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Predictive Analysis Using the Internet of Medical Things to Develop a Smart Patient Monitoring System

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Abstract: - The current patient monitoring system is primarily designed to cater to emergency and elderly patients, aiming to protect them from critical situations. It relies on the Internet of Things and related medical devices and equipment strategically placed around the patients' bodies, beds, and the ward where they stay to record their health and related data. However, the existing system has its limitations. For instance, patients' health needs to be monitored, and this may change due to their emergency condition, staying in the intensive care unit, age, and other factors. These factors need to be considered to provide immediate and accurate treatment. However, the patient versus medical practitioner ratio is 1:25, and caring nurses is 1:10, which is not sufficient and efficient in providing smart healthcare. This underscores the need for a more advanced and efficient patient monitoring system. The earlier methods proposed defined computer-aided systems to analyze the patients' records and monitor them indoors and outdoors. IoT devices can provide various kinds of data but cannot be processed simultaneously using a single analytical model. This paper proposed a Multi-Modality Split Learning (MMSL) model for analyzing different medical data obtained from multiple Internet of Medical Things and aggregating the predicted output to the server to allocate the doctors and nurses for immediate treatment to save the patients. The IoMT data is transferred from the devices to the server in parallel and sequential models to increase the transmission speed. The proposed MMSL model is implemented in Python, and the results have been verified. From the output, it is verified that it outperforms the others.

Keywords: Internet of Medical Things, Patient Monitoring System, Multi-Modal Split Learning, Data Analytics, Medical Data Analytics.

Introduction

The patient monitoring system, a complex amalgamation of technology and machinery, plays a crucial role in healthcare. It continuously measures the patient's BP level, oxygen level, heart rate, respiratory rate, BMI, etc., to provide a comprehensive health profile. This data is instrumental in providing care to sick patients and can be used by patients with multiple pre-existing conditions to monitor their health. The system can gather patient data and securely transmit it to a database, facilitating comprehensive patient care.

This monitoring system is intelligently connected to IoMT devices, a type of IoT technology. IoMT (Internet of Medical Things) empowers medical devices to communicate independently over a network. The IoMT network efficiently collects patient data and transmits it to healthcare providers without needing patient or medical professional intervention. These parameters are ideal for analyzing the performance of various IoT-enabled applications, focusing on secure data transmission, energy efficiency, network performance, and data storage management. The data collected from the patient monitoring system is securely transmitted to the IoMT data Hub. The IoMT hub amalgamates multiple data into a single container through prediction and analysis, akin to data aggregation. Data analytics then process this data aggregation to delve deep into each patient's condition. Thus, IoMT introduces the deep learning model in Artificial intelligence. Deep learning, a branch of Artificial Intelligence, is not just a solution but a catalyst for innovation in various domains, including data science, biomedical engineering, data analytics, and promising exciting patient monitoring and healthcare advancements.

Deep Learning for Data Analytics

The DL-based data analytic technique is widely applied in large types of environmental applications. Generally, the DL models are structured based on artificial neural networks that depend on the multiple layers of nonlinear processing, assets learning steps into two ways: supervised and unsupervised learning, pattern recognition, and classification. The DL model transmits the data through the layers, which helps the systems to analyze and process complex data sets. Deep learning algorithms remove the high-level, complex data and process these complex data formulated in the preceding level of the hierarchy. The author focuses on data analytics methods to solve complex data for medical applications. In deep learning, the data should be trained with deep algorithms, and patterns

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should be analyzed using layer processing. It is mainly used for analysis and learning large amounts of unsupervised data to categorize the data.

Deep learning works in three types: Feature representation, Deep learning layers, and Deep learning results. Our patient monitoring system uses deep learning layers. This layer uses the data to predict the latent features of data. The data in the predictive layer is used to analyze the new variable, select the analytic model, and evaluate the model's unknown parameters. In this layer, the overall performance is analyzed based on the quality and features of the model. The DL-based approach is more suitable for learning the hidden features of the model and replacing the traditional models by implementing hierarchical layers. After this process, collected data is moved on to data analytics, which has five types: descriptive, diagnostic, predictive analysis, prescriptive analysis, and discovery analysis. Each has a different role in healthcare, but predictive analysis is mainly used in the patient monitoring system.

This paper proposed a deep learning model for predictive analytics for analyzing the health data generated using IoMT, a wearable body sensor and IoT devices collection. This data analytics is used to predict patient data, analyze the type, and then move on to the next step. It is a pre-final step of the patient monitoring system. In the data analytics portion, the prediction of the patient's health condition is analyzed. After the prediction process, immediately meet the doctor and start the treatment. This smart monitoring system, which uses the IoMT device, helps healthcare providers prevent patient death. This paper contributes to developing an efficient Patient Monitoring System Using IoMT and Deep Learning Algorithms.

- A detailed conceptual overview is provided to understand the importance of patient monitoring systems, the necessity of IoT devices, and the need for deep learning algorithms to analyze the data.
- The overall architecture of the problem statement is illustrated figuratively and explained well to understand it.
- The need for and the functionalities of the Multi-Modality Split Learning algorithm are explained and demonstrated.
- The experimental results are provided and discussed, along with the performance comparison, to understand the efficiency of the proposed model of this paper.

A detailed literature survey is conducted to understand the existing issues and challenges of the various research methods used for patient monitoring systems, IoT applications, deep learning algorithms, and related aspects. It helps to plan for the proposed model to improve the system's overall efficiency.

Literature Survey

Innovations in IT and its established services lead to the development of novel solutions and products day by day. IoT is a recent innovative product to improve lifestyle and quality of life. Chronic diseases are rising every day on par with the increasing rate of the universal population. Effective medical services at low cost are to be designed accordingly [1, 2, 3, 4]. Healthcare monitoring applications are enabled using various IoT devices nowadays. The primary objective of such implementation is to perfectly track people and connect them to the internet world where monitoring, analyzing, exchanging, and storing real-time data are possible [5]. The IoT is a novel model in which each object in an internet-based implementation, such as a smart home or intelligent healthcare, is brought under remote management. Monitoring every patient and diagnosing their health issues are the ultimate tasks in medical services. These tasks are easily attained when the sensor networks are applied to the human body. Above all, round-the-clock access to information is possible worldwide [6]. There are several difficulties in reaching a hospital, such as severe injuries, distance, transportation, etc. This is why streaming applications are used to consult with physicians. This will be helpful to the patients, as they can experience a cost-effective, ideal medical service on time. Moreover, the technology lets patients store their health conditions on smartphones [7]. IoT and its benefits are expected to improve well; this enhances personalized, cost-effective medical care for good health improvement among people. Physicians can remotely monitor patients' health conditions and schedule the corresponding appointments using IoT devices. On the other hand, patients can improve home care, reducing the need for visiting physicians. Additionally, a few unwanted treatments that are taken in hospitals are avoided. As a result, quality and safety are ensured at a low cost, where IoT plays a vital role in medical services [5, 8]. Implementing an uninterrupted medical service with a comfortable home-based health monitoring option will be easily possible shortly.

Numerous IoT-based sensors should be used to monitor the human body and the surrounding atmosphere regularly. This will be useful for tracking severe diseases and taking further steps. Virtual medical consultation is a promising solution using IoT in the future [9]. Medical scholars and scientists are highly focused on healthcare monitoring; they have successfully executed many projects, and various projects are currently being conducted [10]. Proper and even health care and the related gap are negatively impacted due to the sudden increase of chronic diseases and elderly people. In reality, health care is possible only in clinics, creating difficulties for senior citizens and physically challenged people. [11]. The elderly's health can be effectively monitored using IoT devices that read sensor values. IoT, incorporated with intelligent approaches, will enhance several services. Researchers utilized sensors to develop several techno-emergency applications for wireless and remote operations. These technical applications are utilized for different uses, especially in monitoring people's health conditions, where data can be gathered that reveal the signs of both standard and severe conditions [12].

In [13], the authors developed a wearable device that monitors several medical parameters, such as ECG, heart rate, and body temperature. Because of the complex framework in the design, there is clear communication between the monitoring system and the people. The low power consumption feature of the devices helps attain accessible wireless communication for customized physiological values of a particular signal. The BLE module can be used to transmit those values wirelessly. The data encryption is done to ensure security and privacy. The sensor-based wearable devices are connected to the cloud system through Raspberry Pi and smartphone, and a module is employed as a communication gateway. An automatic and intelligent patient monitoring system is developed in [14]. The system helped collect physiological parameters and environmental conditions such as the room's carbon dioxide and humidity levels. This system is more beneficial to the Medical sector to monitor the patient's health conditions remotely. Theoretically, the approach could be helpful during epidemics due to the possibility of immediate access to the original data. The design and utilization of the model are simple and easy. These kinds of devices would help regulate infectious disease epidemics like COVID-19. Possibly, this system would save more people by enhancing the effectiveness of the current healthcare system. Conversely, infectious-disease-related sensors were unavailable in the sensors, and those should be deployed, and their performance should be assessed. In [15], the authors developed an IoT-based patient health-monitoring system for smartphones with remote monitoring features over various signs such as ECG and SpO2. This system utilized Wi-Fi connectivity for cloud service-based data transmission using IoT, termed Blynk, where real-time data monitoring was enabled. To ensure privacy and security, the data could be viewed only on the smartphone that the physician approved, but Wi-Fi cannot establish long-distance wireless communication.

In [16], the authors delivered an IoT-based healthcare-monitoring system functional on Android. The system was developed to monitor the health conditions of patients and elderly people. The sensors were able to collect HR, BT, and GSR data. An Android Studio application is developed and implemented with healthcare applications to monitor and view essential patients' records. The application enabled prescribing and tracking options for the doctors at any time. A Raspberry Pi-3 implemented IoT-based health monitoring system is proposed in [17]. This model is mainly applied to medical data (HR, BP, BMI, etc.) acquisition, creation, communication, and process. These data are accessed through an internet gateway, GSM, Wi-Fi, etc. Low latency was observed, resulting in ideal two-way transmission. The simulation result shows that the accuracy result of the model is proportional to the sensor device accuracy used in the patient monitoring system [18]. This model is more suitable to analyze patient BT and HR parameters. The device was found to be optimal for carrying out proper and regular monitoring. The system utilized an Arduino board for medical data storage and Wi-Fi connectivity for data transmission, which was helpful for remote monitoring. Physicians can analyze the stored data to identify patients' health conditions from time to time. However, the system was unsuitable for applications based on long distances.

From the above discussion, it is identified that connecting and accessing patients reliably requires a fast internet connection. Accessibility issues happen for a limited number of patients. Devices used in the IoMT network and medical field can avoid these issues. All the devices are not generating the same kind of data, and it needs to be analyzed using separate deep learning models, but earlier methods do not integrate many methods. Once data is generated using multiple IoMT devices, they must be transferred to the other processing places and storage units/locations speedily and effectively. After processing and proceeding to the other new patients, their data units and hubs should be garbage for new incoming data. Thus, this research work has motivated me to design and implement a novel framework for smart patient monitoring systems with IoMT and Deep learning algorithms.

Problem Statement

The proposed model is developed to monitor in-house patients' health conditions by deploying multiple IoMT devices. It is expected to monitor the patient's health conditions, namely HR, EMG, oxygen level, fever level, ECG, arrhythmia, body mass index values, and other essential medical images. The proposed model integrates the potential of IoMT, data analytics, deep learning algorithms, and data transmission processes. The IoMT devices generate the health data seamlessly without interruption and transmit it to the data hub. An efficient high data transmission rate model transmits the data by connecting the whole network with 5G technology. Finally, a multi-modality split learning algorithm is used to analyze the health data to predict abnormalities and alert the server or the administrator. The IoMT plays a major role in health data generation from the patient's body, whereas the deep learning algorithm plays a big role in analyzing healthcare data. The proposed model uses split learning algorithms to analyze the multi-modality data.

Figure-1 shows the overall architecture of the proposed model. It shows the IoMT devices connected to the patient's body and generates health data. Then, they are aggregated and transmitted to the server and administrator through IoT-data hub and 5G technology. Finally, the split learning algorithm is used to analyze the data. It is assumed that before starting the data analytical process, the data is pre-processed due to noise and missing data. Since multi-modal data is generated, the split learning algorithm is virtualized to process them and provide predicted output. Based on the prediction, the decision was made.

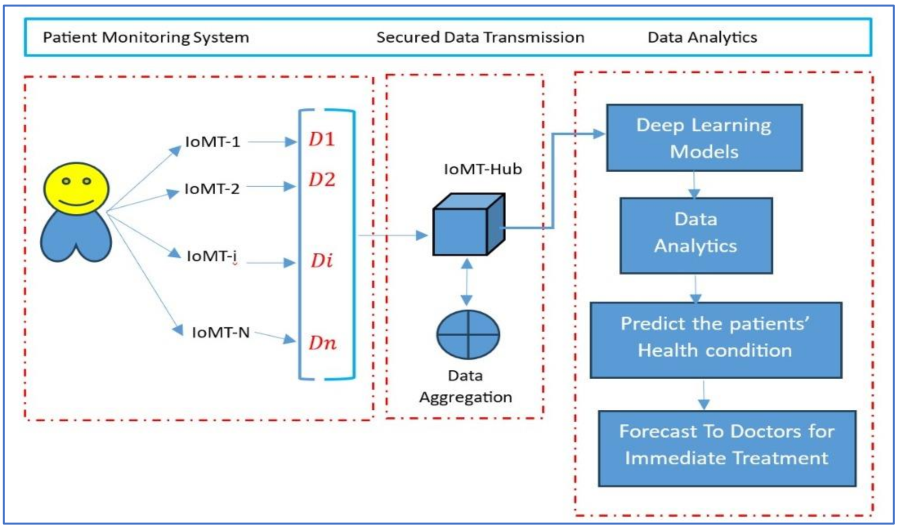

Figure-1. Architecture Diagram for Patient Monitoring System

Split Learning Model

The split learning model has N number of DL layers with server-side and device-side models divided by the cut layer. The device-side model extracts the feature data of the raw input, and this extracted output is known as smashed data. The Forward and backward propagation in every training round needs to traverse from device to server or vice versa, respectively. This is due to the partial model structure available in both the server and device. The below Figure-1 shows the structure of the Split Learning (SL). Figure-2 shows the structure of split learning, where the cut layer separates the IoMT-side and server-side layers. It also shows the various layer arrangements on both sides, which help to achieve the Forward and Backward Propagation of Split Learning.

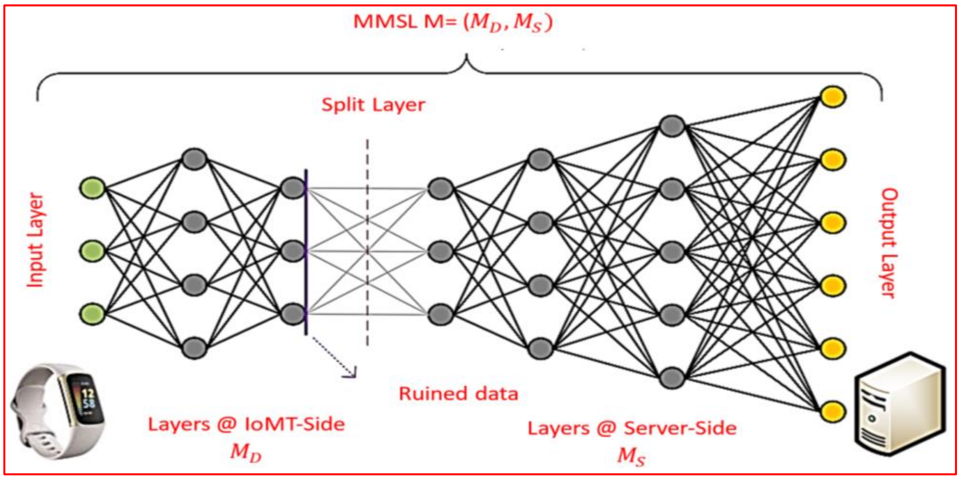

Figure-2. Split Learning Model (IoMT connected to Server)

Split Learning Forward Propagation

The forward propagation functions will happen on the server side. $\boldsymbol{F_S}$ (.) and IoMT side $\boldsymbol{F_D}$ (.). Similarly, the model weights $\boldsymbol{w_D}$ and $\boldsymbol{w_S}$ are denoted for the server side and IoMT side, respectively. The feature vector, $\boldsymbol{x}$**,** and the ground-truth table $\boldsymbol{y}$ are represented as input data. The cut layer gives the ruined data output with the mathematical expression of

$$ \expression{c}_D = F_D (\expression{w}_D, \expression{X}).

Then, the remaining model training is completed on the server; after receiving the ruined data, $\boldsymbol{s_D}$ with its label, $\boldsymbol{y}$**.** After receiving the necessary data from the device, the server starts the execution of Forward propagation in the server-side model with the help of

$$\expression{c}_S = F_S (\expression{w}_S,\expression{c}_D.

One cycle of forward propagation is completed without transferring the raw data from the device, and then backward propagation is carried out.

Split Learning Backward Propagation

When the forward propagation is completed, the server sends the output obtained from the output layer, and back propagates it to the IoMT-side model's input layer. This action will update the model weights. $\boldsymbol{w_D}$ and $\boldsymbol{w_S}$. The loss function during this action is calculated as L(.). The output of the server side is transferred in the form like

\expression{g}S = \nabla{\expression{w}_S} L(\expression{c}_S, \expression{y}.

The Server-side model's first-layer gradients are represented as $\boldsymbol{g}_S^1$. This first layer gradient is then returned to the IoMT side to calculate the backward propagation. Similarly, the IoMT-side model is provided by the \ expression {g}D = \nabla{\ expression {w}_D} L (\expression {c}_S, \ expression {y}).

The gradient descent model is used to update the model weights of the server and device. The update rule for both the device and server is provided by

\ \expression{w}_D := \ expression {w}_D - \eta \ expression {g}_D

and

\ expression {w}_S := \ expression {w}_S - \eta \ expression {g}_S

respectively. Until the time runs out or the DL model is trained during the SL training process, the forward and backward propagation iteration process is repeated many times for the proper results.

Proposed Multi-Modal Split Learning Framework

A Multi-Modal Split Learning (MMSL) framework is proposed to achieve distributed machine learning with multi-resource constrained devices. The MMSL is shown in Figure 3 to understand its working of it. Figure 4 shows the workflow or data flow between the IoMT and the server side of the MMSL. The Forward and Backward propagation of the model is also illustrated in the figure for the understanding. In that, the device–side trains a small shallow neural network by every client. On the server side, the edge server compiles and synchronizes the low-level sub-networks along with the computational task of the high-level sub-network.

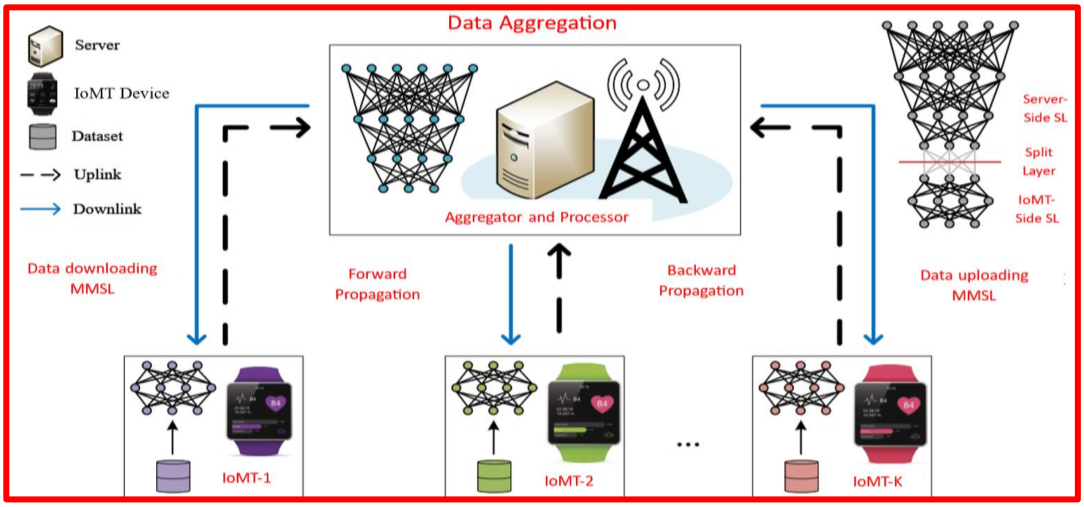

Figure-3. Workflow of MMSL.

The computation and the interaction process of the MMSL model are given in Figure-3. The proposed model contains two main levels, multi-user split learning, and federated sub-network averaging, for each training round of MMSL. They are multi-user split learning and federated sub-network averaging. At different levels, data are transferred between the devices and the server. In the first stage, the smashed and ground-truth data are transferred to the server to process the forward propagation step. Then, the server transmits the data to the local devices to process the backpropagation step. At the same time, the server sends the gradients to the local devices for backward propagation. During the second stage, the synchronization of model parameters is achieved by sharing the sub-network parameters from the device to a server.

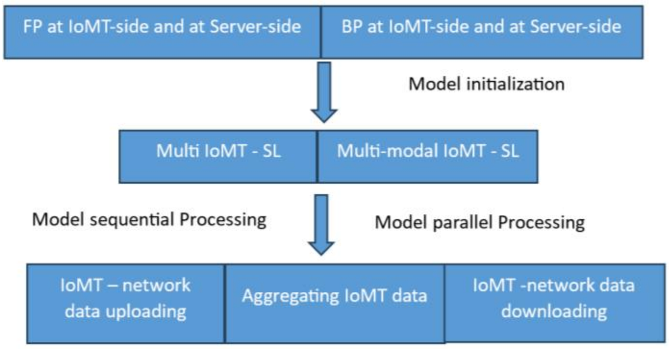

Figure-4. Stages of the MMSL Process

Figure 4 shows the interactions of the MMSL model and its training process. It also shows various processes at various stages to attain forward and backward propagation. During the time t1 and t2, the entire model is initialized using the server-side and IoMT-side initialization tasks. The whole data uploading, aggregation, and downloading process is carried out during t3, t4, and t5, and the overall processes are carried out sequentially and in parallel. The novelty of this paper is that the data analytical process using MMSL is efficiently done using sequential and parallel processing methods.

The proposed MMSL agrees to take the input of multiple IoMT devices to train the shared model parallelly. Figure 5 outlines the process and shows the parallel model training of the MMSL. Every device processes its data with the help of the model and reverts the key data to the server. In return, the server transfers the gradients to each device to enhance their local models after updating all the device data. It repeats until the model gets the preferred accuracy.

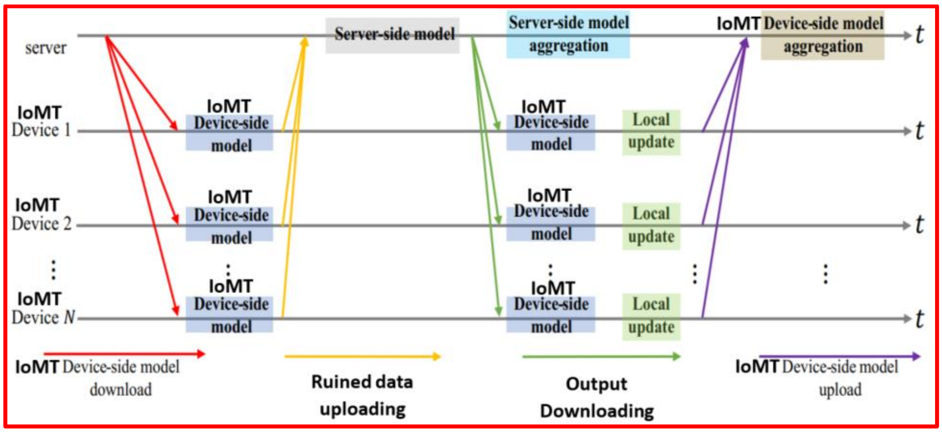

Figure-5. Parallel Process of MMSL

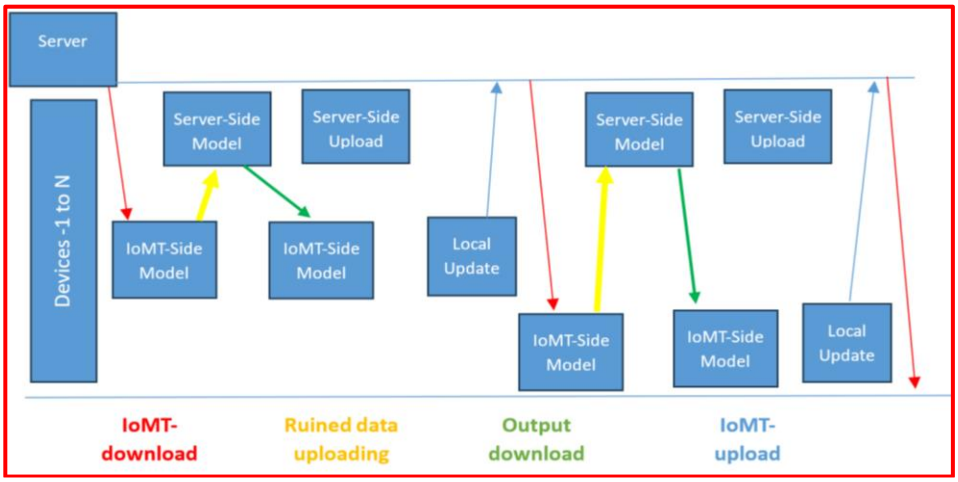

Figure 6. Sequential Process of MMSL

The sequential model training of MMSL is a process where every device trains individually with the edge server, as shown in Figure-6. The sequential training model is similar to the Parallel type, except for the model aggregation after every update. The knowledge gained after training is given to the new device connected after the training, and the training is finished when the last connected device is trained. Once this training is completed, one round will be completed. This makes the training process flexible and the devices' participation in the training dynamic.

Comparison of SL, FL, and MMSL.

Table 1 compares the communication overhead of individual clients and across all clients in the IoT network. In that, the number of clients is denoted by K, the size of the whole model is given by W, the total dataset size is given by p, the size of the smashed data is q, the fraction of the model size with the client in SL is denoted by η, and the fraction of the model size with the server is 1- η.

Table.1. Comparison Of SL, FL, And MMSL On Communication Overhead.

Scheme	Training Approach	Communication overhead per client	Total communication overhead
SL	Sequential	2pq/K +2ηW	2pq +2ηWK
FL	Parallel	2W	2WK
MMSL	Parallel or Sequential	2pq/K +2ηW	2pq +2ηWK

Table 2 compares the SL, FL, and MMSL to better understand each model's key features and advantages.

Table.2. Comprehensive Comparison of SL, FL, and MMSL.

Scheme	Number of Users	Model Aggregation	Applicable to low-end devices	Distributed computing	Sharing Raw data
SL	One	No	Yes	Yes	No
FL	Multiple	Yes	No	Yes	No
MMSL	Multiple	Yes	Yes	Yes	No

Considering ResNet-18 as a sample, it needs 28.85M floating-point operations for local computing in one training round when the third layer is divided. Regarding Most wearables that can handle 1.2 G floating-point operations per second, the proposed MMSL can control edge servers to support medical image analysis on limited-resource IoMT devices excellently.

This research uses a transfer learning-based neural network model, ResNet-18, to detect patient health reports observed from multiple IoMT devices. The input medical data are collected from two datasets: the chest X-ray and optical coherence tomography (OCT). The Chest X-ray dataset includes 4273 pneumonia data and 1583 normal data, and the optical coherence tomography (OCT) dataset includes 51390 normal, 37455 CNV, 11598 DME, and 8866 DRUSEN data. All the input data are analyzed using 5 IoMT devices based on two distributions. (1) with independent and identically distributed (IID) and (2) non-IID. In IID distribution, all the data transferred between the devices are the same. In non-IID distribution, all the data transferred between the devices is different. The model's overall performance is evaluated in 400 iterations with a learning rate of 0.0001. Table-3 shows the parameter setup of the proposed model.

Table-3 Proposed Parameter

Parameters	Description	Value
Neural Network	Split Learning derived from ResNet-18	[64 64 64 64 64 128 128 128 128 256 256 256 256 512 512 512 512 2 or 4]
Dataset 1	Chest X-Ray	Two categories (PNEUMONIA: 4273, NORMAL: 1583)
Dataset 2	Optical Coherence Tomography (OCT)	Four categories (NORMAL: 51390, CNV: 37455, DME: 11598, DRUSEN: 8866)
Distribution 1	Independent and identically distributed (IID)	Data distributions between devices are the same
Distribution 2	Non-IID	Data distributions between devices are different
K	Number of IoMT devices	5
L_c	Index of the cut layer	3
T	Maximum number of training rounds	400
η	Learning rate	0.0001

Results and Discussion

This research evaluates the model's performance and simulation results by comparing four schemes, as shown in Table 4. The proposed model's performance in assessing health data in two datasets is analyzed based on four schemes: Centralized Learning (CL), Federated Learning (FL), Sequential MMSL, and Parallel MMSL. Table 4 elaborately discusses the functionality of each learning approach.

Table-4 Model Comparison Scheme

No.	Name	Description
Scheme 1	Centralized learning (CL)	All data samples are sent to the server for model training
Scheme 2	Federated Learning (FL)	Devices train their models without sharing datasets
Scheme 3	Sequential MMSL	Only a single device trains the model with the server using split learning in one-time slot.
Scheme 4	Parallel MMSL	All devices train models simultaneously, and the server computes different models in parallel.

Figure-7 shows the proposed model accuracy results in processing the chest X-ray dataset. Figure-7(a) shows the accurate resultant image of the proposed model when evaluating the chest X-ray images with IID distribution. The accuracy result is evaluated over 100 iterations using four different schemes. Figure-7(b) shows the chest X-ray image accuracy analysis result without IID. The overall analysis result shows that both setup centralized learning (CL) and Sequential MMSL approaches have achieved high accuracy with 98%.

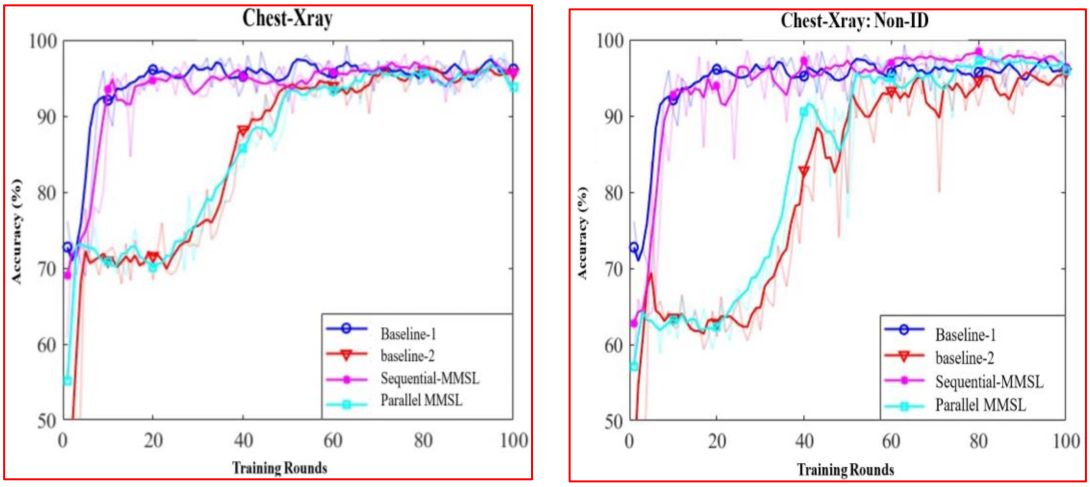

Figure-7 Accuracy result of chest X-ray dataset

Figure-8 represents the loss rate result of the proposed model for processing the chest X-ray dataset. Figure-8 (a) shows the loss rate result of the proposed model in evaluating the chest X-ray images with IID distribution. The loss rate result is evaluated over 100 iterations using four different schemes. Figure-8(b) shows the loss rate result of chest X-ray image analysis without IID. The overall analysis result shows that both setup centralized learning (CL) and Sequential MMSL approaches have achieved less than 0.1 compared to others.

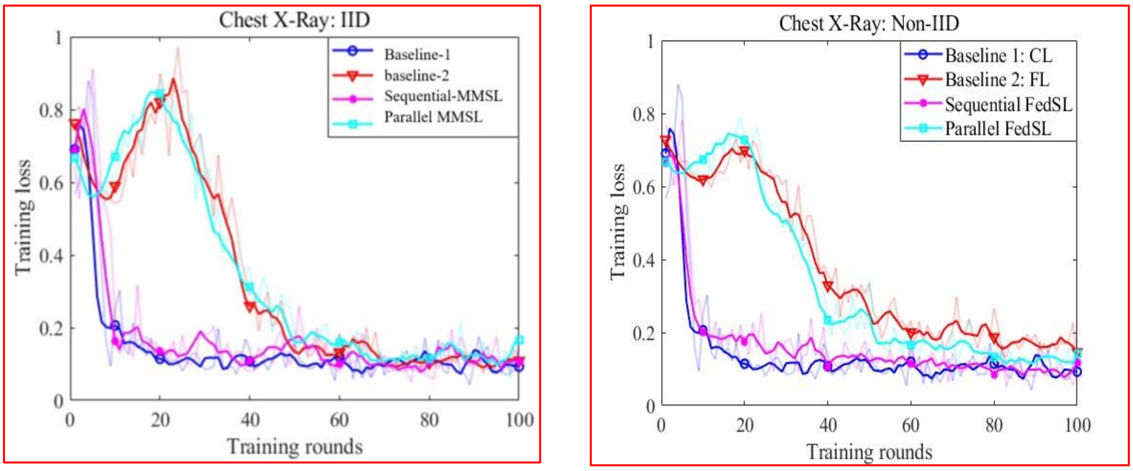

Figure-8 Loss Rate Result Of The Chest X-Ray Dataset

Figure-9 illustrates the accuracy result of the proposed model in processing the OCT image dataset. Figure-9(a) shows the accuracy result of the proposed model in evaluating the OCT image with IID distribution. The accuracy result is evaluated over 400 iterations using four different schemes. Figure-9(b) shows the accuracy of the OCT image analysis without IID. The analysis result of Figure-9(a) shows that the proposed model has achieved 87% accuracy in processing with a centralized learning approach when detecting the OCT images. followed by this Sequential MMSL model, which achieved 83% accuracy. Similarly, Figure-9(b) analysis shows that both CL and sequential MMSL approaches achieved a high accuracy of 87%.

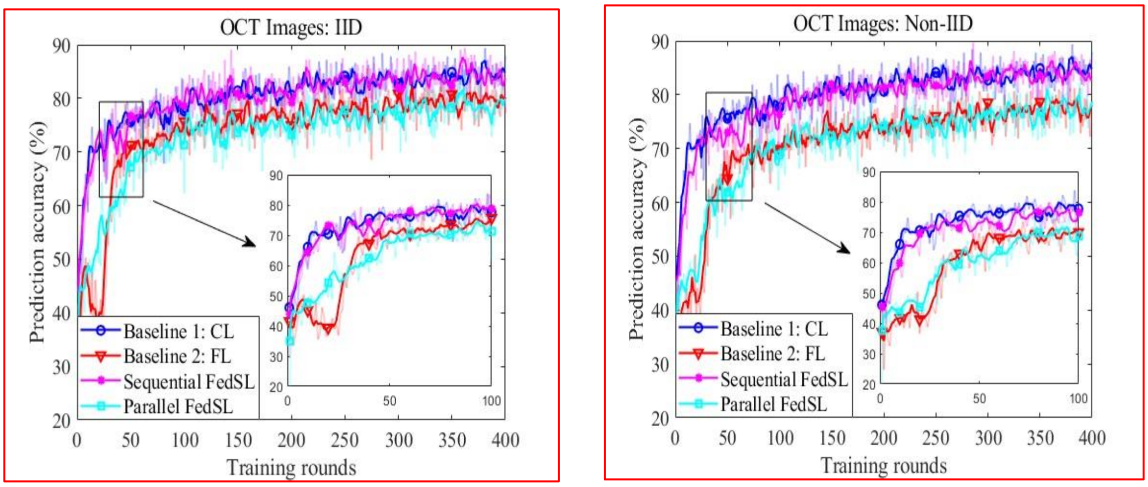

Figure-9. Accuracy Result Of The OCT Image Dataset

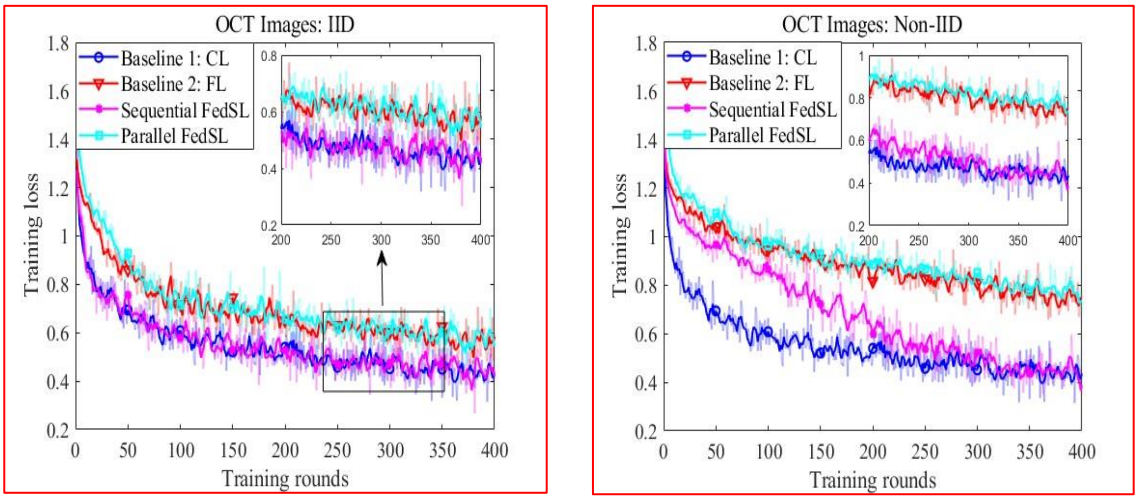

Figure-10 Loss Rate Of The OCT Image Dataset

Figure-10 illustrates the loss rate result of the proposed model for processing the OCT image dataset. Figure-10(a) shows the loss rate result of the proposed model in evaluating the OCT image with IID distribution. The accuracy result is evaluated over 400 iterations using four different schemes. Figure-10(b) shows the loss rate result of OCT image analysis without IID. Figure-10(a) analysis shows that the proposed model detected the OCT images with a 0.5 loss rate on processing with a centralized learning approach, followed by this Sequential MMSL model, which achieved a 0.53 loss rate. Similarly, the analysis result of Figure-10(b) shows that the CL approach detected the diseases with a minimum loss rate of 0.4 compared to others. Following this sequential MMSL approach, the input data was processed with a minimum loss rate of 0.43.

Conclusion

This paper applies a transfer learning-based neural network ResNet-18 model to create an efficient patient monitoring system. The model's performance is evaluated using four schemes, CL, FL sequential MMSL, and Parallel MMSL, in terms of accuracy and loss. The overall analysis shows that the proposed neural network model is more suitable for detecting normal and abnormal data from the chest X-ray dataset. With high accuracy (98%), the proposed model classifies the input medical data with less than 0.1 loss rate.

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