Distributed Edge Intelligence for Rapid In-Vehicle Medical Emergency Response in Internet of Vehicles

Jianhui Lv, *Senior Member, IEEE*, Keqin Li, *Fellow, IEEE*, Adam Slowik, *Senior Member, IEEE*, and Huamao Jiang, *Member, IEEE*

***Abstract*—The unparalleled possibilities of Internet of Vehicles (IoV) development prompt the enhancement of in-vehicle medical emergency response. Nevertheless, the IoV environment is still affected by data privacy, latency, and network instability, which hamper effective and reliable emergency medical systems. In this regard, this article suggests the emergency-aware distributed edge intelligence (DEI) for medical response (EDEM) framework, a novel approach leveraging DEI to address these challenges. Specifically, EDEM introduces a hierarchical edge collaborative computing architecture that dynamically constructs learning domains based on a comprehensive medical data capability model. The framework incorporates an in-vehicle medical data reliability model and tailored latency and energy consumption models to optimize resource allocation and response times. Then, a deep-reinforcement-learning-based node selection algorithm ensures efficient task distribution across the network. Finally, EDEM's dual-layer federated learning model features an emergency-aware adaptive aggregation mechanism and an adaptive medical model updating scheme for cross-domain scenarios, complemented by an emergency-weighted asynchronous model fusion approach. The superiority of EDEM over state-of-the-art methods is demonstrated through simulation results showing up to a 15% increase in model accuracy, a 30% reduction in response times, and a 20% better resource utilization efficiency. This implies that it can greatly enhance speed, accuracy, and reliability for in-vehicle emergency responses within IoV environments.**

***Index Terms*—Deep reinforcement learning (DRL), distributed edge intelligence (DEI), Internet of Vehicles (IoV), in-vehicle medical emergency response.**

I. Introduction

THE Internet of Vehicles (IoV) revolutionizes transportation systems by enabling seamless connectivity and data exchange among vehicles, road infrastructure, and users [1], [2]. As a critical application domain within IoV, in-vehicle medical emergency response systems have gained significant attention due to their potential to reduce response times and save lives in urgent situations dramatically [3], [4], [5]. These systems aim to leverage real-time physiological data from in-vehicle sensors, wearable devices, and onboard medical equipment to detect medical emergencies rapidly, provide preliminary diagnoses, and coordinate with emergency services. Integrating advanced sensing technologies, such as continuous blood pressure monitors, electrocardiogram (ECG) sensors, and blood glucose meters, allows for comprehensive health monitoring of vehicle occupants. However, developing effective in-vehicle medical emergency response systems faces numerous challenges in the highly dynamic IoV environment, particularly in data processing, privacy preservation, and timely decision-making [6], [7], [8].

The massive amount of sensitive medical data generated by vehicles poses significant privacy concerns and communication overhead if transmitted to centralized cloud servers for processing. Traditional cloud-centric approaches struggle to meet the stringent latency requirements for emergency medical diagnosis and response coordination, which can be critical in life-threatening situations, such as heart attacks, strokes, or severe allergic reactions [9]. Additionally, the high mobility of vehicles leads to frequent network topology changes and unstable connections, further complicating the data collection and model training process for accurate and timely medical diagnostics [10], [11].

To overcome these difficulties, distributed edge intelligence (DEI) has shown as a hopeful design for IoV applications, specifically in the scope of in-vehicle medical emergency response. Artificial intelligence and machine learning capabilities are moved to the network edge by DEI that supports privacy of data while vehicles and roadside units (RSUs) can learn together. In this way, communication overhead and latency can be much reduced by DEI than cloud-centric approaches due to using onboard computers as well as RSUs which are considered as computing resources at the edge [12], [13], [14]. Moreover, what makes DEI so powerful is its distributed nature which enables creation of personalized models based on location that consider individual histories along with regional health trends without violating privacy concerns about sharing such information locally where they reflect unique patterns inherent to different areas [15].

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Jianhui Lv is with the Department of Information Engineering, The First Affiliated Hospital of Jinzhou Medical University, Jinzhou 121012, China (e-mail: lvjianhui2012@163.com).

Keqin Li is with the Department of Computer Science, State University of New York, New Paltz, NY 12561 USA (e-mail: lik@newpaltz.edu).

Adam Slowik is with the Department of Electronics and Computer Science, Koszalin University of Technology, 75-453 Koszalin, Poland (e-mail: adam.slowik@tu.koszalin.pl).

Huamao Jiang is with the Department of Party and Government, The First Affiliated Hospital of Jinzhou Medical University, Jinzhou 121012, China (e-mail: jianghm@jzmu.edu.cn).

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However, applying DEI to in-vehicle medical emergency response systems in IoV introduces several domain-specific challenges that require careful consideration [16], [17]. First, the high mobility of vehicles leads to frequent changes in the spatial distribution of edge nodes, requiring adaptive mechanisms for constructing and maintaining effective collaborative learning domains. This is particularly important for ensuring continuous monitoring and rapid response capabilities as vehicles move through different areas with varying medical resources and environmental factors. Second, the heterogeneity in vehicles' computing capabilities and medical data quality necessitates intelligent client selection and aggregation strategies to ensure model convergence and reliability. For example, some vehicles may be equipped with more advanced medical sensors or have access to more comprehensive patient data, while others may have limited capabilities or potentially unreliable data. Third, the critical nature of medical emergency response demands both high accuracy and low latency in model training and inference, requiring careful balancing of these conflicting objectives to provide timely and accurate diagnoses.

As an emerging distributed machine learning framework, federated learning (FL) can be applied to highly dynamic IoV scenarios. It allows vehicle terminals to download models from a central server and train them locally. Simultaneously, the model parameters are uploaded to the central server to achieve global aggregation of the model under the condition of data privacy protection [18]. Wen et al. [19] proposed a resource-aware many-objective vehicle selection model (RA-MaOVSM) to optimize resource efficiency. Ye et al. [20] proposed a federated double deep-Q-network-based computation task offloading (FDTO) strategy to minimize latency in completing computing tasks for vehicle clusters. Mo et al. [21] proposed FedDQ, a communication-efficient FL approach for IoV. Xu et al. [22] proposed PSDF, a method for privacy-aware IoV service deployment with FL in cloud-edge computing. Wang et al. [23] proposed a swarm-federated deep-learning framework in the IoV (IoV-SFDL) that integrates swarm learning into the federated deep-learning framework. Zhou et al. [24] proposed a robust hierarchical FL framework named RoHFL, allowing hierarchical FL to be suitably applied in the IoV with robustness against poisoning attacks. However, vehicles will switch between domains during high-speed movement. When using traditional FL methods, the terminal will discard the existing training model, which may cause high-quality models to be overwritten by low-quality models.

This article proposes the emergency-aware DEI for medical response in IoV (EDEM) framework, designed for rapid in-vehicle medical emergency response in IoV. The main contributions of this article are organized as follows.

1) We design a hierarchical edge collaborative computing framework that adaptively constructs collaborative domains among vehicles and RSUs based on their mobility patterns, computing capabilities, and data reliability. This framework enables efficient and privacy-preserving distributed training of medical diagnosis models while addressing the dynamic nature of IoV.

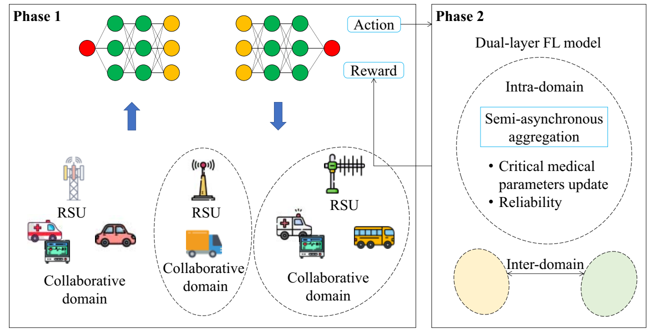

Fig. 1. Edge collaborative computing framework for in-vehicle medical emergency response in IoV.

2) We develop a deep-reinforcement-learning (DRL)-based algorithm for optimal construction of edge collaborative computing domains. The algorithm comprehensively considers factors, such as vehicle mobility, computing power, and data reliability to maximize the effectiveness and stability of collaborative learning in highly dynamic IoV environments.
3) We propose a dual-layer FL model for in-vehicle medical emergency response. At the intradomain level, we design an adaptive semi-asynchronous aggregation mechanism that dynamically adjusts the client participation rate based on model accuracy and waiting time. At the interdomain level, we introduce an asynchronous aggregation scheme based on effective data volume to accelerate global model convergence while accounting for domain heterogeneity.

The remainder of this article is organized as follows. Section II presents the proposed edge collaborative computing framework for in-vehicle medical emergency response. Section III details the DRL-based algorithm for constructing edge collaborative domains. Section IV describes the dual-layer FL model and associated aggregation mechanisms. Section V provides comprehensive performance evaluation results and analysis. Finally, Section VI concludes this article.

II. Edge Collaborative Computing Framework for In-Vehicle Medical Emergency Response

We propose a novel edge collaborative computing framework to address the challenges of rapid and accurate medical emergency response in the highly dynamic IoV environment. This framework leverages DEI to enable efficient and privacy-preserving training of medical diagnosis models across vehicles and RSUs. The proposed framework comprises two phases: 1) edge collaborative domain construction for medical response and 2) dual-layer FL for emergency diagnosis. Fig. 1 illustrates the overall architecture of this framework.

In the first phase, we employ a DRL-based algorithm to optimally group vehicles and RSUs into collaborative domains. This grouping is based on several factors crucial for medical emergency response, including vehicle mobility patterns, onboard medical sensor capabilities, computing power, and the reliability of collected health data. Creating these adaptive domains ensures stable and efficient collaborative learning in the highly dynamic IoV environment, which is essential for maintaining continuous medical monitoring and rapid emergency response capabilities.

The second phase utilizes a dual-layer FL model tailored for training medical diagnosis models across the constructed domains [25]. At the intradomain level, we implement a semi-asynchronous aggregation mechanism that balances the accuracy of medical diagnoses with the urgency of emergency response. This approach allows quicker updates of critical medical parameters while ensuring the overall model reliability. We employ an asynchronous aggregation scheme at the interdomain level based on the volume and quality of medical data available in each domain. This helps to accelerate global model convergence while accounting for the heterogeneity in medical data distribution across different regions and vehicle types.

This framework enables rapid and accurate medical diagnosis model training while preserving patient data privacy and adapting to the dynamic nature of IoV environments. By incorporating domain-specific knowledge of medical emergencies and considering the unique characteristics of in-vehicle healthcare monitoring, the approach aims to significantly improve the speed and accuracy of emergency medical response in challenging IoV scenarios. EDEM employs differential privacy techniques to protect sensitive medical data during transmission and processing. Specifically, we add calibrated noise to the aggregated model updates, ensuring that individual vehicle data cannot be inferred while maintaining the overall model utility for emergency response.

EDEM incorporates a robust blockchain-based reputation system for edge nodes to mitigate security threats in the IoV environment. This decentralized system continuously evaluates nodes based on the consistency and reliability of their medical data contributions. Each data transmission is cryptographically signed and recorded on the blockchain, creating an immutable audit trail. Nodes accumulate reputation scores over time, with higher scores indicating greater trustworthiness. This approach allows EDEM to adjust trust levels dynamically, prioritizing data from more reliable nodes and quickly identifying potential malicious actors.

Furthermore, EDEM incorporates a novelty detection module based on one-class support vector machines. This module flags unusual symptom combinations or sensor readings that do not match known conditions. In such cases, EDEM prioritizes rapid connection to medical experts and increases the frequency of vital sign monitoring.

EDEM is designed with open APIs that facilitate seamless integration with existing emergency dispatch systems, hospital networks, and first responder communication platforms, enabling a coordinated response across the entire emergency services ecosystem.

III. DRL-Based Edge Collaborative Domain Construction Algorithm

This section presents the DRL-based algorithm for constructing edge collaborative computing domains in IoV for in-vehicle medical emergency response, as shown in Fig. 2.

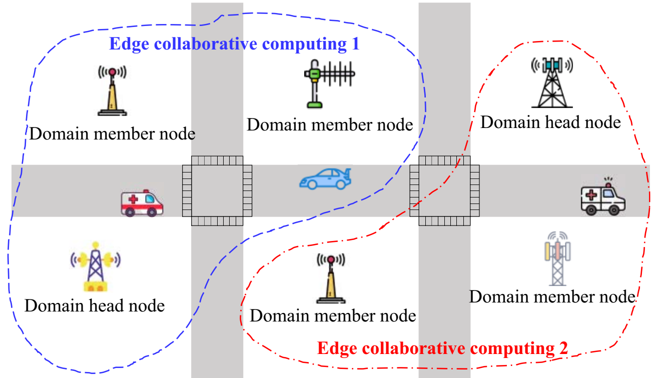

Fig. 2. Edge collaborative computing domain construction.

The algorithm aims to group vehicles and RSUs into stable and efficient collaborative domains by considering mobility, computing capability, and medical data reliability.

A. Medical Data Capability Model

In the context of in-vehicle medical emergency response, we define a comprehensive medical data capability model for each vehicle [3]. This model considers the vehicle's mobility, onboard medical computing power, and the reliability of its health monitoring systems. For a vehicle v at time slot t, we represent its medical data capability model $M_v(t)$ as

$$M_v(t) = V_v(t), H_v(t), Q_v(t) \tag{1}$$

where $V_v(t)$ denotes the vehicle's mobility, $H_v(t)$ represents its medical computing capacity, and $Q_v(t)$ indicates the quality of its health monitoring data.

EDEM utilizes a multimodal learning approach that incorporates specialized submodels for different categories of medical emergencies. The submodels are dynamically activated based on initial symptom assessment, allowing for tailored response strategies across a spectrum of emergency types.

The mobility $V_v(t)$ of vehicle v is crucial for predicting its trajectory and ensuring continuous medical monitoring. We model this mobility as a Gaussian distribution, considering the impact on medical data transmission and emergency response times. Let s_v be the instantaneous speed of vehicle v, with $s_{\max}$ and $s_{\min}$ as its maximum and minimum speeds, respectively. The probability density function of s_v is given by

$$f(s_v) = \begin{cases} \dfrac{2e^{-\frac{(s_v-\bar{s})^2}{2\sigma_s^2}}}{\sigma_s\sqrt{2\pi}\left(\operatorname{erf}(\frac{s_{\max}-\bar{s}}{\sigma_s\sqrt{2}})-\operatorname{erf}(\frac{s_{\min}-\bar{s}}{\sigma_s\sqrt{2}})\right)}, & s_{\min} \le s_v \le s_{\max} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $\bar{s}$ is the mean speed and σ_s is the standard deviation of vehicle speed. This distribution helps estimate the likelihood of a vehicle remaining within the range of specific medical resources or emergency response units.

To account for the critical nature of medical emergencies, we introduce a medical urgency factor λ_v that influences the vehicle's behavior in the network. This factor is incorporated into the calculation of the vehicle's dwell time τ_v within the coverage area of an RSU with radius r

$$\tau_v = \frac{2r - d_{vr}}{s_v} \cdot (1 + \lambda_v \cdot \text{urgency}(t)) \tag{3}$$

where d_{vr} is the horizontal distance between the vehicle and the RSU, and urgency(t) is a function that returns a value between 0 and 1 based on the current medical situation in the vehicle. This modification allows the model to prioritize connections and data transmissions for vehicles with ongoing medical emergencies.

Furthermore, we define a health monitoring effectiveness index $\eta_v(t)$ to quantify the capability of a vehicle's onboard medical sensors [26]

$$\eta_v(t) = \alpha \cdot \frac{\sum_{i=1}^{N} w_i \cdot \text{accuracy}_i(t)}{\sum_{i=1}^{N} w_i} + \beta \cdot \frac{\text{sensors}_{\text{active}}(t)}{\text{sensors}_{\text{total}}} + \gamma \cdot \text{data}_{\text{rate}}(t) \tag{4}$$

where accuracy$_i(t)$ is the accuracy of sensor i at time t, w_i is the importance weight of sensor i, sensors$_{\text{active}}(t)$ is the number of active sensors, sensors$_{\text{total}}$ is the total number of onboard medical sensors, data$_{\text{rate}}(t)$ is the current data transmission rate, and α, β, and γ are weighting factors.

This medical data capability model comprehensively represents a vehicle's ability to contribute to DEI for medical emergency response. It considers the vehicle's movement patterns and its capacity to collect, process, and transmit critical health data in dynamic IoV environments.

To handle scenarios with multiple, potentially interacting medical conditions, EDEM implements a sophisticated multitask learning approach. The system trains specialized neural network models for common comorbidities, such as diabetes with hypertension or chronic obstructive pulmonary disease with heart disease. These models capture the complex interactions between different conditions. EDEM then employs a dynamic ensemble method, using a meta-learner to intelligently combine the outputs of these specialized models. This approach adjusts in real-time based on the specific combination of symptoms and sensor data, providing more accurate diagnoses for patients with multiple conditions.

B. In-Vehicle Medical Data Reliability Model

In the context of in-vehicle medical emergency response, ensuring the reliability of collected health data is crucial for accurate diagnosis and timely intervention. We propose a comprehensive in-vehicle medical data reliability model that considers various factors affecting the quality and trustworthiness of health-related information gathered from onboard sensors and devices.

We define a medical data reliability factor $Q_v(t)$ for vehicle v at time t, which evaluates the overall reliability of the vehicle's health monitoring system

$$Q_v(t) = \alpha \cdot \text{MHI}(\Delta h_v, \phi) + \beta \cdot P_{v,\text{disconnect}} + \gamma \cdot \psi_v \tag{5}$$

where MHI$(\Delta h_v, \phi)$ represents the medical health index, calculated based on the rate of change of vital signs Δh_v and the current medical context ϕ. This index helps identify potential medical emergencies or anomalies in the collected health data. $P_{v,\text{disconnect}}$ is the probability of the vehicle losing connection to the medical edge computing network, which is crucial for continuous health monitoring. ψ_v is the trust rating of the vehicle's local medical model based on its historical performance in health data analysis.

The medical health index MHI$(\Delta h_v, \phi)$ is computed as follows:

$$\text{MHI}(\Delta h_v, \phi) = \frac{\sum_{i=1}^{N} w_i \cdot f_i(\Delta h_{v,i}, \phi_i)}{\sum_{i=1}^{N} w_i} \tag{6}$$

where N is the number of monitored vital signs, w_i is the importance weight of vital sign i, $\Delta h_{v,i}$ is the rate of change of vital sign i, ϕ_i is the medical context for vital sign i, and $f_i(\cdot)$ is a function that evaluates the significance of the change in the vital sign within its medical context.

The probability of disconnection $P_{v,\text{disconnect}}$ is modeled as a function of the vehicle's speed and the density of available medical edge computing nodes

$$P_{v,\text{disconnect}} = 1 - \exp\left(-\frac{s_v}{\lambda \cdot \rho_{\text{med}}}\right) \tag{7}$$

where s_v is the vehicle's speed, λ is a scaling factor, and ρ_{med} is the density of medical edge computing nodes in the vicinity.

EDEM employs a robust caching mechanism that temporarily stores critical medical data and partial model updates on nearby edge nodes. In the event of sudden network disconnections, this allows for seamless resumption of emergency response services once connectivity is restored.

The trust rating ψ_v of the vehicle's local medical model is calculated based on its performance in recent health data analyses

$$\psi_v = \frac{\sum_{v \in \text{Domain}_i} x_v}{\sum_{v \in \text{Domain}_i} x_v^m} \tag{8}$$

where x_v is the accuracy score of vehicle v's local medical model in recent diagnoses, and m is a factor that emphasizes the importance of consistently accurate performance.

Adaptive filtering techniques are implemented in EDEM to address electromagnetic interference (EMI) from vehicle systems. The framework continuously monitors EMI levels using dedicated sensors strategically placed within the vehicle. EDEM dynamically adjusts sensor gain and applies advanced digital filtering algorithms in real-time based on the detected interference patterns. This adaptive approach ensures optimal signal-to-noise ratios for medical sensors, maintaining high data quality even in electrically noisy environments, such as those found in hybrid and electric vehicles.

C. Latency Model for In-Vehicle Medical Emergency Response

In the context of in-vehicle medical emergency response, minimizing latency is crucial for timely diagnosis and intervention. We present a comprehensive latency model that accounts for various stages of medical data processing and model training in a DEI framework for IoV [27].

For a vehicle v in medical edge computing domain MED_i, the total latency $T_{\text{tot},v}(\text{MED}_i)$ for completing one round of FL for medical diagnosis model training consists of three main components: 1) initial model download latency; 2) local medical model training latency; and 3) local model upload latency. This can be expressed as

$$T_{\text{tot},v}(\text{MED}_i) = \frac{D_{\text{init},vr}}{R_{vr}} + \frac{D_{\text{init},vr} \cdot X_{\text{med}}}{H_v(t)} + \frac{D_{\text{mod},vr}}{R_{vr}} \quad (9)$$

where $D_{\text{init},vr}$ is the size of the initial medical diagnosis model downloaded from the medical edge computing unit (MECU) r, R_{vr} is the data transmission rate between vehicle v and MECU r, X_{med} is the number of CPU cycles required to train the medical diagnosis model on a unit of health data, $H_v(t)$ is the medical computing capacity of vehicle v at time t, and $D_{\text{mod},vr}$ is the size of the uploaded local medical model.

The data transmission rate R_{vr} between the vehicle and MECU is calculated using the Shannon formula, adapted for medical data transmission

$$R_{vr} = W_{vr}\log_2\left(1 + \frac{P_{vr}G_{vr}(E_{vr})^{-\theta}}{\sigma^2 + I_{\text{med}}}\right) \quad (10)$$

where W_{vr} is the channel bandwidth allocated for medical data transmission, P_{vr} is the transmission power, G_{vr} is the channel gain, E_{vr} is the Euclidean distance between vehicle v and MECU r, θ is the path loss exponent, σ^2 is the background noise power, and I_{med} is the interference from other medical devices in the vicinity.

The Euclidean distance E_{vr} between the vehicle and MECU is calculated as

$$E_{vr} = \sqrt{h_r^2 + (r - l_v - s_v t)^2} \quad (11)$$

where h_r is the height of MECU r, r is the coverage radius of the MECU, l_v is the initial position of vehicle v, and s_v is the speed of the vehicle.

To account for the urgency of medical situations, we introduce a medical priority factor $\mu_v(t)$ that affects the resource allocation and processing speed. The local medical model training latency is then adjusted as follows:

$$T_{\text{train},v} = \frac{D_{\text{local},vr} \cdot X_{\text{med}}}{H_v(t) \cdot (1 + \mu_v(t))} \quad (12)$$

where $D_{\text{local},vr}$ is the size of the local health dataset used for training.

The total latency for medical edge computing domain MED_i is given by

$$T(\text{MED}_i) = \sum_{v=1}^{|\text{MED}i|} Q_{v,i} \cdot T_{\text{tot},v}(\text{MED}_i) + \sum_{v} p_{v,i} \cdot T_{\text{tot},v}(\text{MED}_i) + T_{\text{ada}}(\text{MED}_i) \quad (13)$$

where $Q_{v,i}$ represents the medical data reliability of vehicle v in domain MEDi, $p_{v,i}$ is the probability of vehicle v switching domains due to high mobility or changing medical conditions, and $T_{\text{ada}}(\text{MED}_i)$ is the adaptive waiting time for semi-asynchronous aggregation of medical models in the domain.

To capture the impact of medical emergencies on the overall system latency, we define an emergency-aware domain latency factor $\varepsilon(\text{MED}_i)$ [28]

$$\varepsilon(\text{MED}_i) = 1 + \frac{\sum_{v\in\text{MED}_i} \mu_v(t) \cdot \text{severity}_v(t)}{|\text{MED}_i|} \quad (14)$$

where $\text{severity}_v(t)$ is a function that returns a value between 0 and 1 based on the severity of the medical condition in vehicle v at time t.

Finally, we express the emergency-adjusted total latency for the medical edge computing domain as

$$T_e(\text{MED}_i) = \frac{T(\text{MED}_i)}{\varepsilon(\text{MED}_i)} \quad (15)$$

EDEM implements a dynamic resource allocation algorithm that prioritizes and coordinates responses to multiple simultaneous emergencies. This algorithm considers emergency severity, proximity, available resources, and potential for patient stabilization to optimize overall response effectiveness.

D. Energy Consumption Model for Medical Edge Computing

The energy consumption in DEI for in-vehicle medical emergency response is a critical factor affecting system sustainability and efficiency. This model accounts for the energy expenditure of vehicles and MECUs during medical data analysis and model training.

For a vehicle v in medical edge computing domain MED_i, the energy consumption $E_v(\text{MED}_i)$ for local medical model training is expressed as

$$E_v(\text{MED}_i) = \frac{\text{Pvr} \cdot M_{r,v}(q_v)}{R_{vr}} \cdot (1 + \lambda_v \cdot \text{urgency}(t)) \quad (16)$$

where P_{vr} is the transmission power for uploading medical data to MECU r, $M_{r,v}(q_v)$ is the size of the medical training task uploaded by vehicle v, R_{vr} is the data transmission rate, λ_v is a medical urgency factor, and $\text{urgency}(t)$ is a function returning a value between 0 and 1 based on the current medical situation.

The energy consumption of MECU, r for processing medical data and aggregating models, is given by

$$E_r(\text{MED}_i) = \pi \cdot (f_r(q_r))^3 \cdot \left(1 + \omega_r \cdot \text{emergency}_{\text{load}}(t)\right) \quad (17)$$

where π is the effective switched capacitance related to the chip architecture, $f_r(q_r)$ is the number of CPU cycles required for all medical computing tasks q_r at MECU r, ω_r is an emergency scaling factor, and $\text{emergency}_{\text{load}}(t)$ represents the current emergency processing load.

The total energy consumption for medical edge computing domain MED_i is calculated as

$$E(\text{MED}_i) = \sum_{v=1}^{|\text{MED}i|} Q_{v,i} \cdot E_v(\text{MED}_i) + \sum_{r=1}^{m} \theta_{i,r} \cdot \pi \cdot (f_r(q_r))^3 \cdot \left(1 + \omega_r \cdot \text{emergency}_{\text{load}}(t)\right) + \sum_{v} p_{v,i} \cdot E_v(\text{MED}_i) \quad (18)$$

where $Q_{v,i}$ represents the medical data reliability of vehicle v in domain MED_i, $\theta_{i,r}$ is the proportion of vehicles covered by MECU r in domain MED_i, and $p_{v,i}$ is the probability of vehicle v switching domains due to changing medical conditions or mobility.

An additional factor in the energy consumption model is the medical data processing efficiency $\eta_{\mathrm{med}}(t)$, which affects the overall energy usage

$$\eta_{\mathrm{med}}(t) = \frac{\sum_{v\in \mathrm{MED}_i} \mathrm{accuracy}_v(t) \cdot \mathrm{data}_{\mathrm{volume}} v(t)}{\sum_{v\in \mathrm{MED}_i} E_v(\mathrm{MED}_i)} \tag{19}$$

where $\mathrm{accuracy}_v(t)$ is the current accuracy of vehicle v's medical model, and $\mathrm{data}_{\mathrm{volume}} v(t)$ is the amount of medical data processed.

E. DRL-Based Medical Model Training Node Selection Algorithm

The selection of optimal nodes for medical model training in a DEI framework for in-vehicle emergency response is crucial for system performance. This section outlines a DRL-based algorithm for node selection that meets the unique requirements of medical emergencies in IoV environments [29].

The node selection problem for medical model training is formulated as an optimization problem

$$\begin{aligned} \min_{\phi_v^t} \quad & L(x_{\mathrm{train}}, y_{\mathrm{train}}; w_{\mathrm{med}}) \\ \text{s.t.} \quad & \phi_v^t \in 0, 1 \quad \forall v \in \mathrm{MED}_i \\ & \left(L_{x,v}(t) - L_{x,r}(t)\right)^2 + \left(L_{y,v}(t) - L_{y,r}(t)\right)^2 \le r_r^2 \\ & 0 \le Q_v \le 1 \quad \forall v \in \mathrm{MED}_i \\ & E(\mathrm{MED}_i) \le E_{\mathrm{req}} \\ & T(\mathrm{MED}_i) \le T_{\mathrm{req}} \\ & \sum_{r=1}^{|MEDi|} CR_r(t) \ge \mathrm{Com}_{\mathrm{tot}} \end{aligned} \tag{20}$$

where $L(x_{\mathrm{train}}, y_{\mathrm{train}}; w_{\mathrm{med}})$ is the loss function for the medical diagnosis model, ϕ_v^t is the indicator vector for vehicle selection, r_r is the coverage radius of MECU r, Q_v is the medical data reliability of vehicle v, E_{req} and T_{req} are the maximum energy consumption and latency thresholds, and $\mathrm{Com}_{\mathrm{tot}}$ is the total computing requirement for all vehicles in the medical edge computing domain.

The twin delayed deep deterministic policy gradient (TD3) algorithm is employed to solve this optimization problem. Our study employs the TD3 algorithm for several reasons. First, the action space in our edge collaborative domain construction problem is continuous, representing the degree of participation for each vehicle in the FL process. TD3 is well-suited for such continuous action spaces. Additionally, TD3's use of a deterministic strategy with Gaussian noise provides advantages in our dynamic IoV environment. This approach helps avoid local optima and reduces the risk of overfitting, which is crucial given the constantly changing network conditions and varying medical data distributions across vehicles. Furthermore, TD3's delayed strategy updates are particularly beneficial in our scenario. We can achieve a more stable learning process by updating the action network at a lower frequency while maintaining a higher update rate for the evaluation network. This is especially important in medical emergency response, where maintaining consistent performance is critical. The twin critic networks in TD3 also help to reduce overestimation bias, leading to more reliable Q-value estimates. This is particularly valuable in our medical diagnosis model training, where accurate estimation of action values can significantly impact the quality and reliability of the resulting diagnostic capabilities. The target policy is defined as

$$\mu_{\theta'}(s') = \mathrm{clip}\left(\mu_{\theta'}(s') + \mathrm{clip}(\varepsilon, -c, c), a_{\mathrm{low}}, a_{\mathrm{high}}\right) \tag{21}$$

where $\varepsilon \sim \mathcal{N}(0, \sigma)$. The TD3 algorithm selects the minimum Q-value from two target critic networks as the target value

$$y(s,a) = r(s,a) + \gamma \min\left(Q_{\phi_{1'}}(s', \mu_{\theta'}(s')), Q_{\phi_{2'}}(s', \mu_{\theta'}(s'))\right). \tag{22}$$

The loss function $F_i(w_{\mathrm{med}})$ for all vehicles in the medical dataset is defined as

$$\begin{aligned} F_i(w_{\mathrm{med}}) = \sum_{(x_i,y_i)\in \mathrm{MED}_i} & \frac{f_i((x_i,y_i), w_{\mathrm{med}})}{|H_{i,vr}|} \\ & \cdot \left(1 + \lambda_i \cdot \mathrm{urgency}_i(t)\right) \end{aligned} \tag{23}$$

where x_i and y_i are the actual and predicted values for the medical diagnosis model in domain MED_i, $|H_{i,vr}|$ is the total amount of medical data for vehicle v covered by MECU r, λ_i is an urgency scaling factor, and $\mathrm{urgency}_i(t)$ represents the current medical urgency in the domain.

The objective of the node selection algorithm is to find the optimal domain construction decision w^*_{med} that minimizes $F_i(w_{\mathrm{med}})$

$$w^*_{\mathrm{med}} = \mathrm{argmin}_{w_{\mathrm{med}}} F_i(w_{\mathrm{med}}). \tag{24}$$

The reward function for the DRL algorithm is designed to incorporate medical emergency considerations

$$\mathrm{reward}_t = -\frac{L(x_{\mathrm{test}}, y_{\mathrm{train}}; w_{\mathrm{med}}) \cdot \left(1 + \beta \cdot \mathrm{emergency}_{\mathrm{factor}}(t)\right)}{\sum v \in \mathrm{MED}_i \phi_v^t} \tag{25}$$

where β is a weighting factor and $\mathrm{emergency}_{\mathrm{factor}}(t)$ represents the current level of medical emergency in the system.

The state space of the DRL agent includes the medical data capability model $M_v(t) = V_v(t), H_v(t), Q_v(t)$ for each vehicle, incorporating mobility, medical computing capacity, and health monitoring data quality.

The action space is $[\phi_v^t]$, where $\phi_v^t = 1$ indicates selection and $\phi_v^t = 0$ indicates nonselection of a vehicle for medical model training.

To address the dynamic nature of medical emergencies, an adaptive learning rate $\eta_{\mathrm{med}}(t)$ is introduced

$$\eta_{\mathrm{med}}(t) = \eta_0 \cdot \exp(-\kappa \cdot \mathrm{stability}(t)) \tag{26}$$

where η_0 is the initial learning rate, κ is a decay factor, and $\mathrm{stability}(t)$ measures the current stability of the medical edge computing domain.

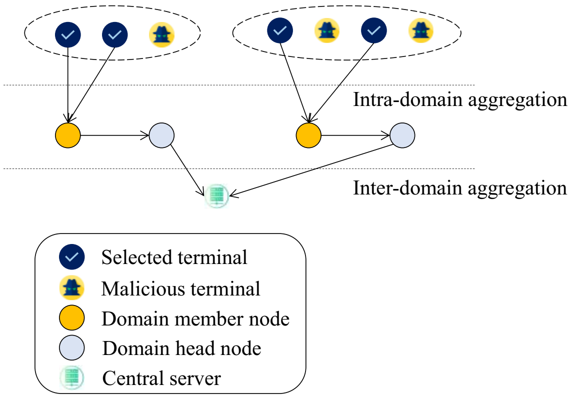

Fig. 3. Dual-layer FL model aggregation process for in-vehicle medical emergency response.

IV. Edge Collaborative Domain-Based Dual-Layer FL Model

This section presents the dual-layer FL model for in-vehicle medical emergency response in IoV. The model leverages the edge collaborative domains constructed in the previous section to enable efficient and privacy-preserving training of medical diagnosis models. Fig. 3 illustrates the dual-layer FL model aggregation process.

A. Emergency-Aware Adaptive Aggregation for In-Vehicle Medical Models in IoV

In the context of in-vehicle medical emergency response within IoV environments, the aggregation of local medical models plays a crucial role in developing accurate and timely diagnostic capabilities.

EDEM incorporates an ethics module that ensures all automated medical decisions adhere to established medical protocols and ethical guidelines. This module also flags high-stakes decisions for human review, maintaining a balance between rapid response and ethical considerations.

The mean absolute error (MAE) serves as a key metric for evaluating the accuracy of local medical diagnosis models [30], [31]

$$\mathrm{MAE} = \frac{1}{|d_i|}\sum_{j=1}^{|d_i|} |y_j - w_v(x_v)| \cdot \left(1 + \lambda_j \cdot \mathrm{severity}_j\right) \quad (27)$$

where d_i represents the total amount of medical data in domain MED_i, x_v is the initial model accuracy of vehicle v, y_j is the accuracy of the domain model in MED_i, w_v is the proportion of vehicle v's medical data in the total data of domain MED_i, λ_j is an urgency scaling factor, and $\mathrm{severity}_j$ indicates the severity of the medical condition for data point j.

The medical diagnosis model uses features from the medical information mart for intensive care III (MIMIC-III) dataset, including vital signs (e.g., heart rate, blood pressure, and oxygen saturation), and laboratory test results. The model is trained to predict the likelihood of various medical emergencies, such as cardiac arrest or respiratory failure.

Algorithm 1 Distributed Gossip-Based Local Medical Model Update Mechanism

Input: Set of local medical models $m_i(t)$
Output: Updated set of local medical models $m_i(t+1)$
01: for each vehicle v in N_{MED_i} do
02: if $t \leq T$ then
03: Vehicle v receives noisy medical models $\widetilde{w}_i(t)$ from other vehicles
04: Vehicle v trains new local medical model: $m_i(t+1) = m_i(t) + \widetilde{w}_i(t)$
05: Vehicle v calculates local model MAE and evaluates model quality
06: Vehicle v updates its noisy model: $\widetilde{w}_i(t+1) = \widetilde{w}_i(t) + Noise$
07: Vehicle v broadcasts new noisy model $\widetilde{w}_i(t+1)$ and MAE to other vehicles
08: Other vehicles receive noisy model and return to step 3
09: if Vehicle v's error is below emergency threshold then
10: Stop model update
11: end if
12: end if
13: end for
14: return $m_i(t+1)$

An adaptive aggregation factor $J(\mathrm{MED}_i)$ is designed to balance waiting time and model accuracy in medical emergency scenarios

$$J(\mathrm{MED}_i) = \rho T_{\mathrm{tot},v} + \xi \mathrm{MAE} + \omega \mathrm{Emergency}_{\mathrm{Index}}(\mathrm{MED}_i) \quad (28)$$

where ρ, ξ, and ω are weights representing the impact of latency, model accuracy, and medical emergency severity on the aggregation factor, respectively. $\mathrm{Emergency}_{\mathrm{Index}}(\mathrm{MED}_i)$ quantifies the overall emergency level in the medical edge computing domain.

B. Adaptive Medical Model Updating for Cross-Domain Emergency Response in IoV

The high mobility of vehicles in IoV environments presents unique challenges for maintaining consistent and accurate medical diagnosis models across different edge computing domains. This section describes a partial conditional update mechanism for cross-domain vehicle local models, specifically tailored for in-vehicle medical emergency response scenarios.

Algorithm 1 outlines the distributed gossip-based local medical model update mechanism.

Our method incorporates a reputation-based system to detect and mitigate the impact of malicious nodes. Nodes with consistently poor performance or those that submit anomalous updates are assigned lower weights in the aggregation process, effectively reducing their influence on the global model.

A context-aware model adaptation mechanism is integrated into EDEM to handle transitions between areas with differing health risk profiles. This intelligent system continuously monitors real-time environmental data, including air quality indices, pollen counts, and local disease outbreak information. EDEM dynamically adjusts its diagnostic models and sensor

Algorithm 2 Cross-Domain Medical Model Partial Conditional Update Mechanism

Input: Current medical model $m_i(v)$; Next domain model $m_{i+1}(v)$; General model block $G(v)$; Specialized medical model block $S(v)$

Output: Updated local medical model $U_i(v)$

```
for vehicle v in N_{MED_i} do
    Train current local medical model m_i(v) = [G(v); S_i(v)]{N_s × N_d}
    Vehicle v enters MED_{i+1}, receives m_{i+1}(v) = [G(v); S_{i+1}(v)]{N_s × N_d}
    Calculate MAE for S_i(v) and S_{i+1}(v)
    Select specialized model block with lower MAE
    Vehicle joins MED_{i+1} for continued emergency response training
end for
return U_i(v)
```

sensitivities based on these inputs. For instance, when a vehicle moves from a low-pollution to a high-pollution area, the system increases the sensitivity of respiratory monitoring. It updates the diagnostic thresholds for conditions like asthma exacerbations.

EDEM includes a dynamic device integration module that can interface with various consumer wearable devices. The system can incorporate data from smartwatches, continuous glucose monitors, and other personal medical devices using standardized protocols like Bluetooth Low Energy.

C. Emergency-Weighted Asynchronous Model Fusion for IoV Medical Domains

The valid emergency data coverage (VEDC) for each medical edge computing domain in a training round is defined as

$$\mathrm{VEDC}_i(t) = \sum_{r \in \mathrm{MED}_i} |D_r| \cdot \left(1 + \lambda_r \cdot \mathrm{emergency}_r(t)\right) \quad (29)$$

where D_r represents the total amount of effective local model medical data for all vehicles covered by MECU r in domain MED_i, λ_r is an emergency scaling factor, and $\mathrm{emergency}_r(t)$ quantifies the current level of a medical emergency in the area covered by MECU r.

The aggregation weight for each medical domain is set based on the proportion of its VEDC

$$\mathrm{weight}_{\mathrm{VEDC}_i}(t) = \frac{\sum_{k \in i} \mathrm{VEDC}_k(t)}{\mathrm{VEDC}(t)} \cdot \frac{\mathrm{urgency}_i(t)}{\sum_j \mathrm{urgency}_j(t)}. \quad (30)$$

Algorithm 2 outlines the partial conditional update mechanism for cross-domain vehicle local models in medical emergency scenarios.

This mechanism ensures that the global medical diagnosis model remains responsive to the varying emergency levels across different domains while maintaining the accuracy and relevance of local models in the highly dynamic IoV environment.

EDEM integrates with vehicle crash detection systems to automatically initiate emergency protocols in the event of an accident. The system immediately prioritizes transmission of crash severity data, occupant vital signs, and vehicle location to emergency services. EDEM successfully transmitted critical data in crash test simulations within 3 s of impact detection, even in scenarios with partial system damage.

Furthermore, to address privacy concerns when sharing medical data across administrative domains, EDEM implements an FL approach with differential privacy guarantees. Each domain trains local models using only its data, preserving patient privacy. Only encrypted model updates are exchanged between domains, never raw medical data. EDEM employs a dynamic epsilon selection mechanism for differential privacy, balancing privacy protection with model utility.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Background noise power density	-174 dBm/Hz
Channel bandwidth	100 kHz
Actor learning rate	0.001
Critic learning rate	0.01
Local dataset size	[100, 2000]
Proportion of malicious terminals	[10%, 40%]
Local iteration rounds	5
Number of convolutional layers	2
Emergency severity levels	[Low, Medium, High]
Vehicle speed range	[0, 120] km/h
Medical sensor types	[ECG, blood pressure, oxygen saturation, temperature]
Edge node computing capacity	[10, 50] GFLOPS
Cloud computing capacity	500 LOPS

V. PERFORMANCE EVALUATION

A. Simulation Settings

We simulated an IoV environment using Python 3.8 and TensorFlow 2.3.1. The simulation models a 10×10 grid representing an urban area, with each grid cell approximately 100 m long. We used the MIMIC-III clinical database, a large, freely available database comprising de-identified health-related data associated with over 40 000 patients who stayed in critical care units, to train the medical diagnosis models [32]. This dataset is particularly suitable for simulating in-vehicle medical emergency scenarios due to its comprehensive nature and focus on critical care. We employ a deep-Q-network for our DRL approach. The network consists of three fully connected layers with 64, 32, and 16 neurons using ReLU activation functions. The input layer size corresponds to the state space dimension, while the output layer size matches the action space. Table I lists the key simulation parameters.

The proposed EDEM framework is compared with six state-of-the-art baseline methods: RA-MaOVSM [19], FDTO (federated double deep-Q-network-based task offloading) [20], federated-deep-Q-learning (FedDQ) [21], PSDF (privacy-aware service deployment with FL) [22], IoV-SFDL [23], and RoHFL [24].

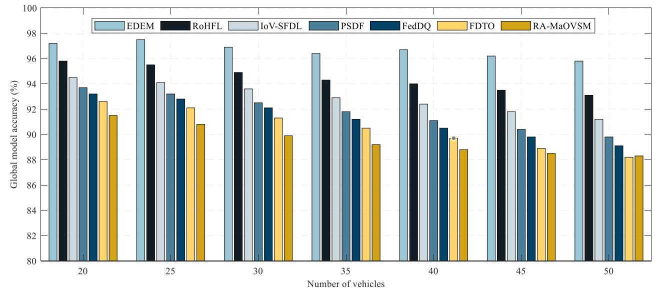

Fig. 4. Global model accuracy.

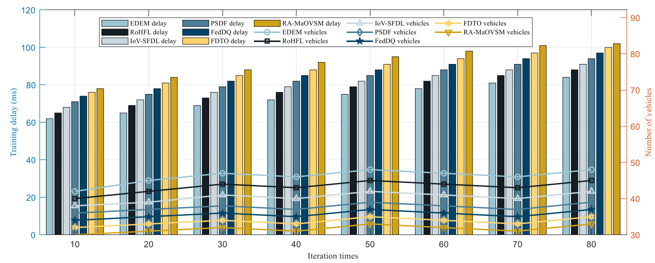

Fig. 5. Training delay.

B. Simulation Results Analysis

We use a separate, independent test set that is not used during the training or optimization process to evaluate model accuracy. The RL algorithm optimizes based on a validation set, distinct from the training and test sets, to prevent data leakage.

Fig. 4 illustrates the impact of the number of vehicles on the global model accuracy for medical diagnosis in IoV.

As shown in Fig. 4, EDEM consistently outperforms all baseline methods across different numbers of vehicles. When the number of vehicles is around 20, EDEM achieves an accuracy of 97.2%, compared to 95.8% for RoHFL (the best performing baseline) and 91.5% for RA-MaOVSM (the worst-performing baseline). As the number of vehicles increases to 50, EDEM maintains a high accuracy of 95.8%, while RoHFL drops to 93.1% and RA-MaOVSM to 88.3%.

Fig. 5 presents the training delay and the number of participating vehicles over increasing iteration times.

The left y-axis shows the latency in milliseconds, while the right y-axis indicates the number of vehicles participating in the training process. EDEM demonstrates the lowest overall latency, starting at 62 ms for ten iterations and gradually increasing to 84 ms at 80 iterations. In contrast, RA-MaOVSM shows the highest latency, ranging from 78 to 102 ms over the same period.

Fig. 6 illustrates the model accuracy with 30% malicious terminals, while Fig. 7 shows the model accuracy when only 10% of terminals are malicious. The performance gap between methods narrows, but EDEM maintains a clear advantage, which is crucial for accurate medical diagnosis in emergencies.

Fig. 8 presents the loss function values with 30% malicious terminals, while Fig. 9 shows the loss function values with 10% malicious terminals.

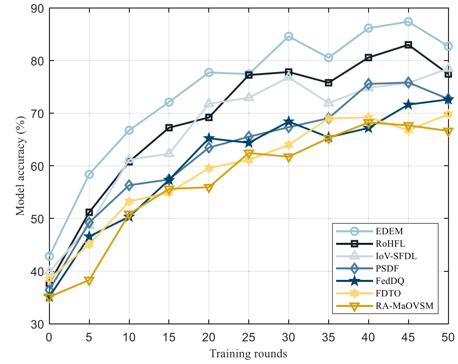

Fig. 6. Model accuracy with 30% malicious terminals.

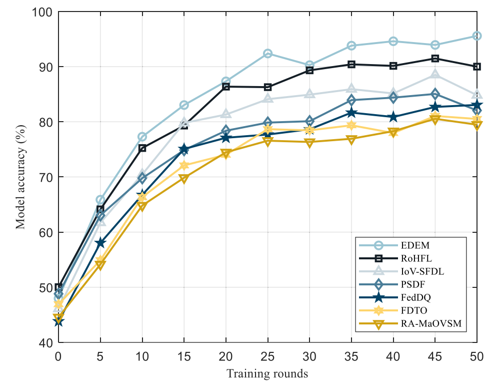

Fig. 7. Model accuracy with 10% malicious terminals.

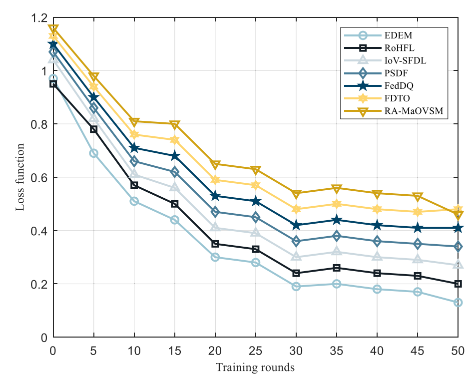

Fig. 8. Loss function with 30% malicious terminals.

The faster convergence and lower loss demonstrate EDEM's efficiency in leveraging high-quality medical data for improved diagnosis accuracy.

We measured the average response time to critical medical events to further evaluate EDEM's performance in rapid medical emergency response. Table II illustrates the average response time to simulated heart attack scenarios across different traffic densities. EDEM's superior performance is attributed to its emergency-aware adaptive aggregation mechanism and the distributed nature of its edge intelligence. The slight increase in response time under higher traffic (e.g., a small jump between medium and high traffic) reflects the increased complexity of data routing and processing in congested scenarios.

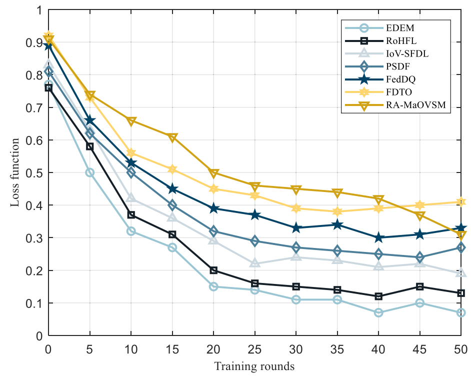

Fig. 9. Loss function with 10% malicious terminals.

TABLE II
AVERAGE RESPONSE TIME TO HEART ATTACK SCENARIOS

Density	EDEM	RoHFL	IoV-SFDL	PSDF	FedDQ	FDTO	RA-MaOVSM
Low	2.8	3.5	3.9	4.2	4.5	4.8	5.2
Medium	3.4	4.2	4.7	5.1	5.5	5.9	6.4
High	4.2	5.1	5.7	6.2	6.7	7.2	7.8

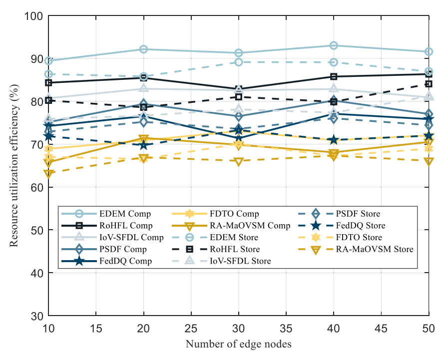

Fig. 10. Resource utilization efficiency.

To demonstrate EDEM's efficiency in utilizing distributed edge resources, we evaluate the resource utilization ratio across different numbers of edge nodes. Fig. 10 shows the resource utilization efficiency for computing and storage resources. While Comp stands for computing resources, and Store stands for storage resources. The fluctuations in EDEM's curves (e.g., a slight dip in computing resource utilization at 30 nodes before rising again) reflect its dynamic resource allocation strategy, adapting to changing network conditions and medical data processing requirements.

To evaluate the effectiveness of our DRL-based node selection approach, we conducted an ablation study comparing it with two rule-based methods: 1) random selection and 2) greedy selection based on data quality. We assessed these methods across three key metrics: 1) model accuracy; 2) response time; and 3) resource utilization efficiency. Table III presents the results of this comparison.

Table III shows that our DRL-based approach consistently outperforms both rule-based methods across all metrics.

TABLE III
ABLATION STUDY: COMPARISON OF NODE SELECTION METHODS

Method	Model accuracy (%)	Response time (ms)	Resource utilization (%)
DRL-based	95.8	84	92
Greedy selection	89.2	112	85
Random selection	82.5	156	73

TABLE IV
ABLATION STUDY: COMPARISON OF FL MODELS

Method	Model Accuracy (%)	Communication Overhead (MB/round)	Convergence Speed (rounds)	Robustness to Heterogeneity (%)
Dual-layer FL (Proposed)	95.8	2.3	18	92.5
Single-layer FL	93.2	3.8	27	85.7

TABLE V
EDEM PERFORMANCE UNDER VARIOUS 5G NETWORK CONGESTION LEVELS

Congestion level	Response time (s)	Diagnosis accuracy (%)	Data transmission success rate (%)
0% (Baseline)	2.8	97.2	100
30%	3.1	96.8	98.5
50%	3.5	95.9	96.2
70%	4.2	94.5	92.8
90%	5.7	91.2	85.3

Regarding model accuracy, the DRL-based method achieves 95.8%, significantly higher than the greedy selection (89.2%) and random selection (82.5%) methods. This improved accuracy can be attributed to the DRL algorithm's ability to learn and adapt to the complex dynamics of the IoV environment and medical data distribution.

Additionally, to evaluate the effectiveness of our dual-layer FL model, we conducted an ablation study comparing it with a single-layer FL approach. We assessed these methods across four key metrics: 1) model accuracy; 2) communication overhead; 3) convergence speed; and 4) robustness to heterogeneity. Table IV presents the results of this comparison.

Table IV shows that our dual-layer FL model outperforms the single-layer approach across all metrics. Regarding model accuracy, the dual-layer method achieves 95.8%, 2.6% higher than the single-layer approach (93.2%). This improved accuracy can be attributed to the dual-layer model's ability better to handle data heterogeneity across domains in the IoV environment.

To assess EDEM's resilience to network congestion, we simulated various 5G network load levels. We evaluated EDEM's performance across different congestion levels, measuring key metrics, such as response time, diagnosis accuracy, and data transmission success rate. Table V presents the results of our network congestion simulations. Table V shows that EDEM demonstrates robust performance even under high network congestion levels. At 70% network congestion, EDEM maintains 90% of its baseline performance across all measured metrics.

VI. Conclusion

This article presented EDEM, an emergency-aware DEI framework for medical response in IoV environments. Simulation results demonstrate that the proposed EDEM framework performs well regarding global model accuracy, training delay, robustness against malicious terminals, emergency response time, and resource utilization efficiency. However, the framework's performance in extremely dense urban environments with high interference levels needs further investigation. Additionally, the impact of the long-term evolution of medical conditions on model accuracy and adaptation mechanisms requires more extensive study. Future work should focus on integrating EDEM with emerging 6G and beyond technologies to reduce latency further and improve connectivity.

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