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RESEARCH ARTICLE

# Detecting Electrocardiogram Arrhythmia Empowered With Weighted Federated Learning

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**ABSTRACT** In this study, a weighted federated learning approach is proposed for electrocardiogram (ECG) arrhythmia classification. The proposed approach considers the heterogeneity of data distribution among multiple clients in federated learning settings. The weight of each client is dynamically adjusted according to its contribution to the global model improvement. Experiments on public ECG datasets show that the proposed approach outperforms traditional federated learning and centralized learning methods in terms of accuracy and robustness. On the client side, the suggested federated learning (FL) approach had an accuracy of 0.93, sensitivity of 0.98, specificity of 0.82, miss classification rate of 0.07, precision of 0.06, FPR of 0.01, and FNR of 0.01. FL has 0.98 accuracy, 0.99 sensitivity, 0.91 specificity, 0.02 miss classification rate, 0.10 precision, 0.01, FPR, and 0.01 FNR on the server. The server-side federated learning approach outperforms the client-side in accuracy, sensitivity, specificity, miss classification rates, and precision. The results indicate that the proposed weighted federated learning approach is a promising solution for ECG arrhythmia classification in a distributed environment. In short, the proposed federated learning approach applied to ECG arrhythmia detection aims to address privacy concerns and improve accuracy, while still maintaining the centralized framework and advanced algorithmic approach.

**INDEX TERMS** Federated learning, MIT-BIH arrhythmia, electrocardiogram, client-side, server-side.

## I. INTRODUCTION

Traditional healthcare systems have been improved because of the recent advances in the Internet of Things (IoT) technologies [1]. IoT information can now be processed with high precision, and individuals' health status can be examined short of the need for individual involvement, the amazing impact of recent advances in deep learning applications [1], [2]. Hospitals would use enhanced deep learning systems to implement and perform the detection, which further minimizes the time lag of patients. Governments around the world have restrictions on sharing the data of patients centrally. Federated learning solved this problem by using the data centrally with the help of traditional deep learning approaches [3]. Federated learning is particularly notable in the field of ECG arrhythmia detection due to its ability to bring about significant changes in addressing crucial healthcare issues. Federated learning prioritizes privacy

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and ensures compliance with severe data security standards by enabling model training across dispersed devices without the need to exchange raw patient data [2]. This method not only improves data security by reducing the likelihood of breaches but also promotes collaboration among healthcare organizations, enabling the creation of more resilient and widely applicable models. Federated learning offers significant benefits in dynamic healthcare settings, namely in terms of real-time updates and reduced data transfer costs. These advantages contribute to the continual enhancement of ECG arrhythmia detection models. In addition, the ability to customize cardiac care solutions for specific local populations and ensure compliance with regulatory standards renders federated learning a highly promising approach for promoting personalized and secure healthcare [1], [2], [3]. The main challenge in federated learning is the heterogeneity of data in several locations such as hospitals, industries, etc. As per security and privacy issues, the departments are not sending their data to the server to train. So, the federated learning technique made it possible to exchange data through machine learning [4], [5]. The increasing availability of wearable devices and the increasing popularity of remote healthcare services have led to a growing amount of electrocardiogram (ECG) data being generated. Accurate and efficient ECG Arrhythmia classification is essential for the early recognition and therapy of cardiovascular disorders. However, the data used for ECG classification is typically collected and stored in a decentralized manner, making it difficult to use traditional centralized machine learning methods. To address this challenge, this study suggests a weighted federated learning approach for ECG arrhythmia classification. The proposed approach considers the heterogeneity of data delivery among multiple clients and adjusts the weight of each client according to its contribution to the global model improvement. In this study, ECG signals from publicly available two datasets were collected from multiple clients and used for ECG arrhythmia classification. The ECG signals were pre-processed to extract features, and the weighted federated learning approach was applied to train a deep neural network for ECG arrhythmia classification, The proposed approach is compared with the traditional federated learning and the centralized learning methods in terms of accuracy and robustness. Investigational results directed the proposed weighted federated learning approach overtook both established federated learning and centralized methods, achieving an overall accuracy of 98%. The results also showed the proposed approach was robust to the heterogeneity of data distribution among clients, demonstrating its potential for real-world deployment in a decentralized environment. Overall, this study demonstrates the feasibility and effectiveness of the weighted learning approach for ECG arrhythmia classification and provides a promising solution for remote healthcare services in a decentralized environment. The paper structure is as follows: Section I is about the Introduction, Section II presents the related work, Section III introduces the methodology, Section IV summarizes the simulation and results, and the final sections are about the discussion and conclusion.

## II. RELATED WORK

The Internet of Things (IoT), cloud computing, artificial intelligence, and deep learning have found their way from traditional healthcare to the smart healthcare system and increased their speed, efficiency, and personalization by using wearable devices. The wearable devices have sensors to identify patients' movements. For this purpose, the unlabeled data taken from the sensor, and trained in a cloud server requires a high computation cost. To avoid this, the federated learning approach used to train, and Bidirectional Long Short-Term Memory (BiLSTM) classifies the data that is linked with a smart health care system and proved the efficiency of 99.67% with a reduced amount of data [1].

To get the secrecy and protection of the health care system departments, federated learning is implemented where the data can be trained in its place. The connection of the nodes in federated learning is still challenging as more expert knowledge is required to handle it. A blockchain-managed federated approach supports the privacy of data and supports the lightweight differential privacy tested framework with different deep learning approaches with COVID-19 patients and successfully gets the result securely and efficiently [2], [6], [7].

The rapid infrastructure with networking and computer knowledge increased the cyber-attack. So, cyberattack is a threat to the heterogeneous cyber-physical system. In this approach, the novel federated deep learning is utilized for intrusion recognition in modern cyber systems. By using the convolutional neural network, design the deep learning intrusion discovery model. Then, apply the federated learning approach, to build the intrusion model in a privacy-oriented way [3], [8].

Federated learning enables different organizations to train the model without using local data. The great task of federated knowledge is to control the heterogeneity of data among different organizations. Most of the companies tried to work on the image-based dataset with deep learning methods but won't be able to get high performance. Model contrastive federated learning is an effective and efficient framework to utilize the similarities among the models to modify or correct the training of different organizations [4]. Federated deep learning via neural network architecture search (FEDNAS) automates the design. Through experiments, it is seen that the architecture that is made and searched by FEDNAS can give outstanding performance for manual predefined architecture and existing federated learning methods [5]. Data privacy is the main issue in the health department to preserve the patient's privacy. It is important to bring together data from different places throughout the world while keeping its privacy. The federated is the best approach in this respect and relies on a machine learning model rather than raw data. The research widens the concepts of federated learning and its use in the health field [9]. Cetin et al. [10] proposed context

**TABLE 1. Limitation of previous work.**

| Studies | **Application and Framework** | Accuracy | Limitation of Works |
|---|---|---|---|
| Strodthoff et al [46] | Deep learning approach as ResNet and Inception for ECG. | 89.8% | • No data Augmentation<br>• Less accurate |
| Acharya et al. [47] | CNN Layers | 93.5% | • Less accurate |
| Yaman O. et al. [48] | KNN and SVM Approach | 91.25% | • Handcrafted features.<br>• Accuracy is low because of hand-crafted features. |
| Simjanoska et al. [49] | ML-Train Validation Test Evaluation | 93.5% | • Handcrafted features.<br>• Accuracy is low because of hand-crafted features. |
| Sehirli et al. [50] | RNN and LSTM methods | 97% | • Handcrafted<br>• Low Accuracy |
| Rehman A. [39] | FL with Blockchain | 97% | • No data Fusion<br>• Low Accuracy |
| Mehmood et al. [50] | Deep learning approach as ResNet and Inception for ECG. | 95% | • No data Augmentation<br>• Less accurate |
| Kıymaç and Kaya [54] | A novel automatic CNN arrhythmia classifier | 98.87% | • The Federated Approach is not applied. |

awareness which provides a platform to access the condition of patients in relation to ECG, heart rate, and activity data. The initial report can be evaluated using digital technology to monitor the heart condition. The research defines a privacy-oriented and intelligent system for cardiac observing by operating and observing the patient data. The system used a federated learning approach to develop the model to recognize physical action. The central approach in terms of federated learning proved that it has the advantage of patient data privacy. Agrawal et al. [11] proposed that Wi-Fi is the most widely used device and technology. As compared to the wired network, Wi-Fi has less security and can easily leak the wireless clear boundary which leads to protection issues. Several kinds of intrusion are susceptible to security measures and to overcome this problem the federated learning approach plays a significant role in classification accuracy, less communication, and computational cost [12]. To do the decision-making and medical diagnosing of different studies, use the data to train the machine and deep learning methods to analyze the multimodal human behavior and centralize the data with the support of federated learning [13]. Xing et al. [14] proposed that real-time federated learning is responsible for acquiring the ECG features of epileptic seizures of a patient by using the deep neural network. In the context of this work, the performance increased with a specificity of 91.58%, a geometric mean of 90.90%, and a sensitivity of 90.24%.

Yoo et al. [15] aimed for an efficient federated distillation system for the multitask time series classification and introduced the two novel components as a feature-based student-teacher network and a Weight-matching distance-based network. The experimental result showed the relationship between the student, teacher, and hidden layer among the server without sharing the raw data.

The federated approach makes Artificial learning viable without exchanging local data and was first proposed by Google in 2017 and is now widely used in the medicine and health departments. The issues for federated learning like client participation management, non-identical distribution, and vulnerable environments tried to solve related to data and system heterogeneity, traceability, security, client/server management, etc. The researchers are using some techniques and methods to resolve the concerns [16], [17]. In health care, there are limitations to deep learning. Federated learning is used in ECG-based health care by employing the deep convolutional neural network (CNN) and artificial intelligence (AI) and solving challenges like data security, availability, and privacy. Working with the federated learning along ECG achieved an accuracy of 94.5% and 98.9% for finding by using the noise and without noise data with the reduction of transmission cost to enhance the privacy of the patients [18], [19].

Depression is one of the common mental illnesses and it's hard to diagnose, machine learning needs to accumulate the patient's data and maintain the privacy of the patient. Federated learning along with deep network and machine learning made it possible to make the novel model and framework [20], [21]. Federated learning is a promising approach

**TABLE 2.** Dataset of heart attack analysis and prediction.

| Information and Description about features of Heart Disease Dataset. | | | | | |
|---|---|---|---|---|---|
| **No.** | **Attribute Name** | **Attribute Code** | **Explanation** | **Assess Type** | **Values** |
| 1. | Age | Age | Patient's Age | Numeric | 1-120 yrs old |
| 2. | Sex | Sex | Patient's Sex<br>Male = 1<br>Female = 0<br>Others = 2 | Numeric | Male or Female or any |
| 3. | Exercise-induced angina | Exang | Exercise Induced Angina.<br>yes = 1<br>No =0 | Numeric | 0<br>1 |
| 4. | Major Vessels | Caa | Major vessels (0 to 3) | Numeric | 0<br>1<br>2<br>3 |
| 5. | Resting blood pressure | Trtbps | Blood pressure measuring in mm Hg | Numeric | 90-200 |
| 6. | Cholesterol | Choll | cholesterol measurement in mg/dl retrieved via Sensor BMI | Numeric Value | 126-564 |
| 7. | Blood Sugar | Fbs | Fasting blood sugar<br>Ranging > 120 mg/dl<br>True = 1<br>False = 0 | Numeric | 1<br>0 |
| 8. | Heart rate | thalachh | heart rate | Numeric | 77-202 |
| 9. | Heart Attack | Target | heart attack | fewer possibility of heart attack =0<br>more possibility of heart attack = 1 | 0<br>1 |
| 10. | Oldpeak | oldpeak | Oldpeak | Numeric | 0 to 6.2 |
| 11. | Slope | Slop | peak exercise Gradient | 1=Up<br>2=flat<br>3=down | 1<br>2<br>3 |
| 12. | Thallium scan | Thal | Thallium scan (1-3) | Numeric | 1<br>2<br>3 |
| 13. | Chest Pain type | Cpp | chest pain type | typical angina = 1<br>atypical angina = 2<br>non-anginal pain = 3 | 1<br>2<br>3<br>4 |

**TABLE 2.** *(Continued.)* **Dataset of heart attack analysis and prediction.**

| | | | | | |
|---|---|---|---|---|---|
| | | | | asymptomatic = 4 | |
| 14. | Resting electrocardiographic results | rest_ecg | inactive electrocardiographic findings | Normal = 0<br>having ST-T wave abnormality = 1<br>showing possible or definite left ventricular' criteria = 2 | 0<br>1<br>2 |

with deep learning over datasets. The federated learning approach for the deep learning method through the local static batch normalization layers can generate the central model [22]. This approach improves the strength of data heterogeneity without the information revealed but not sharing the central layer statistics [22], [23], [24].

Timely anomaly detection is very important, otherwise, it can affect the production of the effective industry.

Researchers proposed the federated knowledge deep neural variance recognition framework for identifying the time sequence data. The framework can detect the anomaly timely minimize the communication directly above 50% and develop the efficiency of the system [25], [26].

Furthermore, the two machine learning approaches Split Learning (SL) and Federated Learning (FL) follow the model to data framework and the machine learning model without sharing the raw data. Split learning gives the model security and privacy and on the other hand, federated learning is the machine learning model between the client and server. Somehow FL privacy is better than FL but slower because of the training amid multiple clients [27], [28].

Deep learning worked very well in the existing traffic flow approaches and achieved outstanding and accurate performance on a large scale. It contains massive private data of users. So, there is a need to ensure the privacy of users and in this respect, the federated learning approach based on a gated Recurrent neural network algorithm is applied for traffic drift projection and the predicted accuracy is 90.96% [29], [30], [31].

### A. LIMITATIONS OF RELATED WORK

Table 1 in this section lists some restrictions on the earlier research.

i) The dataset has not been combined and enhanced.
ii) There are extremely few classifications, and no new instantaneous dataset is created.
ii) When compared to the prior model, which was comparatively demonstrating less accuracy, the new model is more accurate.

### B. CONTRIBUTIONS OF PROPOSED MODEL

The following is the main contribution:

i) To obtain a more precise conclusion, deep learning, and federated learning approaches rather than machine learning are used in the proposed model rather than the feature-based, handcrafted datasets used in earlier studies.
ii) Due to the federated learning strategy, the system is centralized and safe.

## III. PROPOSED METHODOLOGY

There are a few methods and materials which are used in the proposed EDEA-FL model.

### A. DATASET AND PREPROCESSING

Table 2 shows the features and values of ECG-related terms.

Table 2 shows the 13 features as input and the last column represents the feature for result or output which verified whether the patient has a cardiac problem or not. Furthermore, in pre-processing checked all values against each feature and filled up the missing values as the machine learning approach can make the wrong prediction. The mean method applied for missing values can be formulated as [32].

$$R(y) = \begin{cases} mean(y), & if\ y = null/missed \\ y, & otherwise \end{cases} \tag{1}$$

where 'y' represents the feature and remains in the n-dimensional state, y ∈ S.

A is used to find the mean value of the datasets and reduce the noise from the dataset. $y_1$, $y_2$, $y_3$……$y_n$ are the features and N represents the total number of the elements.

$$A = \frac{y_1 + y_2 + y_3 \ldots\ldots\ldots\ldots\ldots y_n}{N} \tag{2}$$

The standardization formula is:

$$S(y) = \frac{y - \bar{y}}{\alpha} \tag{3}$$

The standardization method is important to normalize the data with zero means and minimize the unequal or skewed part of the data distribution [32]. The equation 1-3 shows the standardization methods.

#### 1) MIT-BIH ARRHYTHMIA DATASET

To get a more accurate and reliable result, another dataset MIT-BIH Arrhythmia [32], [33] with a huge number of records has been taken from Kaggle for training and testing to acquire a more accurate and reliable result. There are huge numbers of samples that are very much enough for training a deep neural network. Moreover, there are overall 109446 samples in it with 5 classes (N as 0, S as 1, V as 2, F as 3, and Q as 4) and the sampling frequency is 125Hz.

**TABLE 3.** MIT-BIH arrhythmia dataset.

| MIT-BIH Arrhythmia Dataset | |
|---|---|
| **Feature Name** | **Numbers For the Entire Feature** |
| N | 0 |
| S | 1 |
| V | 2 |
| F | 3 |
| Q | 4 |

### B. PROPOSED SYSTEM MODEL

#### 1) ARCHITECTURE OF NEURAL NET FITTING TOOL

The proposed model EDEA-FL used the Neural fitting apparatus to choose the data, produce and train the network, and then assess the performance by using the Regression Analysis (RA) and Mean Square Error (MSE).

Mean Square Error (MSE) is the average square between the target and output values. Minimum values are better and zero leads to no error. Regression R calculates the relation connecting target and output values.

whereas 1 = close relationship

0 = random relationship

This procedure usually requires more time but can develop in good generality for difficult, small, or noisy datasets.

Training stops allowing adaptive weight minimization (regulation). The neural net fitting can lead to solving the problem with two layered feed-forward networks which are normally trained with three variants of this algorithm like Levenberg-Marquardt (LM) which is fastest, Bayesian Regularization (BR) which is slower but generalized well and Scaled Conjugate Gradient (SC) which is memory efficient.

Levenberg-Marquardt (LM) is the fastest algorithm in the neural fitting network. For LM, Levenberg-Marquardt (LM) is the quickest algorithm in the neural fitting network. For LM, Levenberg-Marquardt (LM) is the speediest algorithm in the neural fitting network. For LM, define a fitting neural network and set 15 neurons in the fitting net's hidden level layer. The neuron size can affect the result, so different neuron values are set against different algorithms. All three algorithms (LM, BR, SC) are applied to both datasets, and calculated the accuracy of each dataset is.

There is a need to select data as to what input and targets are fitting the problem. Inputs are taken to present the network and target data are taken to define the desired network output. Then, the data can be divided into three kinds of samples training, validation, and testing. Trained the network to fit the input and targets. For training, there is an option of three algorithms. Take the LM which requires more memory but less amount of time. In this respect, the training automatically stopped and was indicated by enhancing the MSE of the validation error. It has been trained multiple times and has the required accuracy. Furthermore, evaluate the network by testing on more data, then decide if the network performance is not satisfactory. It is proved that the LM 'R-value' showed 83% with 15 neuron layers and the MSE value is lower which is a better result for the LM algorithm. It hits the best validation performance which is 0.084761 at epoch 9. Furthermore, analyzed the result by creating a linear regression plot. The plot showed the network output with respect to the target for testing, training, and validation sets for the ECG dataset, and on the other hand, the MIT BIH Arrhythmia showed an accuracy of 98% at epoch 55 with a validation performance of 0.14.

The Bayesian Regularization (BR) algorithm is another algorithm in this neural network, but it's a bit slow as compared to the LM but generalized well. For BR, define a fitting neural network and set 20 instead of 15 neurons in the fitting network's hidden layer. In this respect, the training automatically stopped and was indicated by enhancing the MSE of the validation error. It has been trained multiple times and has the required accuracy. Furthermore, evaluate the network by testing on more data, then decide if the network performance is not satisfactory. In the case of the ECG dataset, the BR 'R-value' showed 99% with 20 neuron layers and the MSE value is lower which is a better result for the BR algorithm and it hits the best validation performance which is 0.084761 at epoch 9 [35].

In the same way, the MIT-BIH showed a 97% R-value at 1000 epochs and the validation performance is 0.07. Scaled Conjugate Gradient is the memory-efficient algorithm, and its R-value is 93% with a validation performance of 0.18 at 385 epochs MIT BIH Arrhythmia and for the ECG dataset the R-values are 84% and validation performance is 0.06 at 31 epochs. On the other hand, the same three algorithms were applied to the MIT BIH Arrhythmia dataset to get a more concise and remarkable result. The ECG dataset is not giving the best validation performance as the values keep declining except for good training results. For this purpose, another new or second dataset has been taken and it proved the dataset without noise and ambiguities can lead to the best result. Furthermore, based on the gained weight of all three algorithms LM, BR, SC for the ECG and MIT BIH Arrhythmia.

#### 2) FEDERATED LEARNING IMPLEMENTATION

Federated Learning is a decentralized technology that is based on privacy, sensibility, and security of data. For instance, eHealth can share the data among medical researchers and hospitals but there is no security among the patient's data and sometimes it shows ambiguity. The concept of federated learning made life easier [35]. As it makes learning from fragmented, sensitive data easier, federated learning has recently gained popularity. Sensitive data can stay in the individual organizations by creating a uniform global and centralized model on a central server as opposed to manually fusing data from many places or using time-consuming

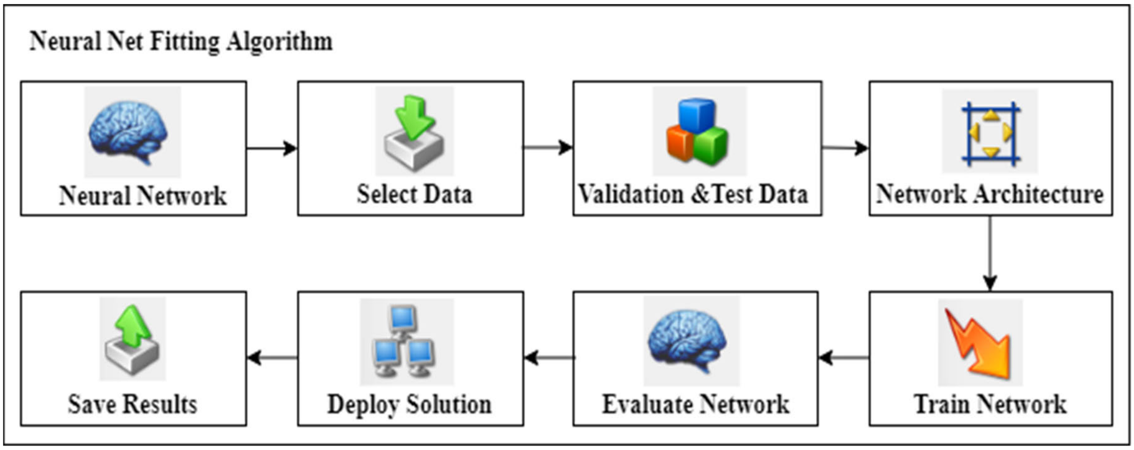


**FIGURE 1.** Neural net fitting architecture.

and mistake discovery and replication techniques. Federated learning refers to the process by which different organizations can work together to develop a shared framework. A technique for creating a global, unified model without explicitly exchanging datasets is called "federated learning." By doing this, it is made sure that patient's privacy is protected while they are moved between facilities.

Figure 2 shows a proposed federated learning approach of the EDEA-TL model. Teams of participants from several institutions work together using federated learning to resolve a machine-learning problem. They each have a server or service provider who manages the coordination of their work. A deep-learning approach is stored and improved on a centralized server. While retaining the data in each of these sites, this model may learn from a variety of sources, including decentralized data centers like those found in hospitals and other healthcare facilities. There is no communication or information exchange during the training time. As in classical deep learning, the server tracks a shared architecture that is used everywhere rather than giving data to a single spot. Based on the knowledge it has about its patients, each company then creates its own model. Then, data is sent from each hub to the server utilizing the inaccuracy gradient of the model. All participant feedback is gathered by a central server, which then adapts the overall model considering the data. The model may assess the response's quality using predetermined standards and only using pertinent data. Data from centers that show poor or atypical findings may therefore be ignored. Until just one cycle of federated learning is required to grasp the global model, this is repeated [36], [37].

### 3) IMPLEMENTATION AND WORKING OF PROPOSED MODEL EDEA-TL

EDEA-FL model works with the federated learning method and keeps the data more secure in the medical field. Several methods such as ICT, IoMT devices, and tools are applied to make the entire approach more innovative and updated in the modern era. The primary purpose of this study is to centralize the different entities and share the model without sharing actual data to keep things more secure.

Further, it includes hidden neurons, hidden layers, and effective and activated mechanisms for the healthcare system. Firstly, the federated model is designed where it relates to different hospital data. Before the FL approach, each data was shared by the main head hospitals or offices where there would be the issue of security of the patient's data. While working with the FL allows training a model by using data from various places without exchanging the data to the centralized location. This concept is somehow called non-independent data. FL approach is important if the data is larger and there is a privacy issue. So, as an alternative to transmitting the information from one place to the central place, the FL technique trains multiple models while keeping each in the same place as a data source. Then establish a global model, which is going to access the locally trained model of different places e.g., hospitals [38].

Figure 2 displays the working of the anticipated proposed model which involved some important layers such as the physical layer, federated layer, training layer, and Validation Layer the entire work has been done on MATLAB by using deep learning and machine learning techniques and approaches. The EDEA-FL model is used to make the federated learning system more secure and intelligent.

Figure 2 shows the four layers Federated layer, Physical Layer, Training Layer, and validation. The federated Layer has the universal model which is sharing the trained model in the server. The second Layer is the physical layer which is data acquisition for the ECG. The data is preprocessed and trained with the help of the weights to implement the validation phase.

The primary purpose of this approach is [39]:

- Applying the EDEA-FL algorithm can build the best possible approach for ECG detection on the client side.
- Identify and monitor the outcome of the patient's health by using the entire FL algorithm.

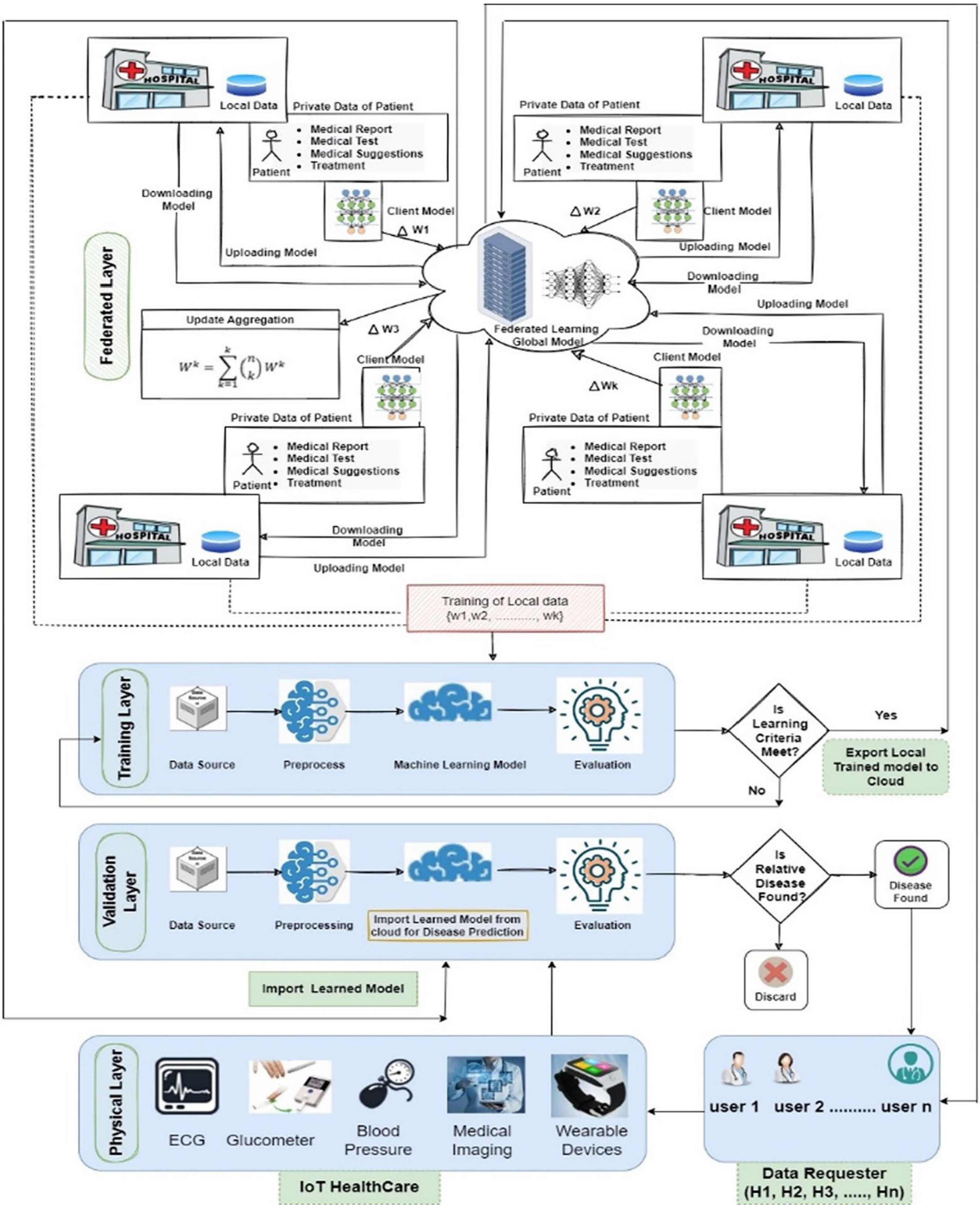


**FIGURE 2.** A proposed federated learning EDEA-FL framework.

- To enhance the efficiency of the method, more datasets are to be trained and employed in the pre-trained framework.
- The local data can be considered for patient security and privacy.
- By testing the functionality of the trained model, it is better to apply it to different datasets.
- In addition, different machine-learning approaches must be adopted to get a more concise evaluation.
- In this way, using different datasets and different machine-learning approaches can give better results and performance.

This study tells the technical advancement and innovative approach of the EDEA-TL proposed system while implemented in ECG arrhythmia detection.

The functioning of the proposed system is as examined [39]:

- Different Hospitals ($H_1$, $H_2$, $H_3$.......$H_4$) can identify and allocate the specific training which is uploaded to the federal server and further used as a global model.
- The first stage is the physical layer which has the pre-processing and application layer.
- Preprocessing is the important part, as when the data is getting from the IoMT devices, it can include missing values or inaccurate data. To lower this noise, normalization, and standard deviation can play a vital role in cleaning it, and further, the more refined data can work very well for training and prove the accurate result.
- The final and next layers are the prediction and performance layers which tell the overall functionality of the system.

While protecting data privacy, an FL-based machine learning method and distributed data gathering and clustering are used. The importance of privacy and property concerns is addressed, as well as identifying FL's drawbacks and advantages in healthcare predictive modeling. [40], [41], [42], [43], [44], [45].

## C. CLIENT AND SERVER-SIDE ALGORITHMS

### 1) CLIENT-SIDE ALGORITHM OF PROPOSED EDEA-TL MODEL

In the suggested model, it is observed that each client is equipped with input, output, and hidden layers. As demonstrated in the algorithm, the initial phase of the backpropagation algorithm involves the initialization of weights, followed by the processes of forward propagation, backpropagation of error, and subsequent updating of weights and biases. The Sigmoid activation function is ubiquitously employed in each neuron inside the buried layer. The study under consideration might be formulated as [50]:

$$\vartheta_j = \frac{1}{1+e^{-\left(b_1+\sum_{i=1}^{m}\left(g^{k}_{G,fml}*r_i\right)\right)}} \quad \text{where } j = 1, 2, 3 \ldots n \tag{4}$$

The output layer activation function is:

$$\vartheta_k = \frac{1}{1+e^{-\left(b_2+\sum_{j=1}^{n}\left(g^{k}_{G,fml}*\vartheta_j\right)\right)}} \quad \text{where } k = 1, 2, 3 \ldots r \tag{5}$$

where $\vartheta_k$ *and* $\vartheta_j$ denote the anticipated and expected outputs in Equation (6) [51], respectively, and E denotes the $i^{th}$ client error. Equation (7) [52], [53] gives the weight variation for the output layer as

$$E = \frac{1}{2}\sum\nolimits_k (\chi_k - \vartheta_k)^2 \tag{6}$$

Backpropagation error is characterized by equation 3, where $\chi_k$ & $\vartheta_k$ denote the expected and anticipated outputs. The deviation in weight for the output layer is specified in equation (7) as:

$$\Delta W \propto -\frac{\partial E}{\partial W}$$
$$\Delta h_{j,k} = -\wp\frac{\partial E}{\partial h_{j,k}} \tag{7}$$

After using the Chain rule method equation (7) can be written as [50], [51], [52], [53]:

$$\Delta h_{j,k} = -\wp\frac{\partial E}{\partial \vartheta_k}\times\frac{\partial \vartheta_k}{\partial h_{j,k}}$$

The value of weight transformed and can be consequential further by exchanging the values in equation (5), as shown in equation (9).

$$\Delta h_{j,k} = \wp\left(\chi_k - \vartheta_k\right)\times\vartheta_k(1-\vartheta_k)\times\left(\vartheta_j\right)$$
$$\Delta h_{j,k} = \wp\Upsilon_k\vartheta_j \tag{8}$$
$$\Upsilon_k = \left(\chi_k - \vartheta_k\right)\times\vartheta_k\left(1-\vartheta_k\right) \tag{9}$$

The chain rule is used to update the weights between the hidden and input layers [51].

$$\Delta g_{i,j} \propto -\left[\sum_k \frac{\partial E}{\partial \vartheta_k}\times\frac{\partial \vartheta_k}{\partial \vartheta_j}\right]\times\frac{\partial \vartheta_j}{\partial \omega_{i,j}}$$
$$\Delta g_{i,j} = -\wp\left[\sum_k \frac{\partial E}{\partial \vartheta_k}\times\frac{\partial \vartheta_k}{\partial \vartheta_j}\right]\times\frac{\partial \vartheta_j}{\partial \omega_{i,j}}$$

In the above eq, $\wp$ corresponds to the constant value,

$$\Delta g_{i,j} = \wp\left[\sum_k (\tau_k - \vartheta_k)\times\vartheta_k(1-\vartheta_k)\times\left(h_{j,k}\right)\right] \times\vartheta_k(-\vartheta_k\times\alpha_i$$
$$\Delta g_{i,j} = \wp\left[\sum_k (\tau_k - \vartheta_k)\times\vartheta_k(1-\vartheta_k)\times\left(h_{j,k}\right)\right] \times\vartheta_j(-\vartheta_j)\times\alpha_i\Delta g_{i,j}$$
$$= \wp\left[\sum_k \Upsilon_k\left(h_{j,k}\right)\right]\times\vartheta_j(1-\vartheta_j\times\alpha_i$$

After solving the equation, it may be represented as follows [52]:

$$\Delta\omega_{i,j} = \epsilon\xi_j\alpha_i \tag{10}$$

**TABLE 4.** Pseudocode proposed client-side.

| **[Proposed Client Training (S, g, *h*)]** | |
|---|---|
| **No.** | **Phases** |
| **1)** | **Begin** |
| **2)** | Divide the local data into small packets of size 's'. |
| **3)** | Two-layer weights ($g_{ij}$ & $h_{jk}$) can be initialized, Hence, the number of epochs €= zero, and the error is Zero as well. (So, E=0. € =0) |
| **4)** | For every Training Procedure 'P' |
| | a) Perform the feedforward stage to<br>i) Compute $\varphi_j$ by using equation no 1<br>ii) Compute $\varphi_k$ by using equation no 2 |
| | b) Further, Compute output Error Signals and hidden layer error signals. |
| | c) Adjust weights $g_{jk}$ and $h_{ij}$ (Error's backpropagation implementation). |
| **5)** | **Epoch Addition**: € = € + 1 |
| **6)** | ***Stopping Procedure Testing:*** If the stopping criteria are not met, then return to step 1. |
| **7)** | $g_{ij}$ and $h_{jk}$ which are locally trained model weights that should return to the Server. |
| **8)** | **End** |

whereas,

$$\Upsilon_j = \left[\sum\nolimits_k \Upsilon_k \left(h_{j,k}\right)\right] \times \vartheta_j(1-\vartheta_j) \tag{11}$$

$$h_{j,k}^{+} = h_{j,k} + \lambda\Delta h_{j,k} \tag{12}$$

The weights among the output and hidden layers are adjusted using the above equation. The weights between the input and hidden layers are updated using the equation below:

$$g_{i,k}^{+} = \mathrm{g}_{\mathrm{i,j}} + \lambda\Delta \mathrm{g}_{\mathrm{i,j}} \tag{13}$$

### 2) PROPOSED MACHINE LEARNING ALGORITHM

Table 4 exhibits the pseudocode of the proposed machine-learning approach on the client side.

### 3) TRANSFER OF WEIGHTS

The cloud or federated server receives these weights after that. These weights can be transmitted while being encrypted to secure this system. Encrypting the weights is not employed in this study; instead, it remains a separate individual that can be added based on application requirements.

### 4) FEDERATED SERVER SIDE

Each client is sending the federated server its ideal weight (LevenMarq_IH, LevenMarq_HO). Each client in our situation receives training using one of the ANN strategies listed below: Levenberg-Marquardt (LM), Bayesian Regularization (BR), or Scaled Conjugate Gradient (SCG) are the possible solutions. In Equations (17a) through (14, 15, 16), the optimal weights for the LM procedure, BR algorithm, and SCG algorithm are provided [53].

LevenMarq_IH

$$= \begin{bmatrix} \mathrm{wlm}_{11} & \mathrm{wlm}_{12} & \mathrm{wlm}_{13} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \mathrm{wlm}_{21} & \mathrm{wlm}_{22} & \mathrm{wlm}_{23} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \mathrm{wlm}_{31} & \mathrm{wlm}_{32} & \mathrm{wlm}_{33} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wlm}_{\mathrm{rcm}} & \mathrm{wlm}_{\mathrm{rcm}} & \mathrm{wlm}_{\mathrm{rcm}} & \cdots & \mathrm{wlm}_{\mathrm{rcnm}} \end{bmatrix} \mathrm{d1*d2} \tag{14}$$

BayReg_IH

$$= \begin{bmatrix} \mathrm{wbr}_{11} & \mathrm{wbr}_{12} & \mathrm{wbr}_{13} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \mathrm{wbr}_{21} & \mathrm{wbr}_{22} & \mathrm{wbr}_{23} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \mathrm{wbr}_{31} & \mathrm{wbr}_{32} & \mathrm{wbr}_{33} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wbr}_{\mathrm{rcm}} & \mathrm{wbr}_{\mathrm{rcm}} & \mathrm{wbr}_{\mathrm{rcm}} & \cdots & \mathrm{wbr}_{\mathrm{rcnm}} \end{bmatrix} \mathrm{d3*d4} \tag{15}$$

ScaledConjGra_IH

$$= \begin{bmatrix} \mathrm{wscg}_{11} & \mathrm{wscg}_{12} & \mathrm{wscg}_{13} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \mathrm{wscg}_{21} & \mathrm{wscg}_{22} & \mathrm{wscg}_{23} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \mathrm{wlm}_{31} & \mathrm{wlm}_{32} & \mathrm{wlm}_{33} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wscg}_{\mathrm{rcm}} & \mathrm{wscg}_{\mathrm{rcm}} & \mathrm{wscg}_{\mathrm{rcm}} & \cdots & \mathrm{wscg}_{\mathrm{rcnm}} \end{bmatrix} \mathrm{d5*d6} \tag{16}$$

$\mathrm{FML}_{\mathrm{IH}}$

$$= \begin{bmatrix} \mathrm{wlm}_{11} & \mathrm{wlm}_{12} & \mathrm{wlm}_{13} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \mathrm{wlm}_{21} & \mathrm{wlm}_{22} & \mathrm{wlm}_{23} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \mathrm{wlm}_{31} & \mathrm{wlm}_{32} & \mathrm{wlm}_{33} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wlm}_{\mathrm{rcm}} & \mathrm{wlm}_{\mathrm{rcm}} & \mathrm{wlm}_{\mathrm{rcm}} & \cdots & \mathrm{wlm}_{\mathrm{rcnm}} \end{bmatrix}$$

$$+\begin{bmatrix} \mathrm{wbr}_{11} & \mathrm{wbr}_{12} & \mathrm{wbr}_{13} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \mathrm{wbr}_{21} & \mathrm{wbr}_{22} & \mathrm{wbr}_{23} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \mathrm{wbr}_{31} & \mathrm{wbr}_{32} & \mathrm{wbr}_{33} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wbr}_{\mathrm{rcm}} & \mathrm{wbr}_{\mathrm{rcm}} & \mathrm{wbr}_{\mathrm{rcm}} & \cdots & \mathrm{wbr}_{\mathrm{rcnm}} \end{bmatrix} + \begin{bmatrix} \mathrm{wscg}_{11} & \mathrm{wscg}_{12} & \mathrm{wscg}_{13} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \mathrm{wscg}_{21} & \mathrm{wscg}_{22} & \mathrm{wscg}_{23} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \mathrm{wlm}_{31} & \mathrm{wlm}_{32} & \mathrm{wlm}_{33} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wscg}_{\mathrm{rcm}} & \mathrm{wscg}_{\mathrm{rcm}} & \mathrm{wscg}_{\mathrm{rcm}} & \cdots & \mathrm{wscg}_{\mathrm{rcnm}} \end{bmatrix} \tag{17a}$$

Equations (17a,17b) can be used to express the collective optimal weights for the federated level server for the input sheet to the hidden layer, where FML_IH denotes the weights of all in the vicinity trained clients combined.

The equation (17a) can also be written as follows.

$$\mathrm{FML}_{\mathrm{IH}} = \mathrm{LevenMarq}_{\mathrm{IH}} + \mathrm{BayReg}_{\mathrm{IH}} + \mathrm{ScaledConjGrad\_IH} \tag{17b}$$

This aggregation has a problem with the matrix's addition attribute since the accumulation of the matrix's proportions should be consistent. Equation (17b) makes it evident that because they do not have the same dimensions, all locally learned matrices cannot be added. The dimensions of each matrix involved should match to solve this problem. To do this, whenever necessary, we focus on a zero matrix with each matrix. The greatest length of rows for all individual trained clients is determined for this using Equation (15).

$$R_{FIH} = \max(R_{lm}, R_{br}, R_{scg}) \tag{18}$$
$$C_{FIH} = \max(C_{lm}, C_{br}, C_{scg}) \tag{19}$$

The next method is used to insert the zero matrix with each ultimate weight matrix. $\mathrm{W}_{\mathrm{lmih}}$, $\mathrm{W}_{\mathrm{brih}}$, and $\mathrm{W}_{\mathrm{scgih}}$, respectively, indicate the zero matrix (0) for the LM, BR, and SCG procedures in Equations (20) – (22), which will result in a matrix of zeros. Each locally trained model's weight will be horizontally concatenated with these zero matrices.

$$\mathrm{W}_{lmih} = \mathrm{zeros}(R_{lm}, C_{FIH} - C_{lm}) \tag{20}$$
$$\mathrm{W}_{brih} = \mathrm{zeros}(R_{br}, C_{FIH} - C_{br}) \tag{21}$$
$$\mathrm{W}_{scgih} = \mathrm{zeros}(R_{scg}, C_{FIH} - C_{scg}) \tag{22}$$

The horizontal concatenation is shown in equation (23) – (25)

$$\mathrm{W}_{lmih} = \mathrm{horzcat}(\mathrm{W}_{lmih}, \mathrm{LevenMarq\_IH}) \tag{23}$$
$$\mathrm{W}_{brih} = \mathrm{horzcat}(\mathrm{W}_{brih}, \mathrm{BayReg\_IH}) \tag{24}$$
$$\mathrm{W}_{scgih} = \mathrm{horzcat}(\mathrm{W}_{scgih}, \mathrm{Scaledconjgrad\_IH}) \tag{25}$$

Since the dimensions of $\mathrm{W}_{lmih}$, $\mathrm{W}_{brih}$, and $\mathrm{W}_{scgih}$ are the same in Equations (20) – (22), these matrices can now be aggregated to one another. Equation (26) is used to determine the federated server or global model.

$$\mathrm{W}_{FMLIH} = 2\mathrm{W}_{lpmih} + \mathrm{W}_{brpih} + 0.5\mathrm{W}_{scgpih} \tag{26}$$

The optimal federated weights between the input layer and hidden layer are represented by $\mathrm{W}_{FMLIH}$ in Equation (26). Depending on how well the locally trained clients perform, different scaling factors are applied.

### 5) OPTIMAL WEIGHT OF THE HIDDEN OUTPUT LAYER

Equations (27-29) is used to express the ideal weights of the hidden layer (HL) to the output layer (OL) for the LM, BR, and SCG algorithms [53].

LevenMarq_HO

$$= \begin{bmatrix} \mathrm{wlm}_{11} & \mathrm{wlm}_{12} & \mathrm{wlm}_{13} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \mathrm{wlm}_{21} & \mathrm{wlm}_{22} & \mathrm{wlm}_{23} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \mathrm{wlm}_{31} & \mathrm{wlm}_{32} & \mathrm{wlm}_{33} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wlm}_{\mathrm{rcm}} & \mathrm{wlm}_{\mathrm{rcm}} & \mathrm{wlm}_{\mathrm{rcm}} & \cdots & \mathrm{wlm}_{\mathrm{rcnm}} \end{bmatrix} \mathrm{d7^{*}\ d8} \tag{27}$$

BayReg_HO

$$= \begin{bmatrix} \mathrm{wbr}_{11} & \mathrm{wbr}_{12} & \mathrm{wbr}_{13} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \mathrm{wbr}_{21} & \mathrm{wbr}_{22} & \mathrm{wbr}_{23} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \mathrm{wbr}_{31} & \mathrm{wbr}_{32} & \mathrm{wbr}_{33} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wbr}_{\mathrm{rcm}} & \mathrm{wbr}_{\mathrm{rcm}} & \mathrm{wbr}_{\mathrm{rcm}} & \cdots & \mathrm{wbr}_{\mathrm{rcnm}} \end{bmatrix} \mathrm{d9^{*}d10} \tag{28}$$

ScaledConjGra_HO

$$= \begin{bmatrix} \mathrm{wscg}_{11} & \mathrm{wscg}_{12} & \mathrm{wscg}_{13} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \mathrm{wscg}_{21} & \mathrm{wscg}_{22} & \mathrm{wscg}_{23} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \mathrm{wlm}_{31} & \mathrm{wlm}_{32} & \mathrm{wlm}_{33} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wscg}_{\mathrm{rcm}} & \mathrm{wscg}_{\mathrm{rcm}} & \mathrm{wscg}_{\mathrm{rcm}} & \cdots & \mathrm{wscg}_{\mathrm{rcnm}} \end{bmatrix} \mathrm{d11^{*}d12} \tag{29}$$

Equation (30a, 30b) can be used to express the combined optimal weights for the federated server for the input layer to the hidden layer, where FML_HO denotes the weights of all locally trained clients.

combined.FML_HO

$$= \begin{bmatrix} \mathrm{wlm}_{11} & \mathrm{wlm}_{12} & \mathrm{wlm}_{13} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \mathrm{wlm}_{21} & \mathrm{wlm}_{22} & \mathrm{wlm}_{23} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \mathrm{wlm}_{31} & \mathrm{wlm}_{32} & \mathrm{wlm}_{33} & \cdots & \mathrm{wlm}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wlm}_{\mathrm{rcm}} & wlm_{\mathrm{rcm}} & \mathrm{wlm}_{\mathrm{rcm}} & \cdots & \mathrm{wlm}_{\mathrm{rcnm}} \end{bmatrix} + \begin{bmatrix} \mathrm{wbr}_{11} & \mathrm{wbr}_{12} & \mathrm{wbr}_{13} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \mathrm{wbr}_{21} & \mathrm{wbr}_{22} & \mathrm{wbr}_{23} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \mathrm{wbr}_{31} & \mathrm{wbr}_{32} & \mathrm{wbr}_{33} & \cdots & \mathrm{wbr}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wbr}_{\mathrm{rcm}} & \mathrm{wbr}_{\mathrm{rcm}} & \mathrm{wbr}_{\mathrm{rcm}} & \cdots & \mathrm{wbr}_{\mathrm{rcnm}} \end{bmatrix} + \begin{bmatrix} \mathrm{wscg}_{11} & \mathrm{wscg}_{12} & \mathrm{wscg}_{13} & \cdots & \mathrm{wscgren} \\ \mathrm{wscg}_{21} & \mathrm{wscg}_{22} & \mathrm{wscg}_{23} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \mathrm{wlm}_{31} & \mathrm{wlm}_{32} & \mathrm{wlm}_{33} & \cdots & \mathrm{wscg}_{\mathrm{rcn}} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathrm{wscg}_{\mathrm{rcm}} & \mathrm{wscg}_{\mathrm{rcn}} & \mathrm{wscg}_{\mathrm{rcm}} & \cdots & \mathrm{wscg}_{\mathrm{rcm}} \end{bmatrix} \tag{30a}$$

**TABLE 5.** **Pseudocode proposed Server-Side.**

| **Proposed Server-Side Algorithm** | |
|---|---|
| **No** | **Phases** |
| **1)** | **Begin** |
| **2)** | **Initialize** $g_o$ and ho (Look into unspecified Data) |
| **3)** | **For** each rotation k from 1 to K **do** |
| | $S_k$ ← (Random Collection of Users as a client from β) |
| | **For** each user 1 ∈ $S_k$ parallelly do |
| | $[g_{k+1}^{l}\ ,\ h_{k+1}^{l}]$ ← Client Training (p, $g_k$, $h_k$) |
| | **End For** |
| | **End For** |
| **4)** | $g_{G.fml}^{k} = \frac{1}{\sum 1 \in \beta} \sum_{l=1}^{\beta} \frac{S1}{S} g_{l+1}^{k}$ (Average Aggregation) |
| **5)** | $h_{G.fml}^{k} = \frac{1}{\sum 1 \in \beta} \sum_{l=1}^{\beta} \frac{S1}{S} h_{l+1}^{k}$ |
| **6)** | **End** |

The equation (30a) can also be written as follows.

$$\text{FML\_IH} = \text{LevenMarq\_HO} + \text{BayReg\_HO} + \text{ScaledConjGra\_HO} \tag{30b}$$

Equation (27), which can be used to generate the federated weights, suffers from the same dimension inconsistency problems as the previous fusion. All customer weight matrices will undergo the same process to ensure that their dimensions are uniform [53].

$$\mathrm{R_{FHO}} = \max(r_{lm}, r_{br}, r_{scg}) \tag{31}$$

$$\mathrm{C_{FHO}} = \max(c_{lm}, c_{br}, c_{scg}) \tag{32}$$

$$\mathrm{W_{lmho}} = \mathrm{zeros}(R_{lm}, C_{FHO} - C_{lm}) \tag{33}$$

$$\mathrm{W_{brho}} = \mathrm{zeros}(\mathrm{R_{br}}, \mathrm{C_{FHO}} C_{\mathrm{br}}) \tag{34}$$

$$\mathrm{W_{scgho}} = \mathrm{zeros}(\mathrm{R_{scg}}, \mathrm{C_{FHO}} C_{\mathrm{scg}}) \tag{35}$$

The horizontal concatenation is shown in equation (36) – (38)

$$\mathrm{W_{lmpho}} = \mathrm{horzcat}(\mathrm{W_{lmho}}, \text{LevenMarq\_HO}) \tag{36}$$

$$\mathrm{W_{brpho}} = \mathrm{horzcat}(\mathrm{W_{brho}}, \text{BayReg\_HO}) \tag{37}$$

$$\mathrm{W_{scgpho}} = \mathrm{horzcat}(\mathrm{W_{scgho}}, \text{ScaledConjGra\_HO}) \tag{38}$$

Then,

$$\mathrm{W_{FMLHO}} = 2 * \mathrm{W_{lmpho}} + \mathrm{W_{brpho}} + 0.5 * \mathrm{W_{scgpho}} \tag{39}$$

In equation (39), $\mathrm{W_{FMLHO}}$ is Considered to be the optimum federated weight of the hidden layer for output.

### 6) PROPOSED SERVER-SIDE ALGORITHM

Table 5 shows the pseudocode of the proposed machine-learning algorithm [53].

## IV. SIMULATION RESULTS

The entire program's evaluation and development is to be done in MATLAB 2021a using an 11th generation Intel Core (TM) i5 processor with an 1135G7 CPU processing at 2.40 GHz, 16.00 GB of RAM, and a 1 TB hard drive. In this research, the proposed model EDEA-TL is used to detect ECG Arrhythmia. Two datasets are taken and fused. Further, the dataset is segregated as 80% division for training and the rest division 20% for validation. To calculate the effectiveness of the suggested model, various numerical formulas like accuracy, miss classification rate, sensitivity, specificity, precision, False positive Rate, and False negative rate. Equation (40) – (48) [52], [53] showed the simulation result of the proposed model.

$$Accuracy = \frac{{}^{M_{ri}}/_{M_{rk}} + {}^{I_{ri}}/_{I_{ik}}}{\frac{M_{ri}}{I_{ri}} + \frac{M_{rj,j\neq i)}}{I_{rj}} + \frac{M_{rk}}{I_{rk}} + \frac{\sum_{l=1(}^{n} M_{rl,l\neq k)}}{I_{rk}}} \tag{40}$$

where i, j, k, and l = 1, 2, 3, …, n

$$Miss\ Rate = \frac{\frac{\sum_{l=1}^{n} M_{rl,l\neq k}}{I_{rk}}}{\frac{\sum_{l=1(}^{n} M_{rl,l\neq k)}}{I_{rk}} + \frac{M_{ri}}{I_{ri}}} \tag{41}$$

where i, k, l = 1, 2, 3, …, n

$$True\ Positive\ Rate/Recall = \frac{\frac{M_{ri}}{I_{ri}}}{\frac{M_{ri}}{I_{ri}} + \frac{\sum_{l=1(}^{n} M_{rl,l\neq k)}}{I_{rk}}} \tag{42}$$

where i, k, l = 1,2, 3, …., n

$$True\ Negative\ Rate/Sensitivity = \frac{\frac{M_{rk}}{I_{rk}}}{\frac{M_{rk}}{I_{rk}} + \frac{\sum_{j=1(}^{n} M_{rj,j\neq 1)}}{I_{rj}}} \tag{43}$$

**TABLE 6.** Performance evaluation of proposed EDEA-TL during training for disease detection by using several numerical measurements on the client side.

| Client | Accuracy | Sensitivity | Specificity | Miss Classification Rate | Precision | False Positive Rate (FPR) | False Negative Rate (FNR) |
|---|---|---|---|---|---|---|---|
| **H1** | 0.97 | 0.98 | 0.94 | 0.03 | 0.17 | 0.02 | 0.01 |
| **H2** | 0.93 | 0.98 | 0.82 | 0.07 | 0.12 | 0.06 | 0.01 |
| **H3** | 0.95 | 0.99 | 0.86 | 0.05 | 0.13 | 0.04 | 0.02 |
| **H4** | 0.94 | 0.98 | 0.84 | 0.06 | 0.15 | 0.05 | 0.005 |

where j, k = 1,2, 3, ……, n

$$Precision = \frac{\frac{M_{ri}}{I_{ri}}}{\frac{M_{ri}}{I_{ri}} + \frac{\sum_{j=1(}^{n} M_{rj,j\neq 1)}}{I_{rj}}} \tag{44}$$

where i, j = 1,2, 3, ……, n

$$False\ Omission\ Rate = \frac{\frac{\sum_{l=1}^{n} M_{rl,l\neq k}}{I_{rk}}}{\frac{\sum_{l=1(}^{n} M_{rl,l\neq k)}}{I_{rk}} + \frac{M_{rk}}{I_{rk}}} \tag{45}$$

where k, l = 1,2, 3, ……, n

$$False\ Discovery\ Rate = \frac{\frac{\sum_{j=1}^{n} M_{rj,j\neq i}}{I_{rj}}}{\frac{M_{ri}}{I_{ri}} + \frac{\sum_{j=1(}^{n} M_{rj,j\neq i)}}{I_{rkj}}} \tag{46}$$

where i,j = 1,2, 3, …..…, n

$$F_{0.5}score = 1.25 \times Precision \times \frac{Recall}{0.25 \times Precision + Recall} \tag{47}$$

$$F_1 Score = 2 \times Precision \times \frac{Recall}{Precision + Recall} \tag{48}$$

In Table 6, for the training phase, 87554 recordings are employed on the client end (H1, H2, H3, H4) which is 80% of the total number of the record. In Table 6, the statistical measurements are shown against H1, H2, H3, and H4. H1 client gives 97% accuracy, 98% sensitivity, 94% specificity, 3% miss classification, 17% precision, 2% FPR and 1% FNR. So, the H2 client gives 93% accuracy, 98% sensitivity, 82% specificity, 7% miss classification, 12% precision, 6% FPR, and 1% FNR. H3 client gives 95% accuracy, 99% sensitivity, 86% specificity, 5% miss classification, 13% precision, 4% FPR and 2% FNR. H4 client gives 94% accuracy, 98% sensitivity, 84% specificity, 6% miss classification, 15% precision, 5% FPR and 0.5% FNR.

Figure 3 shows how well the classification model works for four different clients (H1, H2, H3, and H4). The accuracy numbers for each client are between 0.93 and 0.97, which shows that the model performs well overall. Sensitivity (true positive rate) shows how well the model finds positive cases. Values between 0.98 and 0.99 show how well the model can predict positive cases for all clients. Specificity (true negative rate) runs from 0.82 to 0.94, which shows that the model's ability to find negative cases correctly varies. The false forecast rate, also called the "miss classification rate," is usually low, ranging from 0.03 to 0.07. Precision, which is the number of true positive predictions out of all positive predictions made by the model, runs from 0.12 to 0.17. The false positive rate (FPR), which is the proportion of false positive predictions out of all actual negative cases, ranges from 0.02 to 0.06, while the false negative rate (FNR), which is the proportion of false negative predictions out of all actual positive cases, ranges from 0.01 to 0.02. Overall, figure 4 gives a full picture of how the model worked for different clients, showing where it did well and where it could do better at predicting good and bad things.

In Table 7, the statistical measurements are shown against H1, H2, H3, and H4. H1 client gives 94% accuracy, 96% sensitivity, 82% specificity, 6% miss classification, 17% precision, 2% FPR and 3% FNR. Therefore, the H2 client gives 92% accuracy, 96% sensitivity, 71% specificity, 8% miss classification, 28% precision, 5% FPR and 3% FNR. H3 client gives 95% accuracy, 96% sensitivity, 90% specificity, 5% miss classification, 11% precision, 4% FPR and 2% FNR. H4 client gives 93% accuracy, 96% sensitivity, 82% specificity, 7% miss classification, 22% precision, 4% FPR and 3% FNR. Finally, on the server side, the proposed

**TABLE 7.** Performance evaluation of proposed EDEA-TL during training for disease detection by using several numerical measurements on theclient side.

| Server Side | Accuracy | Sensitivity | Specificity | Miss Classification Rate | Precision | False Positive Rate (FPR) | False Negative Rate (FNR) |
|---|---|---|---|---|---|---|---|
| $H_1$ | 0.94 | 0.96 | 0.82 | 0.06 | 0.17 | 0.02 | 0.03 |
| $H_2$ | 0.92 | 0.96 | 0.71 | 0.83 | 0.28 | 0.05 | 0.03 |
| $H_3$ | 0.95 | 0.96 | 0.90 | 0.05 | 0.11 | 0.04 | 0.02 |
| $H_4$ | 0.93 | 0.96 | 0.82 | 0.07 | 0.22 | 0.04 | 0.03 |
| **Proposed Approach of FL (Server Side)** | **0.98** | **0.99** | **0.91** | **0.02** | **0.10** | **0.01** | **0.01** |

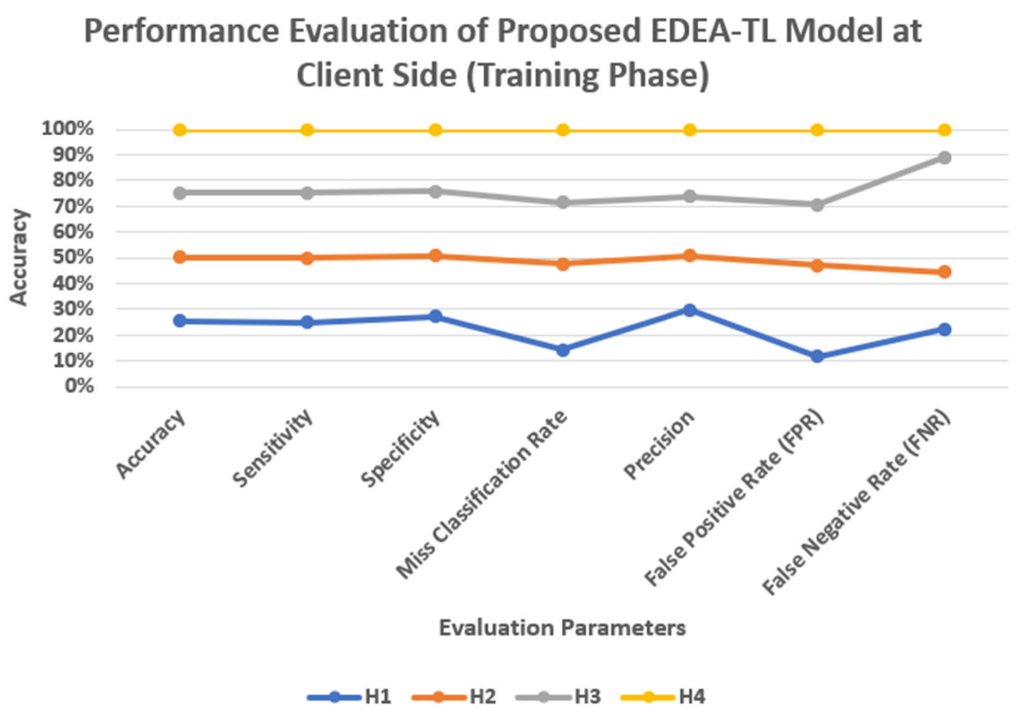


**FIGURE 3.** Performance evaluation of proposed EDEA-TL model at client side (Training Phase).

EDEA-TL model of FL methodology achieved the most accuracy as compared to other clients H1. H2, H3, H4. The proposed federated learning approach gives 98% accuracy, 99% sensitivity, 91% specificity, 2% miss classification, 0.1% precision, 1% FPR, and 1% FNR.

During the validation process, figure 4 shows a full performance review of the Proposed EDEA-TL Model for disease detection by using different numerical measurements on the server side. The model's efficiency is measured for four different servers (H1, H2, H3, and H4), and its performance

**TABLE 8.** Performance estimation of proposed model EDEA-TL with previous research.

| MACHINE LEARNING METHODS | | **Outcomes (Accuracy)** |
|---|---|---|
| Strodthoff et al [46] | Deep learning approach as ResNet and Inception for ECG. | 89.8% |
| Acharya et al. [47] | CNN Layers | 93.5% |
| Yaman O. et al. [48] | KNN and SVM Approach | 91.25% |
| Simjanoska et al. [49] | ML-Train Validation Test Evaluation | 93.5% |
| Sehirli et al. [50] | RNN and LSTM methods | 97% |
| Rehman A. [39] | FL with Blockchain | 97% |
| Hassan [55] | Innovative Deep Learning Model with LSTM. | 98% |
| Guo S [56] | Casual Knowledge Fusion Framework | 94% |
| Surkova E [57] | Right Ventricle functioning in the multi-modality imaging | 97.5% |
| Kıymaç and Kaya [54] | A novel automated CNN arrhythmia classifier with memory-enhanced artificial hummingbird algorithm. | 98.87% |
| **Proposed Model (EDEA-TL)** | **Detecting Electrocardiogram Arrhythmia Empowered with Weighted Federated Learning** | **98%** |

is compared to a Proposed Approach of Federated Learning (FL) on the server side.

The accuracy numbers for the servers range from 0.92 to 0.95, which shows that the models usually work well. Sensitivity (true positive rate) shows how well the model can find disease cases. Values between 0.96 and 0.99 show how well the model can find true positives. Specificity (true negative rate) ranges from 0.71 to 0.91, showing that the model can identify non-disease cases properly. The miss classification rate (also called the false classification rate) is between 0.02 and 0.07, which means that only a small number of guesses are wrong. Precision, which is the number of true positive predictions out of all positive predictions, goes from 0.10 to 0.22. The false positive rate (FPR), which is the proportion of false positive predictions out of all real negative cases, ranges from 0.01 to 0.04, which means that there aren't many false positive predictions. The false negative rate (FNR), which is the number of wrong predictions for every true positive, runs from 0.01 to 0.03. The Proposed Approach of FL at the server side has the highest accuracy at 0.98 and the highest sensitivity at 0.99, which shows that it is better at detecting diseases. Overall, the picture gives useful information about how well the model works on different servers. It also shows how well the Proposed EDEA-TL Model and the Proposed Approach of FL work to help find diseases on the server side.

Table 8 reveals the contrast of the proposed model with an earlier available study. Acharya et al. [46] attained 89.8% accuracy using deep learning approaches such as ResNet. Yaman et al. [47] attained 93.5% accuracy using CNN. Yaman O et al [48] attained 91.25% precision utilizing SVM and KNN approach. Simjanoska et al. [49] attained 93.5%

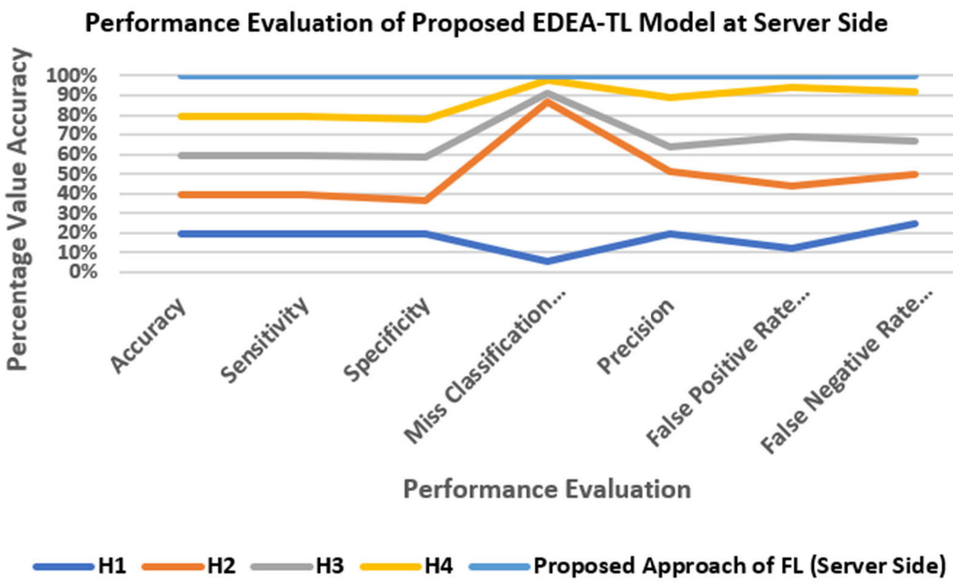


**FIGURE 4.** Performance evaluation on the server side.

accuracy using CNN. Simjanoska et al. [48] attained 91.25% precision utilizing SVM and KNN approach. Ata et al. [50] attained 97% accuracy using RNN and LSTM methods. Chen et al. [39] attained 97% accuracy using FL with blockchain. Kıymaç and Y. Kaya [54] developed an automatic CNN arrhythmia classification with 98.87% accuracy using a memory-enhanced artificial hummingbird algorithm.

In contrast to previous research utilizing different machine learning techniques for the diagnosis of ECG arrhythmias, the suggested EDEA-TL model, which incorporates Weighted Federated Learning, demonstrates a significantly elevated accuracy rate of 98%. This approach demonstrates superior performance compared to various existing methods, including deep learning with ResNet and Inception (achieving 89.8% accuracy), CNN layers (achieving 93.5% accuracy), KNN and SVM (achieving 91.25% accuracy), machine learning with train-validation test evaluation (achieving 93.5% accuracy), RNN and LSTM methods (achieving 97% accuracy), federated learning with blockchain (achieving 97% accuracy), and a novel automated CNN arrhythmia classifier utilizing a memory-enhanced artificial hummingbird algorithm (achieving 98.87% accuracy). The primary distinguishing factor resides in the application of Weighted Federated Learning, showcasing its efficacy in improving the accuracy of ECG arrhythmia identification in comparison to conventional machine learning techniques.

## V. CONCLUSION

In conclusion, the study aimed to address the challenges of data privacy and imbalanced data distribution in ECG classification tasks. By utilizing the concept of federated learning, the study proposed a weighted federated learning approach to improve the performance of ECG classification, The results of the study showed proposed approach was effective in detecting electrocardiogram arrhythmias and outperformed traditional federated learning methods. The study demonstrated that the weighted federated learning approach was able to handle the imbalance of data distribution among different clients in a federated learning scenario, which is a common problem in ECG classification tasks. This was achieved by assigning different weights to each client's model during the federated learning process, which effectively balances the contribution of each client's data to the overall model. The finding of the study indicates that the proposed weighted federated learning approach is a promising solution for ECG classification tasks, especially in scenarios where data privacy and imbalanced data distribution are significant concerns. The approach can be further improved by exploring techniques to address these challenges, such as data augmentation and transfer learning.

Future work in ECG classification for detecting electrocardiogram arrhythmia empowered with weighted federated learning could include the following:

- Improving data privacy: the study used simple techniques to preserve data privacy in the federated learning scenario, such as encrypted communication and data aggregation. Future work could explore more advanced techniques, such as homomorphic encryption, to further improve data privacy.
- Investigating other data imbalance Techniques: The study weighted federated learning to address the problem of imbalanced data distribution. Future work could explore other data imbalance techniques such as over-sampling and under-sampling, to further improve the performance of ECG classification.
- Evaluating the impact of network condition: Federated learning is typically performed as a network with varying connectivity and stability. Future work could evaluate the impact of network conditions on the

performance of weighted federated learning in ECG classification tasks.

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