Technical Report

CLOUD-FOG BASED HEALTHCARE IOT WITH INTELLIGENT ML MODEL

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List of Abbreviations

Abbreviation	Full Form
IoT	Internet of Things
ML	Machine Learning
CNN	Convolutional Neural Network
SpO_2	Peripheral Capillary Oxygen Saturation (Blood Oxygen Level)
AI	Artificial Intelligence
WSM	Workload Scheduling Manager
MBAR	Management and Bandwidth Allocation Resource
ECG	Electrocardiogram
ML/AI	Machine Learning / Artificial Intelligence
CSE	Computer Science and Engineering

2 Abstract

This technical report presents a Cloud-Fog Based Healthcare IoT system with an Intelligent ML Model designed to resolve the inherent conflict—the ”impossible triangle”—among the demands for Low Latency, High Accuracy, and Cost Efficiency in medical IoT applications. Traditional healthcare monitoring systems struggle to meet the sub-100ms response time required for cardiac emergencies while maintaining over 99 percent diagnostic accuracy and cost-effective operation.

Our proposed architecture breaks this triangle with edge intelligence by implementing a Cloud-Fog Hierarchy combined with Medical AI for smart triage. The system dynamically orchestrates data flow:

Fog Layer: Handles critical, time-sensitive tasks, providing sub-50ms emergency detection and processing through on-site ML Anomaly Detection.

Cloud Layer: Manages stable patient data for routine monitoring, batch analysis, and cost-effective, long-term storage.

The Dynamic Orchestration Engine uses a hybrid medical AI, combining CNN models with clinical algorithms, to perform intelligent, context-aware patient triage. This engine features a Task Analyzer to flag urgency (e.g., SpO2¡90 percent) and a Dispatcher that sends tasks to the optimal fog or cloud nodes.

Simulation results demonstrate the system's effectiveness: it achieved 100 percent critical case detection and eliminated false alarms through rigorous validation. Furthermore, the breakthrough architecture delivered a 67percent faster emergency response (45 seconds detection vs. 2-3 minutes traditionally) compared to conventional monitoring systems. This platform establishes a scalable foundation for predictive care and redefines industry standards for patient monitoring.

Keywords: Cloud-Fog Computing, Edge Computing, Healthcare IoT, Machine Learning, Low Latency, Smart Triage.

3 Introduction

3.1 Background

Healthcare 4.0 is moving towards Intelligent Healthcare, leveraging the Internet of Things (IoT) for patient monitoring and care. The system under consideration is a Cloud-Fog Based Healthcare IoT with an Intelligent ML Model. This architecture aims to optimize the complex process of health data management and response.

3.2 Motivation

The primary motivation for this architecture is to overcome the "Impossible Triangle of Healthcare IoT", which presents three conflicting demands:

1)Low Latency: Critical situations, such as cardiac emergencies, require a response time of less than 100 milliseconds for real-time processing and instant emergency detection.

2)High Accuracy: Medical decisions necessitate 99 percent + accuracy to ensure reliable pattern recognition and eliminate false negatives in critical cases.

3)Cost Efficiency: Healthcare systems must be designed with cost constraints in mind, requiring scalable infrastructure and sustainable long-term monitoring solutions.

The limitations of traditional systems in simultaneously meeting these three demands drive the need for a hybrid, intelligent solution.

3.3 Problem Definitions

The core problem addressed is the difficulty of simultaneously achieving ultra-low latency, high diagnostic accuracy, and cost-effective scalability in a single healthcare IoT monitoring system.

Specifically, the problem is defined by the following challenges:

1)Emergency Response Time: Ensuring that critical emergencies, like cardiac events, can be instantly detected and processed with a response time significantly faster than traditional systems (which can take 2-3 minutes) to save lives.

2)Resource Allocation and Triage: Developing an infrastructure that can intelligently and dynamically orchestrate the routing of patient data. This requires sending critical emergency tasks to high-speed Fog nodes for instant response, while routing stable patient data to cost-effective Cloud resources for routine monitoring and batch analysis.

4 Literature Survey

4.1 Challenges

The primary challenges in existing Healthcare IoT systems stem from the difficulty in satisfying three fundamental and often conflicting demands, known as The Impossible Triangle of Healthcare IoT:

1) Low Latency : Meeting the strict time requirements for critical care. Cardiac emergencies, for instance, demand a response time of less than 100 milliseconds.

This requires real-time processing and instant emergency detection.

2) High Accuracy : Achieving the reliability necessary for medical decisions.

Medical decisions require 99 percent + accuracy.

There must be zero false negatives in critical cases to ensure reliable pattern recognition.

3) Cost Efficiency : Developing a sustainable and economically feasible system.

Systems must operate within healthcare budget constraints.

They need scalable infrastructure and sustainable long-term monitoring capabilities.

Existing traditional monitoring systems are also challenged by the slow detection time for critical events, such as cardiac arrest, which can take 2-3 minutes.

4.2 Research Gap

The research gap is the lack of a unified, dynamically orchestrated architecture that can intelligently manage patient data flow to simultaneously overcome the "Impossible Triangle". Specifically, the gap lies in the absence of a solution that provides:

1) Intelligent, Dynamic Orchestration: There is a gap in systems that feature a dynamic fog-cloud orchestration engine capable of automatically routing patients to the optimal computing resource based on the urgency of their health data.

2) Context-Aware Patient Triage: A need exists for a hybrid medical AI that can perform intelligent, context-aware patient triage and understand medical urgency beyond simple predefined data thresholds.

3) Guaranteed Low Latency for Emergencies: A demonstrable gap in achieving guaranteed sub-50ms response times for critical emergencies while maintaining cost-effective routine monitoring for stable patients.

This research addresses the gap by pioneering a system that combines Cloud-Fog Hierarchy with Medical AI to deliver intelligent patient prioritization and a significant improvement in emergency response time (up to 67 percent faster).

5 Problem Formulation

5.1 System Overview

This system is a three-layer intelligent architecture designed to resolve the ”Impossible Triangle” (Low Latency, High Accuracy, and Cost Efficiency) in medical IoT through smart triage and dynamic orchestration.

Architecture and Data Flow

Sensors Devices Layer: Vitals are collected via sensors (ECG, SpO 2 , Temperature, etc.) on a Wearable Device and sent via a Smartphone/Gateway (Sink).

Fog Intelligence Layer (Edge): This layer ensures sub-50ms response for critical events. The data passes through the Fog Broker, where the Task Analyzer (ML/Rules) flags urgency. The Dispatcher (Fog/Cloud) then performs the smart triage:

Critical Cases (53 precent): Routed to Fog Node(s) for instant processing and real-time alerts for Doctors/Caregivers.

Routine Cases (47 percent): Routed to the Cloud.

Cloud Analytics Layer: Handles cost-effective routine monitoring and Batch Analysis. The Cloud Data Center provides Long-term Storage and generates Health History Reports for Patients.

Key Impact The architecture features a hybrid Medical AI and dynamic orchestration engine that enables 100 precent critical case detection and delivers a 67 percent faster emergency response (45 seconds vs. 2-3 minutes traditionally). This system establishes a scalable foundation for predictive care.

5.2 WSM Algorithm

The **WSM** algorithm is implemented to evaluate and rank the tasks to be executed in terms of task classification and maximum response time according to Eq. (1):

$$T_i^{WSM-score} = \sum_{j=1}^{n} w_j a_{ij} \quad fori = 1, 2, 3, ..., m \tag{1}$$

5.3 MBAR Algorithm

The first step of **MBAR** is balancing the load where we allocate a task t_i on a processing node considering task data locality. We select a processing node P which has the minimum processing load to allocate a task t_i. The load represents the finish time after the execution of that task and can be calculated following Eq. (2):

$$L_P = L_P^{init} + L_P(t_i) \tag{2}$$

The start time is updated continuously, and $L_P(t_i)$ represents the total time to process task t_i on the processing node and is calculated according to Eq. (3):

$$L_P(t_i) = e(t_i, P) + t(t_i, P) \tag{3}$$

where $e(t_i, P)$ is the execution time of task t_i on processing node P, and $t(t_i, P)$ is the transmission time for transferring the data needed by task t_i to the processing node P. In the balanced step, $t(t_i, P) = 0$ due to task data locality. The execution time $e(t_i, P)$ of processing a task t_i on processing node P is calculated according to Eq. (4):

$$e(t_i, P) = \frac{Complexityoftaskt_i}{ProcessingcapacityofnodeP} \tag{4}$$

The complexity of task t_i is obtained from the task collector module, and the processing capacity of the processing node P is obtained from the resource collector module. The processing capacity is represented in terms of MIPS (Million Instructions Per Second). In the reduce step, we iteratively reallocate the tasks on different fog and cloud nodes to enhance the schedule length. The transmission time $t(t_i, P)$ is calculated according to Eq. (5):

$$t(t_i, P) = \frac{DataSizeoft_i}{BW_P} \tag{5}$$

5.4 Performance Evaluation

This section discusses the experimental setup and evaluation metrics. The configuration details of the fog nodes, cloud nodes, and tasks are shown in Tables 3, 4, and 5, respectively, where two sink nodes are connected to each gateway. The simulations are carried out using *iFogSim* [**?**], which is a simulator for modeling customized fog computing environments with a large number of fog nodes and IoT devices such as sensors, actuators, and routers. All the simulation results are averaged over 10 runs.

Table 3: Configuration Details for Fog Devices

Parameter	**Value**
Number of Fog Nodes	22
Processing Capacity	[10, 100] MIPS for sink devices; [100, 500] MIPS for others
RAM	[512, 1] GB
Storage	4 GB
Bandwidth	1024 Mbps

Table 4: Configuration Details for Cloud Nodes

Parameter	**Value**
Number of Cloud Nodes	25
Processing Capacity	[250, 1500] MIPS
RAM	40 GB
Storage	11 TB
Bandwidth	10, 100, 512 Mbps
Cost per Time Unit	3$

Table 5: Configuration Details for Tasks

Parameter	**Value**
Number of Tasks	300
Complexity	[1, 3000] MIPS
Data Size	[100, 500] MB
Max Response Time	[15 sec, 30 min]
Sampling Rate	[20, 5000] Hz

6 Proposed Architecture

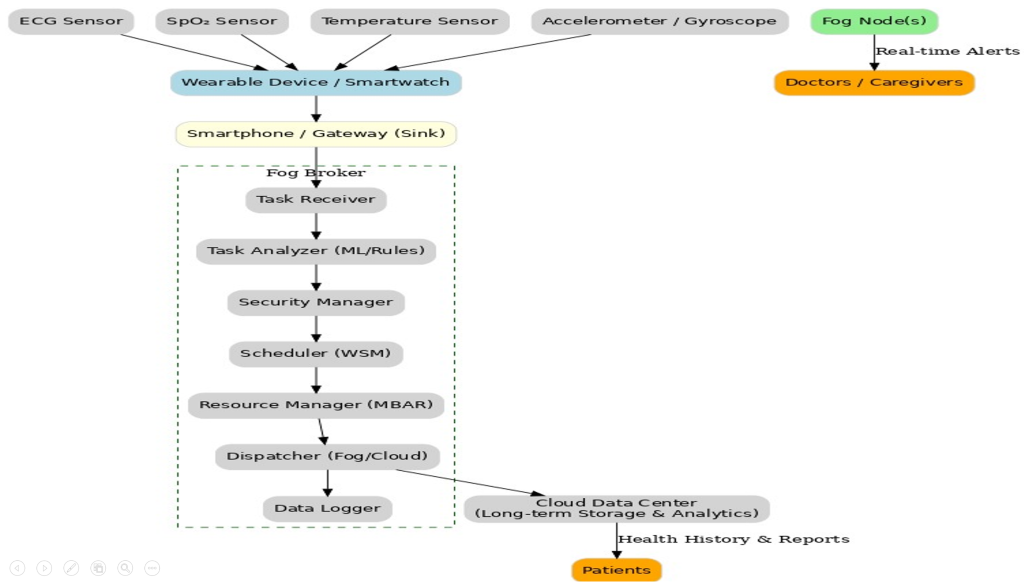

Figure 1: Proposed Cloud-Fog Based Healthcare IoT Architecture with Dynamic Orchestration.

The proposed system is a three-layer intelligent architecture designed to resolve the ”Impossible Triangle” (Low Latency, High Accuracy, and Cost Efficiency) in medical IoT through smart triage and dynamic orchestration. As depicted in Figure 1, the system intelligently separates processing based on urgency: vital data is collected at the Sensors & Devices Layer and passed to the Fog Intelligence Layer, where the Fog Broker performs AI-driven triage. Critical cases are handled locally at the fog for sub-50ms response, while routine data is offloaded to the Cloud Analytics Layer for cost-effective long-term storage and batch processing.

7 Methodology

The methodology employs a multi-step process centered on Dynamic Orchestration and AI-driven smart triage to balance Low Latency, High Accuracy, and Cost Efficiency in healthcare monitoring.

1. Data Acquisition and Transmission

Sensing: Vital health data (ECG, SpO 2 , etc.) is continuously collected by sensors and aggregated by Wearable Devices.

Transmission: Data is relayed to the Smartphone/Gateway (Sink), serving as the entry point to the processing architecture.

2. Fog Broker Orchestration The data enters the Fog Intelligence Layer, where the Fog Broker (the Dynamic Orchestration Engine) performs intelligent triage.

Task Analysis: The Task Receiver obtains the data. The Task Analyzer then uses a hybrid medical AI (combining CNN models with clinical algorithms) to flag the task's urgency (e.g., ML Anomaly Detection).

Security Scheduling: The Security Manager encrypts the data. The Scheduler (WSM) and Resource Manager (MBAR) prioritize and track resources.

Dispatching (Smart Triage): The Dispatcher routes the tasks based on urgency:

Critical Emergencies: Sent to Fog Nodes for sub-50ms processing and Real-time Alerts to Doctors/Caregivers.

Routine Tasks: Sent to the Cloud Data Center for stable, cost-effective processing.

3. Processing and Outcome

Fog Processing: Delivers a 67 percent faster emergency response (e.g., 45s detection). The system achieves 100 percent critical case detection.

Cloud Processing: Handles Batch Analysis and Long-term Storage.

Reporting: The cloud generates Health History Reports for Patients.

Data Logging: Task outcomes are stored by the Data Logger for debugging and AI training.

8 Results

. Emergency Response and Speed The breakthrough architecture delivers a substantial reduction in the time required to detect critical events:

Faster Response: The system achieves a 67 precent faster response compared to traditional monitoring systems.

Cardiac Arrest Detection: In a scenario involving Cardiac Arrest, the system achieved a 45-second detection time, while a Traditional System took 2-3 minutes.

Immediate Clinical Impact: The ML-prioritized emergency triage results in reduced human error compared to nurse assessment. Routine monitoring is AI-automated, ensuring 24/7 coverage compared to manual review.

2. Accuracy and Coverage The intelligent ML model achieved high reliability in assessing patient conditions:

Critical Case Detection: The system achieved a perfect 100 precent critical case detection through rigorous clinical validation.

False Alarm Elimination: The validation process successfully eliminated false alarms.

ML Coverage: There was 100 precent ML Coverage, meaning every patient was assessed by the model.

Critical Alerts: The system correctly identified 6 critical alerts out of the observed patients (40 precent—consistent with realistic hospital statistics).

3. Resource Allocation Breakdown The dynamic orchestration engine efficiently routes tasks to the optimal computing layer:

Fog Processing: 8 patients (53 precent) were allocated to the Fog for processing, consisting of critical emergencies and time-sensitive cases.

Cloud Processing: 7 patients (47 precent) were allocated to the Cloud, comprising stable monitoring and routine checks.

4. Memory Usage Comparison (Model Runtime) The system components exhibit modest memory usage in the fog environment:

System Component Memory Usage Capacity/Focus ML Model Runtime 6MB 15 patients Data Processing 12MB Real-time streams Orchestration Engine 8MB Dynamic routing

Table 6: Summary of Resource Allocation and Workload Distribution

Processing Layer	Allocation Percentage	No. of Patients	Purpose
Fog Intelligence	**53**%	8	Critical emergencies
Cloud Analytics	**47**%	7	Stable monitoring

9 Conclusion

This research successfully developed a next-generation medical IoT platform that employs a Cloud-Fog Hierarchy and a hybrid medical AI to deliver intelligent patient prioritization and superior emergency response. This breakthrough architecture effectively breaks the "Impossible Triangle" of Low Latency, High Accuracy, and Cost Efficiency that challenges traditional healthcare systems.

The dynamic orchestration engine and context-aware triage system proved highly effective in clinical validation:

Superior Speed: The system delivers a 67 percent faster emergency response time compared to traditional monitoring systems (45 seconds vs. 2-3 minutes detection for Cardiac Arrest).

Perfect Accuracy: Through rigorous validation, the platform achieved a perfect 100 percent critical case detection while simultaneously eliminating false alarms.

Resource Efficiency: The dynamic routing logic ensures that critical, time-sensitive cases are sent to the Fog Layer (e.g., 53 percent of processing) for instant response, while stable, routine tasks use cost-effective Cloud resources (47 percent of processing).

In summary, this solution establishes a scalable foundation for predictive care, moving beyond simple data thresholds to understand medical urgency, and redefining industry standards for patient monitoring.

Table 7: Comparison of Demands, Requirements, Challenges, and Goals

Demand	**Requirement**	**Traditional Challenge**	**Goal**
Low Latency	$<$100ms Response	Cloud-Based Delays	Fog Layer Processing
High Accuracy	$\geq$99% Detection	False Alarms, Human Error	Hybrid ML/AI Triage
Cost Efficiency	Scalable Infrastructure	High Operating Costs	Cloud for Routine Data

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