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Collaborative Healthcare Data Management Framework using Parallel Computing and the Internet of Things

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ABSTRACT Healthcare data management has become a critical research area, primarily driven by the widespread adoption of personal health monitoring systems and applications. These systems generate an immense volume of data, necessitating efficient and reliable management solutions for lossless sharing. This article introduces a Collaborative Data Management Framework (CDMF) that leverages the combined strengths of parallel computing and federated learning. The proposed CDMF is designed to achieve two primary objectives: reducing computational complexity in data handling and ensuring high sharing accuracy, regardless of the data generation rate. The framework employs parallel computing to streamline the scheduling and processing of data acquired at various intervals. This approach minimizes processing delays by operating on a less complex scheduling algorithm, making it suitable for handling high-frequency data generation. Federated learning, on the other hand, plays a pivotal role in verifying data distribution and maintaining sharing accuracy. By enabling decentralized learning, federated learning ensures that data remains on local devices while sharing only the necessary model updates. This approach enhances privacy and security, a critical consideration in healthcare data management. It ensures that data distribution and sharing are verified based on appropriate requests while avoiding latency issues. By decentralizing the learning process, federated learning enhances privacy and security, as raw data does not leave the local systems. This cooperative interaction between parallel computing and federated learning operates in a cyclic manner, allowing the framework to adapt dynamically to increasing monitoring intervals and varying data rates. The performance of the CDMF is validated through improvements in two key metrics. First, the framework achieves a 15.08% enhancement in sharing accuracy, which is vital for maintaining data integrity and reliability during transfers. Second, it reduces computation complexity by 9.48%, even when handling maximum data rates. These results highlight the framework's potential to revolutionize healthcare data management by addressing the dual challenges of scalability and accuracy.

INDEX TERMS Cooperative Scheduling, Federated Learning, Healthcare Data, Parallel Computing, Sharing Accuracy

I. INTRODUCTION

Healthcare data management using the Internet of Things (IoT) is used in healthcare data monitoring and applications. IoT is used to enhance the efficiency range of the data management process [1]. A private blockchain-based cloud IoT (PBCI) model is used for data management in healthcare applications. The PBCI model provides necessary policies to analyze the data which are gathered from various wearable sensor devices [2]. The model also evaluates the feasible data that are used during the data sharing and transmission process. The PBCI model provides restrictions to patient data to secure personal data access among third parties [3]. The model enlarges the feasibility and performance range of the healthcare data management process. An improved IoT-enabled healthcare data management framework is also used for applications. The framework monitors the data which produces feasible information for disease diagnosis services. The data management framework analyzes the features which are needed to be managed in a secure database. The framework also reduces the computational complexity and latency level of healthcare applications [4, 5]. Machine learning (ML) enabled computing techniques are used for healthcare data management using IoT technology [6]. An ant lion optimizer (ALO) with a hybrid deep learning (DL)

TABLE 1
Summary of the Related works

Author Name	Method Used	Advantages	Disadvantages
Ahamed et al. [12]	An energy efficient healthcare data management method (EE-HDMM).	Improves the precision, efficiency, and sensitivity rate.	It creates communication delays.
Jan and Sofi [13]	Data management for resource optimization.	Optimizes the problems of the systems.	Data management is limited to a minimum set of users.
Zeshan et al. [15]	An Internet of Things (IoT) enabled ontology-based intelligent framework.	Maximizes the accuracy of the systems.	Precision needs to be increased.
Misra et al. [16]	Software defined network (SDN) controlled resource-tailored analytics.	Minimizes the network response time.	
Lakshmanan et al. [17]	Multimodal healthcare data classification method.	Increases the accuracy, efficiency, and specificity of the systems.	High complexity and computations required
Manogaran et al. [18]	Integrative meta-heuristic framework for monitoring system.	Enhances the privacy and security of the healthcare data.	
Johri et al. [19]	Machine learning-enabled method for e-healthcare systems.	Enlarges the Quality of Service (QoS) rate of the systems.	Shortcomings in request handling and maximum data support
Zeydan et al. [20]	Distributed machine learning lifecycle management method.	Improves the effectiveness of the systems.	Lack of privacy and robustness.

algorithm is used as a data management technique for healthcare systems. The ALO is used to evaluate the feature vectors which are necessary for data management services. The DL algorithm employed in the framework to detect feasible healthcare data for further detection and prediction processes. The ALO-based framework enlarges the accuracy in providing healthcare services to patients [7, 8]. A federated deep recurrent neural network (FDRNN) based data management model is used for healthcare systems. The FDRNN algorithm processes the data that are required for resource allocation and scheduling processes. IoT is used in the model to improve the significance ratio of healthcare information during data sharing. The FDRNN algorithm predicts the requirement of healthcare data and provides a feasible solution to manage data. The algorithm also elevates the quality range of healthcare data in monitoring and management systems [9, 10]. The contributions of the article are:

1) To study different existing methods related to healthcare data management based on access, storage, application response, etc. using various learning methodologies
2) To propose a novel collaborative data management framework using parallel computing and federated learning concepts to improve sharing accuracy
3) To validate the proposed framework's performance using sharing accuracy, computation complexity, response latency, and scheduling rate metrics
4) To verify the proposed framework's efficiency through a comparative analysis with the existing EE-HDMM [12] and OIHF [15] methods

The article's organization is: Section 2 presents the related works followed by the proposed framework's discussion with illustration in Section 3. Section 4 portrays a comparative analysis of the performance metrics using comparative analysis. Section 5 presents the conclusion of the article with limitations and future scope.

II. Related Works

Agarwal and Pal [11] developed a hierarchical blockchain (BC) based data management framework for smart healthcare applications. The framework uses Internet of Things (IoT) enabled sensor nodes to gather the optimal data for the management process. The developed framework identifies the data which are needed to be managed for further disease detection and diagnosis processes. The developed framework maximizes the performance and scalability of the healthcare applications.

Ahamed et al. [12] proposed an energy-efficient healthcare data management method (EE-HDMM). IoT-assisted wearable sensors and devices are used here which monitor the relevant datasets. It is used in healthcare monitoring applications which enhance the effectiveness of the resource allocation process. The EE-HDMM decreases the computational cost and energy consumption ratio of the systems. The proposed EE-HDMM increases the accuracy and efficiency range of the healthcare systems.

Jan and Sofi [13] introduced a data management model for resource optimization in medical IoT applications. The model analyzes the necessary constraints and provides feasible solutions to solve the optimization problems. The introduced model optimizes the issues which enlarges the precision of resource allocation and scheduling processes. The introduced model elevates the optimization process in healthcare applications.

Mishra et al. [14] designed an integration of BC with the inter-planetary file system (IPFS) for data management and sharing in IoT environments. The designed framework is used to secure the data and to decrease the data loss ratio during sharing and management. The IPFS is used here to access the healthcare data according to authorization which minimizes the latency. Experimental results show that the designed framework improves the performance and significance range of the applications.

Zeshan et al. [15] developed an IoT-enabled ontology-based intelligent healthcare framework for remote patient monitoring systems. The developed framework analyzes the healthcare data and identifies the crucial health condition of the patients via remote systems. The developed framework achieves high accuracy during patient monitoring. The framework also enhances the quality of service (QoS) of healthcare systems.

Misra et al. [16] proposed a new software-defined network (SDN) controlled resource-tailored analytics for healthcare IoT systems. The proposed model is used to analyze the actual priority range of resources that are required for services. The model is used to allocate the resources as per necessity which eliminates the time consumption range of the process. When compared with others, the proposed model maximizes the scalability and efficiency level of the healthcare systems. Lakshmanan et al. [17] designed an IoT-BC-based fused conventional neural network (FCNN) for healthcare data classification. A tangent Namib beetle optimization (TNBO) is employed here to measure the routing services for the classification process. IoT-enabled healthcare devices are used in the method that collects optimal healthcare data via wireless sensors. The designed method increases the accuracy and specificity range of the data classification process.

Manogaran et al. [18] introduced an integrating meta-heuristic with data networking for edge computing in IoT-enabled healthcare monitoring systems. It is used as a significant model which analyses and facilitates the data which are gathered from monitoring systems. The model also produces necessary healthcare data while performing diagnosis and detection processes. The introduced model enlarges the performance level of the monitoring systems.

Johri et al. [19] developed a machine learning (ML) based fog computing network for e-healthcare systems. The developed method is used to decrease the delay rate while performing healthcare services to the users. The ML algorithm is used here to analyze the optimal dataset for data management and classification processes. The developed method maximizes the overall QoS range of the healthcare systems.

Zeydan et al. [20] proposed a distributed ML lifecycle for healthcare data in the cloud. The proposed model uses a federated learning (FL) algorithm to evaluate the healthcare data for further processes. It is used to secure data sharing and exchange services among healthcare applications. Experimental results show that the proposed model enhances the effectiveness level of healthcare applications.

Zhang [22] designed a quantum healthcare analysis method based on smart IoT devices. Edge computing technology is used here which provides optimal edge nodes (EN) for analysis. The EN produces an effective set of healthcare data that are examined for diagnosis services. The designed method elevates the overall QoS rate via wireless sensor devices. The designed analysis method improves the performance and significance range of healthcare applications. A summary of the advantages and shortcomings of the above methods are detailed in TABLE 1. This tabulation is presented to relate the possibilities of the proposed method covering the possible drawbacks in the existing methods.

The framework proposed in this article combines optimal functions of parallel computing and federated learning to improve the sharing accuracy of medical data management. As volumes of data are generated from wearable sensors and personalized healthcare applications, handling them with precision is mandatory. This requires congestion and complex free management with concurrent request and response handling characteristics. Considering the significance of the healthcare data, the proposed management framework augments scheduling, less complex sharing, and response processing features.

III. PROPOSED COLLABORATIVE DATA MANAGEMENT FRAMEWORK

A. FRAMEWORK INTRODUCTION

The proposed framework is projected to satisfy high-precision health data management through processing and accurate sharing. To serve this purpose the framework incorporates parallel computing and federated learning concepts. This framework achieves the objective of low computation complexity for high sharing accuracy regardless of the data rate and observation intervals. These features facilitate interrupt-free health data storage, retrieval, and organization. The proposed framework is illustrated below.

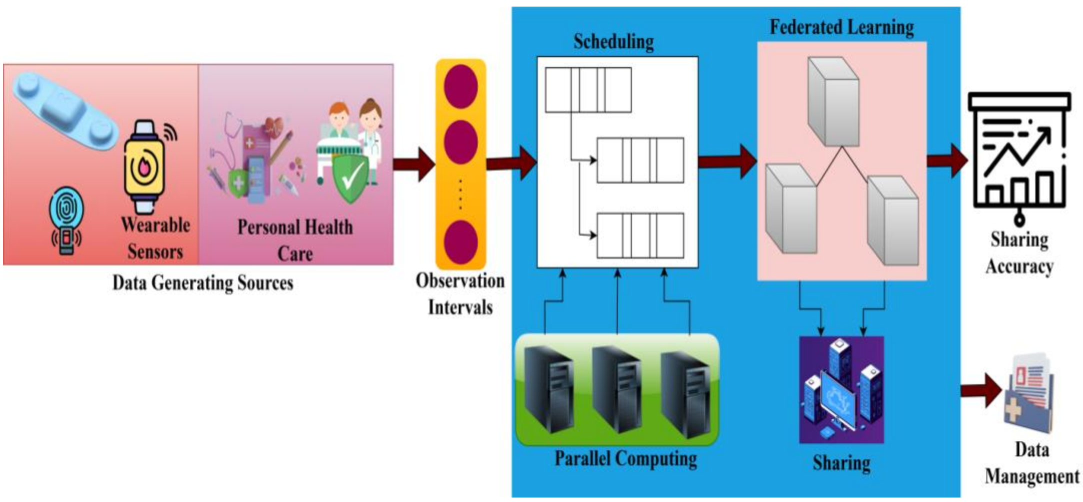

FIGURE 1. CDM Framework Illustration

The CDM framework is diagrammatically illustrated in FIGURE 1 above. The data generating sources such as wearable sensors occupy different intervals to communicate data between various schedules. The scheduling intervals offload the data from one interval to another depending on the number of sharing intervals to reduce the complexity. In this framework, the federated learning concept is employed to ensure maximum support to the scheduling allocation demands such that maximum responses are generated. Based on this recurrent learning process, from the previous allocations, the data management and sharing accuracy are improved. Any change in these factors result in scheduling modification and interval allocation. The data-generating sources usually comprise personal healthcare applications and wearable sensors operating at regulated observation intervals (t_o). The accumulated data is scheduled before storage and after request processing to maximize interrupt-free sharing. This scheduling is governed by the parallel computing process by dividing t_s sharing intervals. The learning is responsible for verifying the (s_a) sharing accuracy is maximum in t_s. This refers to the appropriate response (through data sharing) for the processed request is distributed in t_s. Using this framework, the objectives are defined in Eq. (1) [9].

From the Eq. (1) [9], the first derivative is the computation complexity (ρ_c) reduction for user requests (R_q) and data response (R_s). In the second derivation, the scheduling rate (s_c) directly influences the s_a for maximum R_s. The third is the balancing condition between R_q and R_s for maximum s_a. To achieve this objective parallel computing and federated learning concepts are employed within the framework. These processes are explained in the following sub-sections.

$$\begin{gathered}\forall R_q \; observerd \; in \; t_o, \qquad \rho_c \forall s_a \; must \; be \; argmin_{R_s}\{1,2,\ldots,i\} \; such \; that \; i \in t_s \\ \forall R_s \; processed \; in \; t_s, \left(\frac{1}{R_q \times t_o}\right) \alpha\left(s_c \times R_q\right) \; provided \; argmax_{s_a}\{1,2,\ldots,j\}, j \in R_s \\ and \; \left(R_q \times t_o\right)\alpha\left(s_c \times R_q\right)\alpha\left(R_s \times t_s\right)\forall s_a = 1(maximum)\end{gathered} \tag{1}$$

B. SCHEDULING PROCESS USING PARALLEL COMPUTING

The target operation of this process is to organize health data through the precise implication of s_c using m computing systems. The objective is to maximize the $\frac{R_s}{R_q}$ by reducing ρ_c under different t_s. Before the t_s allocation, the data accumulated through t_o is split for storage and R_s generation. Using the m computing systems, t_o intervals are divided to meet the R_q where ρ_c is observed. This ρ_c is observed between t_o and t_s increases the actual t_s for which the stagnancy is R_s is observed. This stagnancy results in latency and causes interruption to new R_q generated after t_s. Therefore, the s_c allocation is required to be balancing t_o and t_s without ρ_c.

In Eq. (2) [10] , the variable t_a defines the allocation time for the incoming data provided scheduling is required. In a consistent allocation case, $\rho_c = maximum$ is unavoidable that is to be thwarted to ensure maximum accuracy. Therefore, the s_c problem is defined as handling $(t_s - t_o) > 0$ conditions defined in Eq. (3) [12].

$$\left.\begin{gathered}\rho_c = \frac{t_s - t_o + t_a}{R_q} \\ where \; t_s - t_o = 0 \forall \rho_c = 0 \; in \; any \; t_s \\ else \; (t_s - t_o) > 0 \forall \rho_c = maximum \; and \; t_s = t_s + 1 \\ (or) \; (t_s - t_o) < 0 \forall \rho_c = minimum \; and \; t_o = t_o + 1\end{gathered}\right\} \tag{2}$$

$$\left.\begin{array}{c|c} s_c \forall t_1 = \frac{R_1}{m} & s_c \forall t_1 = \frac{R_1}{R_q} \\ s_c \forall t_2 = \frac{R_2}{m} + (t_1 - t_s) & s_c \forall t_2 = \frac{R_2}{R_q} - (\rho_c * R_q) \\ \vdots & \vdots \\ s_c \forall t_o = \frac{R_q}{m} + (t_{o-1} - t_s) & s_c \forall t_s = \frac{R_s}{R_q} - (\rho_c * R_{s-1}) \end{array}\right\} \text{3)}$$

The above scheduling Eq. (3) [12] requirements defined balance both R_q and R_s such that t_o synchronizes with the t_s for any quantity of data rate observed. This case is valid until m is capable of handling R_q in any t_o; if the capacity exceeds the maximum R_q acceptance rate, then offloaded schedules are pursued. This s_c process for t_o and t_s is diagrammatically illustrated in FIGURE 2.

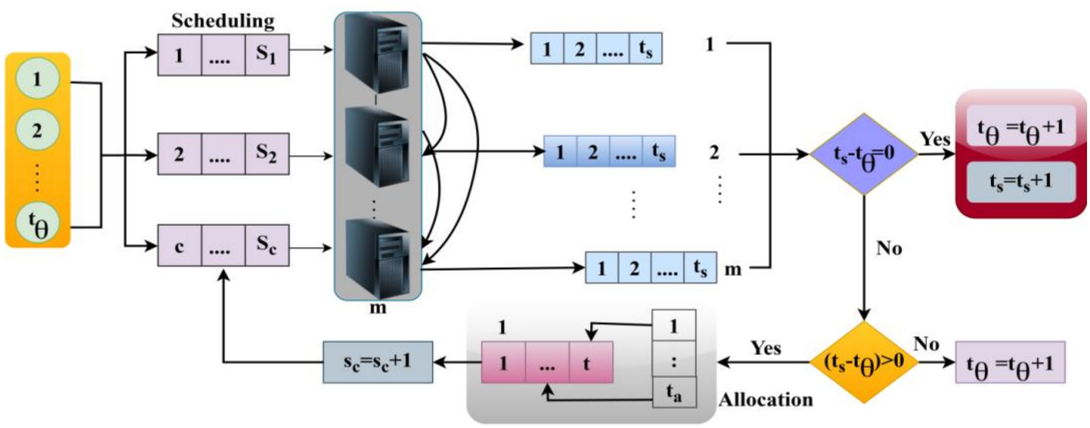

FIGURE 2. s_c Process Representation

The process of s_c decision is described using the maximum t_θ under varying t_s. The incremental cases of t_s and t_θ decides that s_c is high whereas the failure requires a new allocation instance. Depending on the utilized t, the next schedule is decided and therefore the number of m allocated is reliable (after previous s_c); the contrary case requires additional m to meet the s_c requirements. The case of $[(t_s - t_o) > 0]$ is the ρ_c (maximum) causing conditions identified in different t_s. For this purpose, the m dependent s_c includes t_a for multiple t_o and t_s

$$\left.\begin{array}{c|c} \rho_m(1) = \left(\frac{t_o}{t_a}\right)_1 + \rho_{c_1} * \left(1 - \frac{R_s}{R_q}\right)_1 & t_{a_1} = (t_o - t_s)_1 - \rho_{c_1}\left(\frac{R_{q_1}}{m}\right) \\ \rho_m(2) = \left(\frac{t_o}{t_a}\right) + \rho_{c_2}\left(1 - \frac{R_s}{R_q}\right)_2 & t_{a_2} = (t_o - t_s)_2 - \rho_{c_2}\left(\frac{R_{q_2}}{m}\right) \\ \vdots & \vdots \\ \rho_m(t_s) = \left(\frac{t_o}{t_a \cdot t_s}\right) + \rho_{c_{t_s}}\left(1 - \frac{R_s}{R_a}\right) & t_{a_{R_s}} = (t_o - t_s)_{R_s} - \rho_{c_{R_s}}\left(\frac{R_{q_{R_s}}}{m}\right) \end{array}\right\} \tag{4}$$

The above allocation in Eq. (4) [11] is based on t_a and R_s such that the difference between $(t_o - t_s)$ is less. In this case, the available m is allocated to handle the maximum R_q in t_o to reduce t_a and thereby ρ_c. However, the stagnancy for R_q (without R_s) needs to be mitigated along the parallel provided $\left[\frac{R_q}{m} + (t_o - t_s) = \frac{R_s}{R_q} - (\rho_c * R_s)\right]$. If in this case, t_o and t_s are the same, then $\left(\frac{R_q}{m} = \frac{R_s}{R_q}\right)$ and if R_s and R_q are the same, then $R_q = m = R_s$ is the maximum scheduling case achieved. This refers to the maximum m with s_c to enhance the t_a between t_s and t_o. Therefore, the ρ_c is optimally 0 for which m allocation or s_c increment is not required. In the alternate case of $(t_o = t_o + 1)$ or $(t_s = t_s + 1)$, the m schedules are incremented with due data acquisition. If ρ_m defines the parallel s_c processes between t_s and t_o, then computations of t_o. This requires the distribution of R_s for maximum accurate R_q observed. The verification of the same is analyzed using federated learning discussed below.

C. FEDERATED LEARNING FOR SHARING ACCURACY ASSESSMENT

The learning process validates the $\frac{R_s}{R_q}$ for maximum sharing accuracy in any t_s. The learning process identifies ρ_c and ρ_m for multiple t_a to validate the $(t_o - t_s)$ difference. The learning process model for sharing accuracy assessment is illustrated in FIGURE 3 below.

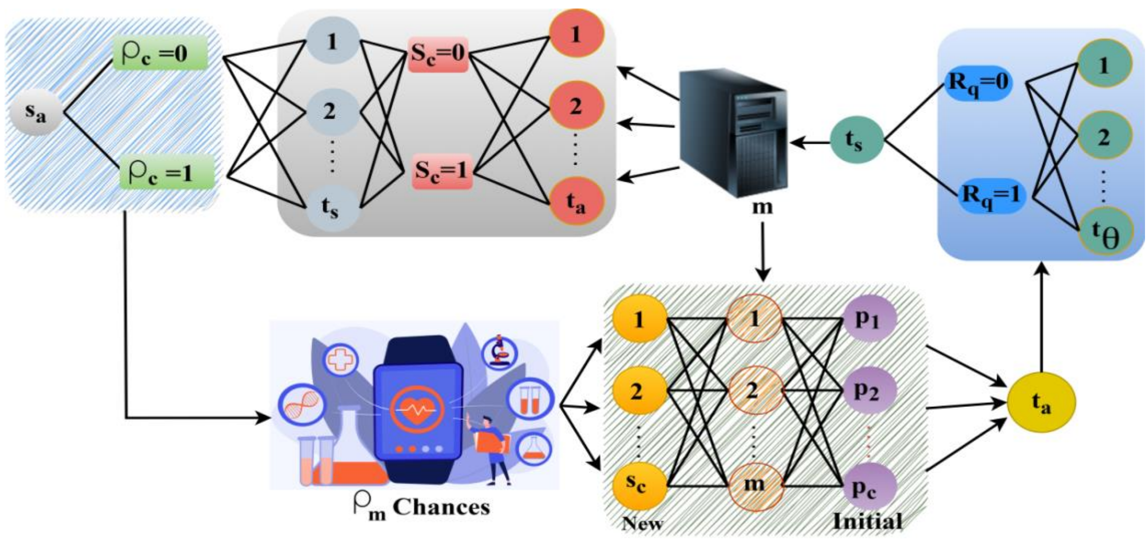

FIGURE 3. FL Process Illustration for s_a Analysis

The FL process is described as in the above FIGURE 3 number of possible chances of ρ_m. Based on the available m, the need for R_q satisfaction is decided and a parallel process is decided. This parallel process includes the t_s allocation and t_θ assignment. In this assignment case, the cases of new s_c and p_c are utilized to ensure maximum of ρ_c is achieved. If this is maximum, then maximum requests are responded and therefore the t_a is reliable. The entire process is recurrent to the number of m availability and the maximum chances observed for response generation. Depending on the number of t_s the dependability between the iterated learning is decided. Therefore, the maximum response generated is optimal to enhance the need for p_c. The ρ_c is either true or false based on the The $\frac{R_s}{R_q}$ for s_a maximization is validated using conventional s_c and its new output. The ρ_c for initial and intermediate (after t_a) are estimated cyclically to maximize m allocation. Based on the m allocation, the ρ_c at initial and t_a intervals are identified. Considering the need for new t_a, the R_q acceptance for s_c or R_s is defined. In this case, the t_s cycles are repeated until m is free. This case is optimal for s_c that achieves high s_a that is concurrently verified using Eq. (5) [13].

$$\left.\begin{array}{c|c} s_{a_1} = \frac{R_{s_1}}{R_{q_1}} & \\ s_{a_2} = \frac{R_{s_2}}{R_{q_2}} - \frac{\rho_{m_1}}{\left(m \times \frac{1}{t_a}\right)_1} & \rho_{c_1} = 0 \\ \vdots & \rho_{c_2} = t_{a_1} - t_{s_2} \\ s_{a_{t_s}} = \frac{R_{s_{t_s}}}{R_{q_{t_s}}} - \frac{\rho_{m_{t_s-1}}}{\left(m \times \frac{1}{t_a}\right)_{t_s-1}} & \vdots \\ & \rho_{c_m} = t_{a_{m-1}} - t_{s_m} \end{array}\right\} \tag{5}$$

The above computation in Eq.(5) [13] is pursued for m devices t_s intervals to maximize the chances of ρ_m. If ρ_m is maximized, then s_a achieved is high satisfying the second constraint of Eq.(1) [9]. In particular, the t_a and ρ_c initial and intermediate are validated using multiple t_θ non-replicated t_s intervals. For the appropriate t_θ, the $\rho_c$is estimated from the previous interval such that the need for $\left(1-\frac{R_s}{R_q}\right)$ is less in any m. Besides the health data handling follows new t_a under varying $(t_\theta - t_s)$ interval to ensure high sharing accuracy. Similar to the other learning methods the above process is also iterated based on ρ_m and s_c available under $(t_\theta - t_s)$interval to ensure high sharing accuracy. Similar to the other learning methods the above process is also iterated based on ρ_m and s_c available under $\left(t_\theta \propto R_q\right)$ or $(s_c \propto R_s)$ for which the learning model is trained.

IV. RESULTS

The results and discussion section presents the metric-based outputs computed from an experimental scenario modeled in a standalone computer. The data from [21] is loaded in the divisional storage and is set to be accessed by 30 users with 2 requests/ second.

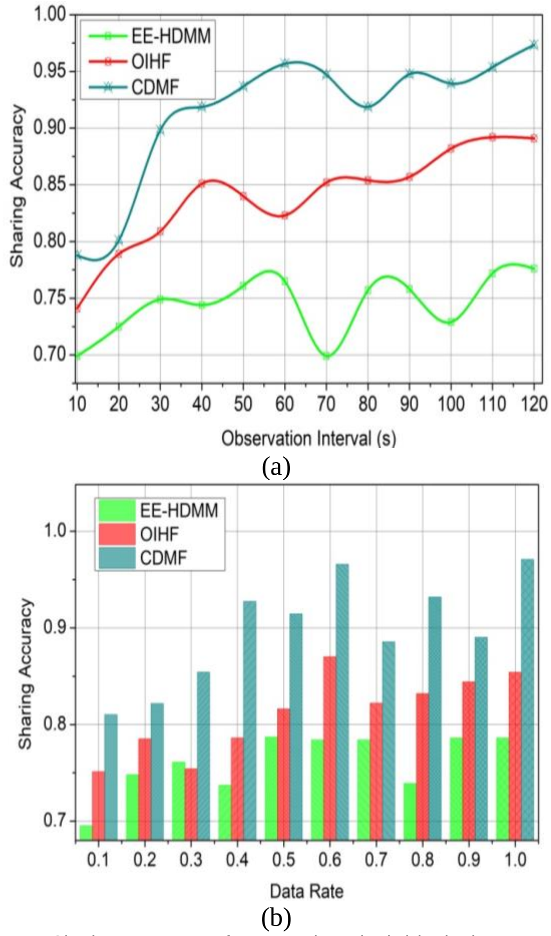

FIGURE 4. Sharing Accuracy of proposed method (a) sharing accuracy vs Observation Interval, (b) sharing accuracy vs Data Rate

The response is provided in the form of statistical values related to the user query. The dataset provides basic information on the patient's health features such as dehydration, acidic nature, cold, cough, heart rate, blood pressure, etc. observed at regular intervals. The processing units for request query and response handling are set as 4 that runs on 8schedules/ min. Using this information, the metrics sharing accuracy, computation complexity, response latency, and scheduling rates are estimated. These metrics are analyzed using the variants: observation interval ranging from 10s to 120s and data rate ranging between 0.1 and 1.0. 0.1 refers to a single user query whereas 1.0 refers to the 30 user queries accepted at the same interval. For an effective validation of the proposed framework, it is compared with the existing EE-HDMM [12] and OIHF [15] methods discussed in Section 2.

A. SHARING ACCURACY

The comparative analysis of sharing accuracy for t_θ and data rates [23] are presented in FIGURE 4. The proposed framework incorporates ρ_c mitigation and ρ_m maximization features using parallel computing and federated learning paradigms. The target of $\frac{R_s}{R_q} = s_a = 1$ (maximum) is achievable using $(s_c \times t_a)$ and t_s balancing factors. Apart from the m allocation instances, the need for $(\rho_c * R_s)$ is identified if $(t_\theta - t_a) > 0$ from where the learning classifies the initial and intermediate sharing factors to augment the maximum s_a. Therefore for t_θ and t_a the allocation is optimal to ensure high sharing accuracy through $(t_\theta - t_a)$ reduction.

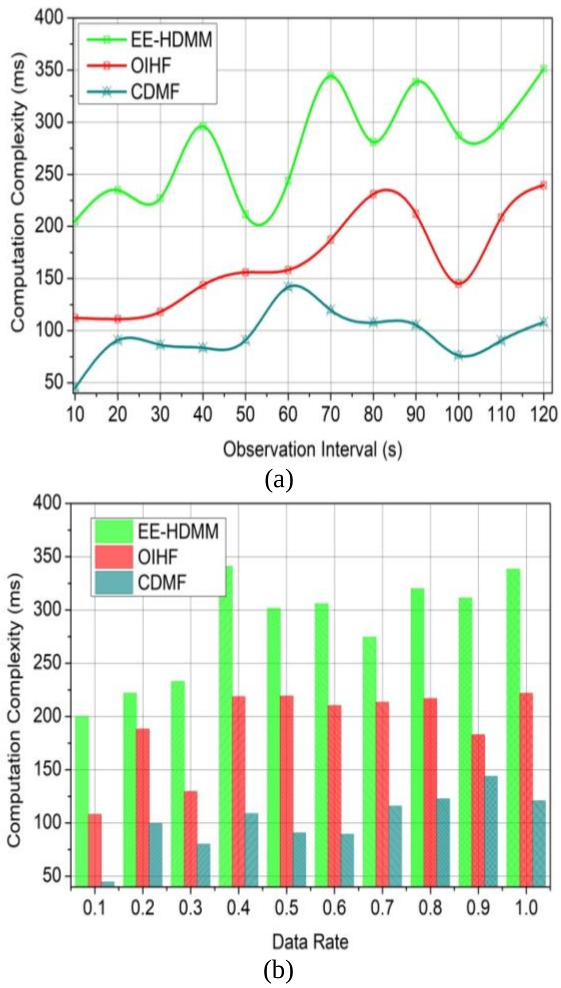

FIGURE 5. Computation Complexity of proposed method (a) Computational complexity vs Observation Interval (b) Computational complexity vs Data Rate

B. COMPUTATION COMPLEXITY

In FIGURE 5 the comparative analysis for computation complexity [24] is presented for the varying t_θ and data rate. The first ρ_c is the dumped data rate for which m is allocated based on t_θ. The second ρ_c is caused by $(t_\theta - t_a)$ difference for which the classification reduces the chances of failures and latencies.

Thus, the constraint $[R_s = m * (1 - \rho_c) = R_q]$ is targeted in $s_c \,\forall\, t_s$ and $\rho_m \forall R_q$ for which the complexity is confined. Besides the stagnancy in ρ_m due to $R_q > R_s$ is thwarted to ensure maximum s_a for ρ_c and ρ_m are concurrent based on federated learning decisions.

C. RESPONSE LATENCY

The proposed framework achieves less latency [25] for the maximum data rates and observation intervals. The proposed framework eyes on low latency objectives of R_q and R_s based on conventional m and ρ_c suppressions. The s_c is performed for pre-allocation and post-response intervals to ensure reliable distribution of R_s.

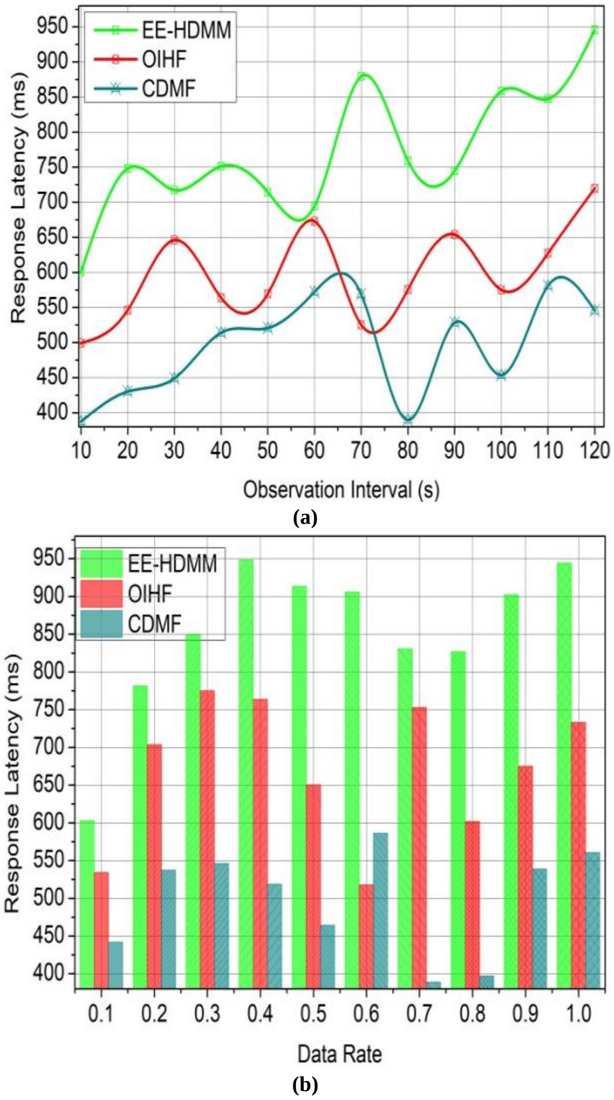

FIGURE 6. Response Latency of proposed method (a) Response Latency vs Observation Interval (b) Response Latency vs Data Rate

Thus, the change in ρ_m or increase in ρ_c are computed with ease of m allocation. Therefore the s_a maximized instances are identified and segregated to ensure optimal R_s distributions are performed. Considerably the modified/ updated ρ_m and t_a intervals ease the distribution with fewer latencies (FIGURE 6).

D.SCHEDULING RATE

The proposed framework achieves a high s_c by balancing t_θ and t_a under different s_a rates. Depending on the available interval s[26] of t_s the first chance of verification is the t_a reduction. In the alternate case of s_c, the m and ρ_m for the appropriate ρ_c is identified to reduce the latency and thereby stagnancies.

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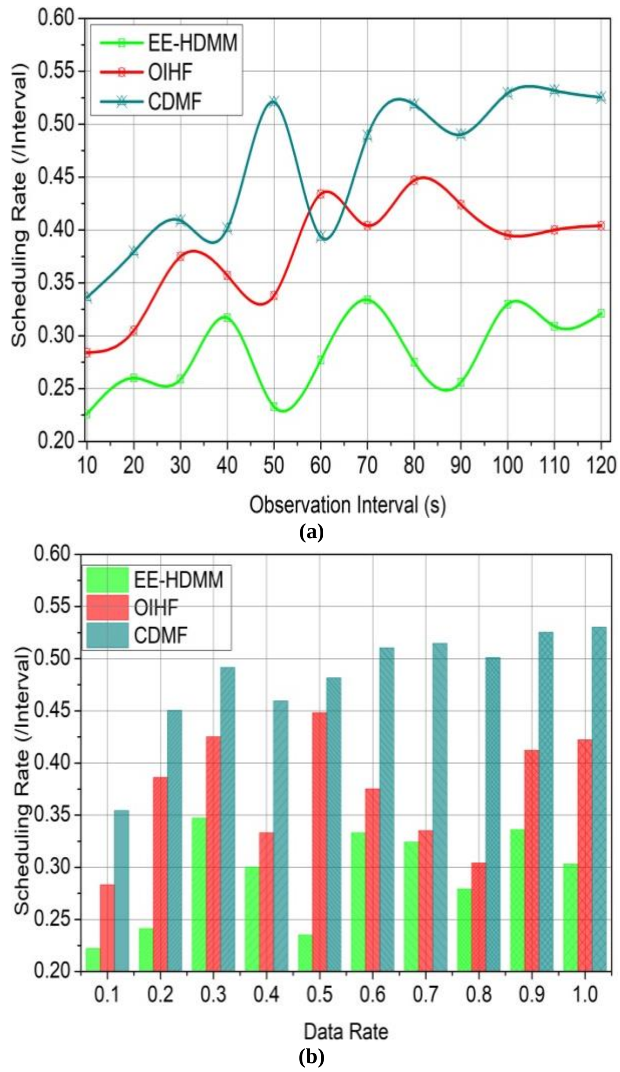

FIGURE 7. Scheduling Rate of proposed method (a) Scheduling rate vs Observational Interval (b) Scheduling Rate vs Data Rate

Thus the process is overseen by the scheduling factors to maximize s_c under invariable t_a. Based on the allocated t_s, the $(t_\theta - t_a)$ the difference is confined to multiple data inputs. The ρ_m factor defines the improvements in multiple t_s and t_θ with the first condition [Eq. (1) [9]] satisfaction [27]. This is commonly used for the varying t_θ and data rates observed (FIGURE 7).

V. DISCUSSION

In the discussion section, the above comparative analysis is summarized using the final X-axis values for ease of comparison. The performance at the maximum range of the proposed method is defined to ensure the highest difference between the existing and proposed methods. The comparative analysis for the metrics defined in the previous section is used for assessment. The above comparative analysis results are summarized in TABLE 2 and 3 for the different observation intervals and data rates.

TABLE 2
Comparative Analysis Summary for Observation Intervals

Metrics	EE-HDMM	OIHF	CDMF
Sharing Accuracy	0.776	0.891	0.9734
Computation Complexity (ms)	351.36	239.56	108.084
Response Latency (ms)	945.79	719.61	545.649
Scheduling Rate (/Interval)	0.321	0.404	0.5253

The proposed framework improves sharing accuracy and scheduling rate by 13.99% and 14.28% respectively. Additionally, this framework reduces the computation complexity [28] and response latency by 10.57% and 11.49% respectively.

TABLE 3
Comparative Analysis Summary for Data Rates

Metrics	EE-HDMM	OIHF	CDMF
Sharing Accuracy	0.786	0.854	0.9708
Computation Complexity (ms)	338.18	221.7	120.777
Response Latency (ms)	944.27	732.81	560.393
Scheduling Rate (/Interval)	0.303	0.422	0.5301

The proposed framework improves sharing accuracy [29] and scheduling rate [30, 31] by 15.08% and 14.76% respectively. Additionally, this framework reduces the computation complexity and response latency by 9.48% and 11.06% respectively.

The implementation of a collaborative healthcare data management framework using Parallel Computing (PC) and the Internet of Things (IoT) faces several limitations. Data security and privacy pose significant challenges, as IoT devices frequently collect and transmit sensitive patient data, increasing the risk of cyberattacks and breaches. Ensuring secure data storage and transmission while complying with stringent regulations like HIPAA and GDPR adds complexity. Interoperability issues arise due to the diverse range of IoT devices and proprietary communication protocols, making seamless integration with legacy systems and other devices difficult. Scalability constraints are another concern, as the infrastructure required for parallel computing, such as high-performance computing clusters, is expensive and often inaccessible to underfunded healthcare facilities. Latency and real-time processing challenges also limit the framework's effectiveness, as the vast amount of data generated by IoT devices can lead to delays in analysis and decision-making, especially over distributed networks. Lastly, regulatory compliance introduces further hurdles, as organizations must navigate a patchwork of laws and standards, which can slow down innovation and implementation. Together, these limitations highlight the need for comprehensive strategies to address technical, financial, and legal challenges in the deployment of such frameworks.

The implications of integrating Parallel Computing (PC) and the Internet of Things (IoT) into collaborative healthcare data management frameworks are far-reaching, affecting healthcare delivery, patient outcomes, and organizational efficiency. On the positive side, this integration enables real-time data processing, improved scalability, and more precise predictive analytics, leading to enhanced patient care, better resource allocation, and streamlined operations. However, it also raises critical concerns, including increased vulnerability to cyberattacks due to the vast amount of sensitive data being transmitted and stored, the high costs of infrastructure and implementation, and potential ethical issues related to data privacy and consent. Additionally, the reliance on interoperable systems and adherence to strict regulatory standards could create barriers to widespread adoption. These implications underscore the transformative potential of such frameworks while highlighting the need for careful planning, robust security measures, and ethical considerations to maximize benefits and mitigate risks.

VI. CONCLUSION

This article introduced the collaborative healthcare data management framework ensuring scheduled distribution responses. The proposed framework addressed the computation complexity and sharing accuracy problem by accommodating a cyclic request and response handling process. These processes are powered by parallel computing and federated learning paradigms to improve the sharing accuracy. The highest possible observation interval collected data is periodically scheduled to meet the user requests for data sharing. The maximum difference between observation and response intervals is suppressed through computation allocation and complexity mitigation using the federated learning process. Therefore, the proposed framework improves sharing accuracy by 13.99%, the scheduling rate by 14.76%, and reduces the computation complexity by 9.48% for the maximum observation interval. Though scheduling and response are ensured through latency-less intervals, the cyclic process requires non-replicated data handling capabilities. To augment this feature, the proposed framework is planned to be equipped with a de-duplication optimization model to reduce replicated data processing time.

REFERENCES

[1] Talpur, M. S. H., Abro, A. A., Ebrahim, M., Kandhro, I. A., Manickam, S., Arfeen, S. U., ... & Uddin, M. (2024). Illuminating Healthcare Management: A Comprehensive Review of IoT-Enabled Chronic Disease Monitoring. IEEE Access.

[2] Krishankumar, R., Dhruva, S., Ravichandran, K. S., & Kar, S. (2024). Selection of a viable blockchain service provider for data management within the internet of medical things: An MCDM approach to Indian healthcare. Information sciences, 657, 119890.

[3] Gupta, S., Chithaluru, P., Stephan, T., Nafisa, S., & Kumar, S. (2024). HSPBCI: a robust framework for secure healthcare data management in blockchain-based IoT systems. Multimedia Tools and Applications, 1-25.

[4] Gopichand, G., Sarath, T., Dumka, A., Goyal, H. R., Singh, R., Gehlot, A., ... & Twala, B. (2024). Use of IoT sensor devices for efficient management of healthcare systems: a review. Discover Internet of Things, 4(1), 8.

[5] Zhou, H., Liu, Q., Liu, H., Chen, Z., Li, Z., Zhuo, Y., ... & Huang, J. (2024). Healthcare facilities management: A novel data-driven model for predictive maintenance of computed tomography equipment. Artificial Intelligence in Medicine, 149, 102807.

[6] Ullah, F., Pun, C. M., Kaiwartya, O., Sadiq, A. S., Lloret, J., & Ali, M. (2023). HIDE-Healthcare IoT data trust managEment: Attribute centric intelligent privacy approach. Future Generation Computer Systems, 148, 326-341.

[7] Ilyas, B., Kumar, A., Ali, S. M., & Lei, H. (2024). Blockchain-enabled IoT access control model for sharing electronic healthcare data. Multimedia Tools and Applications, 1-22.

[8] Gai, Y., Liu, Y., Li, M., & Yang, S. (2024). Markovian with Federated Deep Recurrent Neural Network for Edge—IoMT to Improve Healthcare in Smart Cities. Journal of Grid Computing, 22(1), 1.
[9] Ji, G., Woo, J., Lee, G., Msigwa, C., Bernard, D., & Yun, J. (2024). AIoT-Based Smart Healthcare in Everyday Lives: Data Collection and Standardization from Smartphones and Smartwatches. IEEE Internet of Things Journal.
[10] Alamro, H., Marzouk, R., Alruwais, N., Negm, N., Aljameel, S. S., Khalid, M., ... & Alsaid, M. I. (2023). Modelling of Blockchain Assisted Intrusion Detection on IoT Healthcare System using Ant Lion Optimizer with Hybrid Deep Learning. IEEE Access.
[11] Agarwal, V., & Pal, S. (2023). HierChain: A Hierarchical Blockchain-Based Data Management System for Smart Healthcare. IEEE Internet of Things Journal.
[12] Ahamed, B., Sellamuthu, S., Karri, P. N., Srinivas, I. V., Zabeeulla, A. M., & Kumar, M. A. (2023). Design of an energy-efficient IOT device-assisted wearable sensor platform for healthcare data management. Measurement: Sensors, 30, 100928.
[13] Jan, I., & Sofi, S. (2024). Data management for resource optimization in medical IoT. Health and Technology, 14(1), 51-68.
[14] Mishra, R. K., Yadav, R. K., & Nath, P. (2024). Integration of Blockchain and IPFS: healthcare data management & sharing for IoT Environment. Multimedia Tools and Applications, 1-22.
[15] Zeshan, F., Ahmad, A., Babar, M. I., Hamid, M., Hajjej, F., & Ashraf, M. (2023). An IoT-Enabled Ontology-Based Intelligent Healthcare Framework for Remote Patient Monitoring. IEEE Access, 11, 133947-133966.
[16] Misra, S., Pal, S., Ahmed, N., & Mukherjee, A. (2023). Sdn-controlled resource-tailored analytics for healthcare iot system. IEEE Systems Journal, 17(2), 1777-1784.
[17] Lakshmanan, R., Balakrishnan, S., Mahendran, A., & Subramanian, A. K. (2024). Multimodal healthcare data classification with Tangent Namib Beetle Optimization based routing in blockchain based IoT. Computers and Electrical Engineering, 120, 109614.
[18] Manogaran, N., Nandagopal, M., Abi, N. E., Seerangan, K., Balusamy, B., & Selvarajan, S. (2024). Integrating meta-heuristic with named data networking for secure edge computing in IoT enabled healthcare monitoring system. Scientific Reports, 14(1), 21532.
[19] Johri, P., Balu, V., Jayaprakash, B., Jain, A., Thacker, C., & Kumari, A. (2023). Quality of service-based machine learning in fog computing networks for e-healthcare services with data storage system. Soft Computing, 1-13.
[20] Zeydan, E., Arslan, S. S., & Liyanage, M. (2024). Managing Distributed Machine Learning Lifecycle for Healthcare Data in the Cloud. IEEE Access.
[21] https://www.kaggle.com/datasets/nraobommela/health
[22] Zhang, J. (2024). Quantum healthcare analysis based on smart IoT and mobile edge computing: way into network study. Optical and Quantum Electronics, 56(4), 566.
[23] Balasamy, K., Seethalakshmi, V. & Suganyadevi, S. Medical Image Analysis Through Deep Learning Techniques: A Comprehensive Survey. Wireless Pers Commun 137, 1685–1714 (2024). https://doi.org/10.1007/s11277-024-11428-1
[24] Balasamy, K., Suganyadevi, S. Multi-dimensional fuzzy based diabetic retinopathy detection in retinal images through deep CNN method. Multimed Tools Appl (2024). https://doi.org/10.1007/s11042-024-19798-1
[25] S., S., V., S. FACNN: fuzzy-based adaptive convolution neural network for classifying COVID-19 in noisy CXR images. Med Biol Eng Comput 62, 2893–2909 (2024). https://doi.org/10.1007/s11517-024-03107-x
[26] Suganyadevi, S., Pershiya, A.S., Balasamy, K. et al. Deep Learning Based Alzheimer Disease Diagnosis: A Comprehensive Review. SN COMPUT. SCI. 5, 391 (2024). https://doi.org/10.1007/s42979-024-02743-2
[27] Suganyadevi, S., Seethalakshmi, V. Deep recurrent learning based qualified sequence segment analytical model (QS2AM) for infectious disease detection using CT images. Evolving Systems 15, 505–521 (2024). https://doi.org/10.1007/s12530-023-09554-5.
[28] Suganyadevi Sellappan, Shiny Pershiy, Anand, Finney Daniel, Shadrach Balasamy, Krishnasamy, et al., "A survey of Alzheimer's disease diagnosis using deep learning approaches", Journal of Autonomous Intelligence, vol. 7, no. 3, 2024.
[29] D. Shamia, K. Balasamy and S. Suganyadevi, A Secure Framework for Medical Image by Integrating Watermarking and Encryption through Fuzzy Based ROI Selection, pp. 7449-7457, 2023.
[30] S. Suganyadevi, V. Seethalakshmi, K. Balasamy and N. Vidhya, "Deep learning in Covid-19 detection and diagnosis using CXR images: challenges and perspectives", Digital Twin Technologies for Healthcare, vol. 4, no. 046, pp. 163, 2023.
[31] K. Balasamy and V. Seethalakshmi, "HCO-RLF: Hybrid classification optimization using recurrent learning and fuzzy for COVID-19 detection on CT images," Biomed Signal Process Control, vol. 100, p. 106951, Feb. 2025, doi: 10.1016/J.BSPC.2024.106951.

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