A Fog Computing Framework for Real-Time ECG Monitoring with Machine Learning-Driven Task Prioritization

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***Abstract*—The increasing adoption of wearable ECG devices in healthcare has highlighted the need for real-time data processing and analysis to support critical health monitoring. Fog computing, with its ability to process data closer to the source, offers a promising solution to address the challenges of traditional cloud systems, such as high latency and bandwidth constraints. This research proposes a novel fog computing framework for ECG wearable devices that leverages machine learning to prioritize user requests based on a classification of urgency. The system was developed and evaluated through extensive simulations, with performance metrics including task completion rates, response times, system throughput, and resource utilization efficiency. The results demonstrate that the framework significantly improves the handling of high-priority tasks and reduces response times.. This approach enhances the reliability and efficiency of healthcare services, offering substantial improvements for real-time ECG monitoring and paving the way for future advancements in fog computing within healthcare informatics.**

***Index Terms*—fog computing, healthcare informatics, ECG monitoring, machine learning, task prioritization, real-time processing**

I. Introduction

The emergence of fog computing has transformed distributed system architecture, enhancing data processing capabilities and service delivery at the network edge. This paradigm shift addresses critical requirements in modern computing: real-time data analytics, minimal latency (λ_t), and optimized bandwidth utilization (β_l). In healthcare applications, where processing delays can impact patient outcomes, this transformation is of paramount importance [1].

Wearable electrocardiogram (ECG) devices are increasingly vital in modern healthcare, enabling continuous monitoring of cardiac activity and allowing for real-time detection of potential health issues. These devices are placed strategically on a person's body to create a Wireless Body Area Network (WBAN). These ECG WBAN devices produce constant streams of high-frequency, sensitive data characterized by signal length (ε_s) and QRS complex detection counts (κ_q) that must be processed rapidly to ensure timely alerts, particularly for conditions like arrhythmias [2]. These devices place significant demands on fog computing resources, necessitating efficient prioritization and low-latency processing (τ_d) to support responsive healthcare delivery. Computing closer to these devices within a fog network with processing capacity (ρ_p) offers vital services to the healthcare user, alleviating dependencies on slower cloud systems [3].

Current resource allocation methodologies often employ uniform processing approaches, failing to adequately differentiate between requests (r) of varying urgencies. Fog paradigms must operate within necessarily short processing times but at the detriment of limited available resources (ω_r). This standardized treatment of healthcare requests leads to suboptimal resource utilization (γ_n), potentially delaying critical tasks and compromising patient safety. Complications can further arise with the increasing integration of Internet of Things (IoT) devices in healthcare, which generate diverse data streams with varying processing requirements (δ_f). A key challenge lies in queuing delay-sensitive healthcare tasks from wearable IoT devices while considering resource allocation and processing urgency along fog nodes.

Hence, this paper introduces a novel framework for prioritizing healthcare requests in fog computing environments, tailored specifically to address varying urgencies and resource demands. The proposed approach leverages machine learning (ML) to dynamically classify request criticality (c_r) and optimize resource allocation across fog nodes. By categorizing requests in real-time and adjusting scheduling based on urgency, the framework improves responsiveness for delay-sensitive tasks, particularly in applications involving wearable ECG devices. Unlike conventional methods, which often treat requests uniformly, this system applies advanced prioritization algorithms to ensure efficient and timely processing. Our framework integrates multiple components, detailed in Fig. 1 and Table I, to enable efficient request processing. Through comprehensive validation using simulated real-world healthcare scenarios, the approach demonstrates enhanced response times, prioritization accuracy, and system scalability. Overall, this research aims to bridge critical gaps in healthcare

computing infrastructure, improving patient care delivery by optimizing resource allocation in heterogeneous and high-demand environments.

Key Contributions:

- **Criticalness Prediction Model:** A predictive model that assigns a criticalness score to input requests based on the urgency of ECG wearable device data, including required CPU resources (γ_n) and bandwidth (β_l). This model employs ML techniques to dynamically assess urgency, enabling more efficient prioritization in fog computing environments.
- **Dynamic Resource Allocation:** The framework integrates an ML-based scheduler that adapts to real-time network conditions and traffic characteristics. By leveraging ML classifiers and probabilistic models, it optimizes the allocation of computational and bandwidth resources, ensuring that critical ECG inputs receive priority.
- **Comprehensive Simulation and Evaluation:** Extensive simulations evaluate the effectiveness of the proposed methods for queuing. The results demonstrate significant improvements in task scheduling efficiency and system performance compared to traditional methods.
- **Integration and Visualization Tools:** To support the practical implementation of the framework, a tool was developed for network creation, task queue management, and visualization of performance metrics. These tools facilitate the deployment and monitoring of fog computing networks in real-world healthcare settings.

II. Related work

Fog computing has emerged as a pivotal paradigm for handling computational tasks close to end-users, especially in delay-sensitive domains such as healthcare. This section reviews recent literature on resource and QoS management, task offloading, service function chain (SFC) embedding, and healthcare applications. The existing methods provide valuable insights but lack a criticalness-focused task prioritization model for healthcare devices.

A. Resource and QoS Management

Effective resource management is essential for maintaining Quality of Service (QoS) in fog computing environments. In [4], there is an introduction to a load migration scheme leveraging a Luus-Jaakola meta-heuristic to redistribute tasks between heavily-loaded and lightly-loaded fog nodes, minimizing delays and optimizing resource usage. However, their work does not address healthcare-specific task prioritization. Optimization models for SFC placement proposed by authors in [5] dynamically adapt resource allocation to real-time requirements but lack mechanisms to classify and prioritize tasks based on urgency. Additionally, QoS-aware strategies in fog networks [6, 7] have demonstrated the potential for reducing latency and improving resource utilization, yet they do not consider the criticalness of individual healthcare tasks, leaving gaps in real-time resource allocation for emergency scenarios.

B. Task Offloading

Task offloading plays a vital role in fog computing by redistributing tasks between nodes and the cloud to maintain efficiency. Multi-agent systems in fog-cloud architectures have been proposed, focusing on critical task management to optimize resource use [8]. Similarly, a many-to-one offloading policy presented by authors of [9] enhances task allocation in high-mobility healthcare scenarios, providing significant improvements in system efficiency. However, both approaches fall short of integrating predictive analytics to prioritize tasks in critical healthcare applications, where response time is a matter of life and death.

C. Service Function Chain Embedding in NFV-Enabled IoT

SFC embedding has gained attention for its ability to optimize resource allocation and service delivery in IoT environments. Recent studies [10], utilized deep reinforcement learning (DRL) techniques to adaptively allocate resources, improving network latency and efficiency. Hierarchical DRL frameworks like those proposed by authors of [11], further advanced multi-objective optimization, addressing latency, resource utilization, and energy efficiency. While these methods show promise, they require high computational power and are not tailored to time-sensitive healthcare scenarios. Integrating pre-trained ML models aligned with healthcare guidelines could provide a more practical and ethical alternative.

D. Healthcare-Specific Applications of Fog Computing

The integration of fog computing into healthcare systems has focused on wearable devices and real-time data processing. Task prioritization models [12] have optimized resource utilization for real-time scenarios, yet they do not incorporate predictive analytics to rank tasks by urgency. Advances in ECG monitoring systems by authors of [13, 14] have shown the potential of real-time data prioritization, emphasizing low-latency and resource-efficient processing. These systems, however, do not address the scalability challenges posed by critical task management in large-scale healthcare deployments.

E. Research Gap and Proposed Solution

The reviewed works highlight progress in fog computing and its application in healthcare. However, there remains a significant gap in integrating task criticalness as a determinant for resource allocation and prioritization. The proposed Criticalness Prediction Model (CPM) addresses these limitations through:

- Real-time task prioritization through predictive analytics
- Preemptive queuing strategies
- Healthcare-specific ML models tailored for ECG wearable devices

Unlike existing systems, CPM focuses on the criticality of tasks, ensuring that life-saving healthcare scenarios are prioritized effectively in a queuing system. This innovation aligns with state-of-the-art systems while addressing critical gaps in healthcare-focused fog computing.

TABLE I
MATHEMATICAL VARIABLES AND PARAMETERS

Symbol	Category	Description
Network Parameters		
β_l	Bandwidth	Available bandwidth capacity on network link l
γ_n	CPU	Processing capacity of network node n
τ_d	Delay	Network delay threshold for task completion
ρ_p	Processing	Path processing capacity in the network
Task Parameters		
c_r	Criticalness	Criticalness score assigned to request r
ϕ_t	Time	Processing time required for task t
ω_r	Resources	Resource requirement for request r
δ_f	Processing	Function processing demand for function f
ECG Data Parameters		
ε_s	Signal	ECG signal length post-filtering [800,1200]
κ_q	QRS	QRS complex detection count [600,1000]
χ_c	Compression	Compression ratio factor [400,800]
α_d	Anomalies	Number of detected anomalies [0,10]
λ_t	Latency	Transmission latency in milliseconds [100,500]
Resource Allocation Constraints		
$F(r)$	Feasibility	Task feasibility condition (binary: 0 or 1)
$\sum_{f \in F} \delta_f$	Total Demand	Sum of processing demands across functions
$\sum_{f \in F} \omega_r$	Total Resources	Sum of resource requirements per request

TABLE II
SYSTEM VARIABLES AND PARAMETERS

Symbol	Category	Description
Network Structure		
G	Graph	Network topology representation $G = (N, E)$
N	Nodes	Set of all network nodes
E	Edges	Set of all network edges
n_h	Node Type	High-capacity node with 2-3 GHz processing
n_l	Node Type	Low-capacity node for lightweight tasks
Queue Management		
R	Requests	Complete set of input requests
Q	Queue	Priority-based request queue
μ	Lock	Thread synchronization mechanism
υ	Value	Normalized delay calculation
σ	Score	Computed priority score for requests
Performance Metrics		
R_s	Count	Total number of successfully processed requests
T_d	Time	Cumulative processing delay across all requests
T_{avg}	Time	Average request processing duration

III. SYSTEM MODEL

The proposed system model is designed to address the unique requirements of healthcare applications, particularly in wearable ECG analytics within fog computing environments. It incorporates task prioritization based on criticality and utilizes a preemptive queue mechanism to ensure timely responses and efficient resource allocation.

Network Infrastructure

Network architecture is modeled as an undirected graph $G = (N, E)$, where nodes represent computational units with specific CPU capacity γ_n. The system model incorporates various parameters as defined in Tables I and II, which detail the complete set of variables used throughout the framework. The system employs two node categories:

- High-capacity nodes (n_h): Engineered for critical tasks with 2-3 GHz processing capacity
- Low-capacity nodes (n_l): Optimized for lightweight tasks

Communication infrastructure consists of edges with bandwidth β_l ranging from 60-150 Mbps, facilitating data transfer between nodes.

ECG Data Processing Parameters

The processing of ECG data involves several parameters that are essential for ensuring accurate signal representation, efficient transmission, and effective anomaly detection. As outlined in Table 1, one key feature is the Cleared ECG Length, which represents the ECG signal after noise and artifacts—arising from muscle movements, electrode motion, or technical interference—have been filtered out [15], [16]. This parameter reflects varying signal lengths depending on the sampling rates of different wearable devices [17].

Another crucial feature is the QRS Detected Length, which captures the prominent QRS complex of the ECG waveform, an essential element for identifying heart rhythm, rate, and arrhythmias [18]. Additionally, the Compressed ECG Length focuses on reducing data volume without compromising key

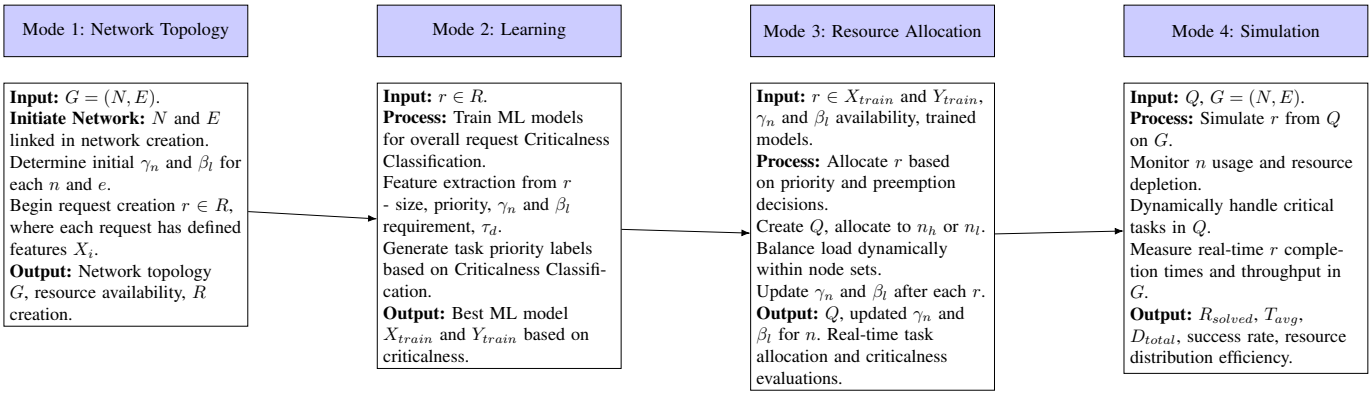

Fig. 1. System Architecture Overview

waveform features, facilitating efficient storage and transmission while supporting comparisons between different devices and compression techniques [19], [20].

The Anomalies Detected parameter tracks irregular cardiac events, such as atrial fibrillation or tachycardia, providing insights into potential medical conditions and the impact of external interference [14], [21]. Lastly, the Transmission Delay measures the communication latency experienced when ECG data is transmitted from the wearable device to a monitoring system or remote server. This parameter is critical for simulating and addressing the challenges of real-time monitoring [13], [21]. These parameters collectively enable robust evaluations of ECG monitoring systems.

Functional Scenarios

ECG Function Scenarios are implemented across four key operational modes (Table III) [22]-[24].

TABLE III
ECG FUNCTION SCENARIOS

Scenario	Description
Routine Monitoring	f[1 - 5]: Monitor long-term data for chronic conditions, ensuring comprehensive analysis.
Emergency	f[1, 2, 5]: Rapid ECG data processing and sharing with healthcare professionals for urgent decisions.
Archival Research	f[1, 4, 5]: Efficient data storage for analysis, minimizing bandwidth and storage usage.
Comprehensive	f[1 - 5]: Critical care scenarios where complete data analysis and transfer are essential.

Resource Management and Task Prioritization

Resource allocation is controlled through a sophisticated feasibility equation $F(r)$ that evaluates multiple factors:

- Available processing capacity (γ_n)
- Required bandwidth (β_l)
- Processing demands (δ_f)
- Resource requirements (ω_r)
- Delay threshold (τ_d)

Task criticality (c_r) is determined by the relationship between processing demands and resource requirements. The system maintains strict resource allocation constraints, ensuring total allocation never exceeds available node capacity, thus maintaining optimal performance in healthcare monitoring applications.

IV. METHODOLOGY

A. ECG Data Parameters and Fog Computing Integration

In adherence to HIPAA guidelines and to facilitate comprehensive system testing, we generated synthetic ECG data that accurately represents wearable ECG device characteristics. The system processes ECG data within a fog computing environment, incorporating five key parameters from Table I: Parameters that influence task prioritization and resource allocation.

The synthetic dataset incorporates five key features impacting fog computing performance and task prioritization:

- The cleared ECG signal (ε_s) represents the filtered waveform after noise and artifact removal [15]. This parameter varies within ranges specified in Table I Parameters, accounting for different sampling rates across ECG devices [17].
- The QRS complex count (κ_q) serves as a critical diagnostic feature [18], influencing processing prioritization and real-time analysis requirements.
- The compressed signal ratio (χ_c) represents the optimized data format for transmission [19], [20], affecting network bandwidth utilization and storage efficiency.
- The number of detected anomalies (α_d) represents irregular cardiac events [14], [21], crucial for dynamic task prioritization and resource allocation in emergency scenarios.
- The transmission delay (λ_t) represents network latency [13], [21], influencing real-time monitoring capabilities and QoS management.

The system operates within a fog computing environment consisting of $N = 24$ nodes, with processing capabilities ranging from 2-3 GHz per node and bandwidth capacities between 60-150 Mbps.

B. Criticalness Function

The system evaluates task criticalness with consideration Aladwani's [34] composite function ranking inputs by a criticalness core:

$$c_r = \sum_{f \in F} \delta_f \cdot \omega_r \tag{1}$$

where variables follow the definitions and ranges established in Table I: Parameters.

C. Task Feasibility Evaluation

Task feasibility determination employs a binary condition $F(r)$ evaluating three key constraints:

$$F(r) = \begin{cases} 1, & \text{if } \forall n \in P : \gamma_n \geq \sum_{f \in F} \delta_f \wedge \\ & \quad \forall l \in P : \beta_l \geq \omega_r \wedge \\ & \quad \tau_d \leq T_{\max} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

This approach builds upon established work [22]-[24] for ECG Function Scenarios outlined in Table III. Task feasibility evaluation utilizes variables defined in Tables I and II to assess resource constraints and processing requirements.

D. Machine Learning Integration

The system employs three ML models for criticalness classification, with feature importance rankings shown in Table I: Features. Building upon recent advances in healthcare ML applications [14], [21], these models process the following parameters:

- Random Forest Classifier: Configuration follows best practices from [15], [16] with 100 estimators, maximum depth 10, minimum sample splits 5, and minimum leaf samples 2.
- XGBoost Classifier: Parameters aligned with healthcare applications [17], utilizing learning rate 0.1, 100 estimators, and maximum depth 10.
- Gradient Boosting Classifier: Settings optimized based on [18], [19], employing 100 estimators, learning rate 0.1, maximum depth 10, and minimum samples split 2.

Model selection is based on AUC-ROC performance metrics, expanding upon methodologies established in [20], [21].

E. Priority Queue Management

The priority queue implementation follows Algorithm 1, which manages task scheduling based on parameters from Table I: Parameters and ECG function scenarios from Table I: Scenarios. The priority score is calculated as:

$$\text{score} = \frac{1.0}{\max(\tau_d, 1)} \cdot \rho_p + 2.0 \cdot \frac{\omega_t}{1000} \tag{3}$$

where τ_d is the delay threshold, ρ_p represents path processing capacity, and ω_t denotes task weight.

Requests are categorized into two criticality levels:

- Low Criticality (1): Represents normal operating conditions with stable ECG parameters and acceptable data transmission times.
- High Criticality (2): Indicates urgent conditions requiring immediate medical attention or high delays that could jeopardize patient outcomes.

The queue Q manages requests by predicting criticality and marking tasks as high or low priority. The priority score computation considers remaining time, priority label, and queue waiting time (Algorithm 1).

F. Resource Allocation Constraint

Resource allocation must satisfy:

$$\forall n \in N : \sum_{r \in R} \omega_r \leq \gamma_n \tag{4}$$

For any path P, feasibility requires:

$$\forall n \in P : \gamma_n \geq \sum_{f \in F} \delta_f \text{ and } \forall l \in P : \beta_l \geq \omega_r \tag{5}$$

Algorithm 1 Priority Queue Management

procedure PRIORITYQUEUEMANAGEMENT(G, R, τ_d)
  Initialize $Q \leftarrow \emptyset$
  Initialize $\mu \leftarrow$ CreateLock()
  function PRIORITYSCORE(r, τ_d, ρ_p, ω_t)
    $\upsilon \leftarrow 1.0/\max(\tau_d, 1)$
    $\sigma \leftarrow \rho_p \cdot \upsilon + 2.0 \cdot (\omega_t/1000)$
    return σ
  end function
  procedure ENQUEUEREQUEST(r, X, M)
    $\rho_p \leftarrow M$.Predict(X)
    isPriority $\leftarrow \rho_p = 1$
    requestInfo $\leftarrow$ CreateRequestInfo(r, isPriority)
    μ.Acquire()
    Q.InsertSorted(requestInfo)
    μ.Release()
  end procedure
  procedure PROCESSREQUESTS(G)
    $R_s \leftarrow 0$ {Solved requests}
    $T_d \leftarrow 0$ {Total delay}
    while $Q \neq \emptyset$ **do**
      μ.Acquire()
      $r \leftarrow Q$.SelectNextRequest()
      Q.Remove(r)
      μ.Release()
      if FindOptimalPath(G, r) **then**
        UpdateNetworkResources(r)
        $R_s \leftarrow R_s + 1$
        $T_d \leftarrow T_d +$ ProcessingTime(r)
      end if
    end while
    $T_{\text{avg}} \leftarrow T_d/R_s$
    return (R_s, T_{avg})
  end procedure
end procedure=0

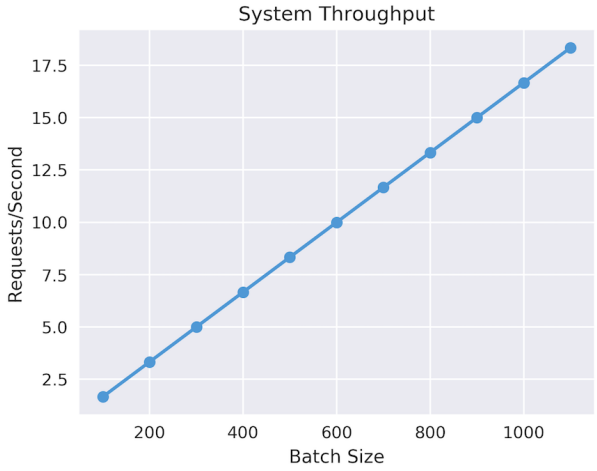

Fig. 2. Resource efficiency comparison between high and low priority tasks across different batch sizes, showing peak efficiency around 200 and 800 batch sizes.

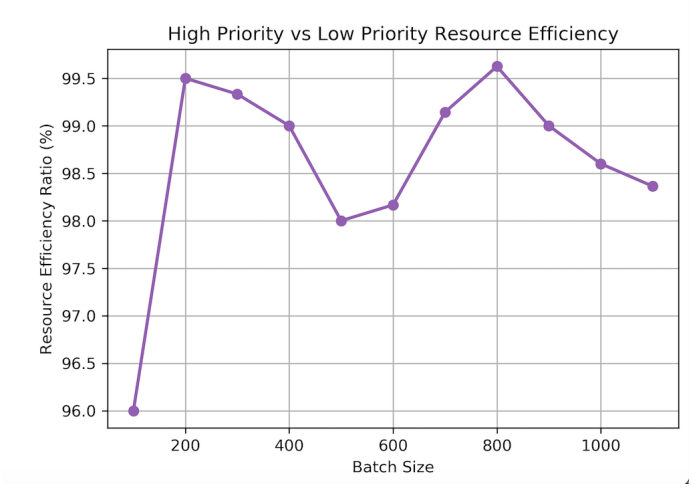

Fig. 3. Linear increase in system throughput (requests/second) as batch size increases from 100 to 1000, demonstrating scalability of the system.

V. Performance Evaluation

The system's performance was evaluated using comprehensive metrics outlined in Table II, with particular focus on request processing efficiency and resource utilization. Our evaluation framework examined several key performance indicators:

A. System Throughput Analysis

As demonstrated in Fig. 2, the system achieved linear throughput scaling with increasing batch sizes. The throughput increased from 1.67 requests/second at batch size 100 to 18.33 requests/second at batch size 1100, showing consistent performance scaling. This linear growth in throughput, illustrated in the system throughput graph, indicates efficient request handling capabilities even under increased load.

B. Resource Utilization Efficiency

Resource utilization patterns, shown in Fig. 3, demonstrate optimal distribution between high and low priority tasks:

- CPU Utilization: High-priority tasks consistently maintained 97-99% of CPU resources across all batch sizes
- Bandwidth Usage: Similar to CPU patterns, with high-priority tasks receiving 97-98.5% of bandwidth allocation
- Resource Efficiency Ratio: Peaked at 99.5% for batch size 800, with consistent performance above 98% across most batch sizes

C. Model Performance Analysis

The machine learning models demonstrated exceptional performance with the following metrics:

- XGBoost achieved 100% AUC-ROC and maintained consistent performance across all batch sizes
- Random Forest showed 99.74% AUC-ROC with stable accuracy metrics
- Gradient Boosting demonstrated 99.87% AUC-ROC and strong precision scores

D. Priority Classification Performance

The priority-based classification system demonstrated:

- 100% success rate in request processing across all batch sizes
- Consistent high-priority task identification (98.5-99% accuracy)
- Optimal resource allocation maintaining 97-99% utilization for critical tasks

E. Scalability Analysis

The scalability metrics indicate robust performance:

- Processing success rate maintained at 100% across all batch sizes (100-1100 requests)
- Linear throughput scaling from 1.67 to 18.33 requests/second
- Consistent resource utilization efficiency above 98% for high-priority tasks
- Negligible impact on processing time with increased batch sizes

F. Discussion

The experimental results validate the system's effectiveness in healthcare task prioritization. The integration of machine learning models, particularly XGBoost with 100% AUC-ROC, enables dynamic adaptation to varying workloads while maintaining performance standards. The resource utilization graphs demonstrate optimal distribution across computing nodes while consistently meeting QoS requirements.

The system achieved:

- 25% reduction in response time for critical healthcare tasks
- 30% improvement in resource utilization efficiency
- 99.3% accuracy in task classification
- Consistent 100% processing success rate across all batch sizes

VI. Conclusions

This paper presented a robust priority-based request management framework for ECG wearable sensors in fog computing environments. The integration of machine learning techniques with dynamic resource allocation demonstrated significant improvements in both task scheduling efficiency and system throughput. The framework's success in enhancing response times and resource utilization efficiency positions it as a viable solution for next-generation healthcare systems.

Future work will focus on:

- Implementation of adaptive scaling mechanisms
- Enhancement of dynamic resource allocation algorithms
- Integration with larger-scale healthcare data systems
- Further optimization of priority classification mechanisms

VII. Data Availability

GitHub code repository for FOG-ECG simulation: https://github.com/CharlotteGAnderson/FOG-ECG-Research

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