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VIABLE SENSOR DATA AGGREGATION AND COMMUNICATION SCHEME FOR AIDING DIAGNOSIS PRECISION OF INTERNET OF THINGS-BASED HEALTH MONITORING SYSTEMS

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ABSTRACT

The rapid growth of the Internet of Things (IoT) has greatly improved smart healthcare systems with wearable sensors and smart data processing. However, continuous health monitoring often encounters problems like data loss, delays in transmission, and communication errors. These issues can lower the accuracy of disease diagnosis. To tackle these challenges, this article suggests a Viable Data Aggregation Scheme (VDAS). This scheme aims to boost diagnosis accuracy by reducing data loss and improving communication reliability in IoT healthcare settings. The proposed scheme uses a distributed federated learning (FL) model to check data availability and identify missing or delayed information during ongoing monitoring periods. By matching sensed and received data over consecutive intervals, VDAS helps consolidate communications from wearable sensors and reduce transmission errors. Experimental results show that this method increases data availability, aggregation efficiency, and communication rate by 9.19%, 8.17%, and 10.31% respectively across various sensing intervals. Although the system has synchronization issues due to non-uniform sensing times, future work will focus on creating interval-based responsive communication methods. This will aim for more reliable and prioritized data delivery in asynchronous healthcare monitoring environments.

Keywords: *Data Error, Diagnosis Accuracy, FL, Healthcare Monitoring, IoT*

1. INTRODUCTION

Today, patients' health conditions are monitored using portable devices, especially wireless sensors. Wearable sensor nodes monitor the patient's physical condition. Some of the recommended sensors include measuring body temperature, breathing, and pulse [1]. These are important for tracking patients' vital signs and making decisions about their health. When data is received from other sensor nodes, the central unit (ideally a smartphone) processes all the data, makes the necessary decisions, and sends it to an external location [2]. To choose a short communication model for the health sector, some things need to be done first. Effects on human health, safety, and delay are as follows [3]. Things that are not good for the human body should be avoided because they will cause more problems for the patient's health. It is critical to secure sensitive patient information to prevent unauthorized access [4]. Finally, in healthcare applications, it is equally important to keep the flow low. This allows the system to call an ambulance in emergencies. Since the time delay is significant in these machines, it is not affected. There are many short-range communication technologies available, but Bluetooth Low Energy (BLE) and ZigBee are most commonly used in IoT [5].

Monitor critical health indicators through IoT-based monitoring and data transmission over the Internet. The purpose of accessing information is to improve the patient's current condition [6]. The latest development in the Internet, especially in health research, is the Internet of Things (IoT). The use of mobile phones and portable devices for remote healthcare has increased significantly [7]. IoT health monitoring helps prevent infection and provides accurate measurements of a person's health regardless of the doctor's location. This also allows him to attend to the patient regularly [8]. Healthcare can reduce costs while increasing access to human resources and allowing patients to receive care outside of the traditional hospital setting as well as at home [9]. There are several important health factors that doctors can use to monitor their patients' health. People with certain chronic conditions need to be monitored regularly due to serious health problems [10]. Heart rate, blood pressure, body temperature, oxygen saturation, respiratory rate, electrocardiogram, and blood sugar are some symptoms. Due to advances in medical technology, most health indicators can now be monitored with electronic devices with sensitive sensors [11].

Machine learning has become a powerful tool for analyzing large, complex data sets in the healthcare industry. When examining patient history data, machine learning algorithms can identify conditions, make predictions, and support clinical decisions [12]. In the healthcare context, machine learning algorithms can analyze sensor data to detect abnormal patterns and predict patient health outcomes [13]. Classification, regression, and integration enable personalized care and disease control. A negative diagnosis is important in healthcare because it can identify abnormal patterns or deviations from the patient's desired health status [14]. Learning algorithms store different patterns and use these differences to classify new observations as normal or abnormal. Detection of abnormalities improves overall health outcomes, increases patient safety, and allows for early intervention [15]. SVM is a popular machine-learning method for regression and classification. SVM has shown excellent results in various medical applications, including risk prediction, vulnerability detection, and disease diagnosis. With the kernel function, SVMs can analyze data linearly and nonlinearly separately, making them useful in analyzing many types of healthcare data [16, 17]. The contributions of the article are:

A novel proposal of viable data aggregation scheme for improving wearable sensor data communication rate to improve diagnosis accuracy. Incorporating IoT-based features to improve the aggregation and communication processes to reduce data errors for diagnosis Employing a distributed federated learning to validate the presence/ absence of communicating and receiving data based on integrity. Performing a comparative analysis and validating the VDAS performance using different metrics.

The issue of reliable data collection in IoT-based healthcare systems is very important. The quality of diagnosis and patient safety depend directly on the accuracy of sensor data. Inaccurate, missing, or delayed health data can lead to wrong clinical decisions, slow emergency responses, and lower trust in automated health monitoring systems. As the number of wearable and IoT medical devices increases, ensuring error-free, continuous, and secure data communication is crucial for large-scale deployment. Additionally, healthcare is moving more toward remote and home-based monitoring, where medical supervision is limited. This makes dependable data transmission a necessity. Therefore, improving data collection and communication is important not just for better diagnosis but also for saving lives and supporting preventive healthcare.

This is a real and ongoing problem because IoT-based healthcare systems work in dynamic, resource-limited, and error-prone environments. Wearable sensors often face power issues, connectivity problems, and unsynchronized data collection times. These can cause data loss, duplication, or communication errors. Furthermore, the diverse nature of medical sensors and network protocols makes it hard to keep data consistent during continuous monitoring. Current systems lack smart methods to check if data is present or missing during real-time transmission. This leads to incomplete or unreliable datasets for diagnosis. These issues emphasize the need for a strong data aggregation framework, such as the proposed Viable Data Aggregation Scheme (VDAS), which uses federated learning to ensure data integrity and improve overall diagnostic accuracy in real-world healthcare settings.

It is believed that the proposed Viable Data Aggregation Scheme (VDAS), which combines distributed federated learning with IoT-based wearable sensor networks, can greatly improve the accuracy and reliability of disease diagnosis. This improvement comes from reducing data omission, communication errors, and transmission delays in continuous health monitoring systems. By checking for data presence or absence during each monitoring interval and improving sensor communication time, the scheme is expected to increase data availability, aggregation efficiency, and the overall communication rate. This should lead to more consistent and reliable healthcare outcomes compared to current IoT-based models.

Section 2 presents the related works designed by different authors in the past followed by the proposed scheme's explanation and illustration in Section 3. Section 4 presents the data and comparative analysis in detail followed by the conclusion, limitations, and future scope in Section 5.

2. RELATED WORK

Islam et al. [17] proposed an integrated scalable framework for the Internet of Things (IoT) green healthcare system. Cloud computing technology is used in the framework which creates an interactive user interface to improve the performance of the systems. It is mainly designed for doctors and patients which uses wearable sensor devices for the dataset. The proposed framework enhances the overall interactive services among the users.

Zeshan et al. [18] developed an ontology-based smart healthcare framework for remote patient monitoring systems. The developed framework is mostly used for patient monitoring to reduce the complexity of the diagnosis process. Patient's condition and context are gathered from the IoT network which minimizes the latency in the computation process. The developed framework increases the accuracy of monitoring which enhances the feasibility range of the systems.

Wu et al. [19] introduced a cloud-edge-based personalized federated learning for in-home health monitoring systems. It is known as a shared global home model which is aimed to achieve personalized healthcare monitoring services for the users. A generative convolutional autoencoder (GCAE) is used in the model to refine the imbalanced data from the network. The introduced learning model ensures the privacy and security policies of patients' data from hackers.

Raza et al. [20] designed an intelligent IoT framework for indoor healthcare monitoring systems. The designed framework is commonly used for Parkinson's disease patient monitoring purposes. It analyses both static and dynamic routing of patient's health conditions to gather relevant data for the monitoring process. It also provides priority-enabled communication services to the patients which produce optimal information for further processes. The designed framework increases the accuracy of the Parkinson's disease prediction process.

Ramkumar et al. [21] proposed an IoT-based patient monitoring system using deep learning (DL) for heart disease (HD) prediction. The main aim of the model is to predict the exact type and condition of HD. A long short-term memory (LSRM) algorithm is used in the model to detect the precision health condition range of the patients. Experimental results show that the proposed model achieves high accuracy in the HD prediction process.

Zovko et al. [22] developed an IoT with wearable device architecture for smart environments. The actual goal of the architecture is to enhance the sustainability and life quality of the patients. It is commonly used for healthcare monitoring systems which provide necessary healthcare information for the diagnosis process. The developed architecture improves the quality-of-life range of the patients and reduces the computational cost ratio in providing services to the users.

Jayaraman et al. [23] introduced a bi-gated recurrent unit (BiGRU) model based on IoT technology for patient healthcare monitoring. IoT sensor devices are used in the model which provides optimal patient detail for disease prediction. The introduced BiGRU model predicts the exact types of kidney and liver diseases. When compared with other models, the introduced model increases the accuracy of kidney and liver disease prediction processes.

Rathi et al. [24] developed an artificial intelligence (AI) enabled IoT healthcare monitoring system for smart cities. The developed system is commonly used to monitor disabled and elderly patients in smart cities. An edge computing technology is also used in the system to collect health-related data of the patients. The developed system reduces both time and energy consumption levels in healthcare monitoring services.

Bhatia et al. [25] proposed an IoT-fog-cloud-based healthcare monitoring system. The main aim of the system is to prevent the Encephalitis (ENCPH) disease from spreading among the patients. A fuzzy C-means (FCM) classifier is used in the system to analyze the categories of the patients based on health conditions. It is used as a prediction model which predicts the performance of ENCPH patient's caregivers. The proposed system enhances the significance range in preventing ENCPH spread.

Balakrishnan et al. [26] designed a machine learning (ML) based IoT for health monitoring systems. A smart health sensor (SHS) is used in the model which produces relevant healthcare details of the patients. The designed model is used as an automatic healthcare monitoring system in hospitals which reduces the complexity of the diagnosis process. The designed model increases the accuracy of the disease prediction process.

Arunachalam et al. [27] proposed a smart Alzheimer's disease patient monitoring system using IoT-assisted technology. IoT is used in the system to gather necessary information for monitoring purposes. A deep residual network and long short-term memory (DRN-LSTM) algorithms are used in the model to detect the exact types of disease. The DRN algorithm monitors the data which are produced by IoT which reduces the latency in the computation process. The proposed system improves the quality of life (QoL) range of the patients.

Verma et al. [28] developed a deep learning-based fog computing and IoT-integrated environment (FETCH). The developed FETCH is commonly used for healthcare monitoring and diagnosing systems. FETCH provides high-quality services that enhance the performance range of healthcare monitoring systems. The developed FETCH improves the accuracy and increases the execution time in providing diagnosis services to the patients.

Umer et al. [29] introduced an IoT-based heart failure patient monitoring system. The introduced system uses AI for better communication which minimizes the complexity of the disease detection process. The AI technology gathers necessary information which contains optimal data from patients for disease detection. The introduced system maximizes the accuracy of heart failure patient monitoring services.

Premalatha et al. [30] proposed a wireless IoT and cyber-physical system (CPS) for health monitoring. The proposed system uses a honey badger (HB) optimization algorithm to classify the complex data that are presented in the datasets. The proposed CPS analyses the optimized data which contain important parameters for the disease detection process. The proposed architecture enhances the overall performance and significance range of the healthcare monitoring systems.

Irshad et al. [31] developed an artificial spider monkey-based random forest (ASM-RF) hybrid framework patient healthcare monitoring system. Identity-based encryption (IBE) is used in the framework to encrypt the key values for providing diagnosing services to patients. The IBE minimizes the execution time which enhances the effectiveness level of the systems. The developed ASM-RF framework increases the accuracy and reduces the latency in the healthcare monitoring process.

Our proposed Viable Data Aggregation Scheme (VDAS) overcomes these limitations by integrating distributed federated learning to validate the presence and absence of data during continuous sensing intervals, thereby reducing communication errors and improving real-time data availability. This critical comparison has now been incorporated to clearly establish the novelty and significance of the proposed work relative to the current literature.

The patient/user information is very difficult to store and analyze conflict due to the growing population. The challenges in smart healthcare systems are to improve the diagnosis accuracy of disease using wireless sensor-based health monitoring scenarios at different time intervals. The maximum/minimum convergence takes place at the time of handling multiple decisions to find particular patient/user information from the big dataset. Verifying patient data and doctor prescriptions are used to identify and classify data presence and absence. Multiple decisions made in smart healthcare systems are used to reduce the omitted patient data from the dataset.

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This work mainly aims to improve the accuracy and reliability of data aggregation and transmission in IoT-enabled healthcare systems through federated learning. It does not address topics like energy optimization, real-time clinical decision-making, security and privacy measures, or managing large-scale multi-patient data, as these are outside its current scope. Future research will tackle these limitations by developing interval-based responsive communication techniques to improve reliability in asynchronous healthcare monitoring environments.

3. PROPOSED METHOD

Decision-making and performance in smart healthcare systems and applications are performed using wearable sensor data and intelligent computations. This proposed scheme continuously monitors intervals to reduce the information eliminated monitoring sequences. Hence, regardless of the diagnosis of the disease is performed for equating the sensed and received data is the considered metric. In this article, the distributed communication and pervasive computations in IoT ML are administrable for computing the data availability and data absence during monitoring and reception intervals to prevent data delivery errors for diagnosis. The proposed aggregation scheme is illustrated in Figure 1.

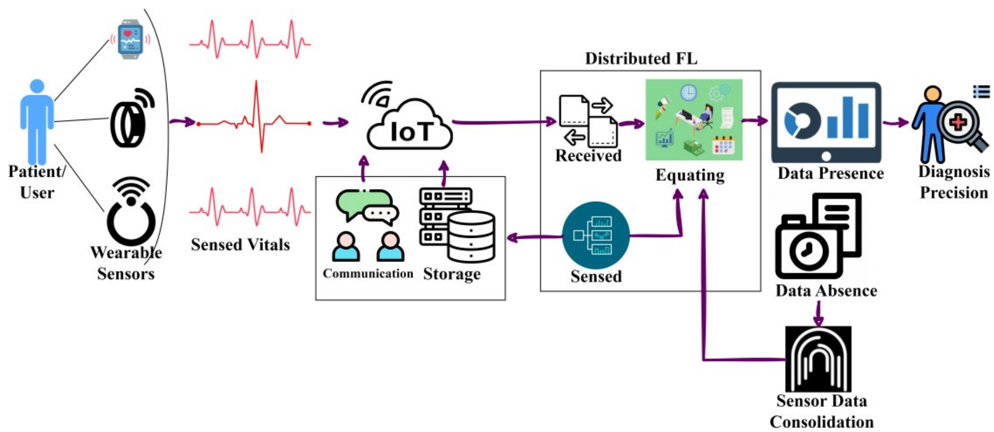

Figure 1: Proposed VDA Scheme Illustration

To simulate the behaviour of the CMOS processor, exhaustive simulations are executed for each clocking arrangement. These simulations make use of complicated algorithms. Since the simulations consider a variety of various operational settings, it can conduct a realistic evaluation of supply noise and delay.

Research conducts a comprehensive study of the results and compare the performance metrics across a variety of clocking arrangements. The study of the accompanying trade-offs allows for the identification of optimal configurations that reduce supply noise while simultaneously increasing latency.

The disease prediction and diagnosis precision is improved using patient-sensitive data analysis through continuous monitoring and reception intervals. VDAS is used to leverage the diagnosis precision of disease with sensor-based health monitoring scenarios. In this manuscript, the communication and storage in IoT for the available patient's clinical records and health monitoring-based area is easy to satisfy high diagnosis precision and identify the data presence/absence for the varying patient data. Further, this proposed scheme aims to provide less omitted data at monitoring sequences to maximize the diagnosis accuracy. The proposed scheme pursues two functions namely data availability and absence verification at the time of monitoring and reception intervals. The data availability and its size are different for all the patients' data to handle multiple verification outputs from the distributed federated learning process for improving health monitoring data. The proposed Viable Data Aggregation Scheme (VDAS) addresses this problem by integrating distributed federated learning to detect data presence/absence across monitoring and reception intervals, consolidating sensor outputs, and reducing omitted or corrupted data. Solving

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this issue is critical because accurate, complete, and timely patient data is the foundation of reliable disease prediction, early intervention, and effective healthcare delivery, particularly in IoT-based remote monitoring systems. First patient health monitoring data is given as (1)

$$HMD_{p_n} = S_i(C_r + \partial_r) \quad (1)$$

Therefore,

$$\arg\max_{p_n \in HMD} S_i \ \forall\ C_r = \partial_r \quad (2a)$$

$$\operatorname{argmin}_{i \in S_i} D_{Prec} \ \forall\ \partial_r \quad (2b)$$

Where,

$$S_i = dv_t - V_d \quad (3a)$$

And,

$$\operatorname{argmin}_{i \in S_i} OM_{D_i} \ \forall\ HMD_{p_n} \in S_i \quad (3b)$$

As per the above equations, the variables HMD_{p_n}, C_r and ∂_r used to denote the health monitoring data of n number of patients/users p in different sensed intervals S_i, communication range, and storage medium for previous successful decisions. The next health monitoring data are verified using the variables D_{Prec}, dv_t and V_d represents diagnosis precision, verification time, and verification delay, respectively. The objective of minimizing the data omitted monitoring sequences under continuous monitoring intervals is expressed as $OM_{D_i}\ \forall\ HMD_{p_n} \in S_i$. If p_n shows the number of patients/users using smart healthcare applications, then the number of received data from the IoT ML is represented as $Receiv_{\Delta}$. Therefore, the communication range is expressed as $(C_r \times dv_t)$ whereas the storage medium is $(HMD_{p_n} \times C_r)$. Both the verification of communication and storage in IoT ML based on the constraints $(HMD_{p_n} \times C_r)$ and $(C_r \times dv_t)$ are the sensitive patient health data analysis for improving diagnosis rates. The equation factor is reliable for identifying and segregating received and sensed data from the continuous monitoring intervals using distributed federated learning. This proposed scheme utilizes IoT features of multiple computations and distributed communication based on the classification of received and sensed data is prominent in identifying the data presence and absence with additional verifications. The diagnosis accuracy of the disease $(\Delta_{\emptyset})$ for all the patients' health monitoring data with appropriate verification time; the remaining time needed for identifying and equating the sensed and received data at continuous intervals to accurately identify data absence/presence is the considered metric. The data absence and presence differentiation is diagrammatically presented in Figure 2.

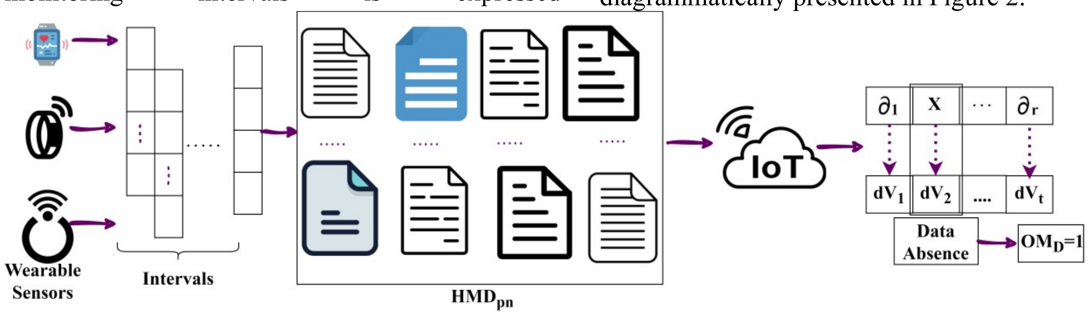

Figure 2: Data Absence and Presence Differentiation

The wearable sensor devices are involved in maximum data accumulation for the allocated intervals. The HMD_{pn} acquired in S_i is communicated through IoT mediums to the diagnosis center. If the $\partial_r \in dV_t$ then data availability is high such that data is present. If either dV_t or ∂_r is not synchronized then data absence is observed. Considering the D_{prec}, the $HMD_{pn} \in s_i = \partial_r \in dV_t$ regardless of the volume; the failing results in $OMD_i = 1$. This case relies on the previous sensing interval for prediction (Fig. 2). The equating of sensed and received data based on continuous monitoring and reception intervals is computed using distributed FL. Later, the data absence is prevented by consolidating the wearable sensor communication time from the verification outputs of the distributed FL is the augmenting factor. For the equating process, identifying and segregating data presence/absence is the prevailing instance for continuous intervals. The data availability and absence verification are prominent in the following manner.

3.1 Received Data Processing

In this received data verification process, the health data of multiple patients are stored in IoT and continuously analyzed for $(C_r \times t)$ for all HMD_{p_n}. Using the distributed FL, the data availability and absence during monitoring and reception intervals are analyzed for computing Δ_Q. The probability of data delivery errors $(\rho(\alpha\beta^{\varepsilon}))$ for improving the diagnosis precision D_{Prec} from the continuous intervals is given as

$$\rho(\alpha\beta^{\varepsilon}) = \left(1 - \rho(DATA^{Abs})\right)^{HMD_{p_n} - 1} \forall\ Receiv_{\Delta} \in i \tag{4}$$

And,

$$\rho(DATA^{Abs}) = \left(1 - \frac{C_r \in HMD_{p_n}}{C_r \in dv_t}\right) \tag{5}$$

From equations (4) and (5), the continuous monitoring of patient's health data follows the probability of data absence taking place in any interval at the time of receiving a large amount of health data in the smart healthcare systems through wearable sensors. Hence, the data availability is evaluated as per equation (1). Therefore, the data availability in IoT ML follows the probability of data absence $\rho(DATA^{Abs})$ per unit time is computed as

$$Availability\left(HMD_{p_n}(data)\right) = \frac{1}{|C_r + \partial_r - \alpha\beta^{\varepsilon} + 1|} \cdot \left(\rho(DATA^{Abs})\right)_i \forall\ S_i \in dv_t \tag{6}$$

However, the verification output for $Availability\left(HMD_{p_n}(data)\right)$ as in equation (6) is to satisfy both the conditions of $(HMD_{p_n} \times C_r)$ and $(C_r \times dv_t)$ ensuring less data absence. The equation process of received and sensed data at sequential monitoring intervals M_i is to reduce data delivery errors and data absence based on $(HMD_{p_n} \times C_r) > (C_r \times dv_t)$. The data absence is prevented by consolidating the wearable sensor from the verification output is descriptive using distributed FL. Therefore, the high diagnosis precision is achievable using the constraints $HMD_{p_n} > dv_t$ and $\rho(DATA^{Abs})$ is valid in the above equations (1), (2a), (2b), (3a) and (3b). The contrary result of sensed data processing is the prolonging $\rho(DATA^{Abs})$. Hence, the high data delivery error occurrence results in data absence. The data availability processing is verified for the diagnosis process as per the decision presented below.

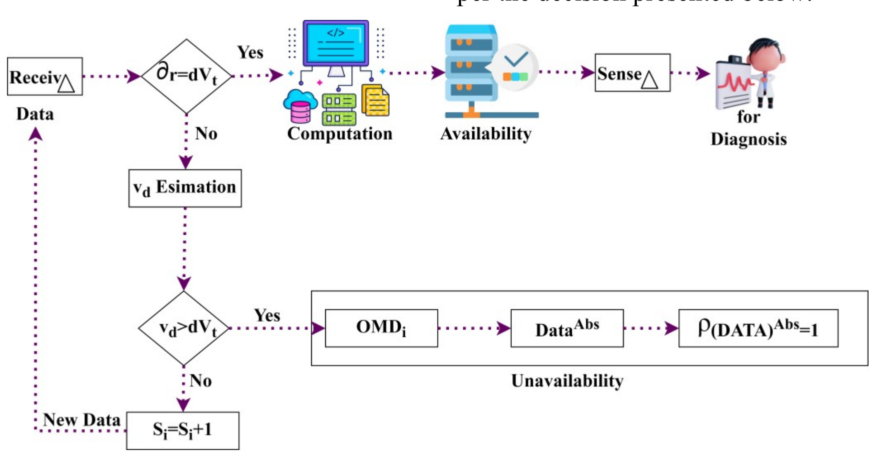

Figure 3: Data Availability Decision Process

The $Receiv_{\Delta}$ is examined for $\partial_r = dV_t$ such that the classification is computed based on $sense_{\Delta}$. This data is utilized for diagnosis and the same is stored for further use. The V_d estimation is equated for dV_t in the same or new S_i intervals. Based on the $V_d > dV_t$ conditions the data emission is identified that results in unavailability. Therefore the receiver is likely to analyze the interval synchronization using S_i (Refer to Figure 3). The failing (absence) is balanced by equating the cumulative data with S_i data that is discussed further.

3.2 Sensed Data Processing

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In this sensed data processing, the less data delivery is achievable using the condition $HMD_{p_n} > dv_t$. Hence, the distributed FL identifies and classifies the data presence and absence from the continuous health data monitoring intervals [33,34]. Along with the verification output of HMD_{p_n}, the communication and storage are accurately identified for a prolonged time, this is the sensed data verification process. The probability of data absence $\left(\rho(DATA^{Abs})\right)$ is computed as

$$\rho(DATA^{Abs}) = \rho(C_r).Availability\left(HMD_{p_n}(data)\right).\left[\left(\frac{S_i(C_r+\partial_r)}{sense_\Delta}\right) * \rho(\alpha\beta^{\epsilon}) - \frac{HMD_{p_n}}{dv_t * V_d}\right] \tag{7}$$

Where,

$$sense_\Delta(\,Receiv_\Delta, DATA^{Abs}) = \int_0^{S_i} C_t^{\,S_i-1}(1-C_t)^{S_i-1}\, dC_t \tag{8}$$

And,

$$sense_\Delta(\,Receiv_\Delta, DATA^{Abs}) \in Availability\left(HMD_{p_n}(data)\right) = \int_1^{C_r} C_t^{\,S_i-1}.\frac{\rho(\alpha\beta^{\epsilon})}{dv_t}\left(1-\rho(DATA^{Abs})\right)^{S_i-1} dS_i \tag{9}$$

From the equations (7), (8) and (9), the variable $sense_\Delta$ represents the sensed data from the continuous health data monitoring intervals to prevent data delivery errors and data absence for diagnosis. Where, the variable C_t illustrates the consolidation of the wearable sensor communication time based on the verification outputs of the learning process. The data delivery error is mitigated by equating the two processing outputs using distributed FL for leveraging the diagnosis accuracy of disease [35]. The learning process verifies the patient's data with high computation time.

From the two processes, the learning equates the sensed and received data observed from the IoT ML platform based on $HMD_{p_n} > dv_t$ for precise diagnosis and $DATA^{Abs}$ is identified and thereby the data availability is also verified. These features are addressable using distributed FL to mitigate the data omitted monitoring sequences through recurrent verification and monitoring with previous data for better decisions. The following section represents the identification of data presence and absence using equating factors to mitigate the above-discussing issues.

3.3 Equating process using Data Presence and Absence

The learning verification output relies on identified data availability and absence using the proposed scheme. It provides the supportive validation of both data presence/absence for reception and monitoring intervals. The current diagnosis accuracy of the disease is compared with the previous data through the proposed scheme and distributed FL. The sensed and received data equating process depends on continuous sensing intervals for improving verification output. Hence, the condition for learning verification output is different for all the health monitoring data that utilizes IoT features of pervasive computations and distributed communications for accurate diagnosis to reduce data delivery errors. The verification output is prescribed for both the sensed and received data processing for improving the maximum functionalities of IoT and thereby improving the efficiency of health monitoring. The first equating factor $\exists q_f$ relies on minimum data delivery error $min(\alpha\beta^{\epsilon})$, $Receiv_\Delta$ and $sense_\Delta$. Hence, it is expressed as

$$\left.\begin{array}{c} \exists q_f[Receiv_\Delta, sense_\Delta, min(\alpha\beta^{\epsilon})] = \left[C_r - \left(\frac{HMD_{p_n}}{dv_t}\right) \times \frac{1}{DATA^{Abs}}\right] - Availability\left(HMD_{p_n}(data)\right) + 1 \\ \text{such that} \\ \sum_{HMD_{p_n} \in S_i} \sum_{S_i \in C_r} \Delta_0 - \sum_{S_i \in \partial_r} dv_t \\ \text{and} \\ HMD_{p_n}(data) = \sum_{S_i \in dv_t} Availability\left(HMD_{p_n}(data)\right)_{M_i} - \left(\rho(\alpha\beta^{\epsilon})\right)_{M_i} \end{array}\right\} \tag{10}$$

In equation (10), the equating factor output relies on both sensed and received data from the IoT ML for improving diagnosis accuracy of disease using the conditions $\left(\rho(\alpha\beta^{\epsilon})\right)_{M_i}$ and $Availability\left(HMD_{p_n}(data)\right)_{M_i}$. Here, the chances of preventing data delivery errors for diagnosis are expressed as

$$\rho(\alpha\beta^{\epsilon}, dv_t) = \frac{1}{\sqrt{2HMD_{p_n}(data)}}\left[-\frac{\partial_r - DATA^{Abs} \times C_r}{V^d}\right] \tag{11a}$$

Where,

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$$V_f = DATA^{Pres} - DATA^{Abs} \quad (11b)$$

Where, the variable V_f represents the verification factor of the learning process. The learning process is illustrated in Figure 4.

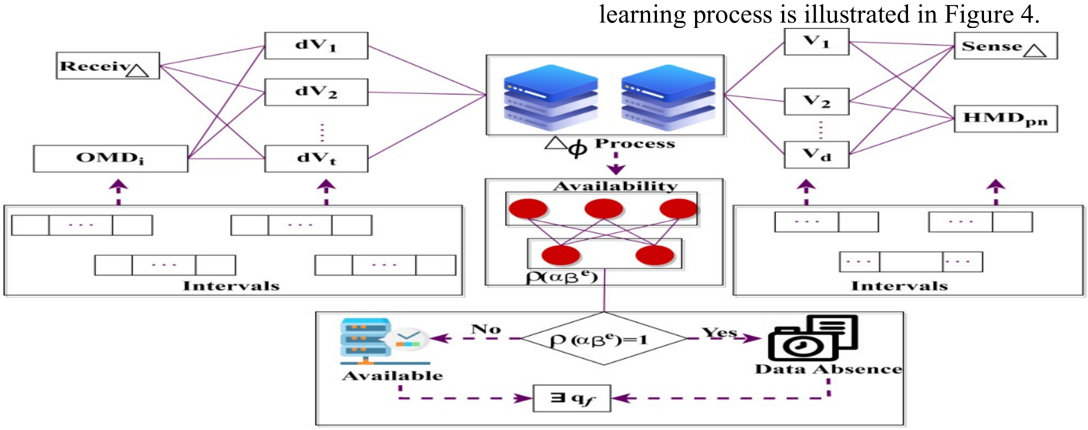

Figure 4: Learning Process Illustrations

The distributed learning process equates to the $\rho(DATA^{Abs})$ using C_t from any interval. Depending on the $Sense_\Delta(Receiv_\Delta, DATA^{Abs})$ the learning is performed for two conditional assessments. In the first assessment the occurrence of OMD_i in and dV_t is verified. From the consecutive instances of s_i the HMD_{pn} replication in V_d is identified. The joint identification verifies the data availability across various S_i aggregated data. This includes both intervals (C_r and Δ_ϕ) for verifying if $\rho(\alpha\beta^e) = 1 \; or \; 0$. The output of this decision case is used for $\exists q_f$ operation against C_t such that diagnosis precision is improved in any S_i (Refer to Fig. 4). Based on the probability computation of data delivery errors and data absence from the continuous monitoring intervals, the aim is to balance sensed and received data to reduce the verification delay and computing time. Hence, the accurate disease prediction δ_x and diagnosis θ_y is given as

$$\delta_x = \max\left[\frac{\rho(\alpha\beta^e) \times C_r}{Availability\left(HMD_{pn}(data)\right)_{M_i} - DATA^{Abs} * \partial_r}\right] \quad (12)$$

And,

$$\theta_y = \frac{\rho(\alpha\beta^e)}{Availability\left(HMD_{pn}(data)\right)_{M_i}} \; \forall \; \partial_r = C_r \; (or) \; \partial_r = \frac{(HMD_{pn}+1)}{C_t} \quad (13)$$

Therefore, the data absence is prevented by consolidating the sensed data with communication time for identifying the particular patient data from the IoT-assisted healthcare applications. The exceeding patient data outputs in data delivery errors and hence the computing time is demandingly high. From this analysis, the equating factor is optimal in identifying data presence/absence with less computing time and verification delay. The verification time (dv_t) for the sequential patient health data monitoring is computed. The proposed scheme is used to verify each patient's data for improving the diagnosis precision. This final health data monitoring $\left(HMD_{p_n}\right)_{M_i}$ is computed for both data availability and absence as in equation (14)

$$\left(HMD_{p_n}\right)_{M_i} = \frac{Availability\left(HMD_{p_n}(data)\right)}{Adv_t} + \frac{\left(\rho(C_r) + \rho\left(DATA^{Abs}\right) - \rho(\alpha\beta^e)\right)}{C_t} \quad (14)$$

In equation (14), the final assessment is performed to achieve high diagnosis accuracy with less data delivery error, data absence, computing time, and verification. Therefore, the verification output for all patient data assessments augments both δ_x and θ_y. The aforementioned problems are reduced under continuous monitoring intervals. The verification of smart healthcare applications or systems-associated data until the diagnosis accuracy based on health monitoring data is improved in any communication intervals with a prolonged time delay for verification. Two processes are recurrently pursued for increasing the decision verification as per the above equations. The varying health monitoring data verification time is reduced and thereby increases communication intervals to satisfy either sensed data or received data. In this both conditions, if $\rho(\alpha\beta^{e}) = 0$, then distributed communication and storage are maximized in healthcare systems whereas if $\rho(\alpha\beta^{e}) = 1$, then the patient data is omitted from the monitoring sequences. Therefore, the condition of $\delta_x = \theta_y$ is an optimal output for this health monitoring data assessment with reception intervals. The diagnosis-improving data availability process is presented in Fig. 5.

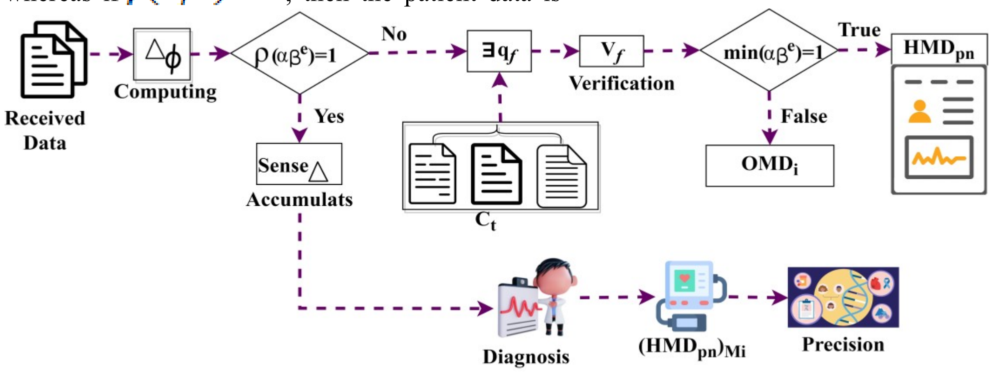

Figure 5: Diagnosis Improving Data Availability Process

The received data is influenced by Δ_ϕ invalidating $\rho(\alpha\beta^{e}) = 1$ or 1 case. If the case is true then equating using C_t is performed followed by V_f. If this V_f generates $\min(\alpha\beta^{e})$ solution, then HMD_{pn} is augmented until the next data from S_i influences the diagnosis accuracy. The other part of $\rho(\alpha\beta^{e}) = 0$ improves the diagnosis precision with $(HMD)_{M_i}$ observation in $(S_i + 1)$. Depending on the $\max(\alpha\beta^{e})$ the data is omitted until the final $\exists q_f$ (Refer to Fig. 5). The equating of sensed data and received data based on distributed communication and storage during monitoring intervals. The data presence and absence identified from the verification outputs is the deciding factor for diagnosis. Hence, multiple diagnosis recommendations are made and provided to the patients until satisfying maximum diagnosis accuracy. In this proposed scheme, distributed federated learning is used to reduce data absence and verification time.

4 RESULTS AND DISCUSSION

4.1 Dataset-Based Analysis

The proposed scheme is validated using the dataset that provides 3 prime wearable sensor data for diagnosis. The oximeter, heart rate, and temperature measuring sensors mounted in 15 human subjects are accounted for study. The minimum observation interval is 10s and the maximum is 120s. The mobile application is responsible for aggregating the sensed data and communicating it for clinical diagnosis. The data aggregation and communication are diagrammatically illustrated in Figure 6.

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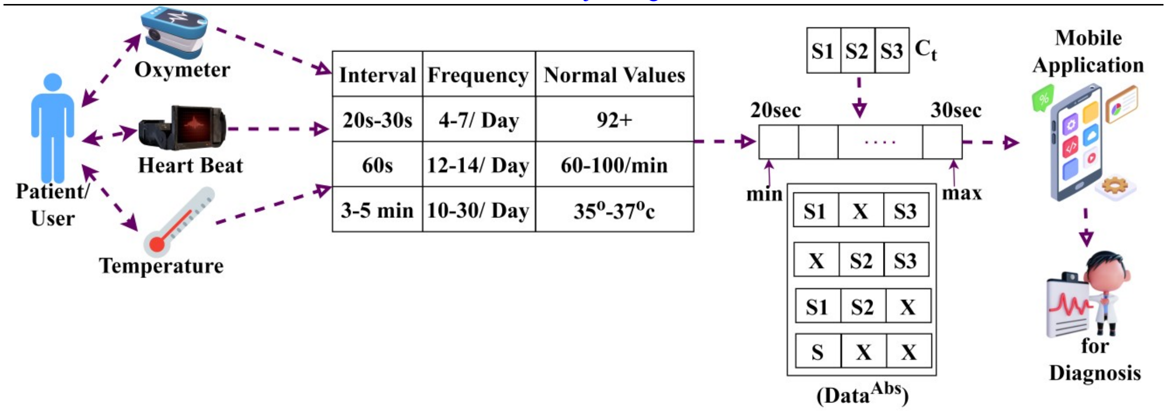
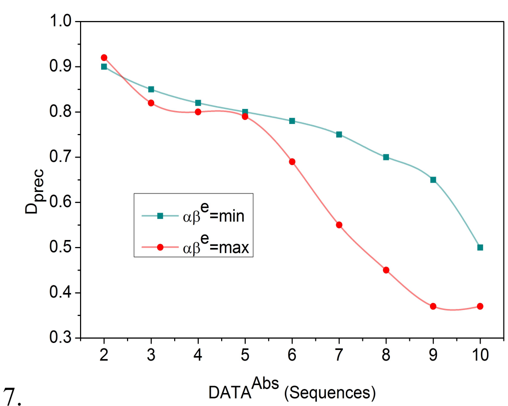


Figure 6: Data Aggregation & Communication

The above illustration in Fig. 6 presents the normal values of the sensors with the presence (C_t) and $DATA^{Abs}$ between minimum and maximum S_i. The accumulated information is transmitted to the diagnosis center using the mobile application. The missing (absence) is analyzed and considered for diagnosis correlated to the normal values. First the impact of $DATA^{Abs}$ over the diagnosis, accuracy is analyzed in Figure



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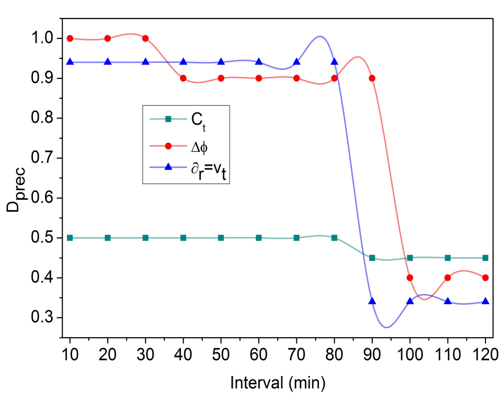
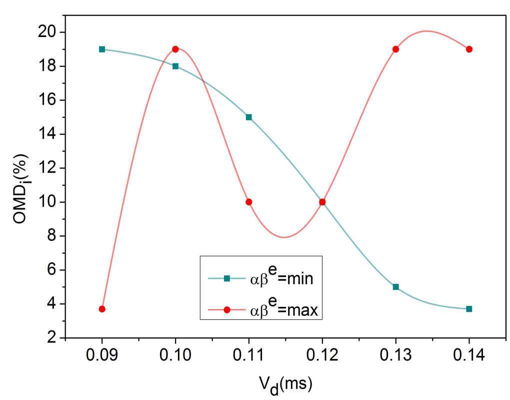


Figure 7: D_{prec} Analysis

The proposed scheme is analyzed for its D_{prec} for $DATA^{Abs}$ sequences and intervals as per the $S1, S2$, and $S3$ wearable sensors represented in Fig. 6. This proposed scheme performs two prime $\Delta\phi$ for $\partial_r = V_d$ and $Receiv_{\Delta} = \rho(DATA^{Abs}) + HMD_{pn}$ for providing sufficient data for diagnosis. Therefore even if the data is unavailable then C_t based equating process is initiated for providing new data augmentation from S_i. This enhances the chances for V_d based diagnosis without reducing precision (Fig. 7). However the data error observed in dV_t is analyzable for preventing OMD_i. This analysis is presented in Figure 8.



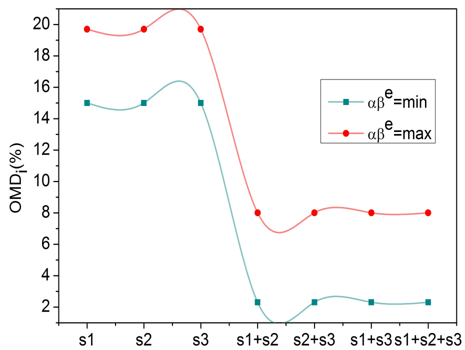


Figure 8: $\boldsymbol{OMD_i}$ *Analysis*

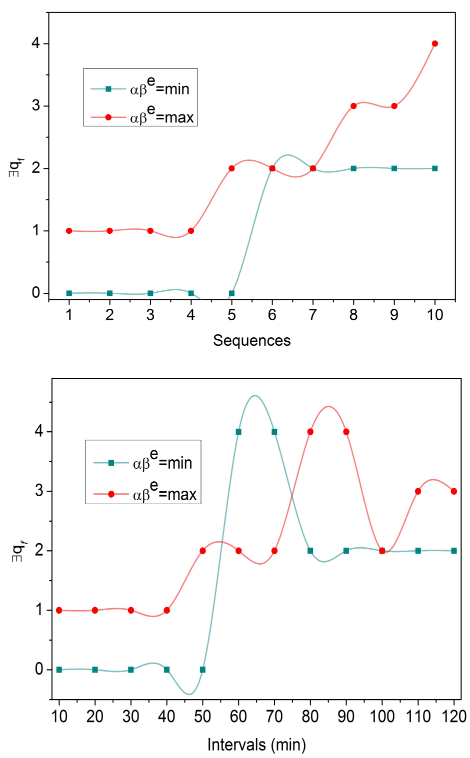


Figure 9: $\exists \boldsymbol{q_f}$ *Analysis*

Based on the federated learning output, $\rho(DATA^{Abs})$ is confined to the proposed scheme. Besides the changes between sensed and received data are equalized from $(S_i + 1)$ that prevents additional errors. Thus the $\exists q_f$ is required only for limited sequences in this scheme.

The OMD_i in the verification process increases the chances of diagnosis error for which the dV_t is increased. Based on the concurrent learning validated for $(Receiv_\Delta, dV)$ and $(V_d, sense_\Delta)$ the OMD_i verification from S_i is initiated. The distributed verification relies on concurrent validation of the ∂_r and $DATA^{Abs}$ factors in V_d and sensor intervals. In both the validation process the learning process identifies $\exists q_f$ sequences for reducing OMD_i (Fig. 8). Such identification of $\exists q_f$ sequences are analyzed in Figure 9.

4.2 Comparative Analysis

The following section presents a comparative study for analyzing the proposed scheme's performance using data availability, aggregation rate, data delivery error, delivery delay, and data communication rate. The sensing intervals and the communication sequences/intervals are varied for verifying the metric outputs. The existing FedHome [19], FETCH [28], and ASM-RF [31] methods from Section 2 are used along with the proposed scheme in the comparative analysis.

4.2.1 Data Availability

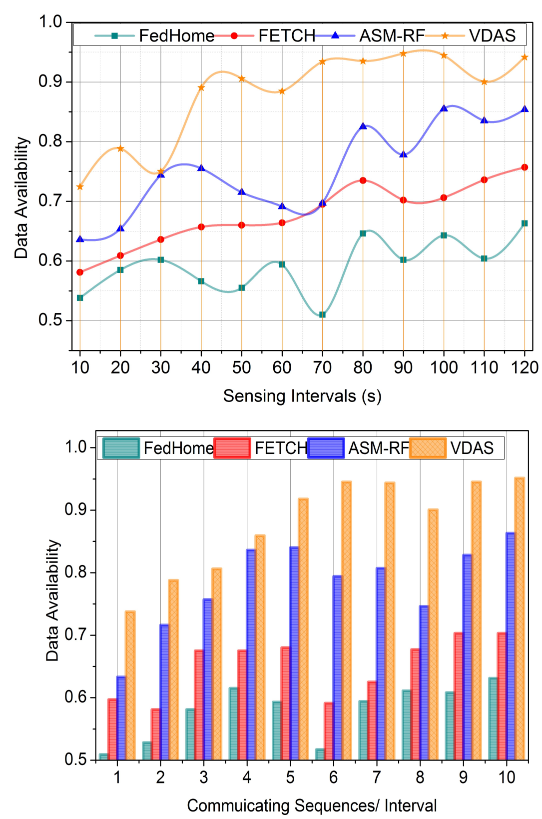


Figure 10: Data Availability

4.2.2 Aggregation Rate

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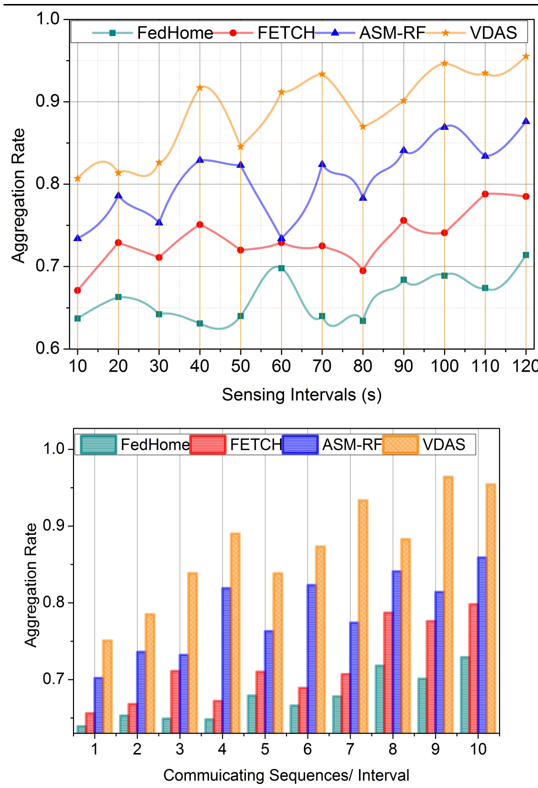

Figure 11: Aggregation Rate

The sequential analysis of health monitoring data from the reception interval improves its efficacy for a prolonged time using the proposed scheme and distributed FL (Refer to Figure 10). Based on the monitoring and reception intervals, a large amount of patient/user data is very difficult to store and analyze due to increasing population. The proposed scheme is designed to reduce the data omitted monitoring sequences using monitoring intervals for identifying the data presence/absence. In this manuscript, high data availability is achieved using maximum data utilization and analysis to improve the data communication rate. The maximum/minimum diagnosis accuracy is identified at the time of handling multiple health data to find particular patient/user data from the monitoring intervals. The distributed FL learning used for mitigating the data delivery error and data absence from the wearable sensor communication time interval is to improve data availability. The high data availability is achieved using distributed FL and the proposed scheme. The learning process is used for identifying data delivery errors in IoT ML. Therefore, a high data delivery rate is achieved in this method.

In this proposed scheme, distributed FL learning is used for equating the received and sensed data at different communication intervals. Therefore, the accurate diagnosis of disease is computed for sequential sensor-based health monitoring data analysis. In this process, multiple decisions are made in smart healthcare systems to reduce the omitted data monitoring sequence from the dataset. The probability of data delivery errors and data absence occurring in the continuous monitoring intervals is analyzed from the distributed communication is difficult to utilize IoT features. The data omitted monitoring sequences through continuous monitoring intervals is identified using the learning process to reduce delivery delay and delivery errors. The wearable sensors' associated data are computed for verifying and classifying the data availability and absence; the verification output is used for improving the diagnosis accuracy of continuous health monitoring data in any communication interval. Therefore, the sensor communication time is computed regardless of the diagnosis of disease based on equating the sensed and received data as the considering factor. Depending upon the verification output, the data aggregation rate is high compared to the other factors as illustrated in Figure 11.

4.2.3 Data Delivery Error

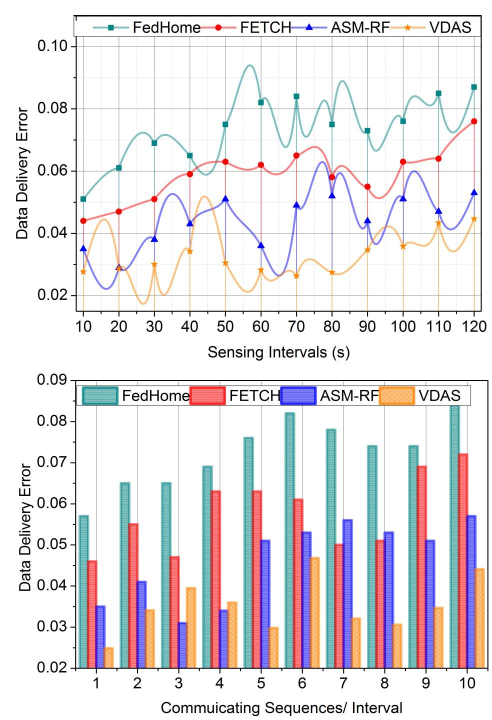

Figure 12: Data Delivery Error

In this proposed scheme, the wearable sensor is placed on the patient's body surface for monitoring health data such as blood pressure rate, temperature, pulse rate, etc. to reduce the data absence represented (Refer to Figure 12). The equating of sensed and received data for diagnosis using distributed FL is to satisfy less data delivery errors and delivery delay in both intervals. Identification of delivery delay from the continuous health data monitoring intervals is reduced for validating data availability and absence using the learning process. Therefore, the distributed communication and pervasive computations in IoT ML are administrable for accurately validating the data presence and absence during sequential monitoring and reception intervals to prevent data delivery errors for diagnosis. VDAS is used to leverage the diagnosis precision of disease with sensor-based health monitoring scenarios. In this manuscript, the data communication and storage in IoT ML for the entire patient's health monitoring-based data is easy to satisfy high diagnosis precision. Hence, the data presence/absence for the varying patient data is identified. Using the proposed scheme, the data delivery errors are controlled in this article.

4.2.4 Delivery Delay

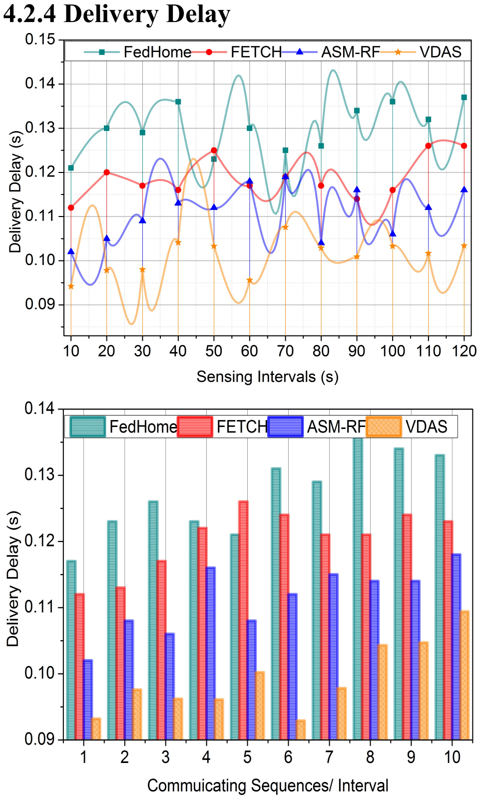

Figure 13: Delivery Delay

In this proposed scheme, the data communication rate and delivery delay are addressed and mitigated from the sequence of health data analysis through distributed FL to satisfy maximum IoT features utilization is illustrated in (Refer to Figure 13). The sequential health monitoring intervals of the patients may vary for each; this variation is addressed for identifying particular patient and their data in IoT environment. The two processes are recurrently performed to improve disease detection ratio and diagnosis precision in IoT ML and then consolidate the wearable sensor communication time from the verification outputs to prevent data losses and delivery delays. In this process, the proposed scheme used to satisfy fewer data delivery errors and verification time while equating sensed and received data is to maximize the data communication rate. In both the monitoring and reception intervals, the changes in sensed intervals are identified for the periodic working of sensors. From the analysis, the sensor-observed patient data are stored and updated to improve diagnosis accuracy. Therefore, it is important to improve the efficacy of health monitoring data analysis. This proposed scheme verifies the maximizing functionalities of IoT for leveraging the diagnosis accuracy of disease. Hence, less delivery delay is achieved in this article.

4.2.5 Data Communication Rate

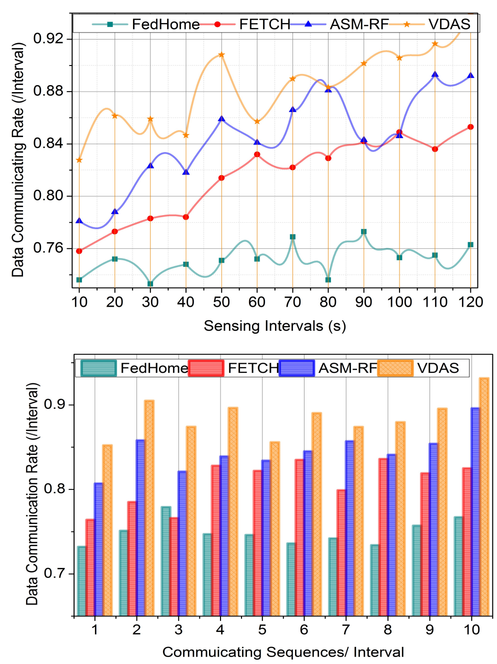

Figure 14: Data Communication Rate

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This proposed scheme used for improving the diagnosis precision of diseases using distributed FL is represented in Figure 14. The proposed scheme reduces omitted data monitoring sequences from the distributed communication and pervasive computation maximizes the diagnosis accuracy. Based on this learning, the proposed scheme processes two functions such as the data availability and absence verification from the monitoring and reception intervals. The data availability and absence are identified to handle multiple verification outputs using a distributed federated learning process to improve diagnosis accuracy. Therefore, the equation factor is reliable for identifying and segregating received and sensed data from the continuous monitoring intervals to improve the data communication rate. The data delivery error, delivery delay, and data absence are addressed and mitigated from the verification outputs by consolidating the wearable sensor communication time, hence high data communication is achieved. This proposed scheme is used to reduce the data communication rate in this manuscript. The comparative analysis is tabulated in the following tables.

Table 1: Comparative Analysis Tabulation for Sensing Intervals

Metrics	FedHome	FETCH	ASM-RF	VDAS
Data Availability	0.663	0.757	0.854	0.9417
Aggregation Rate	0.714	0.785	0.876	0.9551
Data Delivery Error	0.087	0.076	0.053	0.0447
Delivery Delay (s)	0.137	0.126	0.116	0.1034
Data Communication Rate (/ Interval)	0.763	0.853	0.892	0.9391

The proposed VDA scheme improves data availability, aggregation, and communication rate by 9.19%, 8.17%, and 10.31% respectively. This scheme reduces the data delivery error and delays by 8.19% and 9.1% respectively.

Table 2 : Comparative Analysis Tabulation for Communication Sequences/ Interval

Metrics	FedHome	FETCH	ASM-RF	VDAS
Data Availability	0.631	0.703	0.863	0.9513
Aggregation Rate	0.729	0.798	0.859	0.9543
Data Delivery Error	0.086	0.072	0.057	0.0441
Delivery Delay (s)	0.133	0.123	0.118	0.1094
Data Communication Rate (/ Interval)	0.767	0.825	0.896	0.9316

The proposed VDA scheme improves data availability, aggregation, and communication rate by 10.94%, 7.94%, and 10.23% respectively. This scheme reduces the data delivery error and delays by 8.27% and 6.11% respectively.

5 CONCLUSION

This article describes a design and experimental research study focused on improving diagnosis accuracy in IoT-based healthcare systems through a Viable Data Aggregation (VDA) scheme. The study uses a simulation-based method with wearable sensor data to assess how well the proposed scheme performs during continuous monitoring intervals.

The VDA scheme operates within a distributed federated learning (FL) framework, which checks for data presence and absence during sensing and reception intervals. The research employs a clear methodology to meet its goals:

Data Collection: Wearable sensors continuously generate patient-specific clinical data over multiple intervals.

Data Aggregation and Validation: The FL model compares sensed and received data to identify missing or delayed information. It combines current and previous interval data to reduce errors.

Predictive Diagnosis: With corrected aggregated data, predictive models suggest diagnoses with controlled delays.

Performance Assessment: Metrics such as data availability, aggregation efficiency, and communication rate are evaluated, showing improvements of 9.19%, 8.17%, and 10.31%, respectively.

The study also highlights synchronization challenges between intervals due to uneven sensing instances, which can lead to delays in accurate data delivery. Future work will focus on introducing interval-based responsive communication strategies to boost reliability in asynchronous healthcare monitoring settings. Despite its promising performance, the system still faces challenges with interval synchronization due to non-uniform sensing times. This can sometimes delay accurate data delivery. To tackle this issue, future research will focus on developing interval-based communication methods that respond better to improve reliability in asynchronous healthcare settings.

This study also raises several important questions that need further exploration:

- How can the proposed VDA scheme be adjusted for large-scale monitoring systems that track multiple patients, which may use different sensor types and experience changing network conditions?
- Can we incorporate adaptive synchronization algorithms or self-learning time alignment techniques to completely remove interval-based delays?
- What are the energy trade-offs between continuous data validation and the lifespan of sensors in real-world applications?
- How can we further enhance data privacy and model security in federated learning when applied in different healthcare settings?

Addressing these open questions will help develop stronger, scalable, and smarter IoT-based healthcare monitoring systems. This progress will lead to real-time, patient-focused, and reliable medical diagnosis in future healthcare environments.

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Conflicts of interest

The authors have no competing interests to declare that are relevant to the content of this article.

Availability of data and material

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Code availability

The code generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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