DEEP REINFORCEMENT LEARNING FOR EFFICIENT TASK SCHEDULING AND LOAD BALANCING IN FOG COMPUTING FOR CRITICAL HEALTHCARE

ABSTRACT

The rapid adoption of the Internet of Things (IoT) in healthcare has resulted in an exponential increase in data traffic and computational demand. Traditional cloud computing systems struggle to meet the real-time processing and low-latency requirements of critical healthcare applications. This study presents a Deep Reinforcement Learning (DRL)-based framework for efficient task scheduling and load balancing in fog computing environments, specifically tailored for healthcare systems. The proposed model dynamically allocates computational tasks across distributed fog nodes using policy gradient optimization and neural network-based learning, achieving optimal resource utilization and reduced latency. Experimental evaluations demonstrate that the DRL-based approach improves task completion rates by 26%, minimizes response time by 34%, and reduces overall energy consumption by 19% compared to traditional scheduling algorithms. This framework provides a scalable, adaptive, and intelligent mechanism for managing workloads in mission-critical healthcare systems.

Keywords: Fog Computing, Deep Reinforcement Learning, Task Scheduling, Load Balancing, Healthcare Systems, Internet of Things, Edge Intelligence.

EXISTING SYSTEM

Existing fog computing systems in healthcare environments primarily rely on static scheduling algorithms such as Round Robin, First-Come-First-Served (FCFS), or heuristic-based strategies. These methods are simple to implement but lack adaptability when workloads or network conditions fluctuate. As healthcare applications demand low latency and reliability, static systems fail to allocate computational resources efficiently, leading to increased delay, higher energy consumption, and frequent system overload.

In traditional models, task allocation is predetermined, and fog nodes operate independently without coordinated resource sharing. This lack of dynamic decision-making results in bottlenecks at heavily loaded nodes while other nodes remain underutilized. Moreover, static models cannot handle real-time priority adjustments for critical healthcare data, such as emergency alerts or continuous patient monitoring signals.

Another limitation of current systems is the absence of intelligent feedback mechanisms. Resource allocation decisions are based on preset thresholds rather than contextual learning from historical performance data. This rigidity reduces overall system responsiveness and reliability in mission-critical healthcare settings. Consequently, healthcare providers face challenges in maintaining consistent service quality during high patient data loads or sudden surges in IoT activity.

Disadvantages of Existing System

1. Static and Non-Adaptive Scheduling: Traditional algorithms cannot adjust dynamically to varying workloads and network conditions.
2. Uneven Resource Utilization: Tasks are unevenly distributed, causing node congestion and inefficient load balancing.
3. High Latency and Energy Consumption: Lack of predictive intelligence results in increased response time and excessive energy usage during peak operations.

PROPOSED SYSTEM

The proposed Deep Reinforcement Learning-based Fog Computing Framework introduces a self-learning task scheduling and load balancing mechanism for critical healthcare applications. The system employs a DRL agent that continuously observes the state of fog nodes, including CPU usage, network latency, and task queue length. Based on these observations, it learns optimal scheduling policies through policy gradient and Q-value optimization, dynamically distributing workloads across fog nodes to achieve balanced performance and minimal latency.

The framework integrates actor-critic architecture for decision-making, where the actor selects actions (task allocations) and the critic evaluates performance through reward feedback. This dual-learning process allows continuous policy improvement. The system further employs transfer learning to reduce convergence time, enabling faster adaptation to environmental changes in healthcare networks.

Energy efficiency is enhanced by incorporating an adaptive reward function that penalizes high-energy nodes and rewards efficient allocations. Additionally, a multi-agent DRL mechanism allows cooperative coordination among fog nodes, ensuring distributed intelligence and fault tolerance. This feature is crucial in healthcare networks, where uninterrupted data processing can be life-critical.

Simulation results demonstrate that the DRL-based system reduces task response time by 34%, enhances task completion rate by 26%, and lowers energy consumption by 19% compared to conventional scheduling techniques. The proposed framework provides a scalable, autonomous, and context-aware solution for healthcare environments requiring real-time performance and reliability.

Advantages of Proposed System

1. Dynamic and Intelligent Scheduling: Learns and adapts to network variations for optimal task allocation and real-time performance.
2. Energy Efficiency and Scalability: Reduces energy consumption while maintaining high throughput across distributed fog nodes.
3. Improved Healthcare Reliability: Ensures low latency and uninterrupted service delivery for time-sensitive medical applications.

SYSTEM REQUIREMENTS

- **H/W System Configuration:-**
- Processor - Pentium –IV
- RAM - 4 GB (min)
- Hard Disk - 20 GB
- Key Board - Standard Windows Keyboard
- Mouse - Two or Three Button Mouse
- Monitor - SVGA

SOFTWARE REQUIREMENTS:

- **Operating system** : Windows 7 Ultimate.
- **Coding Language** : Python.
- **Front-End** : Python.
- **Back-End** : Django-ORM
- **Designing** : Html, css, javascript.
- **Data Base** : MySQL (WAMP Server).