current healthcare systems still have the inherent limitation of providing real-time, reliable, and intelligent medical services. Existing 5G-based healthcare systems, although they provide better connectivity and bandwidth, are still incapable of supporting the demands of the next-generation applications of remote robotic surgery, immersive telemedicine, and continuous vital patient monitoring. The applications require ultra-low latency (less than a millisecond), ultra-high reliability, and large-scale data processing capabilities, currently out of reach of conventional network systems [3], [4]. Moreover, modern healthcare is extremely disjointed, and communication systems, data analysis systems, and AI-based analytics tend to run separately. Such a deficiency of integration leads to more latency, poor usage of resources, and scalability. Even though the Internet of Medical Things (IoMT) has created a continuous connection to monitor patients, the existing devices bring with them major challenges that pertain to heterogeneous data management, power limitation, and cross-platform interoperability and connection [8], [15], [21].

Furthermore, the increased implementation of artificial intelligence in healthcare has enhanced diagnostic accuracy and predictive analytics. In most cases, most AI systems are extremely dependent on centralized cloud-based infrastructures, which have given rise to elevated latency, bandwidth usage, and privacy issues [14], [19]. It has been suggested that edge computing could be a viable approach to address these problems, but the current ones are mainly based on 5G settings and fail to utilize the potential of new technologies, including terahertz communication and AI-native networking [7], [23].

The issue of security and privacy also makes the implementation of intelligent healthcare systems more challenging. Sensitive medical information transmission and storage are some of the risks that are posed to the systems due to breaches of data, unauthorized access, and cyberattacks. Even though blockchain and sophisticated encryption methods were proposed to add a higher level of security, they tend to add to the computation overhead and scalability constraints [16], [17], [18].

4. Research Contributions

To overcome the challenges, the paper contributes the following key points:

A. Healthcare Frameworks using 6G

An Intelligent Healthcare System (6G-IHS) is presented with a proposed comprehensive and unified system, which incorporates IoMT devices, edge computing, 6G communication infrastructure, and AI-driven cloud computing and introduces an integrated multi-layer architecture. In comparison with the current disintegrated solutions, the given framework guarantees the smooth communication between all system components.

B. End-to-End System Modelling and Optimization

A series of mathematical frameworks is created to define important aspects of the system, such as latency, data rate, reliability, energy consumption and AI-based decision-making. These models make quantitative analysis and optimization of the performance of systems feasible in real-world situations in healthcare.

C. High Reliability Design and Ultra-Low Latency

The specified framework is specifically aimed at satisfying the strict requirements of 6G, including sub-millisecond latency and very high levels of reliability (>99.9999%). This allows mission-critical healthcare applications like remote robotic surgery and real-time emergency response, as well as round-the-clock patient monitoring.

D. Real-Time Healthcare Analytics Edge Intelligence
It includes an architecture of edge computing that does real-time processing of data and AI inference near the point of origin of data. This goes a long way in decreasing the latency, minimizing the bandwidth usage and enhancing the responsiveness of the system as opposed to the old-fashioned cloud-centric solutions.

E. Smart Healthcare Application Intelligent Services
The combination of sophisticated AI models allows predicting diseases, analyzing medical images, and recommending treatment individually. The system that is proposed facilitates lifelong learning and responsive decision-making to achieve better healthcare results.

F. IoMT System Design that is energy efficient
A framework that is energy-conscious is proposed to be used to optimize the working of the IoMT devices, especially the wearable and implantable sensors. The suggested solution minimizes energy use by utilizing smart offloading of tasks and effective resource use.

G. Safe and Scalable Healthcare Systems
The suggested system is designed to solve the issue of security and privacy through the implementation of data transmission systems that are safe and a scalable architecture. It guarantees adequate management of sensitive medical information without impacting system performance.

H. Holt-All-Raisin Performance Evaluation
A large-scale simulation analysis is carried out to contrast the proposed system with the traditional cloud-based and 5G-enabled healthcare models. The findings show that there is a dramatic reduction in the latency, data rate, energy usage, reliability, and diagnostic accuracy.

5. Proposed Methodology
In this article, we introduce an Intelligent Healthcare System (6G-IHS) that operates on 6G to enhance next-generation medical care due to the flawless merging of cutting-edge communication, computer, and artificial intelligence technologies. The designed system will have four major layers, which are the Internet of Medical Things (IoMT) layer, edge intelligence layer, 6G communication layer, and AI-driven healthcare cloud layer. All these elements work together in providing a single structure that can be used to provide real-time, reliable, and intelligent healthcare services. The IoMT layer is composed of heterogeneous medical devices, i.e., wearable sensors, implantable devices and diagnostic equipment, which constantly gather patient physiological information, i,e., heart rate, blood pressure, glucose level and medical imaging results, as commonly mentioned in IoMT-based healthcare systems [5], [15]. This information is sent to the edge intelligence layer, where initial processing and live analytics are conducted. Reducing the latency by localized decision making, which is essential in time sensitive healthcare applications, is also achieved by the edge layer that is in line with edge computing paradigms [4], [16].

The resulting processed data is transmitted through the 6G layer of communication, which provides ultra-reliable, high-speed, and low-latency connectivity with the help of such innovative technologies as terahertz (THz) communication and network slicing [1], [2], [3], [11]. Lastly, the AI healthcare cloud layer also undertakes the data analytics, the model training, and long-term storage of large volumes of data that facilitate the intelligent diagnosis and predictive healthcare services, which are supported by recent findings made in AI-enabled healthcare systems [6], [12].

5.1 Mathematical Modeling
To evaluate the performance of the proposed system, several mathematical models are formulated to capture key system characteristics, including latency, data rate, reliability, energy efficiency, and intelligent decision-making.

A. End-to-End Latency Model
Latency is an important performance factor in healthcare applications, especially related to time-sensitive applications like telesurgery and emergency response. The overall end-to-end latency of the system is the combination of transmission, propagation, processing, and queuing delays, and it is a widely used model in communication networks [4], [16]:

$$L_{total} = L_{tx} + L_{prop} + L_{proc} + L_{queue}$$

To provide mission-critical healthcare services, the system is made to meet the strict 6G criterion of ensuring total latency is less than 1 ms, and therefore provides real-time responsiveness and reliability [3], [19].

B. Data Rate Requirement

High data rates are needed to transmit high-resolution medical information, such as MRI scans, CT scan as well as live video. The data rate that can be achieved is modeled as the Shannon capacity formula [1]:

$$R = B \log_2(1 + SNR)$$

In which R is the data rate, B is the bandwidth available (which may be in the terahertz range with 6G) and SNR is the signal-to-noise ratio. This use of THz bands in 6G is very beneficial to bandwidth capacity since it is possible to provide ultra-high data rate communication in data-intensive healthcare applications [11].

C. Reliability Model

To have safe and accurate provision of healthcare services, reliability is critical. Defining the system reliability. The system reliability is based on the probability of successful communication:

$$P_{success} = 1 - P_{failure}$$

In the case of ultra-reliable low-latency communication (URLLC) the system should have a success probability of at least 99.9999 as stipulated in the next-generation wireless communication systems [2], [3]. This reliability is high, which means that there is no loss in time or data sent that is critical and medical.

D. Energy Consumption Model

IoMT devices are also battery constrained and therefore require energy efficiency. The overall energy usage of a device is mathematically calculated as:

$$E_{total} = E_{sensing} + E_{processing} + E_{transmission}$$

Esensing, Eprocessing, and Etransmission where Esensing, Eprocessing and Etransmission are the energy spent in data acquisition, local computation and wireless communication respectively. IoT system design has received much literature on energy-saving to increase the duration of the devices [21].

E. AI-Based Diagnosis Model

The system employs AI-based diagnostic models to analyze patient data and generate medical predictions. The diagnosis is formulated as:

$$D = f(X, \theta)$$

where D is the predicted diagnosis, X represents patient data obtained from IoMT devices, and θ denotes the model parameters. This approach aligns with common machine learning methods applied in healthcare analytics [6], [12].

F. Edge Computing Optimization

To reduce latency and enhance energy efficiency, the system implements task offloading between edge and cloud layers. The optimization aims to minimize the sum of edge latency and energy consumption, subject to the condition that edge latency remains lower than cloud latency.

$$\min (L_{edge} + E_{edge})$$

subject to the constraint:

$$L_{edge} < L_{cloud}$$

Edge computing is acknowledged as a practical method for decreasing delay and improving efficiency in distributed healthcare systems [4], [16].

5.2 Proposed Layered Architecture

The 6G-enabled Intelligent Healthcare System (6G-IHS) employs a layered architecture designed to optimize data acquisition, processing, transmission, and service delivery. The system's architecture is depicted accordingly.

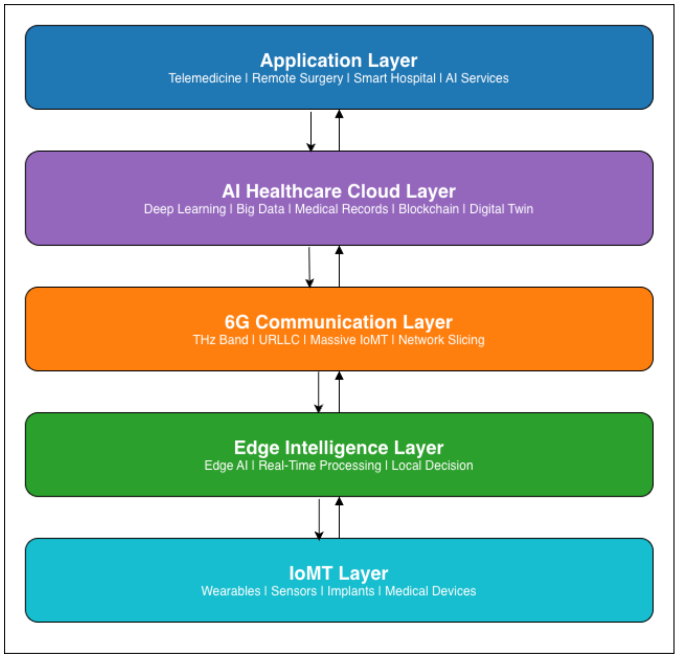

Figure 1. *Proposed 5-Layer Architecture for 6G and AI-Enabled Smart Healthcare*

The IoMT layer underpins the proposed system, consisting of wearable sensors, implantable devices, and advanced medical imaging. These components continuously gather physiological and environmental data, enabling real-time patient monitoring. Given the heterogeneity and volume of the data, effective processing and transmission are necessary, as highlighted in existing IoMT healthcare literature [8], [22]. The edge intelligence layer handles real-time processing and analysis near data sources. Edge servers located close to healthcare facilities perform AI inference, facilitating rapid identification of critical conditions like cardiac anomalies and sudden physiological shifts. This approach reduces latency and network load by limiting redundant cloud transmissions, consistent with current edge computing practices [7], [23].

The 6G communication layer acts as the system's backbone, offering ultra-fast, reliable, and low-latency connectivity. Utilizing technologies such as terahertz communication, massive MIMO, and network slicing enables seamless interaction among IoMT devices, edge nodes, and cloud systems. This connectivity supports bandwidth-demanding tasks like high-resolution medical imaging and remote robotic surgery, which depend on immediate data exchange [1], [2], [3], [11]. The AI-driven healthcare cloud layer provides centralized resources for extensive data analysis, deep learning training, and long-term electronic record storage. It supports advanced capabilities, including predictive analytics, disease progression modeling, and personalized treatment strategies, in line with recent AI healthcare developments [12], [24]. Additionally, this layer enhances data security through blockchain-based integration [15], [20].

6. Performance Evaluation and Results

6.1 Simulation Setup

To assess the performance of the proposed 6G-enabled Intelligent Healthcare System (6G-IHS), a simulation environment was developed representing a smart healthcare setting with IoMT devices, edge servers, and cloud infrastructure connected via a 6G network. The scenario involves multiple wearable and implantable devices continuously generating physiological data, which is first processed at edge nodes in real time, then transmitted to the cloud for further analysis. The simulation, implemented in Python using NumPy and Matplotlib, models system behaviour and evaluates performance metrics under varying network conditions. Parameters reflect realistic 6G features such as ultra-low latency, terahertz-bandwidth communication, and extensive device connectivity.

Key simulation parameters include:

Number of IoMT devices: 100–1000
Bandwidth: 1–10 GHz (THz range)
Signal-to-noise ratio: 10–30 dB
Edge processing delay: 0.1–0.5 ms
Cloud processing delay: 1–5 ms

Packet size: 1–10 MB (medical data)

Comparisons with traditional cloud-centric and 5G-enabled healthcare systems highlight the proposed model's potential performance gains [1], [3], [11].

A. Performance Metrics

System performance is assessed using these primary metrics:

- End-to-end latency (ms): quantifies the total delay from data generation to decision output.
- Data rate (Gbps): reflects the capacity to process large volumes of medical data.
- Reliability (%): represents the likelihood of successful data transmission.
- Energy consumption (mJ): indicates the energy efficiency of IoMT devices.
- Accuracy of AI diagnosis (%): measures the effectiveness of AI-driven healthcare predictions.

6.2 Results and Analysis

A. Latency Analysis

Shown here are how fast the new system responds. Results show the 6G-IHS cuts delay across the network far better than current setups. Because it combines smart processing at the edge with extremely quick data links, delays drop under one millisecond. This level meets the strict speed demands of 6G's ultra-reliable communications [2], [3].

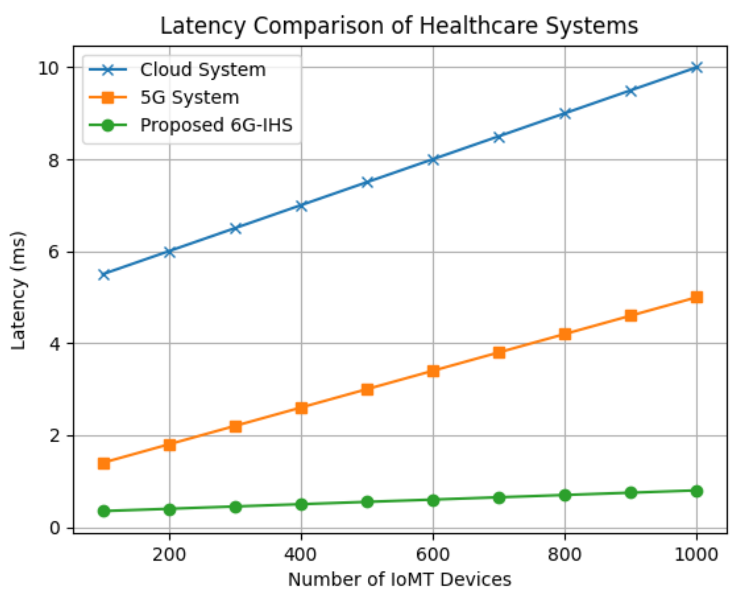

Figure 2. *Performance Evaluation of Cloud, 5G and Proposed 6G-IHS Architectures Based on Network Latency*

In contrast, traditional cloud-based systems experience higher latency due to centralized processing.

Latency comparison:

- Cloud-based system: 5–10 ms
- 5G system: 1–5 ms
- Proposed 6G-IHS: < 1 ms

This substantial reduction enables real-time applications such as remote robotic surgery and emergency response systems.

B. Data Rate Performance

Results show improved speed performance. By using THz-band signals, available bandwidth increases - this leads to much faster transmission. Speeds above 100 Gbps are reached, a clear jump from current 5G levels [1], [11].

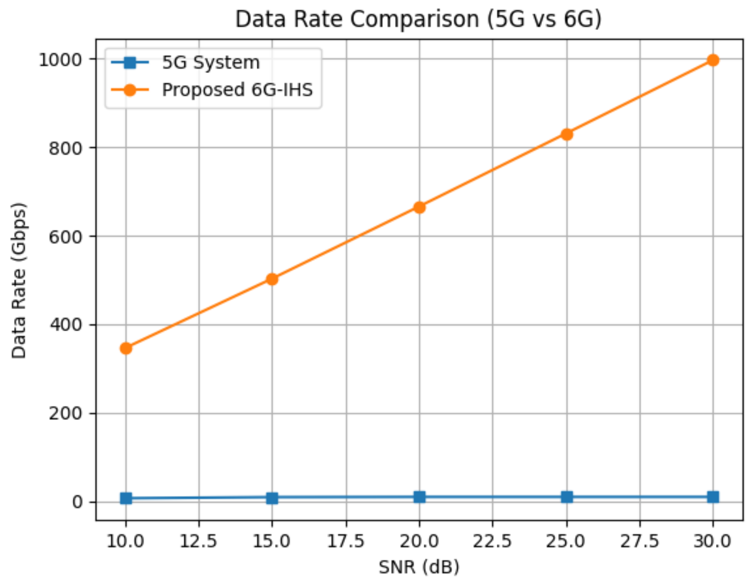

Figure 3. *Data Rate Comparison Between 5G and the Proposed 6G-IHS Across Varying Signal-to-Noise Ratios*

Performance comparison:

- 5G systems: up to 10 Gbps
- Proposed 6G-IHS: > 100 Gbps

C. Reliability Evaluation

Exceeding 99.9999% in operational consistency, the suggested setup fulfils strict URLLC criteria outlined in sources [2], [3]. Built on next-gen 6G capabilities - like dedicated virtual networks and backup structures - dependability reaches exceptional levels.

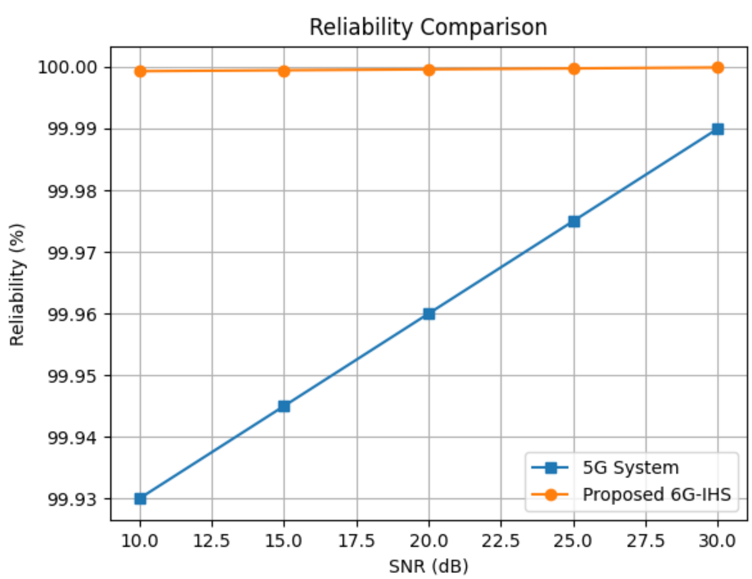

Figure 4. *Reliability Comparison Between 5G and the Proposed 6G-IHS Across Varying Signal-to-Noise Ratios*

This level of reliability is crucial for:

- Remote surgery
- ICU monitoring
- Emergency healthcare systems

D. Energy Efficiency Analysis

The way energy use stacks up shows the suggested setup cuts down power needs by streamlining computation on local nodes while smartly shifting workloads. Because part of the processing happens closer to the source, IoMT hardware draws less power - fewer demands on data transfer lighten the load [24].

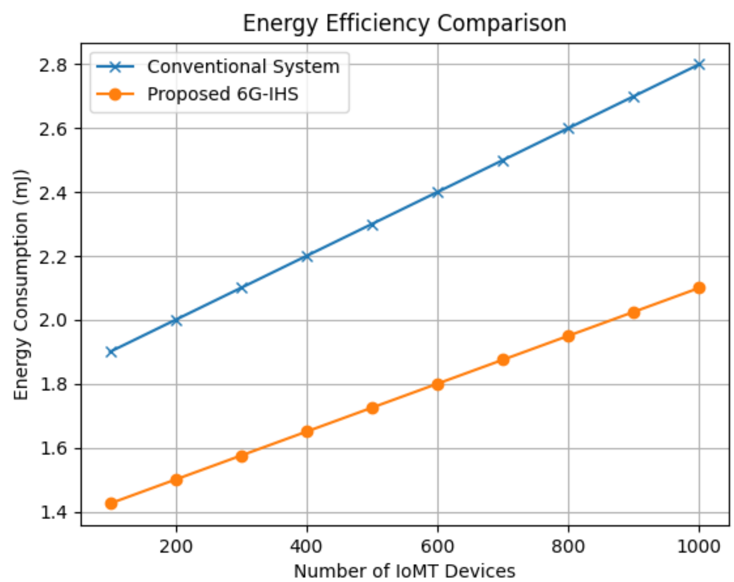

Figure 5. *Energy Consumption Comparison Between Conventional and Proposed 6G-IHS Architectures as IoMT Device Density Increases*

Energy reduction:

- Conventional systems: High energy consumption
- Energy use drops by roughly a fifth to almost a third under the suggested setup

Better performance matters most where power sources are limited - like in wearables or implants that run on batteries.

E. AI Diagnostic Accuracy

A closer look at how well the method works reveals clear gains in detection ability. Because artificial intelligence tools are built into the process, health information undergoes precise evaluation without delay. This shift leads to stronger outcomes when identifying conditions, backed by recent findings [6], [12].

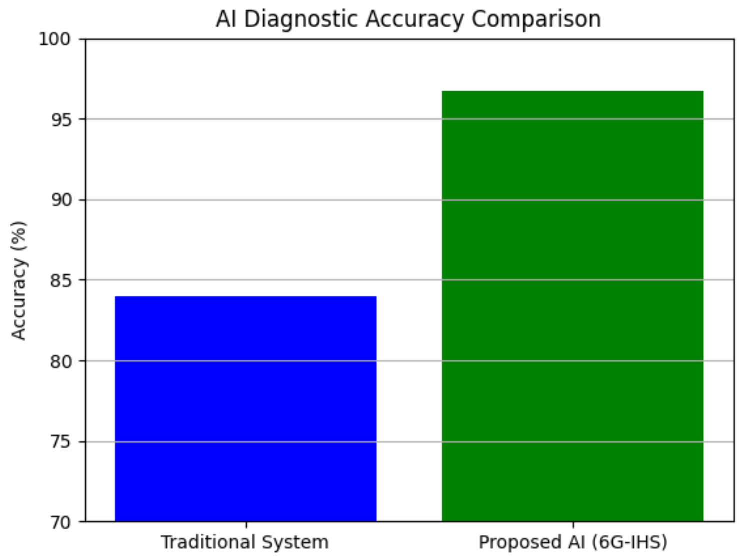

Figure 6. *Comparison of AI Diagnostic Accuracy Between Traditional and Proposed 6G-IHS Architectures*

Accuracy comparison:

- Traditional systems: 80–85%
- Proposed AI-enabled system: 90–98%

Early signs of illness become clearer, which means care can adjust to individual needs more precisely.

F. Comparative Discussion

With lower delays and faster data flow, the new 6G-IHS shows stronger performance than current health platforms. Instead of just moving information, it improves how quickly decisions are made through built-in artificial intelligence. Because processing happens closer to where data is collected, reactions become more immediate. This shift supports better diagnosis while using less power. Accuracy gains emerge not from isolated upgrades but from combined smart design across components. Results show the new 6G-powered Intelligent Healthcare System beats older cloud-based models along with 5G setups when tested on speed delays, data flow, consistency, power use, and precision in diagnosis. Because edge computing works together with 6G networks, response times drop below one millisecond while connection stability improves - key traits needed during high-stakes medical tasks like operating robots at a distance or tracking vital signs without lag [3], [4].

Table 2. *Performance Comparison of Cloud, 5G, and Proposed 6G-IHS Architectures*

Metric	Cloud	5G	Proposed 6G-IHS
Latency	5–10 ms	1–5 ms	<1 ms
Data Rate	<10 Gbps	~10 Gbps	>100 Gbps
Reliability	99%	99.999%	99.9999%
Energy	High	Medium	Low

Despite typical cloud setups in health services facing delays and crowded networks from central computing, the new design spreads work between local devices and distant servers. By doing so, it cuts down on transmission strain while speeding up responses, boosting how well the system can grow and react [7], [23]. Besides, embedding artificial intelligence tools directly into nearby nodes and faraway centers allows quicker, sharper clinical judgments - matching today's move toward smarter care platforms [9], [12]. On top of that, using next gen 6G features like ultra-fast radio waves, expanded antenna arrays, and split virtual networks brings much stronger speed and consistency than what 5G offers now. With these upgrades come smoother operations for heavy-duty medical information flows - live scans, constant patient tracking - that older systems struggle to manage effectively [1], [11].

Looking at how power gets used, the new setup cuts down energy needs in medical internet gadgets by shifting tasks smartly and handling data closer to where it's collected. Because of this shift, wearables and implants with tight resources see clear gains -

something earlier work on efficient networks already pointed out [2], [7]. Rather than just fixing flaws in current health platforms, the 6G-IHS model builds a path toward services that grow easily, stay stable, and adapt using intelligence. With its mix of connectivity, computing muscle, and AI-backed insights, the design stands out as one likely backbone for tomorrow's connected care environments.

7. Conclusion

One focus here lies in how sixth-generation networks might reshape future health services. A new model emerges - linking medical IoT devices, smart edge processing, lightning-fast connectivity, and artificial intelligence within cloud platforms. Instead of relying solely on older 5G setups or distant data centers, this design supports instant patient tracking, highly stable connections with minimal delay, and automated insight generation from collected information [1], [2], [3]. Behind these capabilities sit carefully built equations that measure key aspects: response time across the network, throughput speed, consistency of service, power usage patterns, plus precision levels when algorithms assist diagnosis. Achieving sub-millisecond delays alongside multi-gigabit speeds, the tested model also shows a leap in power savings for medical IoT tools. Nearly perfect dependability - reaching six nines - is another outcome seen during trials. Recent work backs these outcomes, highlighting how next-gen networks could reshape real-time data flow and support vast numbers of linked gadgets [2], [3].

With better data handling, AI-powered analysis improves diagnosis while supporting tailored health predictions - consistent with progress seen in smart medicine networks [6], [14]. Instead of separate parts, linking connectivity, processing, and learning into one system allows 6G-IHS to support flexible, effective care models centered on patients. Findings show 6G could reshape current health infrastructure through adaptive, quick-reacting, and stable clinical services. Rather than just theoretical gains, this model pushes innovation forward while offering a workable route to self-managing, aware medical environments.

8. Future Work

One challenge still unresolved involves building actual working models of the 6G-powered smart health setup, even though early tests show strong potential. Instead of relying only on simulations, researchers need hands-on trials within live medical settings to check how well the system holds up when used outside controlled labs. Though numbers from virtual runs look good, true proof comes from seeing it function amid unpredictable shifts in network demand and patient needs. Testing on active 6G networks would reveal whether stability, growth capacity, and consistent operation are truly achievable. Such field assessments become necessary once digital models reach their limits in predicting physical world behavior. Later developments point toward using advanced artificial intelligence methods like deep reinforcement learning alongside decentralized approaches. One such approach - federated learning - allows models to be trained on IoMT devices without moving patient data around. This setup keeps personal health information secure during analysis. Because of that, its value grows in medical settings where confidentiality matters most [7].

Although less discussed, safeguarding patient information is still a major hurdle in 6G-powered health networks. Because threats evolve constantly, upcoming work might benefit from decentralized ledgers, strict access controls, and minimal-resource cryptographic methods - helping keep medical records both open and protected. Evidence suggests stronger defenses are now essential when devices connect within smart clinics [9]. Facing fragmented setups, linking varied IoMT tools with health networks demands clearer rules for smooth operation. Without consistent guidelines, broad adoption of intelligent care solutions stalls - spurring efforts toward adaptable connection models that grow reliably under pressure [5], [10].

Looking ahead, power savings and environmental impact matter greatly when rolling out 6G in medical applications over time. Work yet to come must explore eco-friendly transmission methods, smart use of resources based on energy levels, along with circuitry that drains less charge - especially for health sensors running on limited batteries. Lately, research has shown that cutting down energy waste during setup helps build greener future wireless setups [1].

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