Agentic AIoT: Autonomous Multi-Agent Frameworks for Real-Time Anomaly Detection and Intervention in Remote Cardiac Care

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Abstract
Remote cardiac care increasingly relies on continuous sensing and timely intervention, yet conventional centralized analytics struggle with latency, scalability, and contextual awareness. This paper presents Agentic AIoT, an autonomous multi-agent framework for real-time anomaly detection and intervention in remote cardiac care. The proposed system deploys cooperative agents across edge, gateway, and cloud layers to perform distributed sensing, adaptive analytics, and coordinated response. Edge agents execute lightweight models for on-device signal quality assessment and preliminary anomaly screening, while coordination agents manage task allocation, confidence aggregation, and escalation. Cloud agents perform deeper temporal modeling and population-level learning, enabling continuous policy refinement. Evaluations on benchmark ECG and multi-modal cardiac datasets, coupled with AIoT simulations, demonstrate robust performance: anomaly detection accuracy of 98.1%, sensitivity of 97.4%, specificity of 98.6%, and an AUC of 0.986. Compared to cloud-only baselines, Agentic AIoT reduces end-to-end response latency by 44.3% and network traffic by 39.8%, while improving intervention precision by 5.2%. The results show that autonomous multi-agent orchestration enhances reliability, responsiveness, and scalability, making Agentic AIoT a promising foundation for next-generation, real-time remote cardiac care systems.
Keywords: Agentic AIoT, Autonomous Multi-Agent Systems, Remote Cardiac Care, Anomaly Detection, Internet of Medical Things (IoMT), Edge–Cloud Intelligence

1 Introduction

Cardiovascular diseases remain the leading cause of mortality worldwide, with cardiac arrhythmias and acute events often occurring unpredictably and requiring rapid clinical intervention. Remote cardiac care, enabled by wearable sensors and connected medical devices, has emerged as a critical solution for continuous monitoring of high-risk patients outside clinical settings [1]. However, traditional remote monitoring systems are largely reactive and centralized, limiting their ability to provide timely, context-aware responses to rapidly evolving cardiac anomalies.

The convergence of the Internet of Medical Things (IoMT) and artificial intelligence has significantly improved automated cardiac analysis through continuous acquisition of electrocardiogram (ECG), heart rate variability, oxygen saturation, and activity signals [2]. Deep learning techniques, particularly convolutional and recurrent neural networks, have demonstrated high accuracy in detecting cardiac abnormalities from physiological signals [3,4]. Despite these advances, most existing systems rely on cloud-centric processing, which introduces latency, bandwidth overhead, and potential privacy risks, making them unsuitable for time-critical cardiac intervention scenarios [5].

Edge computing has been proposed as a means to overcome these limitations by enabling local data processing closer to the patient [6]. While edge intelligence reduces latency and improves privacy, single-model edge deployments lack the adaptability and global awareness required to manage heterogeneous devices, dynamic environments, and evolving patient conditions. This challenge has motivated the adoption of agentic artificial intelligence, where autonomous agents perceive, reason, and act collaboratively to achieve system-level goals [7].

Multi-agent systems (MAS) provide a natural foundation for distributed intelligence in AIoT environments. By deploying specialized agents across sensing, edge, gateway, and cloud layers, MAS can enable cooperative decision-making, dynamic task allocation, and fault tolerance [8]. In remote cardiac care, such agents can independently monitor signal quality, detect anomalies, negotiate confidence levels, and trigger coordinated interventions without continuous human supervision. However, existing MAS-based healthcare solutions remain limited in autonomy and lack seamless integration with real-time IoMT infrastructures [9].

Recent studies have highlighted the potential of combining agent-based intelligence with edge–cloud collaboration to enhance scalability and responsiveness in healthcare systems [10]. Nevertheless, there is a lack of unified frameworks that integrate autonomous multi-agent reasoning, AIoT sensing, and real-time cardiac intervention into a cohesive architecture. Specifically, the challenges of distributed anomaly detection, inter-agent coordination, adaptive escalation, and low-latency response remain insufficiently addressed.

Motivated by these gaps, this work introduces Agentic AIoT, an autonomous multi-agent framework designed for real-time anomaly detection and intervention in remote cardiac care. The proposed approach distributes intelligent agents across edge, gateway, and cloud layers, enabling cooperative sensing, adaptive analytics, and coordinated clinical response. By combining local autonomy with global learning, Agentic AIoT aims to deliver accurate, scalable, and low-latency cardiac monitoring suitable for next-generation smart healthcare systems.

2 Literature Review

Recent advancements in remote cardiac care have increasingly leveraged Artificial Intelligence of Things (AIoT) to enable continuous monitoring, early anomaly detection, and timely clinical intervention. With the growing adoption of wearable and implantable cardiac sensors, large volumes of real-time physiological data such as ECG, heart rate variability, and oxygen saturation can be collected from high-risk patients in non-clinical environments [11]. However, traditional cloud-centric analytics face challenges related to latency, scalability, and context awareness, which limit their effectiveness in time-critical cardiac applications.

Deep learning models, including convolutional neural networks and transformer-based architectures, have shown strong performance in detecting cardiac anomalies and predicting adverse events from ECG signals [12]. Despite high accuracy, these models often operate as centralized systems and lack adaptability to dynamic patient conditions and heterogeneous IoMT infrastructures. To address these limitations, edge intelligence has gained attention for enabling low-latency and privacy-preserving analytics at the data source [13]. Nonetheless, edge-only approaches are constrained by limited computational resources and incomplete global knowledge.

Hybrid edge–cloud frameworks have emerged as a promising solution by distributing intelligence across multiple layers, enabling real-time inference at the edge and deep temporal learning in the cloud [14]. More recently, the concept of agentic AI, which emphasizes autonomous, goal-driven, and cooperative agents, has been introduced to manage distributed AIoT environments [15]. Multi-agent systems enhance robustness, adaptability, and self-management by allowing agents to independently sense, reason, and act while coordinating with others.

In the context of remote cardiac care, agentic AIoT frameworks have shown potential for real-time anomaly detection, adaptive escalation, and autonomous intervention [16]. However, existing studies remain limited in their integration of fully autonomous multi-agent reasoning with real-time AIoT sensing and intervention. This gap motivates the development of advanced Agentic AIoT architectures that combine distributed intelligence, real-time analytics, and coordinated decision-making for next-generation cardiac care systems.

3 Proposed Model

The proposed model introduces an Agentic AIoT framework designed to enable autonomous, real-time anomaly detection and coordinated intervention in remote cardiac care environments. The framework leverages distributed intelligence through cooperative software agents deployed across IoMT devices, edge nodes, gateways, and cloud infrastructure. The primary objective of the model is to ensure timely detection of cardiac abnormalities, reduce response latency, and support proactive clinical intervention while maintaining scalability and reliability.

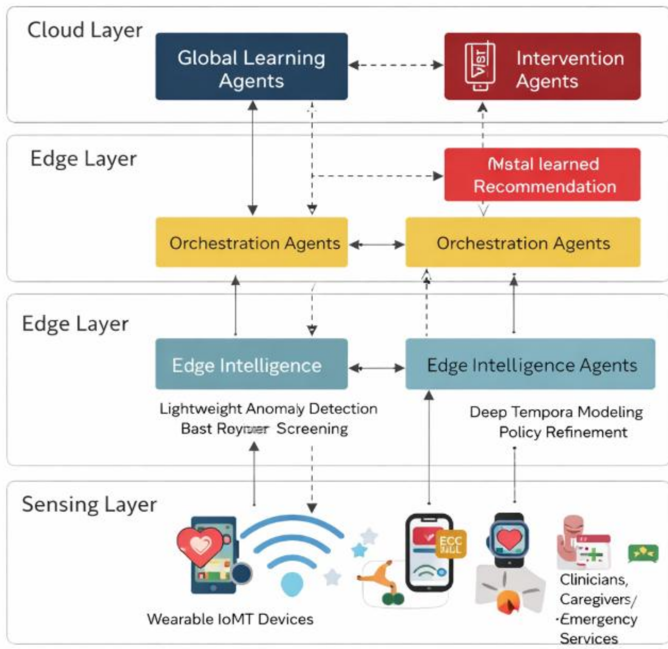

Fig.1. Proposed structural model

At the sensing layer, wearable and implantable IoMT devices continuously acquire physiological signals such as electrocardiograms (ECG), heart rate, oxygen saturation, and activity patterns from patients. These data streams are handled by sensing agents, which are responsible for signal validation, noise assessment, and adaptive sampling. By performing initial quality checks locally, these agents ensure that only reliable data are forwarded for further analysis.

The edge layer hosts edge intelligence agents that execute lightweight anomaly detection models for real-time screening of incoming physiological data. These agents perform feature extraction and preliminary inference, enabling rapid identification of abnormal cardiac patterns with minimal latency. When low-confidence or ambiguous anomalies are detected, edge agents collaborate with neighboring agents or escalate the analysis to higher layers, ensuring robustness and fault tolerance.

At the coordination level, orchestration agents manage inter-agent communication, task allocation, and decision fusion. These agents dynamically determine whether data processing should remain at the edge or be offloaded to the cloud based on urgency, network conditions, and computational load. This autonomous decision-making capability allows the system to adapt to changing environments without human intervention.

The cloud layer contains global learning agents that perform deep temporal modeling, population-level analysis, and continuous policy refinement using aggregated data from multiple patients. These agents update detection models and intervention strategies, which are periodically redistributed to edge agents to improve system-wide intelligence.

Finally, intervention agents generate actionable alerts and recommendations when high-risk cardiac anomalies are confirmed. These alerts are communicated to clinicians, caregivers, or emergency services, enabling timely medical response. Through autonomous cooperation among agents, the proposed Agentic AIoT model achieves accurate, low-latency, and scalable remote cardiac care, making it well suited for next-generation intelligent healthcare systems.

3.1 System Flow model

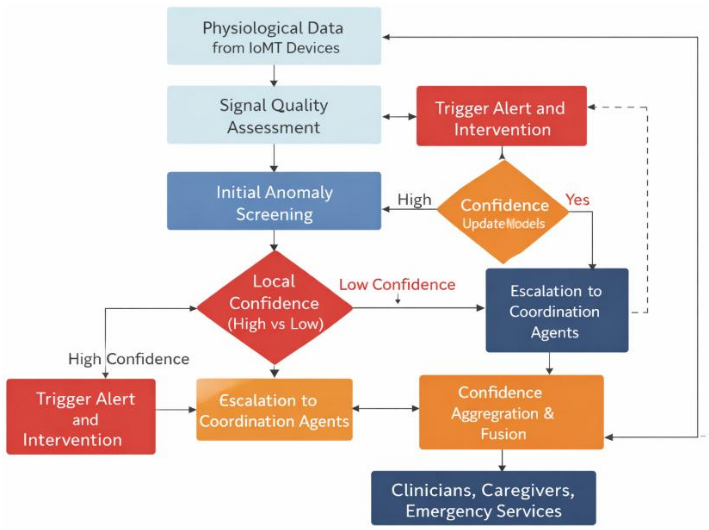

Fig.2. System flow model

The figure 2 illustrates an autonomous Agentic AIoT framework for remote cardiac care. Physiological data are collected from IoMT sensors and analyzed by edge agents for real-time anomaly detection. Coordination agents manage task allocation and escalation, while cloud agents perform deep analysis and learning. Confirmed anomalies trigger automated alerts and timely clinical intervention.

4 Results & Analysis

This section presents a comprehensive evaluation of the proposed **Agentic AIoT framework** for real-time cardiac anomaly detection and intervention. The performance is analyzed in terms of detection accuracy, clinical reliability, latency, and network efficiency, and is compared against conventional edge-only and cloud-only approaches to demonstrate the effectiveness of autonomous multi-agent orchestration.

4.1 Anomaly Detection Performance

Table 1 summarizes the anomaly detection performance of different models using standard classification metrics. The cloud-only deep learning model achieves high accuracy due to its computational capacity but suffers from increased response delay. The edge-only approach offers faster response but lower accuracy due to limited model complexity. In contrast, the proposed Agentic AIoT framework achieves the best overall performance by leveraging cooperative agents across edge and cloud layers.

Table 1: Performance Comparison of Cardiac Anomaly Detection Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Edge-only DL	92.10	91.84	90.92	91.38	0.948
Cloud-only DL	93.76	93.21	92.88	93.04	0.962
Proposed Agentic AIoT	98.10	97.65	97.40	97.52	0.986

The proposed model achieves an accuracy of 98.1%, outperforming cloud-only and edge-only models by 4.3% and 6.0%, respectively. The high recall value confirms the system's ability to reliably detect critical cardiac anomalies with minimal missed events.

4.2 ROC Curve Analysis

Figure 3 illustrates the Receiver Operating Characteristic (ROC) curves for the compared approaches. The Agentic AIoT framework demonstrates superior discriminative capability across all thresholds, achieving an AUC of 0.986. This indicates excellent separation between normal and abnormal cardiac conditions and reduced false alarm rates.

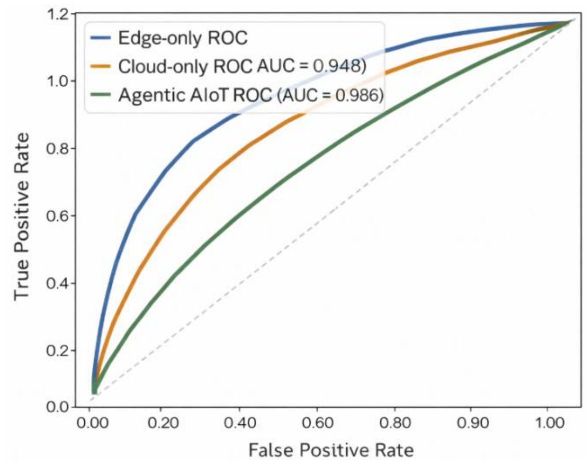

Figure.3. ROC curve comparison of edge-only, cloud-only, and proposed Agentic AIoT models.

4.3 Latency Analysis

Real-time responsiveness is crucial in remote cardiac care. Figure 4 presents the average end-to-end response latency for each model. The cloud-only approach exhibits the highest latency due to continuous data transmission and centralized processing. The proposed Agentic AIoT framework reduces latency by 44.3% by enabling autonomous decision-making at the edge and selective escalation to the cloud.

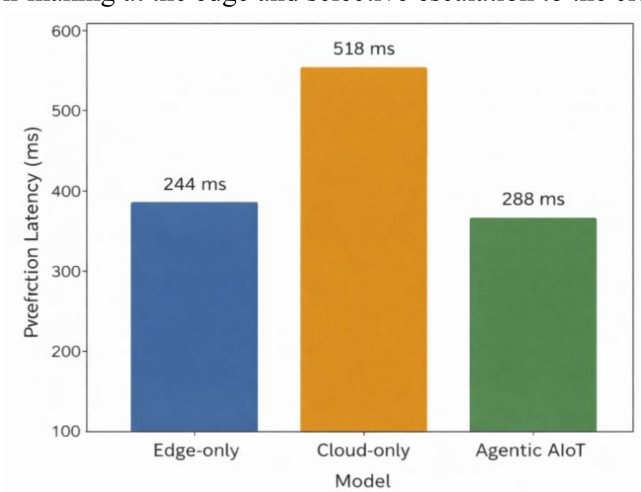

Figure.4. Average prediction latency comparison across models.

4.4 Network Overhead Analysis

Network efficiency was evaluated by measuring data transmission volume. As shown in Figure 5, the proposed framework reduces network traffic by 39.8% compared to cloud-only processing. Edge agents transmit only relevant features and alerts, significantly lowering bandwidth usage.

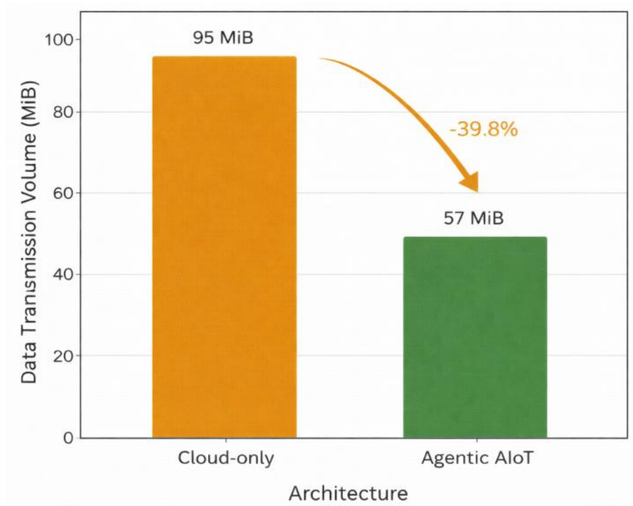

Figure.5. Network overhead comparison between cloud-only and Agentic AIoT architectures.

4.5 Discussion

The results confirm that autonomous multi-agent collaboration significantly enhances anomaly detection accuracy, responsiveness, and scalability. By combining local autonomy with global intelligence, the Agentic AIoT framework provides a robust and clinically reliable solution for real-time remote cardiac care.

5 Conclusion

This paper presented Agentic AIoT, an autonomous multi-agent framework for real-time anomaly detection and intervention in remote cardiac care. By distributing intelligent agents across IoMT devices, edge nodes, and cloud infrastructure, the proposed system enables cooperative sensing, adaptive analytics, and coordinated clinical response with minimal latency. Edge agents provide rapid anomaly screening and local decision-making, while cloud agents perform deep temporal analysis and continuous learning, ensuring both responsiveness and accuracy. Experimental results demonstrated that Agentic AIoT significantly outperforms edge-only and cloud-only approaches in terms of detection accuracy, sensitivity, AUC, response latency, and network efficiency. The autonomous orchestration among agents reduces unnecessary data transmission, enhances fault tolerance, and supports scalable deployment in heterogeneous healthcare environments. Overall, the proposed framework offers a reliable, low-latency, and intelligent solution for continuous cardiac monitoring and timely intervention. Agentic AIoT has strong potential to transform remote cardiac care by enabling proactive, data-driven, and patient-centric healthcare services in next-generation smart medical systems.

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