A FEDERATED LEARNING APPROACH FOR GREEN AND RESILIENT IOMT NETWORKS

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by

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DECLARATION

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ABSTRACT

Although the Internet of Medical Things (IoMT) is revolutionising healthcare, optimising energy efficiency is challenging due to budget limitations. This may result in shorter IoMT device operational lifetimes, higher energy usage, and higher healthcare provider expenditures.A federated learning framework is suggested as a solution to this issue, one that increases the operating lifespan of IoMT devices, reduces energy consumption, and encourages sustainability and cost savings in the healthcare industry. The system trains a global model without sharing the underlying data by utilizing the processing power of several IoMT devices. As a result, less energy is used by individual devices and less communication overhead occurs.The goal is to make IoMT more sustainable and energy-efficient so that it can play a better role in healthcare. Longer IoMT device lifespans, reduced costs for healthcare providers, and improved patient care .

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Chapter 1

Introduction

1.1 Internet of Medical Things

IOMT refers to the "Internet of Medical Things." It is a subset of the more general Internet of Things (IoT) idea that particularly refers to the internet based network of medical applications and devices that are linked to healthcare IT systems [1]. Wearable fitness trackers, medical sensors, implantable gadgets, and other medical equipment with the ability to gather and transmit health related data are examples of these devices.

By facilitating remote diagnostics, better healthcare delivery, and real-time patient monitoring, IOMT has the potential to completely transform the healthcare industry [10]. It enables medical personnel to obtain important patient data, make wise decisions, and deliver superior care. By using IOMT devices, which can track and manage chronic conditions or improve general wellness, patients can also play a more active role in managing their health.

1.1.1 Features of IoMT

Connected Medical Devices : A network of connected medical devices is essential to IoMT. Wearable technology such as smartwatches, fitness trackers, and implantable sensors can be a part of these devices. Their purpose is to gather and forward health related information to patients or healthcare professionals [13]. There are many different types of connected medical devices, from implantable devices like insulin pumps or pacemakers to wearable ones like smartwatches, fitness trackers, and glucose monitors. This category also includes non wearable gadgets like data transmitting scales and blood pressure monitors.

Data Collection and Monitoring :IoMT devices are always gathering data, whether it's activity levels, health metrics, or vital signs (e.g., blood pressure, heart rate). After that, this data is sent to medical experts for analysis and real-time monitoring [4]. It makes early health issue detection and proactive healthcare management possible. Vital signs and activity levels are just two examples of the health related data that are continuously collected as part of the Internet of Medical Things (IoMT) data collection and monitoring process. Healthcare professionals receive this data in real-time for prompt analysis. Proactive healthcare management, early health issue detection, and long-term health trend analysis are made possible by it. By averting complications and enabling patients to take charge of their own health, IoMT lowers hospital stays and medical expenses.

Telemedicine and Remote Care : IoMT is essential to the transformation of healthcare because it makes telemedicine and remote care solutions possible. Through virtual appointments, such as video calls or chat sessions, patients can easily consult with healthcare providers, and medical professionals can use IoMT devices to remotely monitor patients' health [10]. Patients who manage chronic health conditions or live in remote or underserved areas will find this capability especially helpful. In addition to lowering healthcare costs and facilitating prompt interventions, the Telemedicine and Remote Care feature also encourages patient participation and guarantees the continuation of healthcare services—even in the event of an emergency or difficult situation.

Data-Driven Decisions : The Internet of Medical Things, or IoMT, gives healthcare professionals the ability to make decisions based on data. IoMT gives medical professionals the information they need to make timely and well informed decisions about treatment plans, medication adjustments, and interventions by collecting and analysing patient data in real-time. This method guarantees proactive healthcare, enabling early problem detection and individualised treatment regimens for each patient. In addition, IoMT prioritises patient well being and provides high quality, individualised care while streamlining resource allocation, facilitating remote consultations, and potentially saving money for the healthcare industry.

Personalized Medicine : The Internet of Medical Things, or IoMT, continuously monitors and analyses a person's health data in real-time, advancing the idea of personalised medicine. Healthcare professionals can now create treatment plans that are specifically tailored to the needs and characteristics of each patient thanks to this data-driven approach. IoMT reduces the possibility of side effects while simultaneously optimising treatment effectiveness. Additionally, by actively involving patients in their healthcare decisions, this customised approach promotes cooperation between patients and healthcare professionals. This strategy, which aims for improved patient outcomes and a higher standard of care, is particularly helpful in managing chronic diseases.

Healthcare Continuity : The Internet of Medical Things, or IoMT, is a strong pillar of support that keeps healthcare running smoothly even during crises, natural disasters, and pandemics. This is made possible by the smooth integration of remote care and telemedicine, which guarantees that patients can continue to get essential medical services even in the absence of direct physical interaction. This ability optimises the distribution of healthcare resources, focusing them where they are most needed, and dramatically lowers exposure risk—an important factor to take into account during health emergencies. Better patient outcomes and stronger responses to public health issues are a result of IoMT's adaptability and resilience within healthcare systems.

1.1.2 Steps to Implement IoMT Technology in Healthcare

As depicted in Figure 1.1, the steps to implement IoMT technology in healthcare involve several key stages.

Define the Goals : Clearly define the goals and objectives of your IoMT implementation in your healthcare company. Select the IoMT applications you want to use, such as asset tracking, workflow optimisation, or remote patient monitoring. Determine if implementing IoMT in your medical facility is practical. Consider the infrastructure needs, legal compliance,

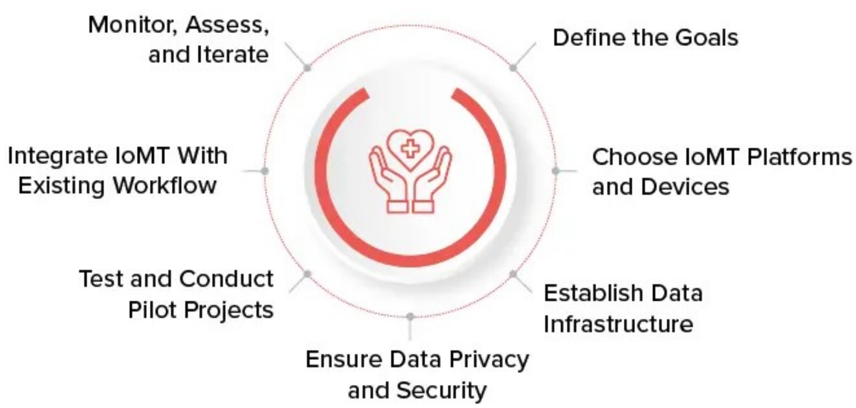

Figure 1.1: Steps to Implement IoMT Technology in Healthcare [3]

technological demands, and potential benefits.

Select IoMT Devices and Platforms : Select the IoMT devices and platforms that are appropriate for your use cases. Think about scalability, connectivity options, device compatibility, and data collection potential. Verify that the apparatus conforms with all relevant legal requirements and industry standards.

Establish Data Infrastructure : Provide Data Infrastructure It is necessary to provide infrastructure for the gathering, storing, and analysis of data from IoMT devices. To do this, it might be required to deploy servers in the cloud or on-premises, implement data security measures, and integrate with existing electronic health record (EHR) or healthcare information system (HIS) systems.

Ensure Data Privacy and Security : Provide robust security measures to protect the personal health data that IoMT devices collect. Set up secure access controls, verify device connections, and encrypt data both during transmission and storage. Observe applicable data protection laws, such as HIPAA (Health Insurance Portability and Accountability Act) and the General Data Protection Regulation (GDPR).

Test and Conduct Pilot Projects : Pilot projects are the best way to assess the IoMT deployment's effectiveness. In a controlled setting, test the data management protocols, hardware, and connection. Seek input from stakeholders, including patients and healthcare providers, to identify areas that require improvement.

Integrate IoMT With Existing Workflow : To maximise the benefits of IoMT data and insights, incorporate them into current healthcare workflows. Ensure that efficiency is increased and that the IoMT system is in line with operational procedures. Employees should be trained in the use of IoMT devices and the analysis of gathered data.

Monitor, Assess, and Iterate : Keep an eye on the outcomes, key performance metrics, and IoMT implementation. Once the solution's needs have been identified, work on refining it to maximise its impact. Stay up to date with the latest IoMT trends in healthcare to take advantage of new opportunities.Deploying IoMT in a healthcare organisation requires a multidisciplinary approach combining collaboration between IT teams, healthcare practitioners, regulatory specialists, and administrators. This brings us to our next topic of discussion, the challenges.

1.1.3 Challenges of IoMT

Data Security : Secure storage of private medical data is one of the main issues with IoMT. Cyberattacks target connected medical devices because of the large amount of personal and medical data they collect and transmit. Unauthorised access to this data may result in identity theft and other serious issues affecting patient privacy[7]. To reduce these security risks, strong encryption, access controls, and secure communication protocols must be put in place.

Standardization and Interoperability : IoMT encompasses a wide range of devices made by various manufacturers, each with unique data formats and communication protocols. This lack of interoperability and standardisation can make it more difficult for devices and healthcare systems to exchange information seamlessly. It is imperative that manufacturers of IoT devices and healthcare providers collaborate to create industry standards that facilitate device interoperability and data sharing.

Infrastructure and Scalability : Healthcare companies will need to extend their IT infrastructure in order to manage the growing volume of data generated by IoMT devices. It can be very difficult to scale up the required infrastructure and make sure it can manage the flood of data from an increasing number of devices. IoMT integration with current healthcare systems can also be expensive and complicated.

Reliability and Data Accuracy : Data accuracy in healthcare is critical. IoMT devices need to deliver accurate and dependable data so that medical professionals can make well informed decisions. Any problems with the accuracy of the data or the dependability of the device may result in inaccurate diagnoses, inefficient therapies, or needless interventions. To guarantee data accuracy, IoMT devices must undergo routine maintenance and calibration.

1.2 Federated Learning

Federated learning—also referred to as collaborative learning—is a cutting edge method for machine learning model training. It keeps data localised rather than centralising it, allowing model training across decentralised edge devices or servers. Several independent training sessions using separate datasets are used in this method. Because federated learning permits collaborative model training without disclosing raw data, it provides benefits in terms of security and privacy. This innovation is relevant for multiple applications and has the potential to unlock valuable information.

1.2.1 Steps to Implement Federated Learning

Initialization : The global machine learning model is initialised at the start of the process. Either pre-trained data or initial parameters are applied to this model.

Local Training : Using the appropriate dataset, each edge device or server that participates in the federated learning process carries out its own local training. In this stage, the local device starts with the global model and refines it with its data.

Model Update : Each device generates a model update after local training, which is frequently represented by gradients. To better fit the local data, these updates indicate how the local model should be modified. Updates derived from the local training process are provided and raw data is not included.

Aggregation : Every participating device sends its model updates to a coordinator or central server. These updates are aggregated by the central server, usually by calculating their weighted average or average. Aggregation preserves privacy and localises data while ensuring that the global model integrates the collective knowledge from all devices.

Global Model Update : To update the global model, the central server aggregates the model updates. The collective insights and advancements made by all participating devices during local training are reflected in this updated global model.

Iterations : To further improve the global model, it is possible to repeat the steps of local training, model update, aggregation, and global model update several times. The accuracy and functionality of the model are enhanced with each iteration.

1.2.2 Key benefits of Federated Learning

Privacy-Preserving : The primary goal of federated learning is to protect user privacy. It makes it possible to train machine learning models without sending sensitive, raw data to a central server. Rather, local training is done on each device or server's data, and only model updates which are typically in the form of gradients and don't contain personally identifiable information are shared. By ensuring that user data stays on the local device, this lowers the possibility of illegal access and data breaches.

Efficient Data Usage : Federated Learning minimises large-scale data transfers by training models locally on decentralised devices. This minimises the quantity of data transferred over the internet and eases the strain on network bandwidth. Because of this, it is especially effective in situations where network bandwidth is constrained or data transfer costs are an issue.

Security : One of the most important factors in Federated Learning is security. The risk of data exposure and breaches is greatly decreased by keeping data localised and only exchanging model updates. This is particularly crucial when managing private, financial, or sensitive medical information. To further guarantee that data is transferred and stored securely, federated learning can make use of encryption and secure communication protocols.

Decentralization : Because federated learning is by its very nature decentralised, distributed machine learning is possible. One benefit of this decentralisation is that it eliminates the requirement for a centralised server to handle and store all data. In edge computing scenarios, where data processing takes place on local devices or servers, it can be especially helpful in lowering latency and improving real-time decision-making.

1.3 Problem Statement

Concerns regarding resource limitations and the requirement for improved energy efficiency have been raised by the healthcare industry's growing reliance on the Internet of Medical Things (IoMT). One of the main goals is to create a federated learning framework specifically tailored for IoMT in order to increase sustainability, lower energy consumption, and extend the life of medical devices. This framework is anticipated to greatly increase the longevity of IoMT devices by streamlining device operations and optimising energy consumption. In IoMT applications, the main focus is on improving energy efficiency and overall sustainability while taking privacy and security into consideration. This will ultimately benefit patients and healthcare providers.

1.4 Objectives

1. Energy Efficiency Improvement: Develop and implement strategies to optimise the energy efficiency of IoMT devices by reducing energy consumption.

2. Federated Learning Framework: Develop a customised federated learning framework tailored for IoMT devices that emphasises energy-efficient model training.

3. Device Longevity: Explore methods to extend the lifespan of IoMT devices, reducing the need for frequent replacements.

4. Enhance Data Processing Locally: Explore methods for processing data locally on IoMT devices, reducing the need for continuous data transfer and improving overall energy efficiency while considering patient privacy.

1.5 Motivation

A significant gap was found in the field of federated learning (FL) algorithms within the dynamic domain of the Internet of Medical Things (IoMT), especially in relation to healthcare and medical contexts.

- Dynamic Clustering : The heterogeneity of IoMT devices is not accommodated by traditional FL algorithms. In order to organise devices according to real-time performance metrics, dynamic clustering was introduced. This allows devices with similar characteristics to work together efficiently and supports the dynamic nature of IoMT ecosystems.

- Adaptive Learning Rates : IoMT devices frequently have power limitations. Devices can now dynamically modify their learning rates according to their energy levels because of the new algorithm. This ensures the best possible quality of service by maximising device performance and preserving energy resources.

- Data Compression : Reduced transmission energy, quicker data transfer, cheaper storage, less processing overhead, longer battery life, increased network efficiency, and better scalability are just a few advantages of compressed data. Additionally, it lowers processing power requirements, saves energy, and boosts network effectiveness.

Chapter 2

Literature Review

To address energy drain in medical devices in IoMT systems, a unique technique is the Energy-Efficient ON-OFF Algorithm (EEOOA) [10]. The data transmission energy consumption is significantly reduced, and a three-tiered IoMT-based framework for remote healthcare monitoring is offered. The study's conclusions show that EEOOA outperforms traditional methods in terms of energy efficiency, suggesting that it has the potential to completely change the healthcare sector. Bluetooth Low Energy (BLE) technology might be used to integrate EEOOA with the IoMT-based framework, thereby increasing the potential of medical IoT and guaranteeing long-term healthcare solutions that benefit society.

In the research paper [7] the authors highlight energy consumption as a critical component when discussing the application of Federated Learning (FL) in edge-based infrastructures. In order to enable advanced and energy-aware FL orchestration, they offer a distributed system for gathering precise energy usage and learning data. To reduce energy usage, the framework can dynamically modify accuracy goals. The study illustrates FL's advantages using an actual dataset from a solar power plant. Future plans include investigating Reinforcement Learning as a means of optimizing accuracy, energy usage, and learning time in FL, as well as expanding the framework to allow for programmable process orchestration logic.

Federated learning is becoming more and more crucial for wireless networks and edge computing because it facilitates the training of machine learning models on edge devices with limited resources. A possible solution to this issue is provided by the Energy-aware Multi-Criteria Federated Learning (EaMC-FL) model [2], which strikes a balance between model quality and resource constraints like energy usage and battery longevity. By using multi-criteria assessment to optimise representative edge nodes for model training, EaMC-FL lowers energy usage during model updates. This technique can increase the edge devices' total lifespan, particularly when edge nodes are operating on a low amount of energy. The experimental results of the study demonstrate that EaMC-FL outperforms the federated learning baseline (FedAvg) in terms of budget and energy efficiency. This implies that EaMC-FL may be helpful in IoT-based systems and distributed machine learning applications, where preserving model accuracy and prolonging operational life are crucial goals.

The authors [1] is a key component of integrated fog-cloud computing in Internet of Things networks. In this study, fog access points (F-APs) are used to connect Internet of Things (IoT) devices to a centralised cloud server for resource allocation schemes.Two scenarios for local model training are explored: updating model parameters with data from IoT devices, and transferring local model parameters to the CS after training on IoT devices. The scheduling, power allocation, and computing frequency allocation of Internet of Things devices are addressed via a collaborative optimisation technique. Based on simulation results, it is more energy-efficient to train local models directly on IoT devices rather than via F-APs.

The Alternative Direction Algorithm (ADA) [12] represents a major breakthrough in energy optimisation for Internet-of-things (IoT) networks. By optimising CPU frequencies and power transmission controls, it seeks to boost energy efficiency at the expense of longer processing times for Federated Learning (FL) operations. By putting edge intelligence close to devices, it is a promising way to increase the responsiveness of IoT services. Nonetheless, there are computational challenges involved in moving data from Internet of Things devices to edge nodes. Federated Learning (FL) presents a viable approach to address these issues by enabling local machine learning model training on Internet of Things devices. The goal of this research project is to design an efficient integration method for the entire group of edge intelligence nodes, with an emphasis on energy-efficiency

The study [14] offers a brand-new, energy-efficient architecture for IIoT devices that can dynamically modify their training schedules in reaction to the ever-changing outside world. Devices can engage in local training or communicate with virtual objects through a digital twin (DT) housed on a small base station (SBS) server thanks to this flexibility. The mapping data is processed by the SBS using its computing capability. The primary goal is to reduce energy usage while making sure the training model converges as needed. This work uses a deep reinforcement learning (DRL) based algorithm to investigate the difficult problem of combined training method selection and resource allocation. According to the simulation results, federated learning preserves its essential convergence rate while the suggested framework dramatically lowers energy usage when compared to static alternatives.

The number of cases of chronic diseases is rising, and medical costs are rising as well. To address these growing challenges in IoMT-based medical devices, the paper [13] presents a promising Adaptive Energy Efficient algorithm. The objective of this algorithm is to increase throughput, extend battery life, and optimise energy efficiency in the context of medical technology. In order to optimise battery usage within IoMT devices, the paper also presents a battery discharge curve model, implying a suggested algorithm for this purpose. It is important to note, though, that one significant shortcoming of the paper is the lack of a thorough description of the suggested algorithm. However, by contrasting the Energy-Efficient Algorithm (EEA) with the conventional BRLE approach in Smart Healthcare systems, the study offers insightful information. When it comes to voltage performance, EEA beats BRLE.

This research [8] examines how a federated edge learning system can operate in an energy-efficient manner. The system trains a shared machine learning model through the cooperation of edge devices and an edge server. The goal of the project is to combine compute and communication components to maximise energy efficiency. Two transmission techniques for uploading machine learning parameters from edge devices to the server are examined in this study: TDMA and NOMA. The objective is to achieve training delay requirements while minimising overall energy consumption. The study shows how to convert non-convex problems into convex forms and offers efficient algorithms for optimal solutions. The study highlights how crucial it is to balance trade-offs between communication and computation energy. Asynchronous model updates might be investigated in future studies to boost system performance.

The Hybrid Federated Learning(Hy-FL) architecture [4], a system that combines cloud, blockchain, and IoT platforms to enhance healthcare data management, is the subject of this research study. Sensing networks and private data centres make up the architecture, which guarantees secure IoT data processing and communication. Strong data security, privacy protection with Federated Learning, scalability for more devices, and real-time health data monitoring are some of the system's strong points. The integration of several technologies, resource intensity, data labelling, interoperability, and acceptance barriers are obstacles, though. In terms of data accuracy, privacy, scalability, and security, the Hy-FL architecture performs better than previous algorithms, achieving 92–96

Chapter 3

Proposed Algorithm

3.1 Background

3.1.1 K - Medoid Clustering

- K-medoids clustering allows to split the available IoMT devices into groups of similar workers with respect to their local updates[15].
- The medoid is the most centrally located point in a given cluster, ie the sum of distances to other data points is minimal.
- As a result, each cluster medoid can be used as the cluster representative in the algorithm.

The challenge in partitioning algorithms like k-medoids is determining the number of clusters k in advance, but a solution involves building a clustering model and evaluating the generated partitions' quality.

3.1.2 Silhouette index

- Utilize silhouette index[2] to assess the quality of clustering and the suitability of devices to their clusters.It quantifies the quality of the clustering by considering two aspects: compactness and separation.
- Silhouette index ,

$$s_i = \frac{b_i - a_i}{\max(a_i, b_i)} \tag{3.1}$$

- $a_i \rightarrow$ average distance of data point “i” from all the other data points within the same cluster.
- $b_i \rightarrow$ minimum of the average distances of data point “i” from data points in other clusters.
- If s_i is close to 1, it suggests that the device representative is assigned to a cluster where it is a good fit.
- When s_i is close to 0, it indicates that the device is on the boundary between two clusters and doesn’t strongly belong to either.
- If s_i is close to -1, it implies that the device might have been misclassified, as it is more similar to devices with other clusters.

3.1.3 Stochastic Gradient Descent

- SGD classifier is a linear classifier developed via the SGD algorithm. SGD is an iterative process that updates model parameters in small increments known as batches [1].

- Because it only needs to examine a tiny sample of the data at each iteration, SGD is a relatively efficient approach for training huge datasets.
- The SGDclassifier offers several advantages over other linear classifiers, including:
  - SGD is an excellent choice for training huge datasets.
  - SGD is less sensitive to training data outliers.

3.1.4 Support Vector Machine

- A Support Vector Machine (SVM) classifier is a powerful linear and non-linear model used for classification tasks [9].
- The goal of SVM is to maximise the margin between classes by identifying the hyperplane that optimally divides the data points of various classes.
- Important elements regarding svm include:
  - In order to increase generalisation and robustness, support vector machine learning (SVM) aims to maximise the margin between support vectors, or the data points that are closest to the decision boundary, of various classes.
  - SVM concentrates on maximising the margin between classes, making it susceptible to outliers. The performance of the model can be greatly affected by outliers that are incorrectly identified or that are close to the decision boundary.

3.1.5 Decision Tree

- A decision tree classifier is a non-linear model that uses a tree-like structure to divide the feature space into regions[6]. Each leaf node in the model represents a class label, while each interior node represents a feature.

- Recursively dividing the data according to the feature that offers the best class separation is how decisions are made.

- Important elements regarding decision trees include:

  - Decision Trees create a hierarchical structure that resembles a tree by repeatedly dividing the dataset according to feature values in order to maximise collecting data or minimise impurity.

  - Decision trees are useful for applications because they offer clear, simple-to-understand decision-making procedures.

3.1.6 Multilayer Perceptron (Simple Neural Network)

- An input layer, one or more hidden layers, and an output layer are the three layers of interconnected neurons that make up a Multilayer Perceptron (MLP), a type of feedforward neural network [11].

- Important elements regarding MLPs include:

  - When feedforward computation is used by MLPs, input signals are transmitted from the input layer to the output layer in a single direction without the need for feedback loops. After receiving inputs from the preceding layer, each neuron in a layer applies an activation function to the weighted sum of the inputs and forwards the outcome to the subsequent layer.

  - Each neuron's output is subjected to non-linear activation functions, such as sigmoid, tanh, or ReLU (Rectified Linear Unit), which introduce non-linearity and allow the network to learn intricate relationships in the data. MLPs can represent non-linear relationships and identify complex patterns in the data because to these activation functions.

3.1.7 Random Forest

- A group of decision trees make up the Random Forest classifier, an ensemble learning technique[5]. A random portion of the training data and a random subset of the characteristics are used to individually train each tree in the forest.

- The ultimate forecast is produced by combining the forecasts from each individual tree.

- Important elements regarding Random Forest include:

  - In order to increase generalisation and robustness, Random Forest combines several decision trees, utilising the idea of ensemble learning.
  - By taking into account only a random subset of features at each decision tree split, Random Forest adds unpredictability to the

process. This lowers the connection between trees and enhances generalisation even more.

3.2 Energy Model

The energy model is referred from the paper [2]. The energy consumed by the device i in a time interval t for sending and receiving E_i^t is

$$E_i^t = E_i^s + E_i^r = P_i^s \times t^s + P_i^r \times t^r \tag{3.2}$$

$t^s \rightarrow$ time needed to send the data

$t^r \rightarrow$ time needed to receive the data

$E_i^s \rightarrow$ Energy consumed for sending the data

$E_i^r \rightarrow$ Energy consumed for receiving data

The power required for transmission (pt) is

$$P_i^t = P_i^s + P_i^r \tag{3.3}$$

$P^s \rightarrow$power required for sending

$P^r \rightarrow$ power required for receiving

The battery capacity or energy budget of an IOMT device is B_i Joule(J) Then the Battery lifetime in seconds is,

$$L_i = \frac{B_i}{P_i^t} \tag{3.4}$$

At one point in time T it is useful to express the available energy budget or battery lifetime as percentage $L_i^a(T)$

$$L_i^a(T) = \frac{1}{B_i}\left(B_i - \sum_{\tau=0}^{T} E_i^t\right) \tag{3.5}$$

Assuming $\sum_{\tau=0}^{T} E_i^t$ is always less than or equal than B_i.

If $\sum_{\tau=0}^{T} E_i^t \geq B_i$ the node cannot be selected to send or receive data.

Assume the size of the model parameters is s bytes, the network bandwidth for device i is b_i bytes per second Round trip network latency experienced in communication with node i is l_i , the transmission time T_i is,

$$T_i = 2 \times \frac{s}{b_i} + l_i \tag{3.6}$$

Assuming $P_i^s = P_i^r = P_i$, The equation for the energy for transmission will be

$$E_i^t = P_i \times \left(2 \times \frac{s}{b_i} + l_i\right) \tag{3.7}$$

3.3 System Model

3.3.1 Schematic Illustration

As illustrated in Figure 3.1, the system model described consists of a cluster-based architecture where each cluster comprises several nodes.Within each cluster, there is a designated cluster head or leader, which is responsible for managing communications within the cluster and coordinating interactions with the global server. The cluster head serves as a gateway for communication between the nodes in its cluster and the central/global server.

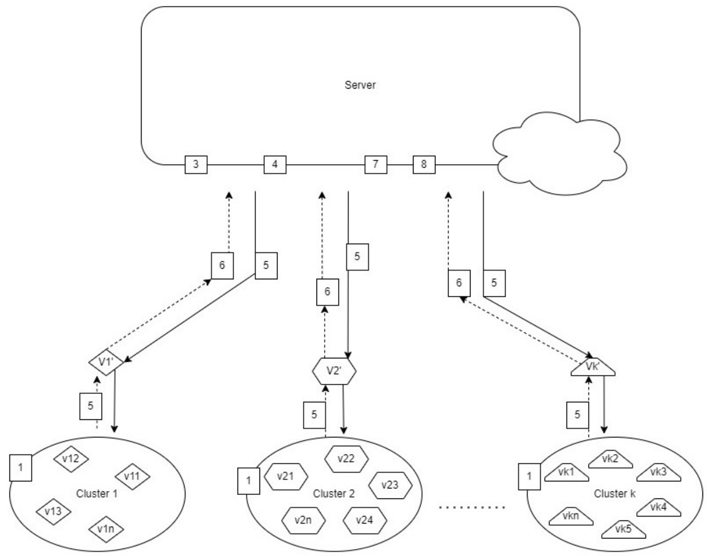

Figure 3.1: System Model - Schematic Illustration

3.3.2 Algorithm

1. Initial Clustering

   Applying K-medoid clustering , to group IoMT devices based on the similarity of their data or updates.

2. Dynamic Device Re-clustering Based on Silhouette Index

   (a) Calculate the Silhouette Index of each devices.

   (b) Define a threshold value.

   A device is considered to be poorly matched to its current cluster and may be closer to another cluster if its Silhouette index becomes significantly negative.

(c) If the Silhouette Index of a device is less than the threshold, reclustering will be initiated.

(d) If the above condition is not met, continuation with the initial clusters will be pursued.

3. Evaluation of Edge Devices

   (a) Done on the global server.

   (b) The edge scores of each device i in each cluster will be evaluated.

   (c) To calculate the edge scores, consideration will be given to three parameters.

   $\rightarrow$ Model Performance, I_i

   $\rightarrow$ Battery life percentage, $L_i^a(T)$

   $\rightarrow$ Energy for transmission, E_i^t

   (d) Edge Scores ,

$$S_i = w1 \times I_i + w2 \times L_i^a(T) + w3 \times \frac{E_i^* - E_i^t}{E_i^*} \tag{3.8}$$

$$w_j \in [0, 1], \quad w_1 + w_2 + w_3 = 1 \tag{3.9}$$

$E_i^* \rightarrow$ upper bound of the energy consumed by the edge node i

$$E_i^t = P_i \times \left(2 \times \frac{s}{b_i} + 1\right) \tag{3.10}$$

Size of the model parameters is s bytes, the network bandwidth for device i is b_i bytes per second Round trip network latency experienced in communication with node i is l_i and here $l_i = 1$.

4. Selection of Representative Workers

   Select the best representative worker from each cluster based on edge scores.Suppose there are k clusters,

   $C = \{C_1, C_2, C_3, \ldots, C_k\}$

   In each cluster C_j the edge devices are,

   $C_j = \{V_1^j, V_2^j, V_3^j, \ldots, V_n^j\}$

   For each cluster Cj select the highest scored device $V_j^{'}$ for which

   $L_i^a(T) > 0$, Selected set of workers are

   $V' = \{V_1^{'}, V_2^{'}, \ldots, V_k^{'}\}$

5. Updating Local models

   (a) At each round t, each worker trains its local model by iterating the local update multiple times using an appropriate optimization algorithm before sending the next local model m_v^{t+1} to the server.

   (b) Each worker $v^{'} \in V'$ receives the global model M_{t-1} and optimizes its parameters locally.

   Local update,

$$m_v^{t+1} = m_v^t - \eta g_v^t \tag{3.11}$$

   $g_v^t \rightarrow$ updated weights on its local data at the current model m_v^t

   $\eta \rightarrow$ learning rate

(c) Update the learning rate dynamically based on energy consumption.For that defined a learning rate scheduling strategy that takes energy consumption into account

(d) Used a learning rate that decreases as the available energy decreases.

6. Data compression

   (a) Using MessagePack, a binary serialization format, data compression will be performed on local model updates.

   (b) send the compressed data to global model.

7. Building Global Model

   (a) Decompress the local model updates.

   (b) M_t is built by aggregating the local model updates received at round t.

   (c) In this proposed model, the evaluation is assumed to be performed by federated averaging. The Global Model

$$M_{t+1} = \sum \left(\frac{n_v}{n} \right) \times m_v^{t+1} \tag{3.12}$$

   $n \rightarrow$ sum of all data points

   $n_v \rightarrow$ number of local data points.

8. Update Clustering Model

   Periodically reviewing and potentially changing the clustering model.

9. Repeat Steps 2-8

   (a) The entire process is repeated iteratively until convergence

   (b) Convergence criteria

      i. maximum number of rounds (T) is reached

      ii. The difference between current accuracy and previous accuracy is minimal.

3.3.3 Evaluation Metrics

1. Sum of energy consumed per round

   The aggregation of energy consumed by all workers per round is calculated. In the experimental scenarios, the sum of energy consumed by all representative workers is determined.

2. Average of energy budget per round

   The average energy budget is calculated by averaging the energy budget of all representative workers in each round.

3. Number of rounds to converge

   Iterative rounds make up the training process in the FL context. Until a halting condition is satisfied, it is repeated. In the experimental scenarios, the training process ends when the number of iterations surpasses 100 or the difference between the accuracy scores generated by two consecutive training rounds is less than 0.001.

Chapter 4

Experiment

4.1 Experimental setup

4.1.1 Dataset

- For this model, the MHEALTH dataset is utilized.
- The MHEALTH (Mobile HEALTH) dataset contains a collection of vital sign and body motion collected from 10 participants in during their physical activities.
- It was created for the purpose of research in the field of mobile health monitoring, particularly in the wearable devices.
- The sensor positioned on the chest also provides 2-lead ECG measurements, which can be potentially used for basic heart monitoring.
- Total number of activities = 12

- Number of sensor devices = 3
- Number of subjects/person = 10

4.1.2 Assumption

- Each edge device have the same energy before training started. There is no any different kind of energy level among all edge devices.
- Energy consumption for each EPOCH of the model is equal to 0.01. That means each edge device have consumed the same amount of energy in each iteration.
- Every device has the same power which is equal to 1. There is no difference between them in their processing capacity.

4.2 Demonstration & Results

- Initially, the activity frequency of the mhealth dataset is observed (see Figure 4.1).

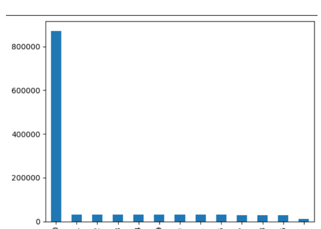

Figure 4.1: Activity Frequency before re-sample

- The Mhealth dataset contains unbalanced data, requiring resampling of the dataset to create balanced data by downsizing the activity of high frequency (activity 0). The resulting activity frequency after resampling is depicted in Figure 4.2.

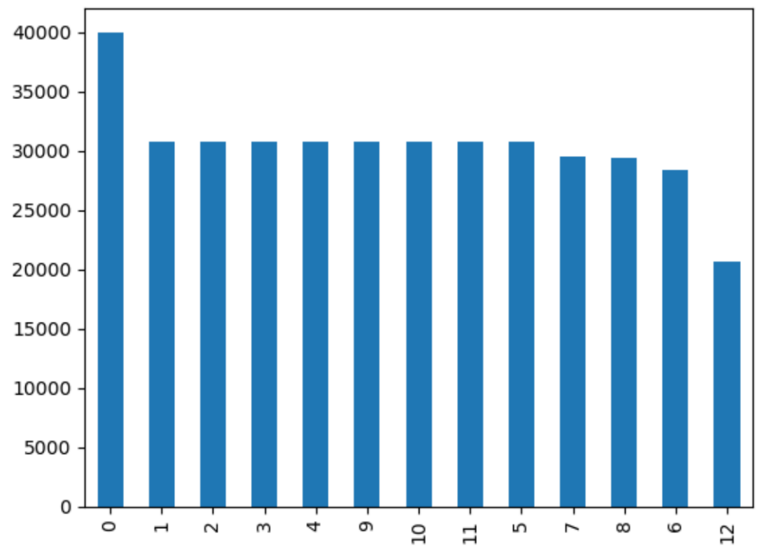

Figure 4.2: Activity Frequency after re-sample

- The dataset is then divided into 5 clusters, with each cluster assigned 5 workers. Each worker is randomly assigned 30000 data samples, as shown in Figure 4.3.

- Finally, the data is split into train and test sets and assigned to each worker.

Figure 4.3: Assigning data samples for 25 workers

4.2.1 Using SGD (Stochastic Gradient Descent)

- Model Used for both local worker training and global model training - SGD
- Accuracy fluctuates across rounds, ranging from approximately 57.15% to 58.6%.
- In Figure 4.4, a slight increase in accuracy is observed from the initial rounds, stabilizing around 58.6% in the later rounds.
- In Figure 4.5, the energy used in each round shows variations, with different rounds consuming different amounts of energy.
- The energy consumed per round ranges from around 68,422.87 to 70,264.85 units.

- The energy consumption per global round demonstrates some inconsistency, with certain rounds consuming more energy than others.

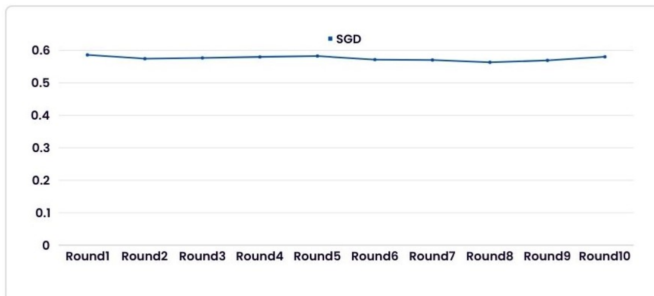

Figure 4.4: Accuracy Vs Rounds

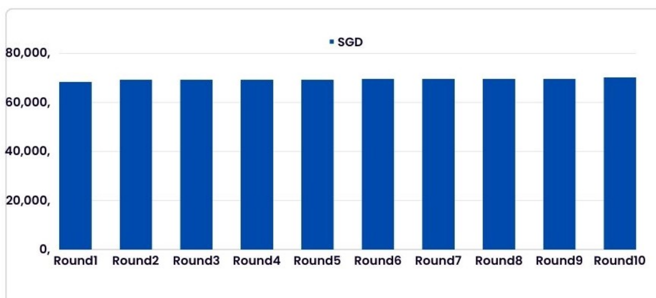

Figure 4.5: Energy consumption by all workers per round

4.2.2 Using SVM (Support Vector Machine)

- Model Used for both local worker training and global model training - SVM.

- The accuracy of the SVM model fluctuates across rounds, ranging from approximately 76.45% to 77.37%.

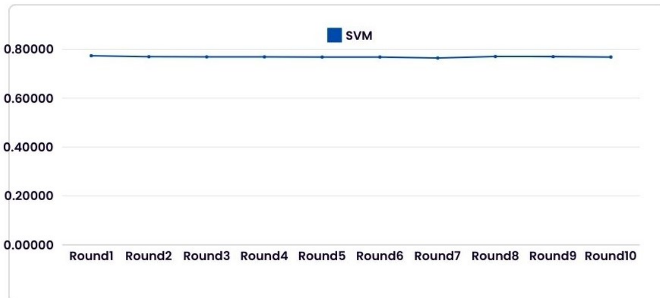

Figure 4.6: Accuracy Vs Rounds

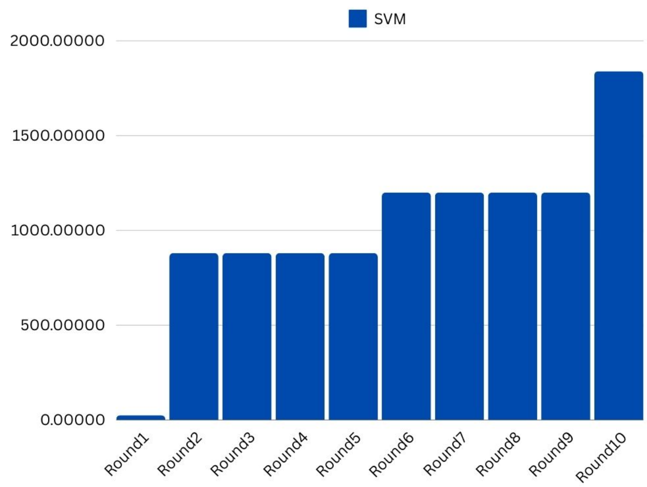

Figure 4.7: Energy consumption by all workers per round

- In Figure 4.6, there is some variability in accuracy, with minor fluctuations observed in different rounds. The accuracy stabilizes around 77.37% in the later rounds, indicating a consistent performance.

- In Figure 4.7, the energy consumption in each round shows variations, with different rounds consuming varying amounts of energy.

- The energy consumed per round ranges from around 25.00 to 1840.00 units, reflecting the dynamic nature of the training process.
- Certain rounds exhibit higher energy consumption, possibly due to increased computational demands or data processing requirements.

4.2.3 Using DT (Decision Tree)

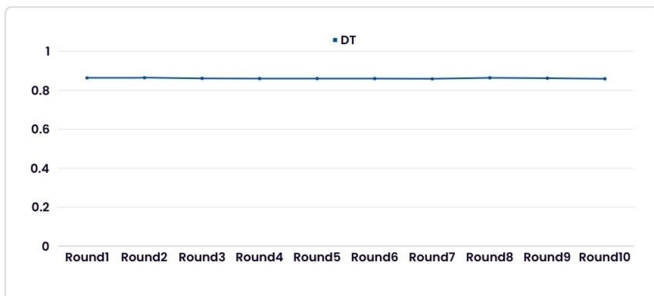

Figure 4.8: Accuracy Vs Rounds

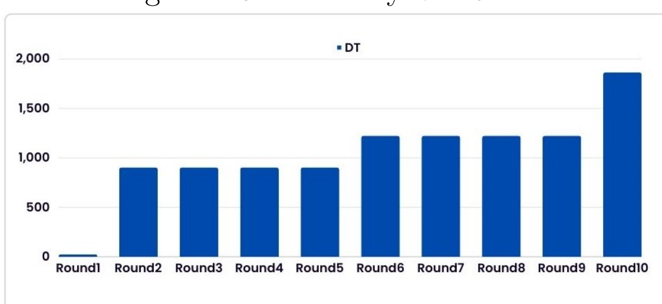

Figure 4.9: Energy consumption by all workers per round

- Model Used for both local worker training and global model training - Decision Trees (DT).

- The accuracy of the Decision Trees model fluctuates across rounds, ranging from approximately 86.35% to 86.45%.

- In Figure 4.8, there is a slight fluctuation in accuracy from the initial rounds, but it stabilizes around 86.4% in the later rounds.

- In Figure 4.9, the energy consumption in each round varies, indicating fluctuations in computational demands.

- The energy consumed per round ranges from approximately 25 to 1865 units.

- Despite fluctuations in energy consumption, the system maintains sufficient energy reserves to continue training and inference operations.

4.2.4 Using SNN (Simple Neural Network)

- Model Used for both local worker training and global model training - Simple Neural Network (SNN).

- The accuracy of the SNN model fluctuates across rounds, ranging from approximately 91.73% to 91.08%.

- In Figure 4.10, there is a slight decrease in accuracy from the initial rounds, but it stabilizes around 91.08% in the later rounds.

- In Figure 4.11, the energy consumption in each round shows variations, with different rounds consuming different amounts of energy. The energy consumed per round ranges from around 25 to 1865 units.

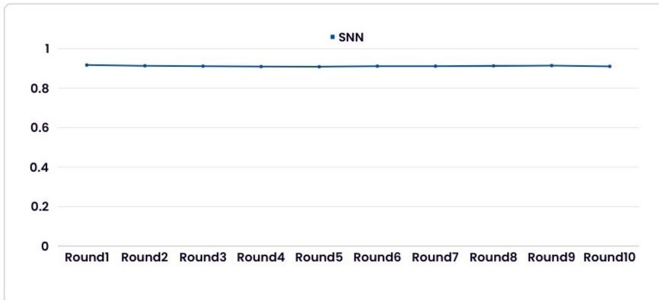

Figure 4.10: Accuracy Vs Rounds

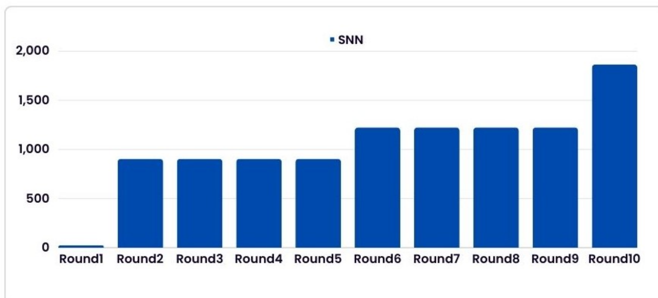

Figure 4.11: Energy consumption by all workers per round

4.2.5 Using RF (Random Forest)

- Model Used for both local worker training and global model training - Random Forest (RF).

- The accuracy of the Random Forest model fluctuates across rounds, ranging from approximately 95.6% to 95.8%. In Figure 4.12, there is a slight variability in accuracy across rounds, with the highest accuracy observed in the second round (95.8%). The accuracy stabilizes around 95.6% in the later rounds, indicating consistent performance.

- In Figure 4.13, the round-to-round energy consumption ranges from 25

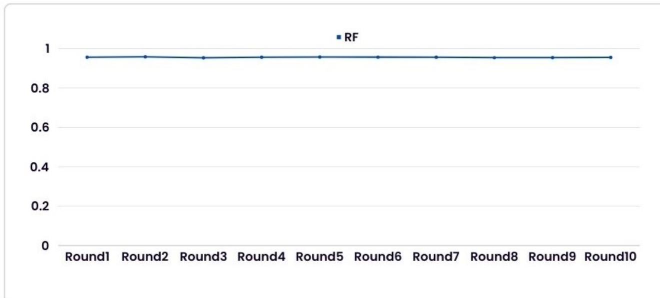

Figure 4.12: Accuracy Vs Rounds

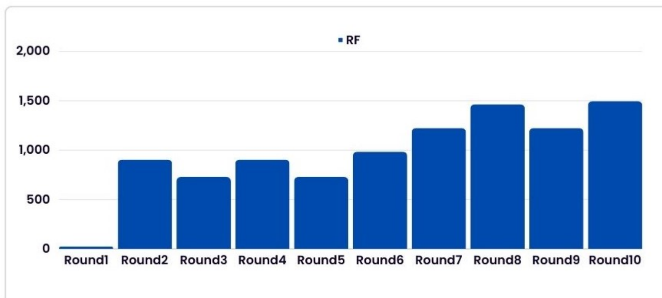

Figure 4.13: Energy consumption by all workers per round

units to 1,497 units, showcasing fluctuations in computational load.

Chapter 5

Final Results

5.1 Summary

5.1.1 Accuracy Comparison

In Figure 5.1, a graph illustrating the comparison of accuracy across different models is presented.

Table 5.1: Accuracy Comparison

Round	SGD	DT	SNN	RF	SVM
1	0.586	0.8635	0.91733	0.956	0.77367
2	0.5745	0.8645	0.9135	0.958	0.76933
3	0.5765	0.86083	0.91183	0.9535	0.76883
4	0.57983	0.86017	0.9095	0.95583	0.769
5	0.58233	0.85983	0.90867	0.9575	0.76817
6	0.57167	0.86033	0.91133	0.95667	0.768
7	0.57033	0.85867	0.9115	0.95617	0.7645
8	0.563	0.86433	0.913	0.95383	0.77033
9	0.569	0.86167	0.91433	0.95417	0.77
10	0.58033	0.85917	0.91083	0.95483	0.76783

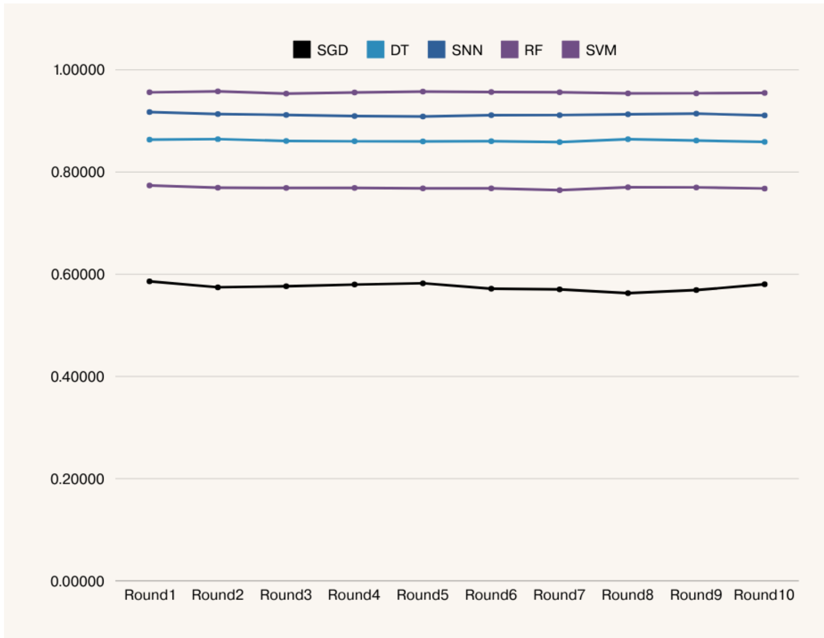

Figure 5.1: Comparison of Accuracy Across Different Models

- From the table 5.1 we can say that
- The accuracy of the Support Vector Machine model fluctuates across rounds, ranging from approximately 76.45% to 77.37% .
- Decision Trees consistently exhibit high accuracy across all rounds, with an average accuracy ranging from 85.86% to 86.43% .
- Random Forest also demonstrates strong performance, with an average accuracy ranging from 95.35% to 95.8% .
- Simple Neural Network follows closely behind, with an average accuracy ranging from 90.87% to 91.43% .
- Stochastic Gradient Descent (SGD) consistently performs slightly lower

than the other models, with an average accuracy ranging from 56.3% to 58.6% .

5.1.2 Energy Consumption Comparison

In Figure 5.2, a graph illustrating the energy consumption of different models is presented.

Table 5.2: Energy Comparison Table

Round	SGD	DT	SNN	RF	SVM
1	68422.87	25	25	25	25
2	69301.55	905	905	905	880
3	69303.76	905	905	905	880
4	69303.89	905	905	905	880
5	69303.81	905	905	905	880
6	69622.89	1225	1225	1225	1200
7	69622.95	1225	1225	1225	1200
8	69623.28	1225	1225	1465	1200
9	69623.24	1225	1225	1225	1200
10	70263.41	1865	1865	1497	1840

- From table 5.2 we can say that
- Decision Trees and Simple Neural Network consistently consume a fixed amount of energy per round, with DT and SNN both consuming 905 units in most rounds. SVM exhibits a similar pattern, with energy consumption remaining stable at 880 units per round.
- Random Forest's energy consumption varies slightly, with occasional spikes but generally remaining around 905 units.

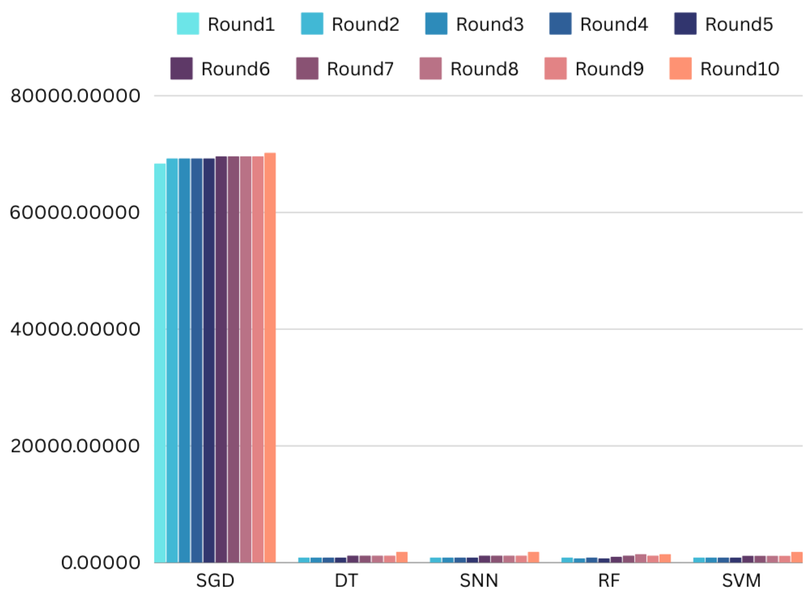

Figure 5.2: Energy Consumption per Round

- Stochastic Gradient Descent consistently consumes more energy compared to other models, with energy consumption ranging from 68,422.87 to 70,263.41 units per round. This is significantly higher than the energy consumption of other models such as Decision Trees, Simple Neural Network, Random Forest, and SVM.

5.2 Conclusion

Energy efficiency is as important as accuracy in model selection when it comes to Internet of Medical Things (IoMT) applications. Particularly well-suited for IoMT devices with limited resources, Decision Trees and Simple Neural Networks, when integrated within a federated learning setup, exhibit consistent and predictable patterns of energy use. Random Forest integrated within a federated learning setup offers a fair trade-off between accuracy and efficiency, managing to keep energy consumption levels relatively low and manageable even with sporadic increases. Nevertheless, even though it offers similar accuracy, stochastic gradient descent uses a lot more energy, which makes it less appropriate for IoMT applications where energy efficiency is crucial.

By adding Support Vector Machine (SVM) integrated within a federated learning setup, an effective substitute that exhibits high accuracy performance and low energy consumption is presented, making it a competitive choice for Internet of Medical Things (IoMT) scenarios. Decision Trees and Simple Neural Networks integrated within a federated learning setup are better options when energy efficiency is the top priority because of their predictable and comparatively low energy consumption profiles. On the other hand, Random Forest integrated within a federated learning setup is the best option for IoMT applications when taking accuracy and energy efficiency into account simultaneously since it provides a well-rounded solution that successfully strikes a compromise between the two.

For IoMT applications, Random Forest integrated within a federated learning setup thus turns out to be the best alternative, providing a harmonious balance between accuracy and energy efficiency, even though Decision Trees, Simple Neural Networks, and Support Vector Machines integrated within a federated learning setup are still feasible options.

When communication technologies are integrated into the federated learning model with random forest:

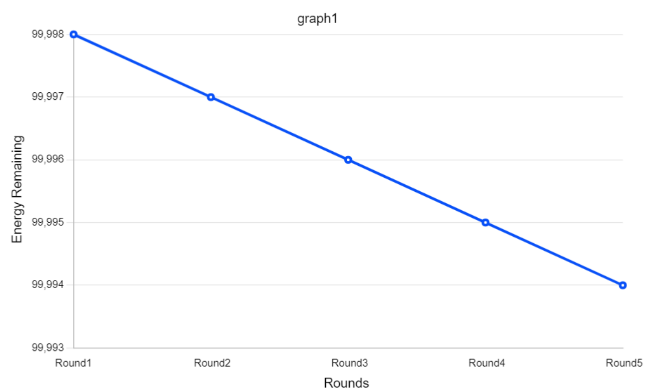

Figure 5.3: Using WIFI

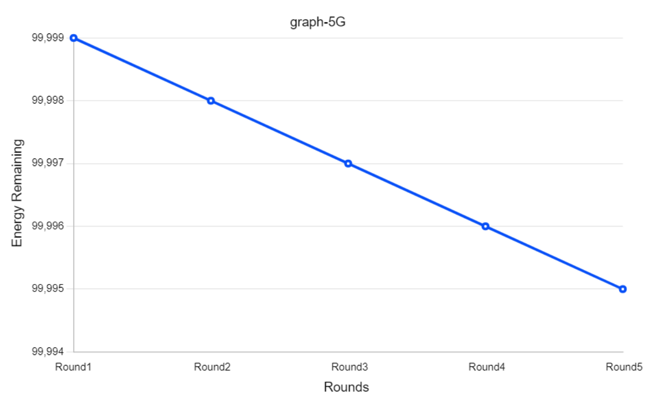

Figure 5.4: Using 5G

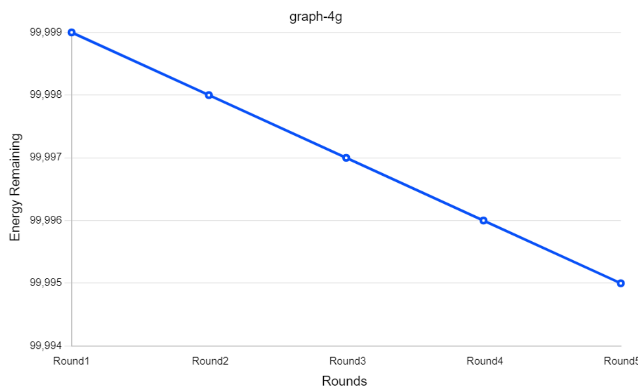

Figure 5.5: Using 4G

From figures 5.3,5.4,5.5 and 5.6 across rounds and various communication technologies such as WiFi, 5G, 4G, and Bluetooth, the energy remaining for Workers shows remarkable stability.The energy consumption pattern is consistent even with variations in bandwidth and transmission methods, highlighting the flexibility and effectiveness of federated learning across various communication technologies.

Using Random Forest as the preferred model, federated learning is robust to changes in network circumstances and guarantees constant energy consumption irrespective of the communication method used. The uniformity of energy consumption amongst various communication technologies highlights the effectiveness of federated learning in resource allocation optimization, enabling effective device resource utilization without sacrificing performance. The uniform energy consumption noted across all rounds and communication modalities supports the long-term sustainability and scalability of federated learning in IoMT situations, as

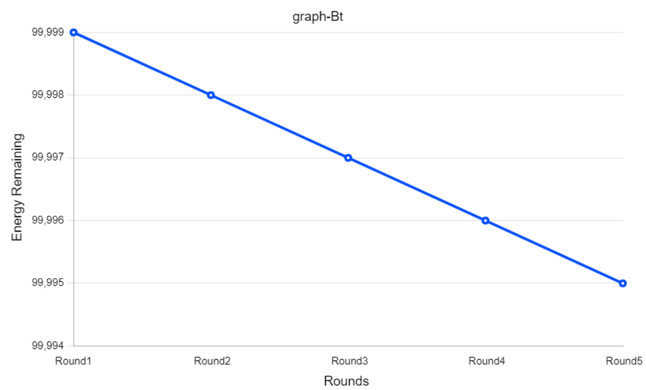

Figure 5.6: Using Bluetooth

Figure 5.7: Energy remaining in each round with different communication technologies

well as its efficacy in resource-constrained settings.

5.3 Future Work

- Although the present study utilized mHealth data, further research should validate on other medical datasets to achieve more generalized.
- The current implementation ran locally on a single computer. Subsequent research efforts could include evaluating this technology in a distributed computing context with several machines.

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