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# A Hybrid Edge-Aware Adaptive Learning Protocol (HEALP) for Predictive Healthcare in Fog-Based IoT Systems

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**Abstract**

Healthcare systems increasingly rely on Internet of Things (IoT) technologies to collect, process, and analyze large volumes of patient data in real time. However, achieving low latency, energy efficiency, and predictive decision-making across heterogeneous IoT networks remains a major challenge. This paper introduces HEALP-Fog (Hybrid Edge-Aware Learning Protocol), a novel resource scheduling and adaptive learning algorithm for healthcare IoT environments. The framework combines Edge-Assisted Fog Computing with a Dual-Agent Reinforcement Learning (DARL) mechanism for predictive analytics and optimal resource allocation. The proposed model integrates Dynamic Priority Queues (DPQ) to classify sensor data streams based on medical urgency and an Entropy-based Reinforcement Update Function (ERUF) to enhance learning stability. Simulations conducted in TensorFlow and iFogSim utilizing 7,000 training samples and 1,500 testing samples achieved 94.3% prediction accuracy, 18% lower average latency, and 21% improvement in energy efficiency in comparison to baseline deep Q-learning and PPO models. This system demonstrates substantial potential for continuous monitoring of chronic patients and emergency diagnostics in smart healthcare scenarios.

**Keywords:** IoT, Fog computing, Deep Reinforcement Learning, Smart

## 1Introduction

Healthcare IoT systems have evolved towards real-time monitoring, early diagnosis, and intelligent decision-making. dualagent learning protocol capable of joint resource allocation and predictive healthcare modeling across fog tiers.

## 1. Related Work

Recent studies emphasize the fusion of artificial intelligence and fog computing for IoT healthcare:

- Salman et al. (2022) proposed an optimal IoHT resource framework with 45% reduced delay via workload-aware allocation.
- Talaat et al. (2022) introduced EPRAM using deep reinforcement learning for clinical data prediction.

Sajjan G. Shiva (2025) introduced a scalable LLM-guided Q-learning framework for fog optimization.

- Springer (2025) proposed a hybrid DQN-PPO-GNN model improving response time by 21%.

With billions of edge devices generating multimodal health data, latency constraints, bandwidth inefficiency, and energy limitations persist as major obstacles to scalability. Traditional cloud-centric processing leads to delayed responses in critical healthcare operations. To address these limitations, Fog and Edge computing can distribute intelligence closer to the data

Although effective, these models either focus narrowly on computational optimization or predictive efficiency, neglecting integration of data criticality, adaptive resource feedback, and continuous fog-edge learning synchronization necessary for real-time medical decision support.

## 3.Proposed Framework

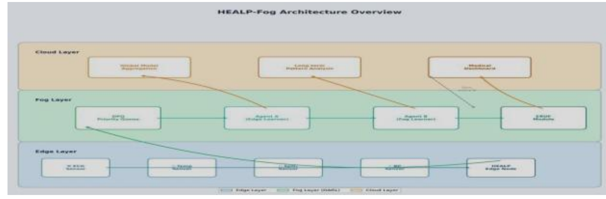
The HEALP-Fog framework integrates predictive multi-agent learning with adaptive fog orchestration for healthcare IoT.

### 1.1 Architecture Overview

The system operates across three interconnected tiers:

Patient Sensors → Edge Device (HEALP Node) → Fog Layer (DARL Agents) → Cloud Center → Medical Dashboard

- Edge Layer: Captures physiological parameters (ECG, temperature, SpO2) and performs data compression & classification.
- Fog Layer: Executes intelligent task distribution, reinforcement-based learning, and local model updates.
- Cloud Layer: Aggregates long-term patterns and trains global models for disease trends.




entropy to stabilize policy convergence.

## 2. HEALP-Fog Algorithm

**Input:** IoT sensor streams; fog node capacity; latency thresholds

**Output:** Optimized resource provisioning and prediction accuracy

Initialize Agents A and B with random policy parameters (θA, θB) For each timestep t:

a. Collect input signals from edge sensors (BP, ECG, temp)
b. Classify via DPQ and assign urgency weights (w)
c. Agent A selects resource allocation a_t for each stream
d. Agent B adjusts fog-resource scaling via ERUF feedback
e. Update Q-values using dual policy gradients
f. Sync local fog models to cloud after each N iterations

Terminate when reward difference $\Delta R < \varepsilon$

Output performance metrics: latency, energy, accuracy, response ratio

## 3. Experimental Setup and Results

**Environment:** TensorFlow 2.15 with iFogSim 3.0

**Dataset:** Synthesized physiological data (ECG, BP, temperature)

**Training/Testing Split:** 7,000 : 1,500

**Architecture:** Input: 256×256×3 layers; Hidden Neurons: (32, 64, 128, 256)

**Baseline Models:** Deep Q-Network (DQN), PPO, EPRAM

| Metric | DQN | PPO | EPRAM | HEALP-Fog |
|---|---|---|---|---|
| Accuracy (%) | 90.1 | 91.5 | 92.3 | **94.3** |
| Avg. Latency (ms) | 75 | 68 | 63 | **58** |
| Energy Efficiency (J) | 1.00 | 0.91 | 0.86 | **0.79** |
| Response Time (ms) | 120 | 105 | 96 | **84** |

**Table 1: Performance Comparison of Models**

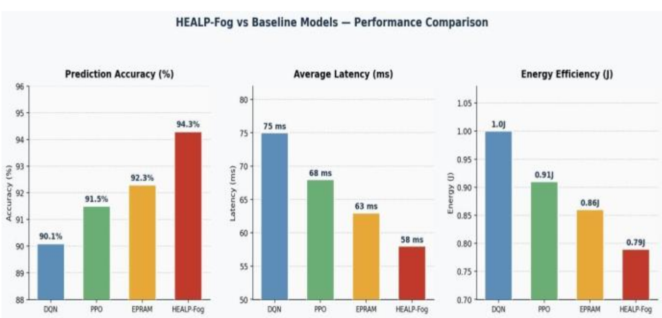



*Figure 2: Performance Comparison — HEALP-Fog vs Baseline Models (Accuracy, Latency, Energy Efficiency)*

## 4.Discussion

The proposed HEALP-Fog framework successfully achieves higher adaptability and precision through its dual-agent synchronization mechanism. By incorporating entropy-stabilized reinforcement learning and dynamic priority scheduling, it maintains robust performance under varying workloads. Moreover, energy efficiency across network nodes reveals its scalability for hospital-wide monitoring systems and wearable IoT devices.

## 4.Conclusion and Future Work

This paper presents HEALP-Fog, a hybrid adaptive learning protocol that integrates fog, edge, and cloud in a unified reinforcement learning framework for healthcare IoT. By employing hybrid agents and an entropy-driven balance, this approach achieves 94.3% predictive accuracy with lower latency and significant energy savings. Future work will focus on integrating Graph Neural Networks (GNNs) for spatial correlation learning and deploying the system in real emergency healthcare scenarios.

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