



# Experiments of Federated Learning for COVID-19 Chest X-ray Images

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**Abstract.** AI plays an important role in COVID-19 identification. Computer vision and deep learning techniques can assist in determining COVID-19 infection with Chest X-ray Images. However, for the protection and respect of the privacy of patients, the hospital's specific medical-related data did not allow leakage and sharing without permission. Collecting such training data was a major challenge. To a certain extent, this has caused a lack of sufficient data samples when performing deep learning approaches to detect COVID-19. Federated Learning is an available way to address this issue. It can effectively address the issue of data silos and get a shared model without obtaining local data. In the work, we propose the use of federated learning for COVID-19 data training and deploy experiments to verify the effectiveness. And we also compare performances of four popular models (MobileNet\_v2, ResNet18, ResNeXt, and COVID-Net) with the federated learning framework and without the framework. This work aims to inspire more researches on federated learning about COVID-19.

**Keywords:** COVID-19 · Federated learning · Chest X-ray image

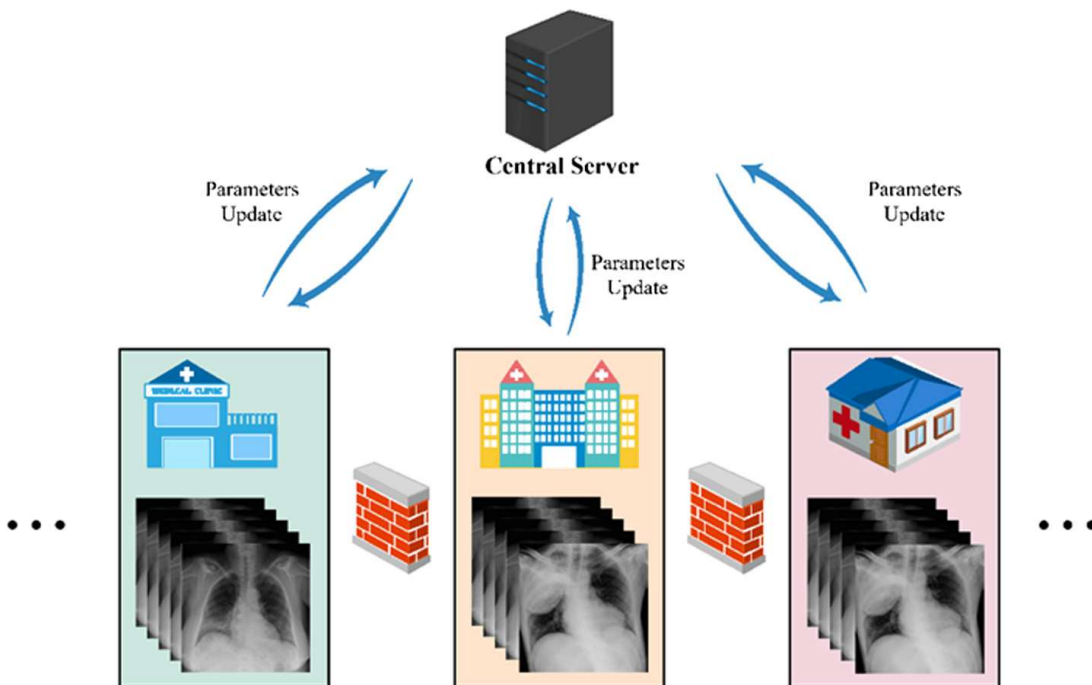
## 1 Introduction

The COVID-19 pandemic has caused continuous damage to the health and normal production of people all over the world. Therefore, researches on detecting and diagnosing COVID-19 patients are very meaningful [20, 21]. The clinical manifestations of COVID-19 infected pneumonia are mainly fever, chills, dry cough, and systemic pain. A few patients have abdominal symptoms. It is worth noting that there are asymptomatic patients in the population. So it is necessary to test more people as soon as possible. A key step in judging and treating COVID-19 is the effective screening of infected patients. One of the key screening methods is the use of chest X-rays image. Computer vision and machine learning technology play an important role in this approach. At present, artificial intelligence, especially deep learning, has become an important technology for

computer-aided medical applications and has achieved remarkable results in medical imaging. Deep learning has made a huge contribution to the classification of chest X-ray radiology in the medical field, and it has become an effective tool for doctors to judge and analyze the condition. To obtain an accurate and robust depth model, the core element is large and widely diverse training data. However, out of the protection and respect of the privacy of patients, the hospital's specific medical-related data did not allow leakage and public research.

Collecting such training data was a major challenge. To a certain extent, this has caused a lack of sufficient data samples when performing deep learning approaches to detect COVID-19. Federated Learning is an available way to address this issue. It can effectively address the issue of data silos and get a shared model without obtaining local data. In the paper, we firstly propose the use of federated learning for COVID-19 data training and deploy experiments to verify the effectiveness.

Federated learning is a framework of learning across multiple institutions without sharing patient data. It has the potential to fundamentally solve the problems of data privacy and data silos. Applications of federated learning in medical big data are promising researches. Federated learning is capable of utilizing the non-shared data from different hospitals, enlarging the sample size of the model training, and improving the accuracy of the model. The core of federated learning is to use data sets distributed on multiple devices to jointly build a shared model and does not require local raw data sharing. This precisely protects patient data. In the case that COVID-19 medical imaging data is still distributed in various countries and hospitals, federated learning experiments for medical images of COVID-19 that conducted in this work are necessary (Fig. 1).



**Fig. 1.** Federated learning framework for COVID-19 CXR images

In this work, we conducted four individual experiments to present the performances in federated learning of four different networks for COVID-19 CXR images: COVID-Net [18], ResNeXt [14], MobileNet\_v2 [13], and ResNet18 [1]. Further, we analyzed the results and proposed possible future improvements to inspire more research in federated learning for COVID-19.

## 2 Related Work

With the continuous development of the new coronavirus epidemic, more and more researchers are committed to joining the ranks of fighting the epidemic through AI-related technologies. Researchers use AI to make it play a role in the epidemic. A series of recent studies on COVID-19 medical imaging analysis and diagnosis have sprung up. These studies have completed the diagnosis of COVID-19 based on medical imaging technology. We use the current chest x-ray technology to complete the image generation of the special radiological features. After that, the researchers used machine learning methods to classify and recognize the images generated during the CT scan diagnosis process. This method greatly reduces the workload of medical staff, and at the same time plays a role in assisting doctors in diagnosing the pathological characteristics of patients. At present, many studies have targeted disease as a binary classification problem, that is, “normal”, “pneumonia” and “COVID-19”. Next, we introduce the application of COVID-Net in COVID-19 image classification and recognition and complete diagnosis of pathological features.

### 2.1 COVID-Net for COVID-19 Identification

COVID-Net specifically proposes a neural network that uses PEPX compression network structure to identify COVID-19 pneumonia CXR images. At the same time, it retains the performance of the network to a great extent and is highly sensitive to the pneumonia characteristics of COVID-19. Based on the advantages of CXR imaging for rapid triage of COVID-19 screening, availability, ubiquity, and portability, they make predictions through the COVID-Net interpretability method. This allows us to not only gain a deeper understanding of the key factors associated with COVID cases. This can help clinicians perform better screening. We can also review COVID-Net, a method based on CXR images to verify that it is making decisions.

### 2.2 Federated Learning

Federated learning is recent emerging research that has been extensively studied in the fields of financial security, artificial intelligence, and robotics [4, 10, 11].

The training data will be distributed on each mobile device, not all of them will be sent to the central server, and only the updated data on each device will be aggregated to the central server. After joint optimization, the central server returns to the global state of each device and continues to accept the updated data calculated by each client in the new global state. This method is Federated Learning [12]. Federated Learning or Federated

Machine Learning [9] can solve the problem of unprotected large-scale private data and complete updating learning of devices without exchanging large amounts of data.

This decentralized training model approach provides privacy, security, regulation, and economic benefits [22]. Federated Learning presents new statistical and system challenges when training models on distributed device networks [15]. Federated Learning, which relies on scattered data, brings many aspects of research: Fei Chen et al. identified the combination of Federated Learning and Meta-learning as a major advance in Federated Learning [3]. Konstantin Sozinov et al. have made some progress in applying Federated Learning to human activity identification [16].

### 3 Federated learning System for COVID-19 CXR Images

In this section, we provide a comprehensive overview of federated learning. Furthermore, the definition, architecture, training process and, parameters update method of the federated learning system [12] for COVID-19 CXR images are considered.

#### 3.1 Basic Definition

In the work, we define  $N$  COVID-19 CXR images owners as  $\{F_1, F_2, \dots, F_N\}$ . We assume that they are from different hospitals. Patient medical data is not allowed to be shared, including CXR images. Under this constraint, all of them want to train their own model by merging their respective data  $\{D_1, D_2, \dots, D_N\}$ . A conventional method exists to put all the data together and use  $D = D_1 \cup D_2 \cup \dots \cup D_N$  to train to get a model  $M_{SUM}$ . Federated learning is a systematic learning process. In this process, the data owners jointly train the model  $M_{FED}$ . During this process, any data owner  $F_i$  will not disclose their own data  $D_i$  to others. In addition to this, the accuracy of  $M_{FED}$  represented as  $V_{FED}$  should be very close to the  $V_{SUM}$  performance of  $M_{SUM}$ . In the form of expression, let  $\varepsilon$  be a non-negative real number; If  $|V_{FED} - V_{SUM}| < \varepsilon$ , we can think that the federated learning algorithm has  $\varepsilon$  error accuracy.

#### 3.2 Framework of the Federated Learning System

In this part, we will introduce the basic framework of federated learning, the training structure, and the way to update the parameters. Federated learning is a distributed learning method. The server is used to maintain the overall main model and distribute it to various agents. For privacy issues, agents train models locally. The server will set the score  $S$ , and select the agents according to the proportion to update the central model of the server. Then upload the agent-improved model parameters to the server to update the server model parameters. Subsequently, it is distributed to agents to improve their models. In this way, we continue to improve the central model of the server and the local model of the agents. This approach is capable of ensuring the accuracy and privacy of the agents, utilize the agents' computing power and a large amount of data to learn, and maintain an excellent central model.

In the FL training system, the owner of the data acts as a participant in the FL process. And they jointly train the machine learning model of the aggregation server center. In

this system, we promise that the data owners are honest and the data they provide is real. This requires data owners to use their more and real private data for training and submit the trained local model to the FL server.

Generally, the FL training process includes the following three training steps. We first define that the local model refers to the model trained on each participating agent, and the global model refers to the model after the FL server has been aggregated.

- Step 1: Implements task initialization. The server determines the training task, which is to determine the target application and corresponding data requirements. At the same time, the server specifies the global model and establishes parameters during the training process, such as the learning rate. Afterward, the server allocates the initialized global model  $W_{tG}$  and training tasks to the participating clients to complete the task allocation.
- Step 2: Implements the training and update of the local model. The training is carried out based on the global model  $W_{tG}$ , where  $t$  represents the current iteration index, and each participating user uses local data and equipment to update the local model parameters  $W_{ti}$ . The final goal of the participant  $i$  in the iteration  $t$  is to find the optimal parameter  $W_{ti}$  that minimizes the loss function  $L(W_{ti})$ .
- Step 3: Realizing the aggregation and update of the global model. The server aggregates the local models of the participating users and sends the updated global model parameters  $W_{t+1G}$  to the users who hold the data.

## 4 Experiments

In this session, we will explain our experiments on the recognition of COVID-19 pneumonia CXR images using various models and federated learning frameworks.

### 4.1 Dataset

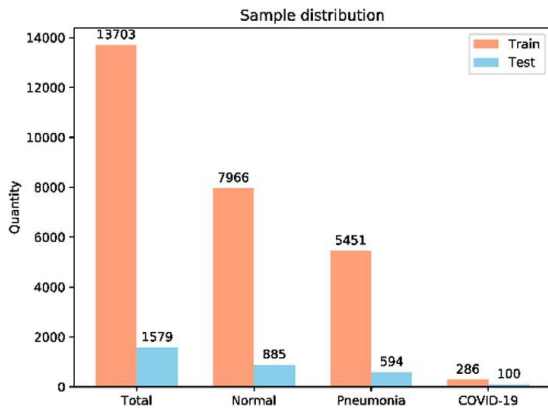
The dataset used to train and evaluate the model is the COVIDx dataset, which is one of the open-access datasets with the largest number of COVID-19 pneumonia CXR images. It contains covid chestxray dataset [5], COVID-19 Chest X-ray Dataset, Actualmed COVID-19 Chest X-ray Dataset, covid-19 radiography dataset which is public on Kaggle and RSNA Pneumonia Detection Challenge's dataset [8]. There are 15,282 images in this dataset, including 13,703 images for training and 1,579 images for testing. There are three kinds of labels in the dataset. They are normal (which is asymptomatic), pneumonia (which is non-COVID19 pneumonia), and COVID-19 (which is pneumonia caused by novel coronavirus). The various data distributions are shown in Fig. 2 below. It is assumed that the data in the training set is representative and can reflect the accuracy of the model.

### 4.2 Experimental Setting

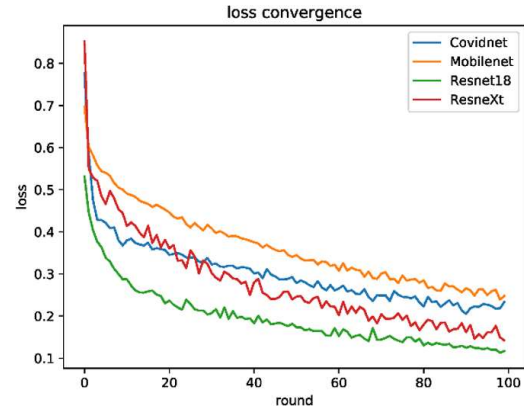
**Model.** The main task in the experiment is image classification. There are already many classic neural networks in this field, and there are models specifically designed for the recognition of COVID-19 pneumonia CXR images. Four models are used in the experiments.



- COVID-Net: A neural network specifically proposed to identify COVID-19 pneumonia CXR images utilizes PEPX to compress the network structure while preserving the network's performance to a large extent. At the same time, it has a high sensitivity to the pneumonia characteristics of COVID-19.
- ResNet18: It is a residual neural network. An identity mapping layer is added to the ordinary neural network to make the network as deep as possible. To a certain extent, it can prevent the accuracy falling caused by overfitting due to the deepening of the network.
- ResNeXt: It is based on the residual neural network using a split-transform-merge strategy to convert single-core convolution into multi-core convolution, but the topology is the same as ResNet18.
- MobileNet\_v2: It is a lightweight convolutional neural network. Unlike the residual neural network, the residual neural network uses a convolution kernel to first compress and extract features and then expand, but it expands and extracts more features and then compresses.



**Fig. 2.** Data distributions in COVIDx dataset



**Fig. 3.** Loss convergence with training rounds

### 4.3 Implementation and Training

Federated learning is a pseudo-distributed training completed on one machine in our experiment. For each agent, there is a separate model, which is reset to the updated central model after each central model update. The models are all implemented by PyTorch, and the training set and test set images are resized to (224,224) for model training. Each agent uses the Adam optimizer with learning rate =  $2e-5$  and weight decay =  $1e-7$ . The framework for federated learning is trained under the GPU acceleration of NVIDIA Tesla V100 (32 GB) on Ubuntu 18.04 system. Other training-related parameters are shown in Table 1.

**Table 1.** Training-related parameters in the experiment

Parameter	Value	Description
Agents number	5	The number of agents
Frac	0.4	The proportion of agents participating in the central model update for each round
Local epoch	3	Epochs update per round
Local batch size	10	Local update batch size
Learning rate	2.00E-05	Learning rate of optimizer
Weight decay	1.00E-07	Decay of learning rate with training epoch

#### 4.4 Experimental Results and Analysis

During the experiment, the loss of several models can converge, and the decline of loss during the training process is shown in Fig. 3.

After using the same parameter training four models for 100 rounds, the result is shown in Table 2. ResNet18 has the fastest convergence speed and the highest accuracy rate (96.15%, 91.26%) on both the training set and the testing set. The ResNeXt convergence rate is closely followed, but the accuracy rate is not as good as the second-ranked COVID-Net. Although MobileNet\_v2 has a loss value similar to COVID-Net, the accuracy rate on the testing set is not satisfactory.

**Table 2.** Model sensitivity to data using federated learning framework

Model	Training set	Testing set
COVID-Net	$92.40 \pm 0.004\%$	$89.17 \pm 0.015\%$
MobileNet_v2	$91.16 \pm 0.005\%$	$86.83 \pm 0.017\%$
ResNet18	<b><math>96.15 \pm 0.003\%</math></b>	<b><math>91.26 \pm 0.014\%</math></b>
ResNeXt	$94.66 \pm 0.004\%$	$90.37 \pm 0.015\%$

To explore the sensitivity of the models to each label, we counted the accuracy of each model for each label, and the performance results of the models are shown in Fig. 4 and Table 3.

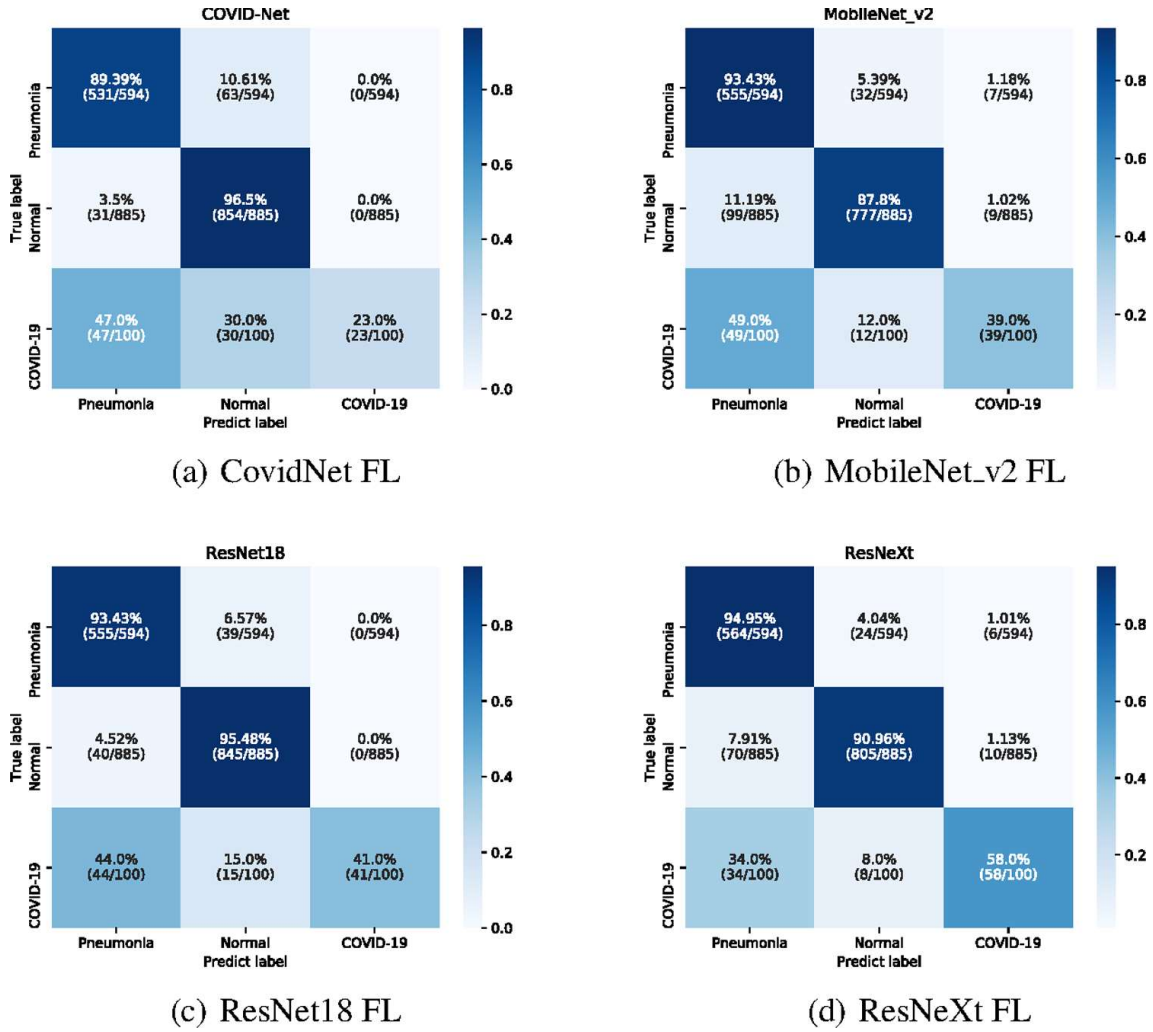


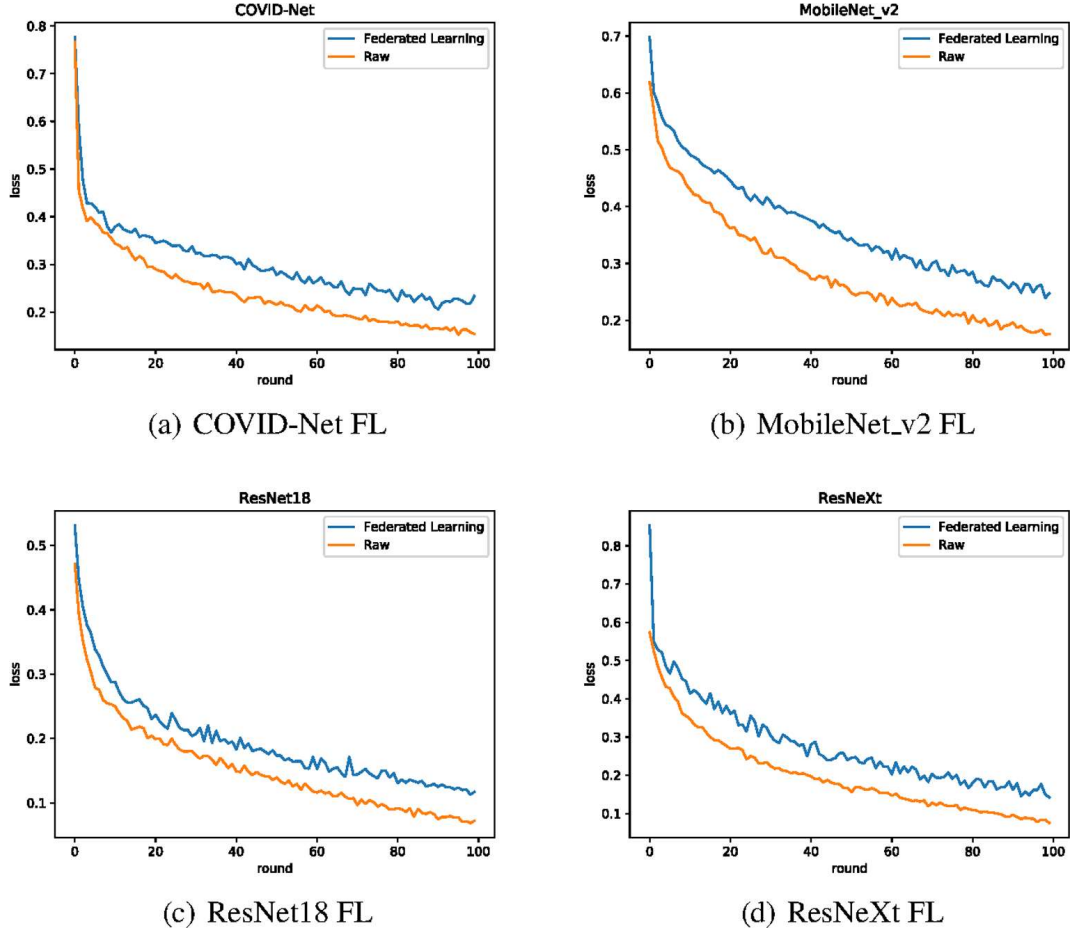
Fig. 4. Four models perplexity of each label

Table 3. Four models perplexity of each label

Model	Normal	Pneumonia	COVID-19
COVID-Net	$96.47 \pm 0.004\%$	$88.24 \pm 0.009\%$	$51.04 \pm 0.05\%$
MobileNet_v2	$94.87 \pm 0.005\%$	$87.20 \pm 0.009\%$	$50.26 \pm 0.05\%$
ResNet18	<b><math>98.16 \pm 0.003\%</math></b>	<b><math>93.91 \pm 0.006\%</math></b>	$66.32 \pm 0.047\%$
ResNeXt	$96.18 \pm 0.004\%$	$92.66 \pm 0.007\%$	<b><math>73.58 \pm 0.044\%</math></b>

We compared the training results without the federated learning framework with those using the federated learning framework. Because the round is 100 and local\_epoch is 3 in the federated learning parameters, we set epoch to 300 when training the model separately, to compare with the loss convergence during the federated learning training process, as shown in Fig. 5. It was found that the loss convergence rate caused by the use of federated learning decreased slightly. The result of the training accuracy of a single network is shown in Table 4.





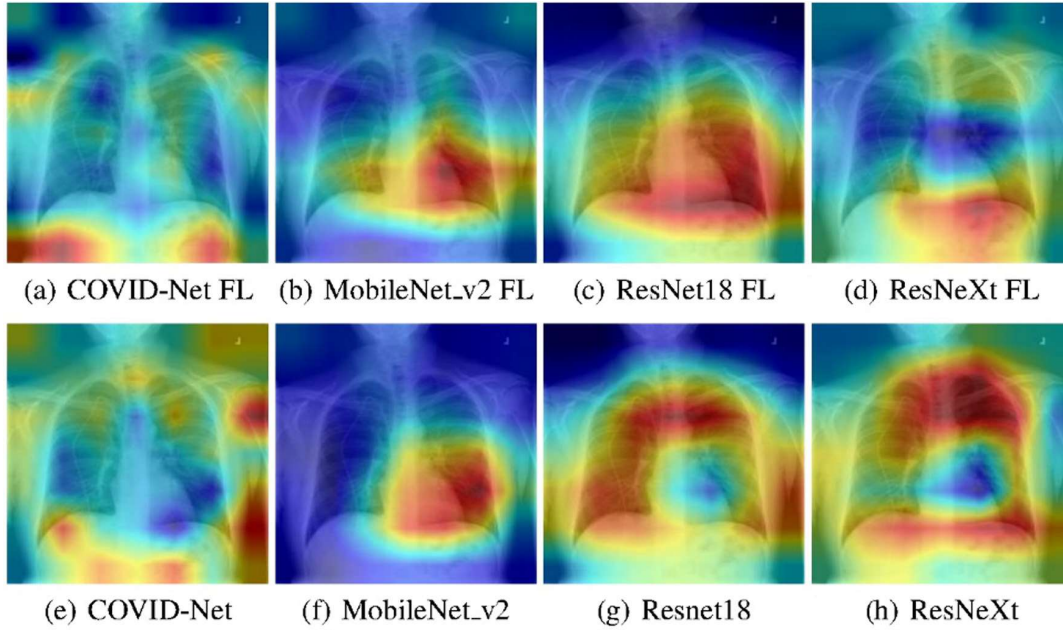
**Fig. 5.** Loss convergence speed comparison of whether to use the federated learning framework

**Table 4.** Loss convergence speed comparison of whether to use the federal learning framework

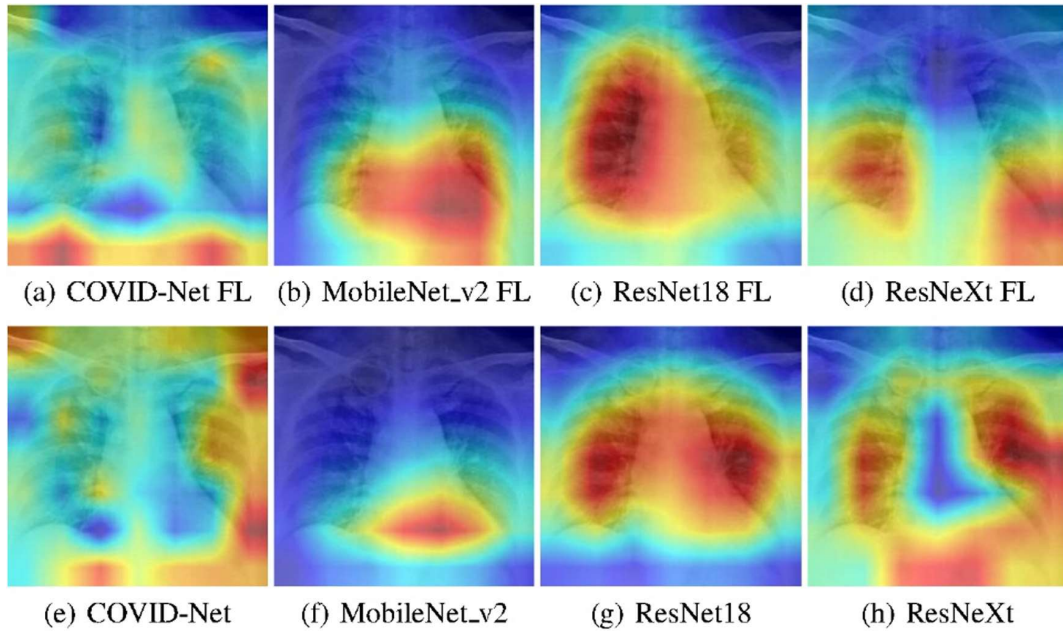
Model	Training set	Testing set
COVID-Net	$94.50 \pm 0.004\%$	$90.06 \pm 0.015\%$
MobileNet_v2	$94.10 \pm 0.004\%$	$88.98 \pm 0.015\%$
ResNet18	<b><math>98.06 \pm 0.002\%</math></b>	$91.07 \pm 0.014\%$
ResNeXt	$97.66 \pm 0.003\%$	<b><math>91.26 \pm 0.01\%</math></b>

As presented in Fig. 5, we compared the training procedure based on federated learning with the training procedure without federated learning. MobileNet\_v2 has a larger accuracy gap between the FL based approach and the individual approach while ResNet18 has a smaller accuracy gap. If considering the number of parameters, MobileNet\_v2 and ResNet18 have a higher performance. MobileNet\_v2 has the fewest parameters and the lowest accuracy. ResNet18 has the second-fewest parameters and the highest accuracy.

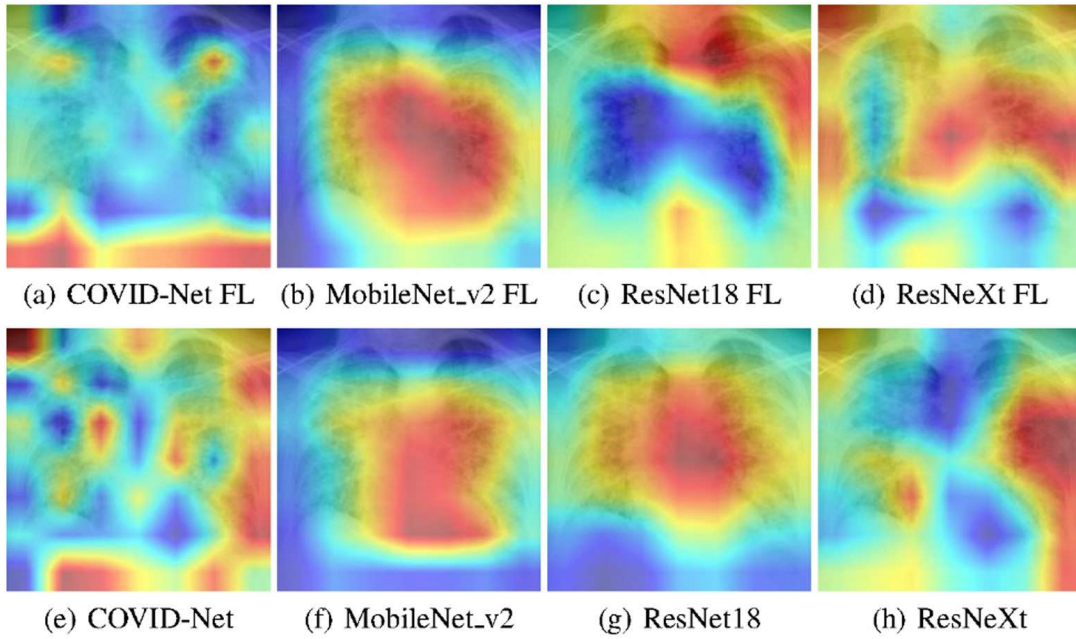
We used the Grad-CAM++ method [2] to perform Visual Explanations on the models, and the results are shown in Figs. 6, 7 and 8. From left to right in each figure are the COVID-Net, ResNet18, ResNeXt, and MobileNet\_v2 models. The first line is the result of training using the federated learning framework, and the second line is the result of training without the federated learning framework.



**Fig. 6.** Visual explanations of the last convolution layer of each model, with COVID-19 label



**Fig. 7.** Visual explanations of the last convolution layer of each model, with normal label



**Fig. 8.** Visual explanations of the last convolution layer of each model, with pneumonia label

## 5 Conclusion

In the work, we conducted experiments on COVID-19 identification with CXR images based on the federated learning framework. We conducted CXR images training with four different models: MobileNet\_v2, ResNet18, ResNeXt, and COVID-Net, and the comparison experiment between training with federated learning framework and training without federated learning framework. The experimental results show that ResNet18 has the best performance both in training with FL and without FL. ResNeXt has the best performance in images with COVID-19 labels. MobileNet\_v2 has the fewest number of parameters. Therefore, the work indicates that ResNeXt and ResNet18 are better chosen for COVID-19 identification among the four popular models.

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