FEDERATED LEARNING – A NOVEL APPROACH FOR PREDICTING DISEASES IN UNPRECENTED AREAS

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Abstract—**According to the World Health Organization (WHO), approximately 75 percent of deaths in rural areas are attributed to delayed disease diagnosis. Some diseases exhibit unforeseeable symptoms, leading to life-threatening conditions. Moreover, emerging and rare diseases with recognizable manifestations in advanced stages pose challenges due to physicians' limited knowledge. In this context, federated learning emerges as a privacy-conscious machine learning approach, ideally suited for smart healthcare applications. It facilitates collaboration among multiple hospitals to conduct training without the need to share raw data, thereby preserving sensitive information. The proposed solution showcases the feasibility of using federated learning to predict diseases based on frontal chest X-rays. The iterative training process of federated learning, occurring at predefined intervals, significantly enhances efficiency, allowing doctors to include specific symptoms for early predictions of novel diseases. A comprehensive evaluation using RESNET-50 on frontal chest X-rays demonstrated that the federated learning approach improves the efficiency of disease detection compared to a normal model by atleast 2 percent.**

I. INTRODUCTION

In recent years, advancements in deep learning and artificial intelligence have paved the way for groundbreaking applications in the field of medical imaging, particularly in the detection and diagnosis of diseases [1]. Chest X-rays are a commonly used diagnostic tool in healthcare, enabling the identification of various pulmonary and cardiac conditions. However, accurately interpreting these images requires expertise and time, leading to potential delays in diagnosis and treatment. Federated learning [2], an emerging paradigm in the field of machine learning, has shown great promise in addressing challenges related to data privacy and security while allowing for collaborative model training across distributed datasets. By leveraging federated learning, we aim to develop an efficient and privacy-preserving approach for detecting diseases based on frontal chest X-ray images, ultimately improving diagnostic accuracy and patient outcomes.

Our research focuses on the detection of a diverse set of classes, encompassing both normal and abnormal findings in chest X-rays. These classes include "Enlarged Cardio Mediastinum," "Cardiomegaly," "Lung Opacity," "Lung Lesion," and similar other diseases. Each of these classes represents a specific pathological condition or medical indication that requires accurate identification for appropriate clinical decision-making. To address the challenges posed by limited access to large, centralized medical datasets due to privacy regulations and ethical concerns, we have devised a distributed learning approach [3]. We curated a diverse and extensive chest X-ray dataset, comprising images collected from multiple medical institutions, ensuring a representative sample of various conditions.

Federated learning represents a machine learning method [4] wherein multiple devices collaborate to train a model without divulging their individual data to a central server. Instead, each system independently trains its own model using its data and shares only the model parameters with the central server. The centralized server aggregates all the model parameters and sends the updated model back to all the systems for further training, aimed at enhancing accuracy [5]. This approach ensures data privacy since the raw data remains decentralized. Figure 1 illustrates the typical structure of a federated learning model.

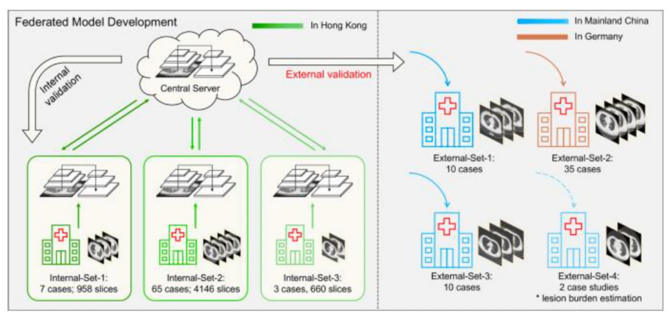

Fig. 1: General Structure of Federated Learning

Our research endeavors to contribute to the field of medical image analysis by exploring innovative and privacy-conscious solutions for disease detection using chest X-ray images [6]. We anticipate that the findings from this study will provide valuable insights into the potential of federated learning for healthcare applications, fostering collaborative efforts in improving medical diagnostics while preserving patient privacy.

II. LITERATURE SURVEY

Federated learning is a decentralized machine learning framework that facilitates collaborative training among multiple participants [7], ensuring that data remains within the local area without being shared externally.

The idea of federated learning was introduced in a research paper by Google, which also presented the renowned federated learning algorithm known as FedAvg [8]. This approach allows multiple users to contribute to the training of machine learning models. Each user utilizes their own local training data to train their individual network models [9]. Afterwards, these participant models are combined into a global model based on specific rules, which helps it adapt to the training samples held by all participants. Over time, numerous researchers have enhanced FedAvg and put forth several novel algorithms for federated learning. Li et al [10] proposed FedProx, which not only performs a direct averaging of each model's parameters but also includes a penalty term to mitigate the impact of variations in data distribution among local training samples. FedMA , proposed by Wang et al. [11], combines the weights of neurons with similar characteristics, leveraging the permutation invariance property of neurons[12]. Addressing the issue of "client-drift" arising from heterogeneous data, Karimireddy et al. [13] presented the SCAFFOLD method, which utilizes variance reduction in its local updates to correct for client-drift. Wang et al. [14] put forward FedNova, a normalized averaging technique that eliminates objective inconsistency while ensuring rapid error convergence.

In environments where resources are constrained, the implementation of chest CT recognition paves the way for swift categorization, thus catalyzing preliminary screenings [15] that may accelerate the process of diagnosing symptoms and arranging corresponding treatments. As artificial intelligence continues to evolve, a multitude of research has emerged that focuses on leveraging AI to anticipate diseases through the analysis of X-ray imagery.

Bharati et al [16] introduced a hybrid model utilizing VGG architecture. However, the model's accuracy was limited to 73% as a result of the insufficient quantity of images used for training and testing. Qinghao et al [17] put forward an automated COVID-19 diagnosis framework utilizing weakly supervised learning. They introduce an innovative method for correcting noisy labels, which involves propagating predictions at the patient level [18]. Additionally, they developed a slice aggregation module to mitigate the shift in data distribution.

Bhattacharyya et al [19] presented a novel approach for identifying COVID-19 and pneumonia using chest X-ray images. They employed a conditional generative adversarial network (C-GAN) to segment the original X-ray images and extract lung images. Deep neural networks (DNN) were subsequently utilized to capture distinctive features. This proposed method proves to be highly efficient in screening patients for COVID-19 infection.

While numerous techniques employing federated learning exist for disease prediction, none of them currently have the capability to predict every single disease. Additionally, the utilization of ResNet-50 [20] in the model will enhance its efficiency in comparison to other existing approaches.

Author(s)	**Method/Algorithm**	**Description/Contribution**
Google	FedAvg [8]	Introduced the idea of federated learning, allowing multiple users to train individual network models using local data, then combining them into a global model.
Li et al. [10]	FedProx	Proposed a direct averaging method with a penalty term to mitigate variations in data distribution among local training samples.
Wang et al. [11]	FedMA	Combined weights of neurons with similar characteristics, leveraging the permutation invariance property of neurons.
Karimireddy et al.	SCAFFOLD [13]	Addressed "client-drift" by utilizing variance reduction in local updates to correct for client-drift arising from heterogeneous data.
Wang et al. [14]	FedNova	Introduced a normalized averaging technique that eliminates objective inconsistency while ensuring rapid error convergence.
Bharati et al. [16]	Hybrid model with VGG	Developed a hybrid model for chest CT recognition, but accuracy was limited to 73% due to insufficient images for training and testing.
Qinghao et al. [17]	Automated COVID-19 diagnosis framework	Proposed a weakly supervised learning method for COVID-19 diagnosis, introducing a method for correcting noisy labels and a slice aggregation module to mitigate data distribution shift.
Bhattacharyya et al. [19]	C-GAN with DNN	Presented a novel approach for identifying COVID-19 and pneumonia using chest X-ray images, employing a C-GAN to segment original X-ray images and DNN to capture distinctive features. Highly efficient in screening patients for COVID-19 infection.

Fig. 2: Related Works

III. Proposed Solution

In this suggested approach, our aim is to use federated learning for disease prediction in regions where such predictions have not been made before. The key advantage of this technique is that it enables training without sharing raw patient data, thus ensuring data privacy and security.

Fig. 2 illustrates the flow of the developed model. The initial stage involves data preprocessing, where the dataset undergoes necessary preparations. In the second stage, individual systems are trained using their respective data. Finally, the generalized model is trained using the output obtained from the second stage. The output from this generalized model is then shared back with all individual clients. This process is iteratively repeated between the individual clients and the generalized model.

A. Dataset

For the proposed model, we are utilizing a dataset from Kaggle that includes images of frontal chest X-rays. This dataset is made up of a total of 223414 images, which are divided into six distinct sets. Five of these sets each consist of 33930 images, while the remaining portion is designated for testing. The dataset comprises various classes, including No Finding, Enlarged Cardio mediastinum, Cardiomegaly, Lung Opacity, Lung Lesion, Edema, Consolidation, Pneumonia,

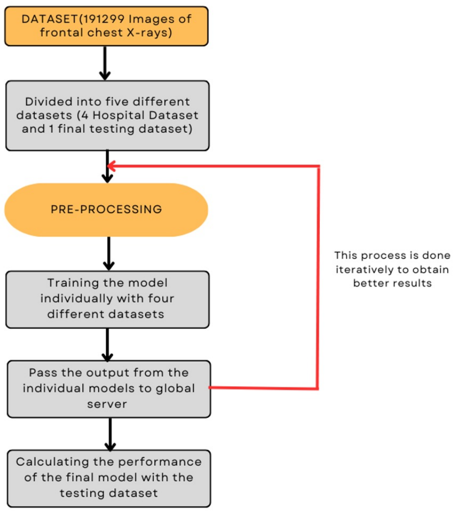

Fig. 3: Flow of the Proposed Model

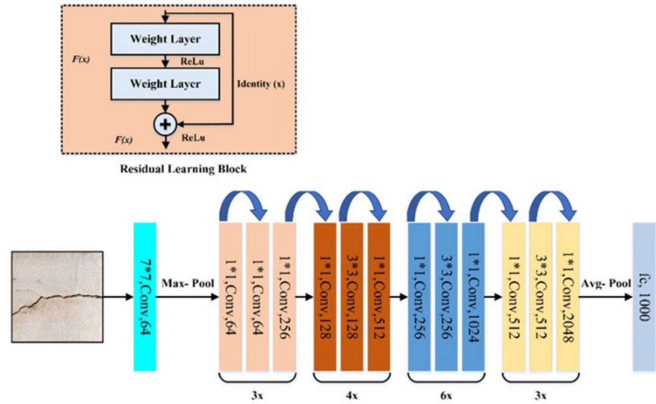

Fig. 4: Structure of ResNet-50 Algorithm

Atelectasis, Pneumothorax, Pleural Effusion, Pleural Other, Fracture, and Support Devices. These classes will denote each disease that are being predicted by our developed model. These specific classes correspond to the various diseases that the developed model is designed to predict.

B. Data Preprocessing

Preprocessing refers to the phase in which the image's quality is enhanced by eliminating unnecessary distortions to obtain a clear picture [21]. When there are challenges in identifying images with changes in brightness, optical character recognition becomes a tool. The advanced approach involves forecasting the pixel values in the original image, so as to calculate the corresponding pixels in the refined image [22]. This process is expressed as

$$\beta(x, y) = \alpha[\mu(x, y)] \tag{1}$$

Here, $\mu(x, y)$ represents the initial (input) image, while $\beta(x, y)$ denotes the enhanced image, and α signifies the alteration between the two images. This method of improvement is referred to as mask processing or a spatial domain approach. Within the spatial domain, techniques utilizing maximum and minimum filters are employed.

C. Federated learning Framework

1) RESNET-50: The federated learning model is developed using RESNET-50 algorithm [23]. ResNet-50 is a prominent deep learning model tailored for image recognition functions [24]. As a member of the ResNet family, it is notable for its significant depth, comprising 50 layers. The architecture overcomes the vanishing gradient problem by employing skip connections, facilitating the training of highly deep networks [25]. ResNet-50 has proven its extraordinary efficiency in different image classification benchmarks and is widely used within the domain of computer vision. The configuration of the ResNet-50 algorithm can be seen in Fig. 3.

The ResNet-50 [26] structure consists of residual blocks arranged in a sequence. Initial feature identification is accomplished through a leading convolutional layer and a subsequent maximum pooling layer. The model is segmented into four clusters, each with a different number of increasingly complex residual blocks. Following the final cluster, the output undergoes average pooling and then passes through fully connected layers for ultimate classification. A significant element of this architecture is the incorporation of skip connections [27], which mitigate the vanishing gradient issue by providing direct routes for gradient flow during the backpropagation phase, enhancing the model's learnability and fine-tuning.

2) Disease Prediction: The proposed solution employs the RESNET-50 model in a two-stage process involving initial implementation and subsequent training for disease prediction. In the first stage, described in Algorithm-1, the model is set up. The second stage, detailed in Algorithm-2, involves training and testing the model. This approach utilizes a collaborative framework where individual models, trained on their own datasets, share output parameters with a centralized global model for further enhancement. After the global model's training, it disseminates the results back to the individual models, enabling them to update their parameters. This collaborative cycle allows both individual and global models to mutually enhance their learning and optimize performance.

After every epoch, the effectiveness of the suggested solution is assessed using the AUC (Area Under the Curve). The outcomes achieved by each client, as well as the overall model, are detailed in the results section.

IV. EXPERIMENTAL RESULTS

A. SYSTEM SPECIFICATION

The developed solution is implemented using Python and has been created on the Google Colab platform. To execute the proposed system, a GPU with at least 16 cores or an

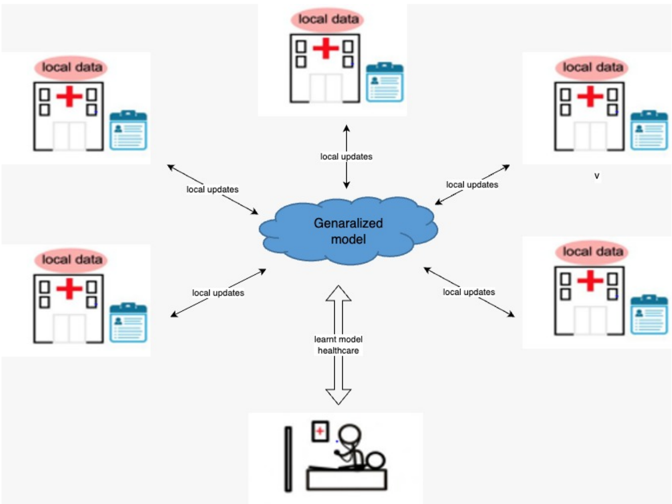

Fig. 5: Structure of Proposed Solution

Algorithm 1 Model Creation

BEGIN
function INIT (pretrained=False, out_size=14):
 if model_name is 'resnet34':
  initialize model with pretrained ResNet-34
 else:
  initialize model with non-pretrained ResNet-34

 get number of input features for fully connected layer replace the fully connected layer with linear layer followed by a sigmoid activation, output size equals outsize

 if model_name is 'resnet50':
  initialize model with pretrained ResNet-50
 else:
  initialize model with non-pretrained ResNet-50

 get number of input features for the fully connected layer replace the fully connected layer with linear layer followed by a sigmoid activation, output size equals outsize

function forward(x):
 x = pass x through the model
 return x
END

NVIDIA GeForce RTX 3090 is required. PyTorch serves as the primary machine learning library for this development, and it necessitates the use of CUDA Version 11.3.

B. PERFORMANCE METRICS

After each epoch, the loss function and the Area Under Curve (AUC) are calculated, serving as key indicators of the effectiveness of the proposed solution. The mathematical expressions for these two metrics are used to evaluate the performance of the model.

Algorithm 2 Training the Model

BEGIN
function TRAIN(client, model, dltrain, dlVal, tmEpoch, loss):
 initialize optimizer with learning rate, betas, epsilon and weight decay
 set lossMIN to a very high value
 set best_auc to 0.0
 initialize train_start and train_end and arrays.

 for epochID from 0 to tmEpoch - 1:
  record training start time
  lost = call epochTrain function with model, dlTrain, optimizer, loss
  record training end time

  loss, aurocIndividual, aurocMean = call epochVal fn with model, dlVal, loss.
  log training and validation losses and mean AUC.
  write aurocMean and lossv to a log file.

  if auc_mean $\geq best\_auc$:
   update best_auc with aurocMean
   save model parameters, epoch, best_loss, optimizer state to file
   log saved epoch information
  else:
   log current epoch information

 calculate train_time as difference between train_end and train_start
 log training time for each epoch
 retrieve model parameters
 return model parameters
END

The loss function of the developed model is computed as follows,

$$Loss = \frac{-1}{n} \sum_{i=1}^{n} \sum_{j=1}^{m} y_{ij} \; log(\hat{y_{ij}}) \tag{2}$$

where n is the no. of samples, m is the no. of classes and y_{ij} and $\hat{y_{ij}}$ are the actual and predicted probabilities of class j for sample i, respectively.

The loss function obtained after each round is mentioned in the table-2 and it's graphically represented in Fig. 5.

The Area Under Curve (AUC) serves as the primary metric to assess the efficiency of the proposed solution. The computation of AUC is conducted according to a specific formula, as follows:

Rounds	Client-1	Client-2	Client-3	Client-4	Client-5
1	.296	.291	.297	.296	.299
2	.289	.294	.289	.288	.292
3	.288	.289	.286	.289	.292
4	.290	.293	.284	.285	.286
5	.286	.289	.284	.285	.286
6	.286	.284	.284	.285	.287
7	.288	.287	.286	.285	.285
8	.286	.290	.283	.287	.283
9	.283	.287	.285	.287	.286
10	.287	.284	.286	.285	.286

Table-2: Loss Value of each Client

Fig. 6: Loss value of each client

$$AUC = \sum_{i=1}^{n-1} \frac{(x_{i+1} - x_i) * (y_{i+1} - y_i)}{2} \quad (3)$$

Here, the x values are the false positive rates, and the y values are the true positive rates for the ROC curve, and n is the number of points on the curve. The results obtained after training the individual models is displayed in table-3 and it's graphically represented in Fig. 6.

Rounds	Client-1	Client-2	Client-3	Client-4	Client-5
1	74	74.8	74	74.2	74.6
2	74.5	75.1	74.6	74.7	74.6
3	75.1	75.4	75.4	75.2	75.1
4	75.5	75.0	75.7	75.7	75.8
5	75.6	75.5	75.8	75.7	75.8
6	75.3	75.7	75.7	75.8	75.2
7	75.5	75.2	75.7	75.7	76.1
8	75.4	75.9	76.2	75.8	75.6
9	75.7	75.8	75.6	75.7	76.0
10	75.6	75.9	75.2	76.2	75.6

Table-3: AUC of each Client

The accuracy of the generalized model is computed as similar to that of the individual model using Area Under Curve (AUC). The obtained results are shown in table-4 and its graphically represented in Fig. 7.

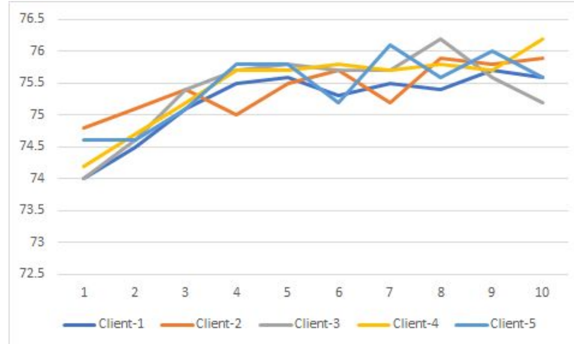

Fig. 7: AUC of each client

Rounds	AUC
1	71.5
2	76.2
3	76.8
4	77.1
5	77.12
6	77.15
7	77.91
8	77.08
9	76.07
10	77.09

Table-4: AUC of generalized model

The results obtained show a noticeable improvement, with an increase of 2 percent in predicting diseases when a generalized model is applied through federated learning. Our proposed model achieved an AUC of 77.91, a value that has the potential to increase with more iterations and a larger dataset. A significant benefit of using federated learning in this context is the preservation of privacy, as the individual data from different clients remains concealed from one another.

V. Challenges Faced

Implementing a disease prediction system using federated learning involves several challenges. Key issues include diverse healthcare data affecting model performance, data privacy and security concerns, and the need for efficient, secure communication between healthcare providers and a central server. The decentralized nature of federated learning demands high computational resources, particularly in environments with varied hardware. Addressing data scarcity for rare diseases requires data augmentation and transfer learning. Additionally, the process of model aggregation can be resource-intensive due to communication overheads, necessitating efficient methods. Crucial to the success of such a system is the willingness of healthcare institutions to collaborate, which depends on overcoming social and organizational barriers with effective communication, incentives, and governance.

VI. Conclusion

In conclusion, this study presents a groundbreaking method for predicting diseases using frontal chest X-rays by employ-

Fig. 8: AUC of generalized model

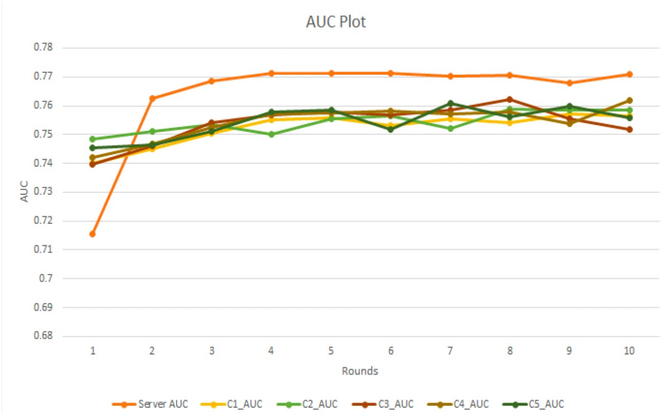

Fig. 9: Comparison between Individual and Generalized Model

ing a federated learning approach. Achieving an AUC of 77.91, the research shows that integrating federated learning can enhance the model's efficiency by 2 percent compared to working with individual models. This underscores the adaptability and potential of the methodology introduced. A key triumph of this paper is its ability to maintain the privacy of patient data, ensuring that each client's information remains concealed from others. This is a critical aspect that aligns with contemporary healthcare needs and ethical considerations. Looking forward, the scope of this research could be broadened to include predictions based on other types of scans and medical records, not just chest X-rays. Furthermore, the model's accuracy could be further refined by incorporating a more diverse and extensive dataset. The progress made in this research lays a promising foundation for future innovation in the field of medical diagnosis and personalized healthcare.

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