This article has been accepted for publication in IEEE Transactions on Consumer Electronics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TCE.2024.3508090

Federated Learning Framework for Consumer IoMT-Edge Resource Recommendation under Telemedicine Services

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Abstract – Medical IoT devices and Telemedicine computation is the growing domain and further involving biomedical computation via machine learning ecosystem has generated an insightful results and analysis. The resources sharing and availability in computing and decision support suffer with a higher latency and energy consumption. In this manuscript, a novel TinyML based model for medical consumer devices resources allocation and resource sharing is discussed. The proposed framework is developed using Federated learning (FL) models for extracting the resource utilization patterns at individual user levels. These locally computed models are further facilitated with edge computation layer for locating resource patterns extraction. The technique is deployed on the dynamic server based resource pooling for effective analysis and resource scheduling and expanded to develop a reliable recommendation model for medical resource management. The framework has trained 128 clusters of 6400 rural and 12800 urban IoT devices samples for resource allocation and scheduling using telemedicine protocol (TelMED). The framework has secured an efficiency of 93.21% in urban user recommendation and 94.72% for rural users.

Keywords – Federated learning, TinyML models, local computational models, medical resource allocation, resource pooling.

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I. INTRODUCTION

In the complex landscape of modern computing, resource management and scheduling represent intricate challenges that demand nuanced solutions. At the heart of this complexity lies the delicate balance between optimizing resource allocation for servers and their associated applications while minimizing the latency inherent in task execution. The process of allocating resources and scheduling cannot be handled under a manual intervention or under an administrator. The process of allocation needs to be automated. The user requests generated from the telemedicine ecosystem is however dependent on the user's network infrastructure but the response and computational requirements vary from one user demand to another. With the inclusion of Internet of Medical Things (IoMT), the process has further complicated the resource governess in dynamic ecosystem.

The idea of telemedicine is to connect the doctor (medical expert) and the patient (User) via a remote channel or a protocol. The approaches in this domain has resulted in a larger solution for telemedicine based algorithm optimization and framework development. With the inclusion on modern technologies and computational speed, the purpose of telemedicine is re-innovated beyond the peer to peer communication. Today the telemedicine includes relatively higher IoMT devices computation, monitoring and data analysis. The regularization of telemedicine has seen wider acceptance since the global pandemic of CoVID-19 since 2019. Due to the unprecedented CoVID-19 scenarios, the inclusion of telemedicine in regulating the medical services and resources was conducted. The countries with modern healthcare infrastructure and connectivity were swift to react on the changing needs.

In this paper, we have proposed a novel framework for resource recommendation in telemedicine ecosystem via TinyML based computational capabilities. Since the resource sharing and the need for centralized information processing were the major take away from the COVID-19 pandemic. The proposed system is expanded and developed on the similar principle grounds. The under-developing countries and under-privileged patients can be governed from the proposed system. The process is to include a framework on IoMT devices connected via the telemedicine to pool the associated resources and compute a reliable sharing and scheduling technique via machine learning approaches.

Problem Statement

According to various studies on internet, a projection of massive expansion in IoMT/IoT consumer devices are recorded. These consumer IoMT devices generate larger data/information via individual patterns and record from the medical smart sensors and telemedicine infrastructure. In the existing scenario the IoMT devices are directly connected via a peer to peer approach or via a client-server approach resulting in natively increasing latency, higher energy consumption and ineffective resource sharing under the cloud based telemedicine services. These result in a complex system design and hence the future expansions of infrastructure with additional IoMT devices or telemedicine aided devices may result into a system delays and network crashes. The objective is to identify the regulating approaches or techniques to improvise the resource sharing and monitoring process and effective data/information management at the server archives.

Contribution

The proposed technique has been developed on the agenda of providing effective resource sharing and scheduling technique for telemedicine users. The major contributions are as follows

- The manuscript has developed a federated learning approach for simplification of centralized data processing compared to the traditional machine learning approaches.
- The technique is developed on the edge-user centric approach and hence the resulting data/information from edge-IoMT devices are privacy enabled
- The resource scheduling is enabled at the edge-IoMT layer resulting in minimizing the demand allocation queries.
- The federated learning layer adds value to the learning patterns of the edge-IoMT devices and the demand and supply ratio prediction of resource allocation and resource scheduling in telemedicine ecosystem.

The manuscript is organized with an introduction in section I and followed by a literature reviews and recent updates in telemedicine and federated learning in section II. The section III and IV provides a brief understanding on the methodology and the edge-federated based local layer and framework setup, followed by section V with a detailed discussion on edge-resource scheduling and indexing technique. The section VI summaries the federated learning layers' influence in streamlining the proposed technique. The results and discussions are in section VII followed by conclusion in section VIII.

II. LITERATURE REVIEW

The demand and supply chain management in the telemedicine is a challenging task. The governing of information and communication technologies used in the telemedicine infrastructure design is discussed in [1] with a preservative observation based implementation model of services to the patients, academicians and medical experts. The dependability of telemedicine has however seen a larger impact of acceptance post COVID-19 [2]. The influence of low-cost telemedicine design was effectively proposed by [3] in 2011 and since then, the technological improvisations in modified the overall resources and computation scope of low-cost telemedicine. many researchers have proposed various resource recommendation techniques as discussed in the survey report [4]. In order to have the study in ease, we have categorized the literature into a primacy section of resource recommendation and scheduling section and the second section on federated learning influences drawn on the telemedicine framework.

Resource Recommendation and Scheduling

The resource monitoring and resource pooling is a challenging task if the resources are governed via a networking channel. The technique [5] has discussed various challenges, matrices and algorithms used in recommendation system in a generic and business model development prospective. In [6] an adaptive recommendation of virtual machines for IoT in Edge-Cloud Environment (ARVMEC) is proposed to assure the allocation of resources with a scheduling queues for effective load-balancing and offloading the computational capabilities. A similar approach in aligned manner to with the IoT resource attack and security enriching model is discussed in [7] with an IoT based Distributed Danial of Service (IoT-DDoS) based on multi-layer DDoS preservation approach for unauthorized user accessing in the resource scheduling paradigms.

Federated Learning Models: Review

The influence of distributed computation via federated learning (FL) is a proven approach for customizing the remote user demand and resource availability patterns. The basic IoMT model [8] allows the patients' healthcare monitoring from remote devices using a Artificial Intelligence (AI) driven algorithms. The Quality of Service (QoS) in Mobile Edge Computing (MEC) devices is relatively lower and the study [9] has included a federated reinforcement learning model for task offloading in IoMT devices. The primary requirement is to analyze and validate the demand ratio using distributed edge learning patterns. The edge-IoT resource optimization under the fog-computing is demonstrated by [10] for effective scheduling via modified particle swarm optimization (MPSO) technique.

With inclusion of federated learning, the demand of securing the privacy and user-identification was a challenge. In [11] a study is developed based on privacy preservation of the user-data and resolve the leakage of private keys in the communication channel suing federated learning. The study further includes policies and laws [12] governed for the implementation. The IoMT edge recommendation is developed on the energy and performance matrices as discussed in [13] [14] for effective alignment using Mixed Integrated Linear Programming (MILP) on health monitoring devices. The advert is further expanded to the 5G communication channel with a study [15] proposing a deep-reinforcement model for energy efficient

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scheduling of resources. The Software Defined Networking (SDN) models based recommendation of service resource allocation is proposed in [16] under a federated learning for improvising the intrusion detection system for unauthorized users claim on resource scheduling requests. The study [17] includes the AI approach for task scheduling in IoMT-Cloud ecosystem with a similar UAV [18] based resource allocation on IoMT-agent in cloud servers for resource/task utilization. Further the study in [19][25] has significant observations on computation offloading and wireless IoMT devices management under fog-computing ecosystem.

III. METHOD AND MATERIALS

In a telemedicine infrastructure, navigating resource recommendation and computational sharing presents a significant challenge. Traditionally focused on facilitating doctor-patient interactions, telemedicine now incorporates IoT devices to ensure dependable communication and resource allocation based on user demand [20]. The proposed system adopts a decentralized approach, coordinating multiple user communities, including those from rural and urban backgrounds. These communities utilize dedicated IoT and IoMT devices, some of which operate with user intervention while others do not. This collective effort is tailored into a user layer, as depicted in Fig. 1. The user layer's primary responsibility lies in defining and optimizing collective data informatics and representation, organizing them in an indexed manner suitable for edge-computing operations.

The second layer within the IoMT device ecosystem, known as the Edge-Computing layer, serves as a pivotal component. This layer initiates the execution of federated learning models derived from local neural network computations and pattern extractions. Specifically, the local neural networking models are tailored to capture the intricacies of resource allocation and sharing through resource demand instructions. The generic representation of these models encompasses resource allocation patterns and resource scheduling schemas, including the frequency of resource requests. This entails independent management of edge and compute resources, ensuring efficient resource allocation within the edge-computing framework.

The novel federated resource pooling in telemedicine is an objective of development in this methodology. As represented in Fig. 1, the TinyML models via remote telemedicine devices assure a resource pooling for a specified task. Typically, the consideration of telemedicine services requires a dedicated resource schedulers and resource pool managers. The federated learning models deployed in remote (telemedicine) devices assure the congregation on resources demand and resource availability via a registered pool of resources. The optimal resources are allocated and shared until the demand exceeds maximum utilization limit. Typically, the utilization of resources and resource request is timely monitored and indexed in the edge computing layer. The extended decision support is further expanded via IoMT TinyML layers represented by Federated learning to extract and re-allocate edge-resource based decision making and indexing.

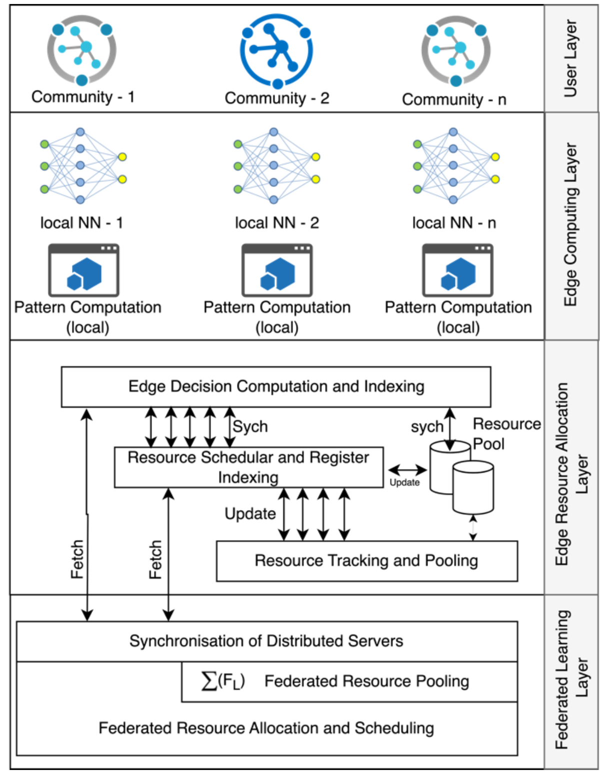

Fig. 1: Layer Distribution and Functionality validation of proposed federated learning based effective resource allocation of IoMT devices under Telemedicine services.

The federated learning approach is a collective processing of distributed servers connoted via edge servers and IoMT devices. The global model of FL is derived from the edge resource layer and federated resource pool alignment. This third layer is developed as a reflexing entity for edge-resource allocation and computation. The layer consists of edge decision computation with a managing and dynamic resource pool at centralized level coordinated within the local neural networking layers of an independent system or IoMT community. The reflecting community is the telemedicine user and expert arrangement and hence the coordination is required at higher reliable order such as dynamic resource pool management and synchronization. To keep the system dynamic, resource tracking and pooling is synchronized with resource allocation and scheduling register. These log consist of information symmetric to the resource request generated via independent communities (i.e.) Telemedicine users or communities. The overall agenda of this system is to develop a reliable resource pool and indexing for effective communication of resources across the users. On dynamic resource pool and indexing register, the federated learning (FL) models are appended and computed.

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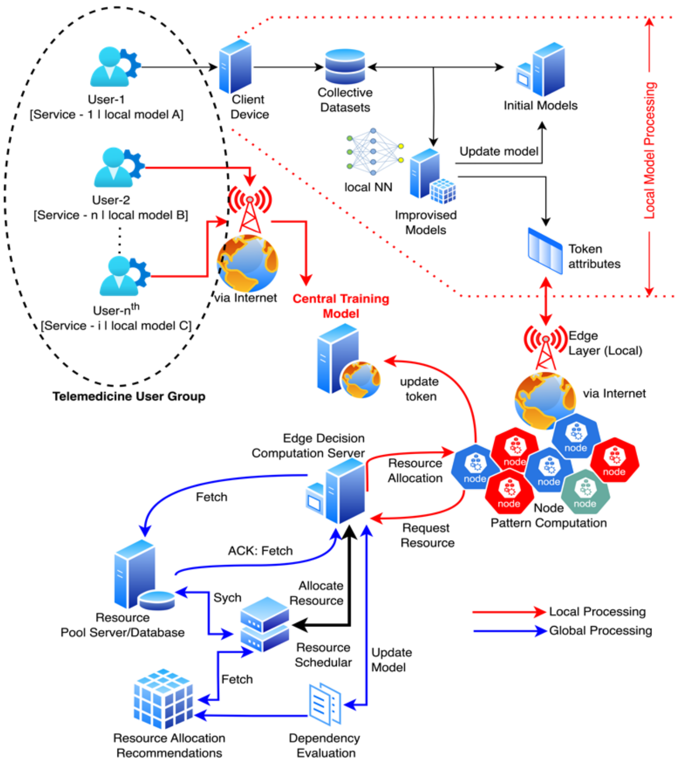

Fig. 2: Architectural model of proposed federated learning approach for consumer resource allocation and recommendation computation

Typically, the foundation of resource allocation is due to the increasing demand of resource request from the users (telemedicine) communities. The resultant learning and training from the federated model is synchronized at distributed servers for global federated model development. This includes, the novel federated resources pooling. The layer is computed with allocation and distribution of resource into multiple slots of requesting users and hence a dynamic scheduler and resources monitoring register is activated to assure balance in resources allocation. In general, the proposed system is aligned with IoMT devices and Telemedicine user's community for TinyML computation within edge-resources allocation. The framework is supported with multiple IoMT devices orders and corresponding environment to assure end-to-end resource sharing and clutter free execution. The designed system is reflected to resolve the conflict of residual resources such as expert allocation, appointment management, allocation of instruments and computational resources allocation are few of the prominent resources allocation in telemedicine framework. The detailed process of allocation and scheduling is represented in Fig. 2.

IV. TELEMEDICINE USER COMMUNITY BUILDING AND EDGE COMPUTATION MODEL ON LOCAL FEDERATED LEARNING

The user community in telemedicine environment is bound with multiple devices and hopping networks from device to computing servers. Consider (D) as devices included in the IoT and (D_M) as specific devices in IoMT environment. Then the telemedicine bound devices (D_T) are fetched from $(D_T \subseteq D_M)$ and $(\forall D_T \in D_M \subseteq D)$ with all operational value in standard approach of defined network (N_T) such that $(\forall D_T \Rightarrow \exists N_T)$ where each computing devices in $(D_T = D_{T1}, D_{T2}, D_{T3} \ldots\ldots D_{Tn})$ on $(\sum N_T \Rightarrow \sum(D_{Ti}).\Delta T)$ such that (ΔT) is the threshold hold time in communication for active informatics channel of (D_{Ti}) under (N_T). The process of building the network community (N_{TC}) on (D_T) device is monitored and validated under third party rules or third party service providers. Considering policy $(\prod_P)$ on operating devices (D_T) such that $(\forall \prod_P \in D_T)$ and optimization function of operating network (N_T) is defined as shown in Eq. 1.

$$N_T = \max_{N_T \in N}\left[L(D_{Ti}, N_{Tk}) \oplus \gamma \sum_{j=1}^{\infty}\left(\frac{\delta(D_T)_j}{\delta t}\right) \times \Delta T\right]_{(i,k)} \tag{1}$$

$$\therefore N_T = \max_{N_T \in N}\left[\frac{1}{\Delta T}\left\{\frac{(\Delta D_{Ti} \to N_{Tk})}{\Delta T}\right\} \oplus \gamma \sum_{j=1}^{\infty}\left(\frac{\delta(D_T)_j}{\delta \prod_P}\right) \times\right]_{(i,j,k)} \tag{2}$$

$$\therefore N_T = \max_{N_T \in N}\left[\left\{\frac{(\Delta D_{Ti} \cup \Delta D_{Tj})}{\Delta T}\right\} \oplus \gamma \sum_{j=1}^{\infty}\left(\frac{N_{Tk}}{\prod_P}\right) \times\right]_{(i,j,k)} \tag{3}$$

Thus from Eq. 1, the process of binding IoMT devices (ΔD_{Ti}) is monitored directly in networking order (N_{Tk}) whereas the Eq. 2 provides a reliable connectivity from $(\Delta D_{Ti} \to N_{Tk})$ at the time interval (ΔT) such that the governing policy $(\prod_P)$ is appended until the operating node (ΔD_{Ti}) is bound within the network (N_T). The thresholding (ΔT) time and networking in overall spectrum is (N) such that $(\forall N_T \in N)$ on a given time internal. The overall speed at which devices are monitored and added into the network (N_T) is directly dependent on third party policies $(\prod_P)$. Thus to belong to the network (N_T), a sub-group of networking (N_{Tk}) is generated and policies are monitored.

The process further deploys edge computation facilities to activate and validate the local federated learning model for individual communities of telemedicine users. Consider the local computational edge model as (M_i) such that $(\forall M_i \in M \in F_L)$ where (F_L) is the distributed federated

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learning model. The interconnected model (M_i, M_k) such that $(\forall(i,j)\in U)$ and (U) is the overall training model of universal FL set. Consider the global model (U) is recorded with smaller-aligned resources then, local model (M_i, M_k) is communicated provided $(\forall(M_i, M_k)\in \Delta\mathrm{T})$ where $(\Delta\mathrm{T})$ is the threshold time interval of resource sharing in edge devices (ΔD_{Ti}).

V. EDGE RESOURCE SCHEDULING AND INDEXING

The customized resources in edge devices (ΔD_{Ti}) are dependent on the factors such as resource availability and resource pooling. The demands for resource scheduling and customizing the availability with respect to the user (edge) devices are governed by edge-resource computation layer as shown in Fig. 1. The resource request from random device (ΔD_{Ti}) is computed against the resources demand threshold value and the mean time on resource occupancy with respect to the edge-devices based services. Consider the demand (ΔD) and the resource pool as (ΔP) with a random recommendation $(\square)$ such that $(\forall D_T \Rightarrow (\Delta D \cong \Delta P))$ at given time (t) interval. The given devices (D_T) are operated under (N_T) such that $(\forall D_T \in N_T)$ in the given operating instructions. The follow-up is represented in Eq. 4.

$$D_T = \sum_{i=1}^{\infty}\sum_{j=i+1}^{n}\left\{\left(\frac{\Delta D_i \oplus \Delta N_{Tj}}{\Delta t}\right)\oplus\int_{k}^{n}\left(\frac{\Delta(D_T)_k}{\Delta P}\right)\right\} \tag{4}$$

$$D_T = \sum_{i=1}^{\infty}\sum_{j=i+1}^{n}\left\{\int_{D_{Ti}}^{D_{Tn}}\left(\frac{\Delta D_i \oplus \Delta N_{Tj}}{\Delta P}\right)\right\} \tag{5}$$

Thus according to Eq. 4 and Eq. 5, the representation of resource allocation to requesting devices (D_T) is forwarded and governed by the Eq. 5 parameter and hence the resource at edge-computation layer is allocated. If the $(D_{Ti} \neq \Delta N_{Tj} \notin \Delta P)$ at given time (t), the capturing resource pool is validated and customized to process a federated learning model based resources allocation schema.

VI. FEDERATED LEARNING MODEL FOR RESOURCE ALLOCATION AND RECOMMENDATION

The optimized resource $(\Re)$ from the edge-computing layer is justified and released with (D_T) devices as shown in Eq. 5. Further to the customization, the TinyML principle is used to secure and relate the learning patterns of resource allocation and resource tracking via distributed learning models $(\sum D_{FL})$. Thus the aligned representation includes a customizable server and resource availability at the edge-computing later. In this section, the TinyML principle of distributed federated learning is used and developed for resources allocation and resources recommendation model. The process flow and representation is demonstrated in Fig. 2. The distributed federated learning models are further collaborated to generate a global model on training and testing of resources pooling, resources indexing and scheduling patterns.

Consider recommendation as $(\Re_R)$ and resource pooling as $(\Re_P)$ with resource indexing as $(\Re_I)$ and scheduling as $(\Re_S)$ such that $(\forall D_{FL} \Rightarrow \sum F_L)$ where $(\sum F_{Li})$ local occurrence model of federated learning at is distributed users such that $(\forall D_{FL} \Rightarrow D_{FL1}, D_{FL2}, D_{FL3}......)$ where (D_{FLi}) generative instance of local is federated learning model (ΔF_L), where $\left(\forall D_{FLi} \Rightarrow \left[(\Re_R \cup \Re_P) \to \Re_I \to \Re_S\right]_t\right)$, $(t \neq 0)$ and $(t \neq \infty)$ as the allocation of resources and de-allocation are equally customizable within a given time frame $(0 < t < \infty)$. The federated learning model (ΔF_L) can be represented as Eq. 6.

$$\Delta F_L = \lim_{n\to t}\left\{\int_{t=1}^{n}\sum_{i}^{n}\prod_{j=i+1}^{k}\left(\phi_{k\to t}\left[\Re_{(R,P,I)_{(i,j)}}, D_{T_i}\right]\right)\right\} \tag{6}$$

Thus, incoordination to limitation of networking infrastructure, the federated local models are substituted and calibrated as shown in Eq. 6. Typically, the oriented model of operation is dependent on group recommendation $(\Re)$ with respect to device (D_{T_i}) under open network (N_T). The federated resources recommendation $(\Re)$ is pooled with indexing and resources monitoring unit via a remote mapping and resources priority planning. The fundamental recommendation unit of resources $(\Re)$ is dependent on $(\sum \Re_P \oplus \Re_S)$ where $(\Re_P)$ resources priority is aligned with $(\Re_S)$ resources scheduling (i.e.) if $(\forall \Re_S \to \Re_P \Rightarrow alloc(\Re) \Rightarrow D_T)$ here, the alignment system is correlatively equivalent to the resource demand and requesting scenarios. The federated allocation model of increasing leaning patterns can be represented as Eq. 7.

$$\sum F_L \Rightarrow \lim_{n\to t}\iiint_{\Delta\mathrm{T}}\left\{\sum_{i=1}^{n}\left[\frac{\delta(\Re)_i}{\delta t}\cup\frac{\delta(D_T)_i}{\delta t}\right]\right\} \tag{7}$$

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$$\therefore \sum F_L \Rightarrow \lim_{n \to t} \iiint_t \left\{ \sum_{i=1}^{n} \left[\frac{\delta(\Re)_i \oplus \delta(D_T)_i}{\delta t} \right] \right\} \tag{8}$$

$$\therefore \sum F_L \Rightarrow \lim_{n \to t} \left\{ \int_v^t \sum_{i=1}^{n} \prod_{j=i+1} \left[\frac{\delta(\Re)_i \oplus \delta(D_T)_i}{\delta t} \cup \Delta \Re_P \right] \right\} \tag{9}$$

$$\therefore \sum^{\infty} F_L \Rightarrow \Delta F_L \big]_0 \oplus \Delta F_{L(i)} \big]_1 \oplus \Delta F_{L(i+1)} \big]_2 \oplus ..... \oplus \Delta F_{L(n)} \big]_\infty \tag{10}$$

$$\therefore \sum^{\infty} F_L \Rightarrow \sum_{i=0}^{n} \left[\Delta F_{L(i+1)} \big]_i \oplus \Delta (N_T)_i \right] \times \delta t \tag{11}$$

ALGORITHM: EDGE RESOURCE SCHEDULING

Input: edge devices (ΔD_{Ti}), resource pool (ΔP), network (N_T)

Output: Compute the requesting devices (D_T)

Computation:
START
Step-1: Compute the correlation mapping of edge devices and resource pool and fetch the requesting devices with $(\forall D_T \Rightarrow (\Delta D \cong \Delta P))$
Step-2: Compute the allocation of resources for edge devices $(D_{Ti} \neq \Delta N_{Tj} \notin \Delta P)$ at (t) instance
Step-3: generate optimizer $(\Re)$ for distributed learning model $(\sum D_{FL})$
Step-4: Computing Optimizer recommendation $(\Re_R)$ with resource indexing $(\Re_I)$ and resource scheduling $(\Re_S)$ from local federated model $(\sum F_{Li})$
Step-5: if Allocate resource $(\forall \Re_S \to \Re_P \Rightarrow alloc(\Re) \Rightarrow D_T)$
Then allocate resource (D_T) and return value time
. else return resources to (ΔP) and
end if
END

Thus according to federated learning model in Eq. 8, the recommendation process and the devices are directly connected within a time interval (t) and accepted range of devices (D_T) alias as (v) allowed in the operations phase. Technically, the model (local FL) is assigned with recommendation priority $(\Re_P)$ and the (ΔF_L) model assigned to it. Thus in Eq. 11, the equivalent contributions are reflected and summarized as $(\sum F_L)$ with operating network (N_T) for the purpose of learning.

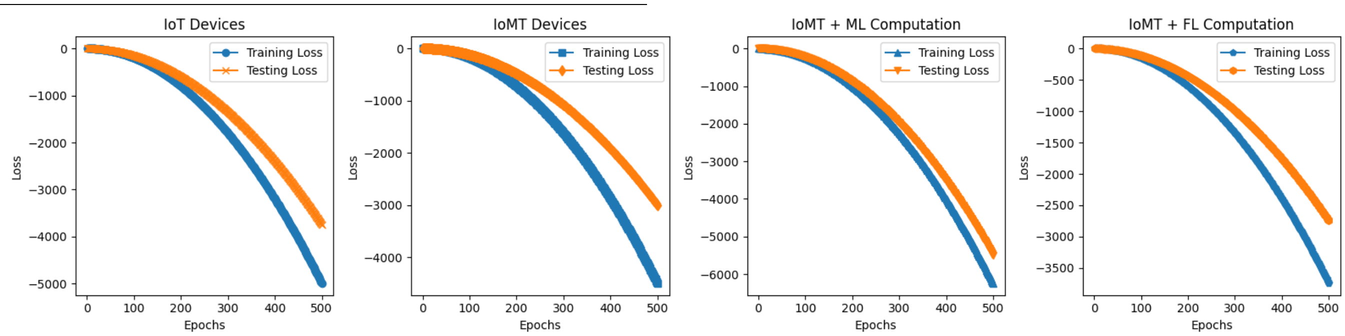

Fig. 3: Training and testing of IoT, IoMT, IoMT + ML Computation model and IoMT + FL Computation model with 500 Epoch

VII. RESULTS AND DISCUSSIONS

The medical IoT (IoMT) devices (D_T) connected in the given monitored network (N_T) is computed and validated on resources allocation and resources scheduling. The proposed framework is developed on the interdependency principle of local federated learning models development and the local FL models $(\sum F_L)$ is computed under distributed infrastructure to allocate telemedicine IoMT resources. The technique is developed on TelMED [22] infrastructure protocol standards on Multi-Objective Optimal Medical (MooM) [21] datasets transmission. The proposed technique has extracted datasets from OpenIoT access repository for resources demand and request pool creation [23 – 24]. The federated learning models are further expanded and evaluated within training and testing phases for effective resources sharing. The Table. 1 demonstrates the cluster size from

4 to 128 in the proposed system whereas the TelMED [22] was computed on 32 clusters max. The observation is recorded on the primary parameter of average waiting time and average life span of active node if allocated the resources is recorded and observed. A structural comparative representation of numerical data representation [26] and federated medical data structuring in [27] for representative analysis.

Table. 1: Comparative analysis on community building with IoT/IoMT infrastructure

Cluster size (nodes)	Community Devices			Avg. waiting time (ms)	Avg. Life_span of nodes (ms)
	IoT	IoMT	IoX		
4	1	2	1	0.321	7.232
8	2	5	1	0.472	8.621
16	7	7	2	0.411	8.917
32	14	14	4	0.500	8.882
64	28	28	8	0.507	8.8917
128	64	60	4	0.511	8.8732

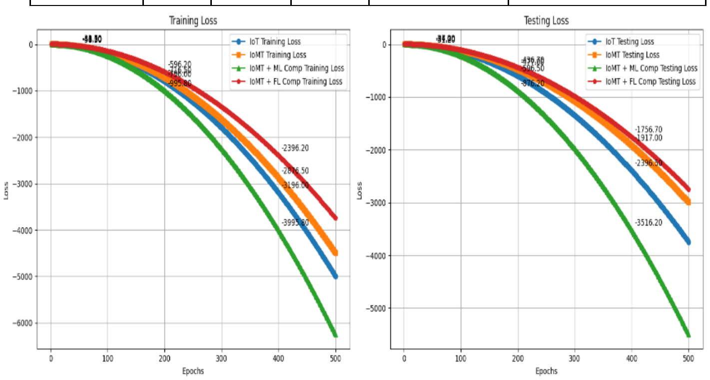

Fig. 4: Recording the training and testing losses under the IoT, IoMT, IoMT + ML Computation model and IoMT + FL Computation model

The occurrence is saturated under the proposed framework from 64 cluster onwards until the 128th cluster node size with minimal waiting time to be 0.507ms to 0.511ms with a difference of 0.004ms thus resulting in enhancing the life span of the active nodes. The training and testing is computed on NVIDIA A40 GPU cards with resource recommendation and resource scheduling models. Fig. 3 demonstrated the training and testing losses incurred with the ratio of devices data computed such as IoT, IoMT, IoMT with ML computations and IoMT with FL computations. These losses are recorded with 500 epochs for higher saturation and effectiveness in resource pattern mapping and learning. The overall training and testing loses in a cumulative form is represented in Fig. 4, with Fig. 4 (Left) is dedicated for the training loss representation and Fig. 4 (Right) is dedicated for testing loss representation. The process has recorded an improvised loss optimization in testing as an observation. In Fig. 5, the clusters of Telemedicine communities are aligned and mapped, the training of clusters from the size 4 to 128 is mapped with respect to the device pattern models for resource requisition and demanding as per Fig. 3 and Fig. 4 respectively.

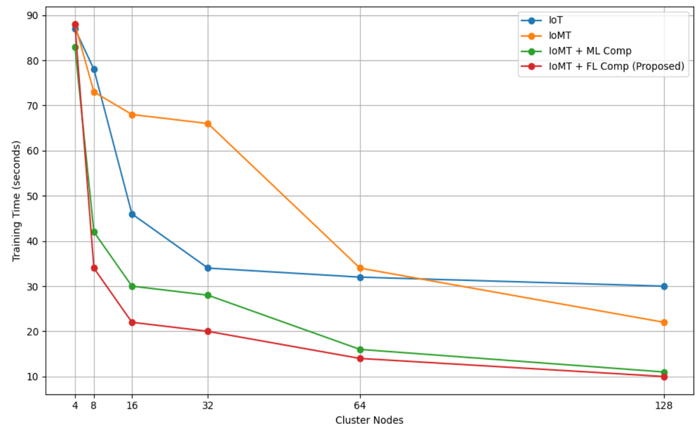

Fig. 5: Training clusters time management and representation of IoT , IoMT, IoMT + ML Computation model and IoMT + FL Computation model

The overall model (local + global) collectively is termed as federated learning model, in Fig. 6, we have demonstrated the representation of local federated learning model against global federate learning model. The global model is fetching information and learning patterns from the local models and hence the local models are swift in decision making at the edge, whereas the dependency is mapped with global FL models for customizing the decision making capabilities as per the raising demand for the resources. The recommendation models accuracy is plotted in Table. 2 with a performance computation of rural and urban telemedicine communities. The representation highlights the process of node alignment and load balancing with respect to average waiting time computation. As per the observation recorded, the saturation of recommendation accuracy is fetched since 3200 nodes (IoT devices) up-to 12800 nodes. The best average waiting time is 0.226ms with 89.27% accuracy in rural telemedicine communities and 0.452ms with 92.33% accuracy in urban communities. The overall performance matrix is compared with TelMED protocol and the same is represented in Table. 3 with a collective accuracy of 94.23% in resource recommendation via Federated learning models or TinyML computations at rural experimental setup and 95.11% in urban computation.

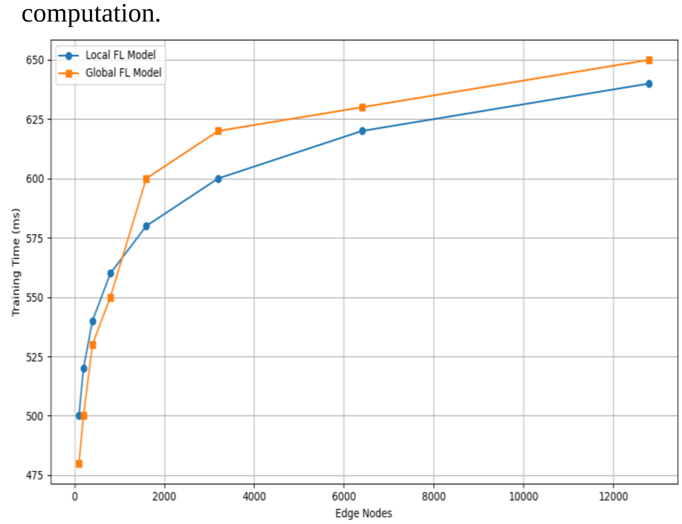

Fig. 6: Local and Global Federated Learning model training instances on 12800 nodes

Table. 2: Performance computation on with variable node size on rural and urban telemedicine communities

Node size (IoT devices)	Rural Communities		Urban Communities	
	Avg. waiting time (ms)	Recommendation accuracy (%)	Avg. waiting time (ms)	Recommendation accuracy (%)
100	0.8172	92.11	0.072	96.32
200	0.8111	91.72	0.087	96.11
400	0.627	90.64	0.091	95.62
800	0.514	84.64	0.246	94.23
1600	0.412	85.72	0.341	91.72
3200	0.412	88.11	0.472	91.11
6400	0.226	89.27	0.411	91.92
12800	0.273	89.67	0.452	92.33

Table. 3: Performance comparison with proposed FL based recommendation system with respect to the TelMED protocol based recommendation model

Technique	F1 Score (%)	Precision (%)	Accuracy (%)
TelMED[22]	91.11	62.42	92.30
Proposed (IoMT + FL) – Rural	94.23	78.14	94.72
Proposed (IoMT + FL) – Urban	95.11	79.72	93.21

VIII. CONCLUSION

The novel framework on resource recommendation based model for medical consumer device resource allocation and sharing, implemented through Federated Learning (FL) models and edge computation layers, demonstrates promising results in the realm of Remote Medical IoT devices and Telemedicine computation. By analyzing resource utilization patterns at individual user levels and integrating location-specific insights, the framework offers efficient resource management and scheduling solutions. The framework's deployment across rural and urban IoT device clusters, coupled with the TelMED protocol, showcases considerable efficiency rates, indicating its potential to significantly impact healthcare delivery. The proposed technique is improvised with a demonstrated accuracy of 94.72% in rural edge-IoMT setup and 93.21% in urban area. Future research could further refine algorithms, enhance scalability and privacy measures, and explore integration with emerging technologies to advance Telemedicine applications.

Acknowledgement: This work was supported by Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2025R432), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia

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