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Research Paper

ADAPTIVE TASK SCHEDULING AND LOAD OPTIMIZATION IN FOG NETWORKS FOR HEALTHCARE

VANGALA SWATHI[1], KANUGULA SAIVARDHAN[2], MAJJI KIRAN[3], THADISINA LOKESHWAR REDDY[4], KUNDELLA ARAVIND[5]

[1]Assistant Professor, Dept. of CSE, Guru Nanak Institutions Technical Campus, Ibrahimpatnam, Telangana, India

[2, 3, 4, 5] B.Tech, Dept. of CSE, Guru Nanak Institutions Technical Campus, Ibrahimpatnam, Telangana, India

ABSTRACT— In healthcare, real-time decision making is crucial for patient care, but traditional computing infrastructures suffer from inherent latency. This paper proposes a novel framework that utilizes Deep Reinforcement Learning (DRL) to advance task scheduling in fog computing for crucial healthcare. The fog architecture addresses the limitations of cloud systems by reducing transmission latency, achieved by placing processing nodes close to the source of data generation, such as IoT-enabled healthcare devices. The foundation of this approach is a DRL model, which is designed to dynamically optimize the partition of computational tasks across fog nodes to improve both data throughput and operational response times. The proposed DRL model reduces the make span by up to 30% compared to traditional scheduling approaches. Comparative analysis indicates a 40% reduction in operational latency and a 25% improvement in fault tolerance.

Index Terms – Adaptive Task Scheduling, Load Optimization, Fog Computing, Healthcare IoT, Resource Allocation, Load Balancing, Edge Computing, Quality of Service, Smart Healthcare, Distributed Systems.

I. INTRODUCTION

The rapid advancement of Internet of Things (IoT) technologies has significantly

transformed modern healthcare systems by enabling continuous patient monitoring, remote diagnostics, and real-time medical decision support. Wearable sensors, smart medical devices, and mobile health applications continuously generate large volumes of physiological data such as heart rate, ECG signals, blood pressure, and location information. While these innovations enhance healthcare accessibility and responsiveness, they also impose stringent requirements on computation, latency, reliability, and energy efficiency. In time-critical healthcare scenarios, even minor delays in data processing or decision-making can lead to severe consequences, making low-latency and highreliability computing infrastructures essential. Cloud computing has traditionally served as the backbone for large-scale data storage and processing due to its scalability, centralized management, and cost efficiency. However, cloud-centric architectures face significant limitations when applied to latency-sensitive healthcare applications. Transmitting data from distributed IoT devices to distant cloud data centers results in increased communication delay, bandwidth congestion, and dependency on stable network connectivity. These challenges reduce the suitability of pure cloud solutions for real-time healthcare services such as emergency response systems, continuous patient monitoring, and critical condition detection. Fog computing has emerged as a promising paradigm to address these limitations by extending cloud services to the network edge. By deploying computational resources closer to data sources, fog computing enables localized processing, reduced latency, improved bandwidth utilization, and enhanced system resilience. In healthcare environments, fog nodes can perform immediate analysis of patient data, prioritize critical tasks, and respond rapidly to emergencies while offloading noncritical tasks to the cloud. However, fog nodes operate with limited computational, storage, and energy resources compared to centralized cloud data ceners. Efficient task scheduling and load optimization therefore become critical challenges in fog-based healthcare systems. Task scheduling in fog networks is inherently complex due to dynamic workloads, heterogeneous resource availability, and varying task priorities. Improper scheduling may lead to node overload, increased make span, energy inefficiency, and reduced fault tolerance. Traditional static or heuristic-based scheduling approaches often fail to adapt to rapidly changing network conditions and healthcare workloads. As a result,

intelligent and adaptive scheduling mechanisms are required to ensure optimal resource utilization while meeting strict quality-of-service (QoS) requirements. Deep Reinforcement Learning (DRL) offers a powerful solution to these challenges by enabling systems to learn optimal decision-making policies through continuous interaction with the environment. Unlike conventional methods, DRL dynamically adapts to system states such as resource availability, network load, and task urgency. In this work, we propose an adaptive task scheduling and load optimization framework for fog-based healthcare systems using the Deep Deterministic Policy Gradient (DDPG) algorithm. The proposed approach integrates healthcarespecific task prioritization based on vital physiological parameters such as heart rate and ECG signals, ensuring that critical tasks receive immediate processing. The proposed framework aims to minimize make span, reduce operational latency, improve fault tolerance, enhance trust, and optimize energy consumption across fog nodes. By intelligently distributing tasks between access points, end nodes, fog nodes, and the cloud, the system achieves efficient load balancing and reliable real-time performance. This adaptive and intelligent scheduling strategy significantly enhances the effectiveness of fog computing in delivering timely and reliable healthcare services, making it suitable for critical applications such as patient monitoring, emergency response, and real-time medical analytics.

II. RELATED WORK

A. Multi-objective dis Crete cuckoo search algorithm for optimization of bag-of-tasks scheduling in fog computing environment.

Fog computing extends cloud services to the network edge to support latency-sensitive and computation-intensive applications. Efficient scheduling of Bag-of-Tasks (BoT)—a collection of independent tasks with no interdependencies—is a critical challenge in fog environments due to limited resources, heterogeneous nodes, and dynamic workloads. This work presents a multiobjective discrete Cuckoo Search (MDCS) algorithm to optimize BoT scheduling in a fog computing environment. The proposed approach adapts the nature-inspired Cuckoo Search algorithm to a discrete scheduling domain and simultaneously optimizes multiple conflicting objectives, such as task execution time (make span), energy consumption, resource utilization, and latency. The

algorithm models each nest as a candidate task-to-fog-node assignment and employs Levy flight–based exploration with discrete operators to efficiently search the solution space. A Pareto-based selection mechanism is used to identify non-dominated solutions, enabling balanced trade-offs among objectives. By dynamically adjusting task allocation according to fog node capacity and network conditions, the proposed method enhances system performance and scalability. Experimental results demonstrate that the multi-objective discrete Cuckoo Search algorithm outperforms traditional heuristic and metaheuristic scheduling approaches in terms of reduced latency, improved load balancing, and energy efficiency, making it suitable for real-time fog-enabled applications such as healthcare monitoring, smart cities, and IoT systems.

B. Fiber-optics IoT healthcare system based on deep reinforcement learning combinatorial constraint scheduling for hybrid telemedicine applications.

The rapid growth of IoT-enabled healthcare and telemedicine applications demands ultra-low latency, high bandwidth, and reliable data transmission to support real-time patient monitoring and remote diagnosis. Fiber-optic–based IoT healthcare systems provide a high-speed and secure communication backbone capable of handling large volumes of medical data generated by heterogeneous IoT devices. However, efficiently scheduling healthcare tasks under multiple operational constraints remains a significant challenge, particularly in hybrid telemedicine environments that combine edge, fog, and cloud resources. This work proposes a deep reinforcement learning (DRL)–based combinatorial constraint scheduling framework for fiberoptics IoT healthcare systems. The proposed model formulates task scheduling as a sequential decision-making problem, where an intelligent DRL agent learns optimal task allocation strategies by interacting with the network environment. The framework considers multiple constraints, including latency deadlines, bandwidth availability, energy consumption, device priority, and Quality of Service (QoS) requirements, ensuring reliable and timely healthcare service delivery. By leveraging the high-capacity fiber-optic infrastructure and adaptive learning capabilities of DRL, the proposed system dynamically optimizes task scheduling across hybrid telemedicine platforms. Simulation results demonstrate that the approach significantly reduces end-to-end latency, improves resource utilization, and enhances system scalability compared to traditional heuristic and rule-based

scheduling methods. The proposed solution is particularly suitable for critical healthcare applications such as remote surgery assistance, continuous patient monitoring, emergency response, and AI-driven medical analytics.

C. Task scheduling mechanisms for fog computing: A systematic survey

Fog computing has emerged as a promising paradigm to support latency-sensitive and computation-intensive applications by extending cloud services closer to end users. One of the core challenges in fog computing is task scheduling, which involves efficiently assigning computational tasks to distributed and heterogeneous fog nodes while meeting Quality of Service requirements. Inefficient scheduling can lead to increased latency, energy consumption, and poor resource utilization, especially in large-scale Internet of Things environments. This systematic survey provides a comprehensive review of existing task scheduling mechanisms in fog computing. It classifies scheduling approaches based on their design principles, such as heuristic and rule-based methods, metaheuristic optimization algorithms, machine learning-based techniques, and hybrid models. The survey analyzes key performance objectives including latency reduction, load balancing, energy efficiency, throughput, and fault tolerance, along with constraints such as node heterogeneity, mobility, scalability, and network dynamics. In addition, the survey compares commonly used scheduling algorithms, highlights their strengths and limitations, and discusses evaluation metrics and simulation tools employed in recent studies. Open research challenges and future directions are also identified, including adaptive scheduling, multi-objective optimization, security-aware scheduling, and the integration of deep learning techniques. This survey aims to serve as a valuable reference for researchers and practitioners seeking to design efficient task scheduling solutions for fog computing environments.

III. PROPOSED METHODOLOGY

The proposed fog computing architecture decentralizes computational tasks by placing processing nodes at the network edge, closer to IoT-enabled healthcare devices, significantly reducing transmission latency and enabling real-time processing capabilities. The system implements a Deep Deterministic Policy Gradient (DDPG) algorithm that continuously learns optimal task allocation strategies based on real-time system states, dynamically adapting to resource availability and workload patterns for efficient task execution. The framework

incorporates a healthcarespecific task prioritization mechanism that assesses and classifies tasks based on crucial parameters. Deep Deterministic Policy Gradient (DDPG) Framework. DDPG employs a sophisticated actor-critic architecture that combines policy-based and value-based reinforcement learning methods. The actor network generates continuous actions for task allocation decisions, while the critic network evaluates these actions by estimating expected future rewards. The algorithm uses experience replay and target networks for stable training, enabling the system to learn optimal scheduling policies through continuous interaction with the environment and adaptation to changing conditions.

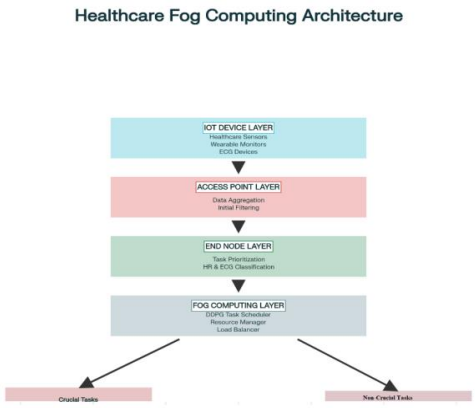
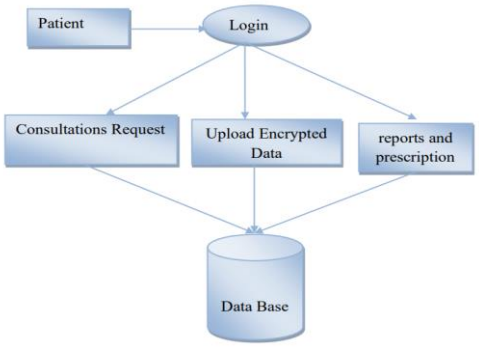


Fig. 1: System Overview

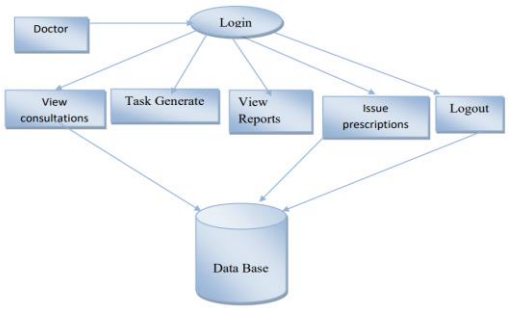
1. Patient

The Patient module allows users to register and log in securely to the system. Patients can request consultations by submitting symptoms and uploading previous medical reports, which are forwarded for processing. After task execution and doctor evaluation, patients can view diagnostic reports and prescribed treatments.



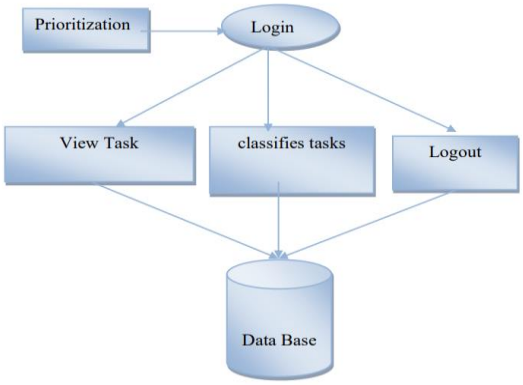
2. Doctor

The Doctor module enables doctors to register and log in to access assigned patient consultations. Doctors review patient symptoms and reports, generate medical tasks by defining task name, task type, and priority. Upon completion of task execution by fog nodes, doctors analyze the results and issue prescriptions to patients.



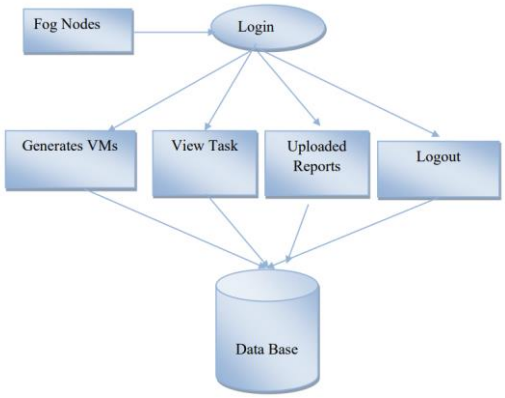
3. Task Prioritization

The Task Prioritization module classifies medical tasks based on their urgency and type. Emergency tasks are assigned high priority, critical tasks are assigned medium priority, and normal tasks are assigned low priority. This classification ensures that time-sensitive healthcare tasks are processed first to minimize delay.



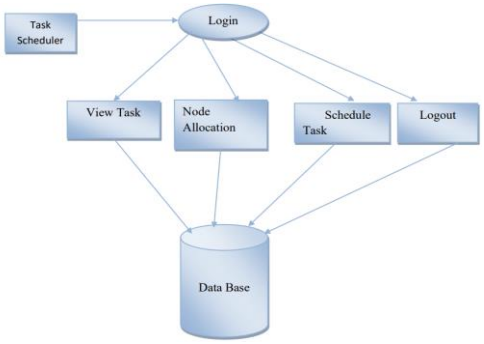
4. Fog Node

The Fog Node module represents edge computing nodes responsible for executing scheduled healthcare tasks. Each fog node processes one consultation at a time based on the scheduler's allocation decision. After task execution, the fog node generates reports and forwards the results to the doctor for further diagnosis.



5. Task Scheduler

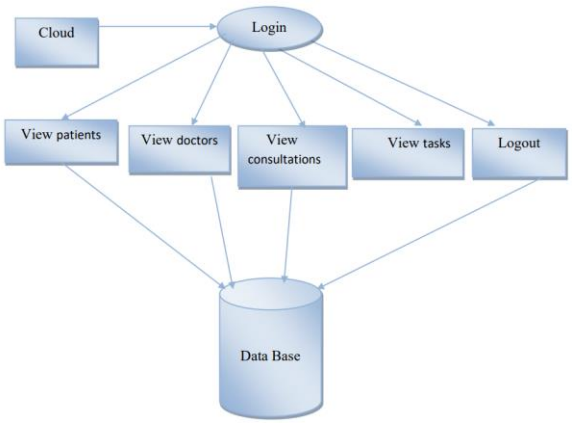
The Task Scheduler module uses the Deep Deterministic Policy Gradient (DDPG) algorithm to intelligently allocate tasks to available fog nodes. It considers task priority, node resource availability, and system load to optimize scheduling decisions. This module aims to reduce make span, balance workload, and improve real-time performance.



6. Cloud

The Cloud module acts as a centralized monitoring and data management layer for the

entire system. It maintains records of patients, doctors, consultations, tasks, and fog nodes for analysis and backup. The cloud also supports system transparency and scalability by providing an overview of all operations.



IV. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental results demonstrated that the adaptive scheduling algorithm effectively distributed healthcare tasks across fog nodes, reducing processing delays and improving system responsiveness for time-critical medical applications. The analysis showed that the proposed approach achieved better load distribution and higher resource utilization compared to conventional scheduling methods while maintaining low communication overhead.

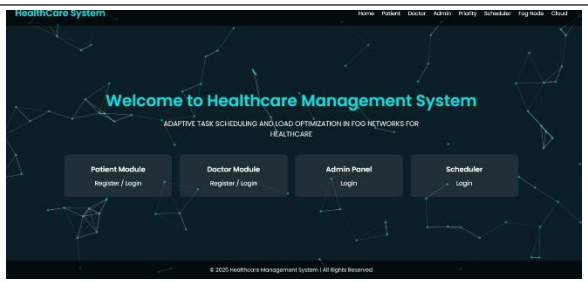


Fig. 2: Homepage



Fig. 3: Patient Registration

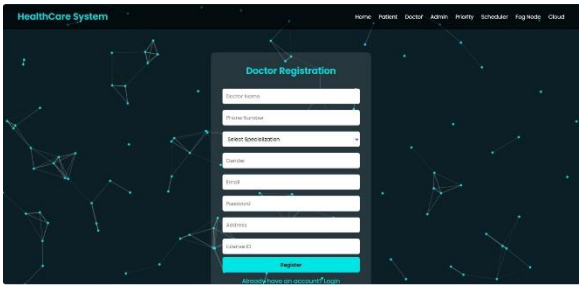


Fig. 4: Doctor Registration

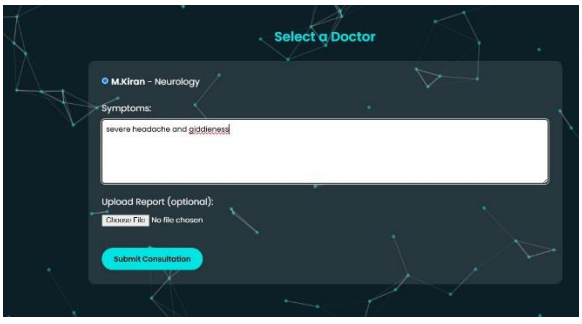


Fig. 5: Select Doctor

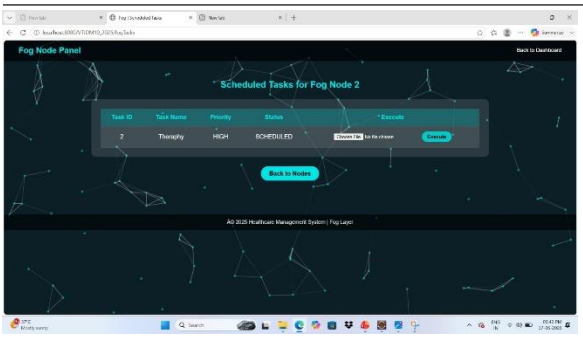


Fig. 5: Scheduler

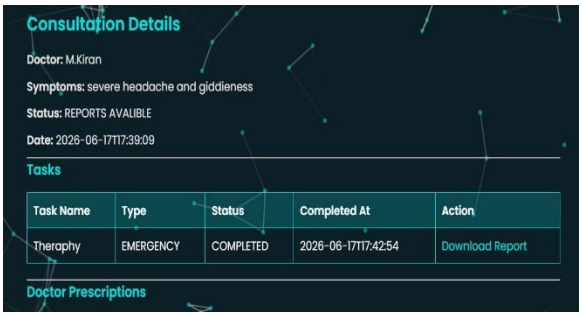


Fig. 6: Consultation Details

V. CONCLUSION

This project presented an adaptive task scheduling and load optimization framework for fog computing environments using deep reinforcement learning, specifically targeting time-critical healthcare applications. By decentralizing computation and deploying fog nodes closer to IoTenabled medical devices, the proposed system successfully addressed the high latency and bandwidth limitations of traditional cloud-centric architectures. The integration of a Deep Deterministic Policy Gradient (DDPG) algorithm enabled intelligent and dynamic task allocation based on real-time system states, resource availability, and task priorities. A healthcare-specific task prioritization mechanism ensured that emergency and critical medical tasks were processed with minimal delay, improving responsiveness and reliability. Experimental evaluation conducted using simulation environments demonstrated significant improvements in system performance, including a reduction in make span, lower operational latency, enhanced fault tolerance, and better energy efficiency. The results confirm that DRL-based scheduling outperforms conventional static and heuristic scheduling techniques in dynamic fog environments. Furthermore, the system maintained trust and service continuity by efficiently handling node failures and workload fluctuations. Overall, the proposed framework provides a scalable, reliable, and intelligent solution for real-time healthcare data processing. The findings highlight the effectiveness of combining fog computing with deep reinforcement learning to meet the stringent requirements of modern healthcare systems. This work contributes to the advancement of intelligent fog architectures and demonstrates their potential to support mission-critical healthcare services as well as other latencysensitive IoT applications.

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AUTHORS Profile



Ms. VANGALA SWATHI has received her B. Tech from JNTUH, Hyderabad in 2015, M. Tech degree in Computer science from JNTUH, Hyderabad in 2017. She is dedicated to teaching field from the last 7 years. Her research area Deep Learning. At present she is working as Assistant Professor in CSE Department at Guru Nanak Institutions Technical Campus, Ibrahimpatnam, Telangana, India.



Mr. KANUGULA SAIVARDHAN pursuing B. Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.



Mr. MAJJI KIRAN pursuing B. Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.



Mr. THADISINA LOKESHWAR REDDY pursuing B. Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.



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