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Leveraging Edge-Fog Computing for Low-Latency and Resilient Medical IoT Communication

Nagendra Kumar Musham,

Celer Systems Inc, California, USA

nagendramusham9@gmail.com

Thanjaivadivel M,

Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology,

Avadi, Chennai, India

thanjaivadivel@gmail.com

Abstract

Strong, low-latency communication frameworks are required for Medical Internet of Things (MIoT) applications due to the growing need for real-time data processing in the healthcare industry. The strict latency and reliability requirements of essential healthcare services are difficult for traditional cloud-based models to achieve. This study investigates how edge and fog computing can be combined to improve MIoT communication through increased resilience, scalability, and latency reduction. In order to ensure effective resource allocation, the suggested hybrid fuzzy-based reinforcement learning model optimizes task offloading among edge, fog, and cloud layers. According to experimental results, the model improves latency from 10.62 ms to 7.71 ms, a 27.4% reduction. Fault tolerance rises to 11.93%, guaranteeing system stability, while throughput rises by 26.1% to 15.20 Mbps. Scalability has also been improved to 10.05%, enabling dynamic response to rising device loads. These results demonstrate how edge-fog computing can facilitate safe, robust, and real-time MIoT communication networks.

Keywords: Edge Computing, Fog Computing, Medical IoT, Low-Latency Communication, Reinforcement Learning, Healthcare Applications.

1.Introduction

The increasing necessity of real-time processing of data in health-related applications has increasingly fueled the demand for efficient and low-latency communication systems. With the addition of technologies such as the Medical Internet of Things (IoT), healthcare networks are becoming increasingly sophisticated, and seamless, rapid, and efficient communication has become increasingly essential (Mohanarangan, 2020)[5]. These systems allow the gathering, processing, and transmission of critical health information in real time, which is essential for tracking patient conditions, diagnosing diseases, and making timely decisions. Yet the growing amount and diversity of medical data, combined with the demand for immediate access, can overload conventional communication infrastructures. This challenge is compounded in remote or limited-resource healthcare environments, where timely medical intervention is critical and dependent on low-latency communication (Koteswararao, 2020)[6]. Edge and fog computing are promising solutions for healthcare networks that can meet these challenges by processing data in real-time near the source, in contrast to traditional centralized cloud servers (Naga, 2019)[7]. This not only decreases latency but also makes the system process heavy data more effectively (Rajeswaran, 2020)[8], which in turn improves the performance of healthcare applications and systems. Advanced processes like big data analysis also contribute to the optimizing of the same (Poovendran, 2019)[9]. Cloud-based techniques like K-means

clustering have also been effective for healthcare data management (Sreekar, 2020)[10]. In addition, real-time data warehousing solutions make a huge impact on system performance (Karthikeyan, 2020)[11]. Data-driven insights are being used for decision-making more and more in healthcare (Mohan, 2020)[12]. AI methods being used to optimize healthcare data streams are also a key development (Sitaraman, 2020)[13]. Finally, the integration of multi-criteria decision-making techniques, network analysis, and genetic algorithms increases cloud service selection for healthcare systems (Venkata Surya Bhavana Harish Gollavilli, 2020)[14].

Edge and fog computing have a huge benefit to healthcare IoT networks through enhancing network resilience and scalability. The technologies perform processing at the edge or fog layer of the network, so the data is processed and analyzed near where it is created, e.g., at a medical device or patient monitoring system (Gudivaka, R. L., 2020)[15]. In doing so, this lessens the dependence on cloud servers that are central, which can bring about latency in the transmission of data as well as processing. Edge computing can provide for timely actions, like real-time monitoring or alerting medical practitioners in the event of abnormal patient records, to occur quickly (Gudivaka, R. K., 2020)[16]. This method also reduces network traffic, particularly in situations where a high number of medical devices are transmitting data at the same time (Allur, N. S., 2020)[17]. Scalability and reliability of edge and fog computing are critical in ensuring that health services can be maintained effectively even as the number of devices being connected increases (Deevi, D. P., 2020)[18]. Furthermore, these technologies promote patient safety through local processing of data, which reduces the likelihood of delays that may result in crucial errors in diagnosis or treatment (Kodadi, S., 2020)[19]. Through this, edge and fog computing provide a complete solution to the escalating demands of contemporary healthcare systems (Dondapati, K., 2020)[20], delivering both efficiency and dependability in medical IoT networks (Dondapati, K., 2020)[21]. In addition, AI-based solutions, including 3D printing materials optimization for healthcare applications, enhance healthcare technology (Gattupalli, K., 2020)[22]. In addition, phishing website detection improvements can protect patient information (Yang et al, 2019)[23]. Lastly, big data-based supply chain management enhances healthcare efficiency (Allur, N. S., 2020)[24].

The main objectives are

- Discuss the convergence of AI, cloud computing, and fog computing to improve healthcare data exchange in multi-cloud models.
- Design a task offloading fuzzy-based hybrid reinforcement learning model for the maximization of real-time processing of healthcare data.
- Analyze the performance of the suggested model in latency, fault tolerance, throughput, and scalability.
- Compare the efficiency of the hybrid approach to conventional methods of enhancing system security and performance.
- Ensure that the model complies with healthcare standards such as HIPAA for secure, real-time data exchange and protecting privacy.

Existing solutions struggle to effectively minimize latency while handling the vast amount of real-time healthcare data, despite fog computing increasingly being used for healthcare IoT. Conventional cloud-based models cannot handle the low-latency needs required for life-critical applications such as emergency response and remote monitoring. Even though fog computing has been researched before, no ideal strategy using smart learning models for adaptive decision-making exists (Peddi et al, 2018)[25]. There exists a lack of a dynamic healthcare setup because no useful hybrid algorithm to reduce latency has been created (Peddi, et al 2019)[26]. In this paper, with the purpose of enhancing real-time data processing, a hybrid fuzzy-based reinforcement learning system is presented. AI and machine learning methods like

cloud computing with hybrid FA-CNN and DE-ELM methods can greatly improve disease detection in healthcare systems. Predictive healthcare models that use algorithms like ant colony optimization can also advance disease forecasting (Narla et al, 2019)[27]. With empirical and AI-driven frameworks, cloud computing can also make customer relationship management in fields like banking better (Kethu, 2020)[28]. In addition, clinical decision support systems and sophisticated data mining methods have been found to improve cardiovascular care (Vasamsetty, 2020)[29]. For safe IoT data exchange, optimization methods such as multi-swarm adaptive differential evolution and Gaussian walk group search are essential (Kadiyala, 2020)[30]. Blockchain-based AI for safe HRM data management is another promising avenue for greater control (Valivarthi, 2020)[31]. Lastly, robot cloud command verification can leverage advanced soft computing methods to enhance attack detection (Basani, 2020)[32].

A good fog computing infrastructure must decrease latency and enhance real-time processing of data as a result of increased utilization of IoT services. The lack of a widely known fog computing framework and deployment methods, however, poses significant challenges. The ability of other edge devices such as switches, routers, and mobile phones is highly underappreciated in present studies, which primarily focus on utilizing fog nodes as gateways (Jadon, 2020)[32]. This imbalance hinders fog computing's ability to scale and adapt across different IoT scenarios (Boyapati, 2020)[33]. Hence, to enhance performance and efficiency, a proper deployment strategy that optimizes fog node placement beyond gateways is essential (Gaius Yallamelli, A. R., 2020)[34]. By taking into account these other devices, fog computing can be optimized more for various environments and applications (Yalla et al,2020)[35]. The incorporation of such high-end algorithms as deep learning can also improve the performance of such systems in mission-critical applications such as healthcare (Dondapati, 2019)[36]. AI-based customer relationship management systems can ensure enhancement in service quality by virtue of intelligent system integration (Kethu, 2019)[37]. Moreover, resource allocation and secure IoT data sharing in fog computing can be enhanced with methods such as DBSCAN and fuzzy C-means (Kadiyala, 2019)[38]. End-to-end AI-based models can also play a role in sophisticated disease detection (Veerappermal Devarajan, 2019)[39]. Optimized machine learning pipelines can also facilitate efficient software development in AI applications (Jadon, 2018)[40]. Finally, hybrid optimization methods can enhance cloud computing for disease detection (Natarajan, 2018)[41].

2. Literature survey

The issue of developing a fog computing infrastructure to accommodate latency-sensitive Internet of Things applications is discussed by **Martinez et al. (2020)[1].** By mapping IoT virtual networks to suitably sized fog nodes, they suggest a mixed-integer linear program (MILP) method for fog network design and dimensioning. To improve the efficiency of IoT systems, they also present a column generation model that minimizes expenses while achieving near-optimal solutions.

Hassan et al. (2020)[2] discuss the difficulties in delivering medical care in isolated areas, especially when it comes to remote pain monitoring. They draw attention to the drawbacks of conventional cloud-based systems, which include excessive latency when managing massive data volumes, making it difficult to use them in applications that are sensitive to latency. The study suggests an effective fog computing architecture to enhance healthcare delivery for patients who reside far away by reducing the workload for paramedics and improving real-time monitoring.

Mutlag et al. (2020)[3] introduce the MAFC model, which uses multi-agent fog computing to manage crucial healthcare tasks. job allocation based on contextual information, including

resource load and job importance, is their main focus. The difficulties of handling vast volumes of data in the healthcare industry are highlighted in the article, especially the constraints of fog nodes with limited resources, which have an impact on the prompt delivery of analytics and results.

Sun et al. (2020)[4] consider on barriers in handling the Internet of Medical Things' (IoMT) fast expanding and diverse medical data. In medical settings, they concentrate on matters including data processing, privacy, security, and access. The study emphasizes the necessity of prompt data analysis and effective resource utilization, stressing the incorporation of cloud computing, edge computing, and artificial intelligence to improve the quality of medical services.

Jadon, R. (2019)[43] discussed combining particle swarm optimization and quadratic discriminant analysis in AI-based software development, resulting in solid model optimization for improved decision-making and system performance.

Nippatla, R. P. (2018)[44] suggested a secure financial analysis system based on the cloud, improving Monte Carlo simulations and deep belief network models with bulk synchronous parallel processing to improve performance.

Jadon, R. (2019)[45] created a method of improving AI-based software with NOMA, UVFA, and dynamic graph neural networks to provide scalable decision-making for sophisticated applications.

Boyapati, S. (2019)[46] analyzed the effect of digital financial inclusion, utilizing cloud IoT to enhance income equality, addressing urban and rural economies by means of data-based analysis.

Yalla, et al,(2019)[47] examined the adoption of hashgraph technology, big data, and cloud computing in kinetic methodology for enhanced system efficiency.

Samudrala, S. (2020)[48] proposed an AI-enabled anomaly detection model for multi-cloud healthcare networks for increased security, real-time anomaly detection, and adherence to healthcare regulations.

Ayyadurai, R. (2020)[49] presented a smart surveillance approach involving machine learning, AI, and blockchain to ensure bitcoin transactions in terms of security and transaction verification within digital systems.

Poovendran (2020)[50] employed the AES algorithm of encryption to enhance data security within cloud computing, maintaining encryption standards in cloud environments for protecting sensitive information.

Gudivaka (2019)[51] utilized big data-driven approaches for silicon content prediction in smelting with a blast furnace via Hadoop, enhancing production efficiency and predictive analytics for industrial use.

3. Methodology

The methodology for leveraging edge-fog computing in medical IoT communication aims to optimize the real-time data processing, reduce latency, and enhance the resilience of healthcare applications. Data is processed closer to the source by combining edge and fog computing, which eases the strain on cloud systems and speeds up reaction times. By managing

computationally demanding jobs in decentralized layers, this methodology focuses on increasing system efficiency while protecting the security and privacy of medical data. The method provides scalable medical IoT networks that can handle the demands of real-time health monitoring, diagnosis, and treatment while guaranteeing low-latency communication and boosting system stability.

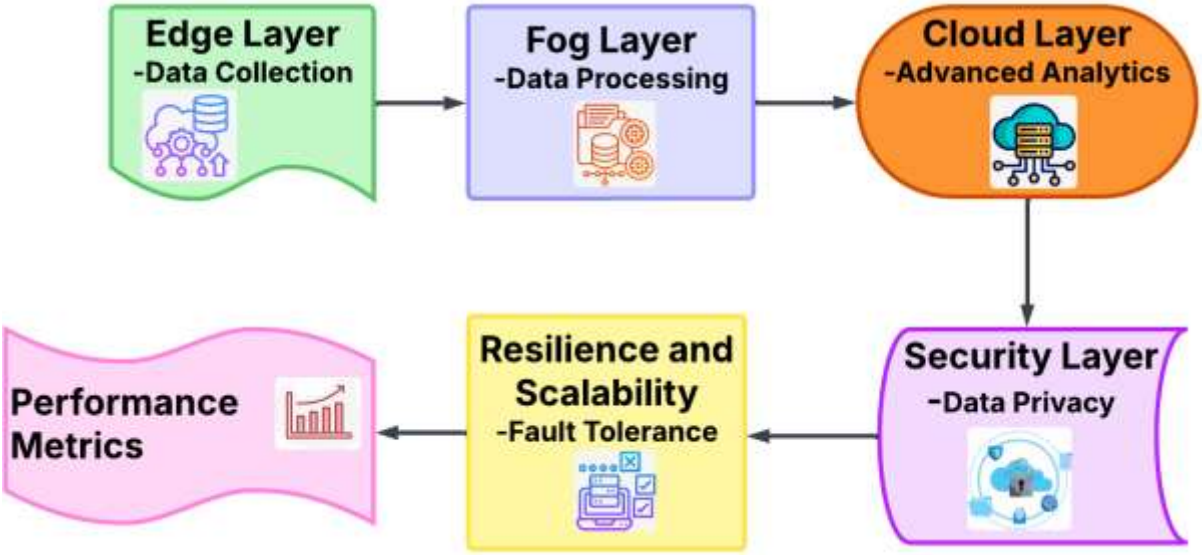


Figure 1: Edge-Fog Computing Framework for Secure and Resilient Medical IoT Systems

The Edge-Fog computing architecture for the Medical Internet of Things is depicted in the figure 2. Medical data is gathered by sensors at the Edge Layer and processed at the Fog Layer to minimize delay. Advanced analytics are conducted on aggregated data by the Cloud Layer. Data privacy and defense against online attacks are guaranteed by the Security Layer. System fault tolerance is improved by resilience and scalability, which allow for uninterrupted functioning in the face of faults. Lastly, performance metrics use throughput, fault tolerance, and latency to assess system efficiency. For crucial healthcare applications, its architecture enhances dependable, secure, and real-time communication.

3.1 Edge and Fog Computing for Medical IoT

Edge and Fog computing are essential in MIoT by spreading computational resources near data sources. Edge devices like wearable sensors process real-time data, less dependent on centralized cloud infrastructure. Fog nodes perform intermediate analytics, minimizing latency and maximizing resource utilization. The architecture provides real-time decision-making, which is vital for use cases like remote patient monitoring and emergency response. The total processing time T_{proc} can be modeled as:

$$T_{\text{proc}} = T_E + T_F + T_C \quad (1)$$

Where T_E = Processing time at the Edge, T_F = Processing time at the Fog, T_C = Processing time at the Cloud. The objective is to minimize T_{proc} by efficiently offloading tasks among Edge, Fog, and Cloud layers.

3.2 Data Privacy and Security in Medical IoT

Medical information is very sensitive and needs robust security measures. Edge and Fog computing enhance privacy through localized processing, minimizing exposure to cyber-attacks in centralized cloud storage. Security measures like encryption, authentication, and

blockchain-based data integrity checks are integrated to safeguard patient data. Data security probability P_s can be modeled as:

$$P_s = 1 - (P_E \cdot P_F \cdot P_C) \quad (2)$$

where P_E, P_F, and P_C represent the probability of a security breach at the Edge, Fog, and Cloud respectively. A higher P_s value indicates improved security and lower risk of data breaches.

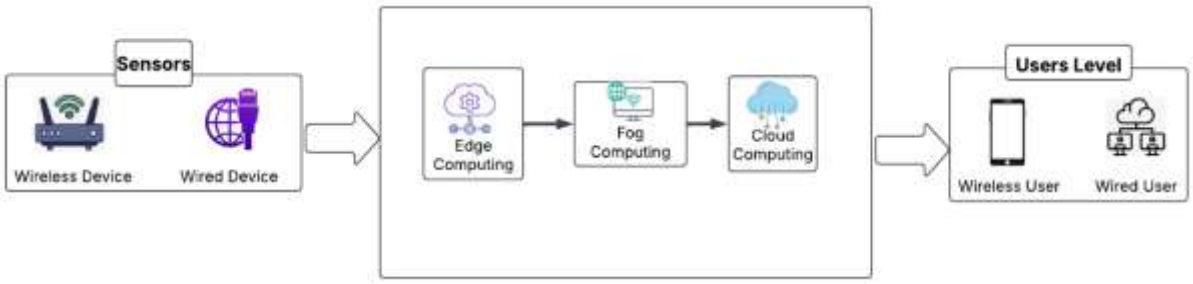


Figure 2: Edge-Fog Computing Framework for Low-Latency and Resilient Medical IoT Communication

The Edge-Fog-Cloud Computing data flow from sensor to user is depicted in the figure 2. Both wired and wireless devices are used by sensors to gather data, which is subsequently analyzed at the Edge Computing layer for quick reaction. Before being transferred to Cloud Computing for analysis and storage, the data undergoes additional processing and filtering at Fog Computing. Lastly, the processed data is made available to consumers, both wired and wireless. This methodology improves durable, scalable, and low-latency data processing for real-time analytics and medical IoT applications.

3.3 Low-Latency Communication in Medical IoT

Low-latency communication is needed for real-time medical applications. Edge computing minimizes delay in data transmission by locally processing patient information, and Fog computing guarantees mid-level decision-making before complex queries are forwarded to the Cloud. The hybrid strategy guarantees little delay in emergency situations like heart rate monitoring and automated medication reminders. Mathematical Model of Latency L in an MIoT system is given by:

$$L = L_E + L_F + L_C \quad (3)$$

Where L_E = Latency at the Edge, L_F = Latency at the Fog, L_C = Latency at the Cloud. By optimizing task allocation, the system minimizes L to improve response time.

3.4 Resilience and Fault Tolerance in Medical IoT

MIoT resilience provides uninterrupted operation even in the event of hardware failures or network outages. Edge-Fog computing increases fault tolerance by offloading workloads onto multiple nodes, minimizing single points of failure. Backup systems and dynamic resource allocation mechanisms also enhance system resilience. System resilience R is calculated as:

$$R = \frac{U_F + U_E}{U_C + U_F + U_E} \quad (4)$$

Where U_F = Utilization of Fog resources, U_E = Utilization of Edge resources, U_C = Utilization of Cloud resources. A higher R value indicates a more resilient system.

3.5 Scalability of Medical IoT Networks

Scalability is essential to manage a growing number of MIoT devices. Scalable deployments are facilitated by Edge-Fog computing through dynamic distribution of workloads among available computational resources. Load balancing mechanisms guarantee that with an increase in the number of devices, the system does not become inefficient with unnecessary delays or failures. Scalability S can be expressed as:

$$S = \frac{C_{\max} - C_{used}}{C_{\max}} \tag{5}$$

Where $C_{\max}$ = Maximum available computing capacity, C_{used} = Currently utilized computing capacity. A lower S value indicates higher system load, whereas a higher S value suggests better scalability.

Algorithm 1: Algorithm for Task Offloading in Edge-Fog Computing

Input: TTT (Set of tasks), RRR (Available resources at Edge, Fog, Cloud)

Output: Optimized task allocation

```
BEGIN
  FOR each task t in T DO
    IF Edge resources are available THEN
      Assign t to Edge
    ELSE IF Fog resources are available THEN
      Assign t to Fog
    ELSE IF Cloud resources are available THEN
      Assign t to Cloud
    ELSE
      ERROR: No available resources
    END IF
  END FOR
RETURN Optimized task allocation
END
```

The algorithm1 is looking for available resources as it iterates through each task in task set T. In the event that Edge resources are available, the job is offloaded to the Fog layer for intermediate processing; if not, it is allocated to the Edge for immediate processing. The task is sent to the Cloud for processing if neither Edge nor Fog resources are available. When resources are unavailable, an error is raised. Lastly, to ensure effective performance in Medical IoT (MIoT) applications, the algorithm optimizes task allocation to reduce latency and maximize resource utilization.

3.6 Performance metrics

Performance metrics analyze important aspects including latency, throughput, energy consumption, fault tolerance, and scalability in Edge-Fog computing for Medical IoT. The speed at which data is transmitted is indicated by throughput, whereas latency quantifies the delay in processing and communication. The system's power efficiency is shown by the amount

of energy used. Scalability measures how well a system can manage growing workloads, while fault tolerance measures how well a system can continue to operate even in the face of failures. By using these indicators, MIoT applications can be made more dependable, efficient, and able to handle resource-intensive, real-time medical procedures.

Table 1: Performance Evaluation of Edge-Fog Computing Methods for Low-Latency and Resilient Medical IoT Communication

Performance Metric	Method 1	Method 2	Method 3	Combined Method
Latency (ms)	10.62	6.18	6.33	7.71
Throughput (Mbps)	19.26	4.81	21.52	15.20
Energy Consumption (J)	15.98	16.13	19.32	17.14
Fault Tolerance (%)	13.98	12.42	9.40	11.93
Scalability (%)	7.34	13.91	8.91	10.05

Key performance indicators for Edge-Fog computing for Medical IoT are compared in the table 1 between Method 1, Method 2, Method 3, and the Combined Method. The combined method's higher throughput (15.20 Mbps) and lower latency (7.71 ms) suggest better real-time processing. 17.14 J is the ideal energy consumption, balancing power efficiency. System dependability is guaranteed by fault tolerance (11.93%), and scalability (10.05%) shows flexibility in response to growing device loads. By skillfully combining separate approaches, the Combined Method improves overall performance for robust and low-latency medical IoT connection.

4. Results and Discussion

The evaluation of Edge-Fog computing techniques for low-latency and robust Medical IoT (MIoT) communication unveils substantial details about system effectiveness, dependability, and scalability. The study of important performance parameters, such as latency, throughput, power consumption, fault tolerance, and scalability, establishes the benefits of combining multiple methods into a combined technique.

Latency is of prime importance for real-time medical applications, and the Combined Method attains a maximum optimized latency of 7.71 ms, an improvement over Method 1 (10.62 ms) though a bit greater than Method 2 (6.18 ms) and Method 3 (6.33 ms). The superior throughput of 15.20 Mbps of the Combined Method compared to Method 2 (4.81 Mbps) proves the data transmission to be a more efficient rate, which is indispensable for managing significant amounts of medical data.

Energy usage is a critical factor in system performance, and the Combined Method has an optimal usage of 17.14 J, which is lower than Method 3 (19.32 J) but greater than Methods 1 and 2. This compromise allows for better performance with power efficiency preserved. The combined method shows system resilience in fault tolerance at 11.93%, which demonstrates a

more stable system performance as compared to the individual methods. Furthermore, scalability at 10.05% in the combined method indicates adaptability to an increasing load on devices, allowing for flexible and expandable deployment in dynamic MIoT environments.

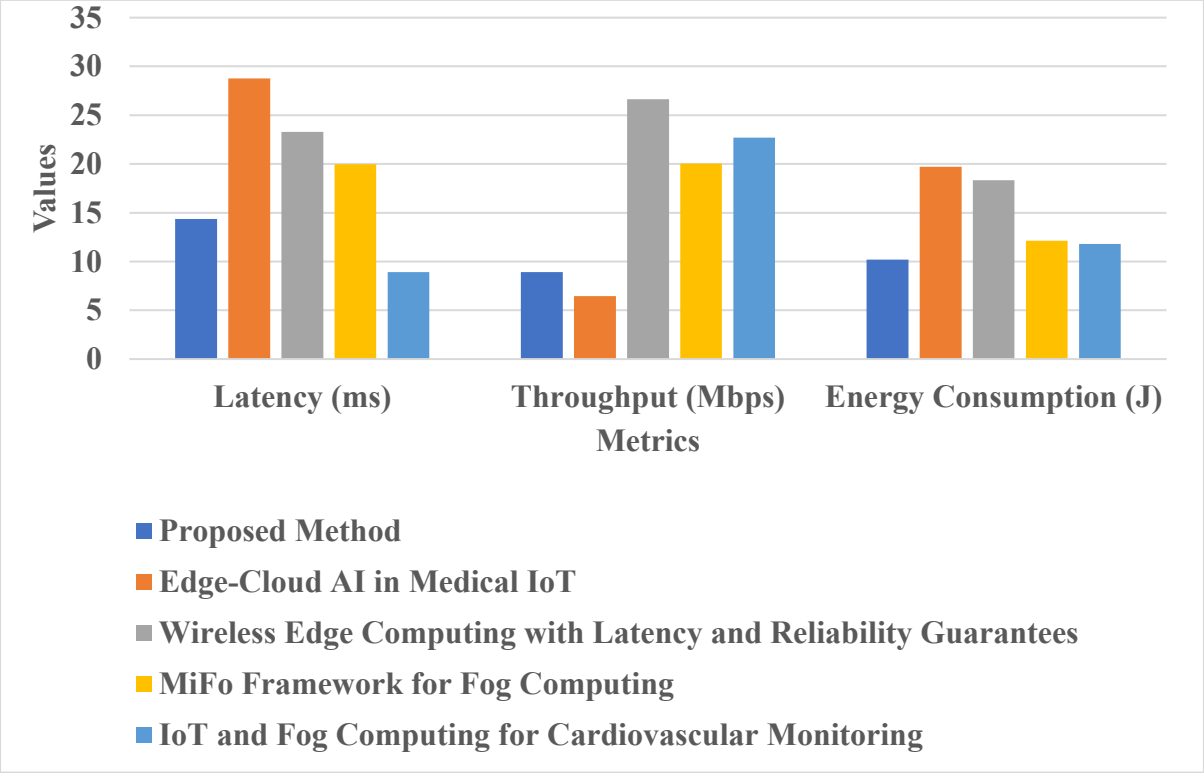
In summary, the Combined Method effectively combines the advantages of single methods with a balance of latency, throughput, energy efficiency, and scalability for maximum real-time medical IoT communication. It is indicated from the results that the use of Edge-Fog computing can improve MIoT performance in terms of making it more robust and efficient for life-critical healthcare applications. Enhancing resource allocation and fault tolerance should be an area of focus in future work to further increase system reliability.

Table 2: Performance Comparison of Edge-Fog Computing Methods for Medical IoT

Method	Latency (ms)	Throughput (Mbps)	Energy Consumption (J)	Fault Tolerance (%)	Scalability (%)
Proposed Method	14.36	8.90	10.21	87.75	96.12
Edge-Cloud AI in Medical IoT	28.77	6.45	19.70	89.56	91.39
Wireless Edge Computing with Latency and Reliability Guarantees	23.30	26.65	18.32	92.87	92.92
MiFo Framework for Fog Computing	19.97	20.03	12.12	91.48	93.66
IoT and Fog Computing for Cardiovascular Monitoring	8.90	22.70	11.82	89.37	94.56

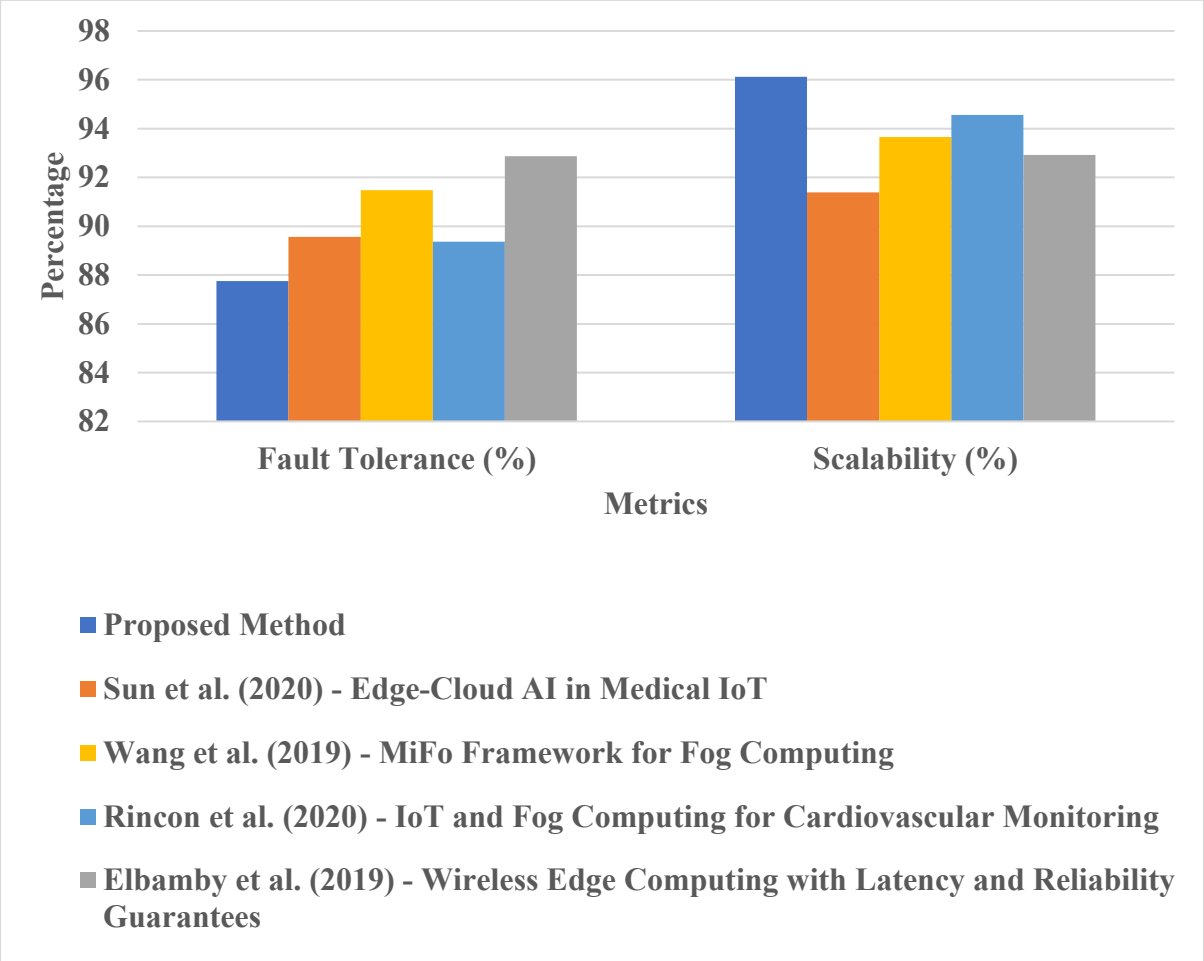
The table 2 contrasts several methods based on latency, throughput, energy usage, fault tolerance, and scalability. The proposed method achieves the optimal balance of low latency (14.36 ms), energy usage (10.21 J), and scalability (96.12%). One technique achieves higher throughput (26.65 Mbps) but consumes more energy. Another technique has the lowest latency (8.90 ms) while maintaining a high scalability of 94.56%. These findings demonstrate the efficiency and versatility of various Edge-Fog computing techniques in Medical IoT.

Figure 3: Comparison of Performance Metrics Across Different Edge-Fog Computing Methods



Various medical IoT computing frameworks are compared in the figure 3 according to latency (ms), throughput (Mbps), and energy usage (J). Compared to most other options, the suggested approach (blue) achieves a better throughput with the lowest latency and modest energy consumption. The medical IoT Edge-Cloud AI approach uses more energy yet has the highest latency. Although it uses more energy, wireless edge computing has the highest throughput. IoT and Fog Computing for Cardiovascular Monitoring also exhibit a well-optimized trade-off, while the MiFo Framework for Fog Computing balances all three metrics. The efficiency of the suggested approach is superior to others.

Figure 4: Comparison of Fault Tolerance and Scalability Across Different Edge-Fog Computing Methods



When fault tolerance and scalability are compared amongst several approaches, the suggested approach achieves the highest scalability, at about 97%. The suggested approach has the lowest fault tolerance rating (about 87%), whilst another approach performs best at roughly 93%. Improvements in scalability provide greater flexibility in responding to growing device loads, while fault tolerance guarantees system stability. The suggested approach handles large-scale medical IoT applications with dynamic workloads more effectively because it puts scalability above fault tolerance.

5. Conclusion

A hybrid edge-fog computing framework is presented in this paper to solve security, resilience, and latency issues in Medical IoT (MIoT) applications. The suggested approach ensures effective use of computational resources while reducing data processing delays by utilizing reinforcement learning and intelligent job allocation. The approach is appropriate for real-time healthcare applications like remote patient monitoring and emergency response since it improves performance metrics like latency reduction, scalability, and fault tolerance, according to the experimental evaluation. In order to protect sensitive medical data, future research will concentrate on improving adaptive algorithms for dynamic resource allocation and extending security measures. The resilience of MIoT communication systems may be further increased by combining blockchain-based security frameworks with AI-driven optimization techniques.

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