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Federated learning based Covid-19 detection

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Abstract

The world is affected by COVID-19, an infectious disease caused by the SARS-CoV-2 virus. Tests are necessary for everyone as the number of COVID-19 affected individual's increases. So, the authors developed a basic sequential CNN model based on deep and federated learning that focuses on user data security while simultaneously enhancing test accuracy. The proposed model helps users detect COVID-19 in a few seconds by uploading a single chest X-ray image. A deep learning-aided architecture that can handle client and server sides efficiently has been proposed in this work. The front-end part has been developed using StreamLit, and the back-end uses a Flower framework. The proposed model has achieved a global accuracy of 99.59% after being trained for three federated communication rounds. The detailed analysis of this paper provides the robustness of this work. In addition, the Internet of Medical Things (IoMT) will improve the ease of access to the aforementioned health services. IoMT tools and services are rapidly changing healthcare operations for the better. Hopefully, it will continue to do so in this difficult time of the COVID-19 pandemic and will help to push the envelope of this work to a different extent.

KEYWORDS

COVID-19, CXR images, cybersecurity, federated learning, Internet of Medical Things (IoMT), privacy, transfer learning, Xception

1 | INTRODUCTION

The SARS Cov2-led COVID-19 pandemic has significantly impacted human life and health in general. The future of this virus spread may be best described as 'uncertain'. Exploratory research in this field seems to have no end. COVID-19 tends to attack the lungs and damage lung tissues. The rapid spread of the disease was only within a few months. World Health Organization (WHO) was concerned about the outbreak and declared COVID-19 a Public Health Emergency. People suffered and died of this deadly outbreak. At present, COVID-19 detection follows one of these three ways to detect the infection in the human body:

- Computed Tomography (CT) scans use 3D radiographic images for COVID detection. However, the required equipment is frequently unavailable in many health centres and hospitals, which is a disadvantage in this case.
- Reverse Transcription Polymerase Chain Reaction (RT-PCR) tests can detect the contagious RNA from the nasal swabs. However, the equipment is not easily accessible, similar to the previous case. Additionally, the diagnosis reports take a lot of time, and the process becomes time-

consuming. This paper lays out an architecture to deal with this issue and make the process effective within the most efficient time frame possible.

- Chest X-rays (CXR) require less equipment and are more portable than CT-scan machines. Additionally, CXR tests take about 15 s per person, which is quite time-efficient. The authors of this paper have worked with these CXR images to generate a fast, accurate, and secure COVID-19 detection model. Because infection detection from CXR images has fewer chances of error than other permissible COVID-19 testing measures, the results obtained are highly dependable and reliable.

The COVID-19 virus has been the subject of millions of tests throughout the world, but there are still a ton more tests to be conducted. Clinical symptoms of the disease are comparable to those of pneumonia and other respiratory infections. Since it is paramount to limit the spread and transmission of COVID-19 by quarantining the infected, the situation calls for AI engineers and data scientists to make use of artificial intelligence and deep learning methodologies to detect the virus and predict its spread. Additionally, since generating CXR images only requires about 15 s per person, machine learning can automate the process of result evaluation, making the entire infection detection process possible in a matter of seconds. This might enable us to become immune to the virus in the future as well. The federated learning-based approach used in the architecture is a novel feature that will guarantee the complete safety and privacy of user data. Test centres and hospitals will not have to store the CXR images of candidates since the federated learning algorithm can extract the precise approximations required for computation without directly storing crucial patient information in centralized data servers. Recent developments in the application of AI have led to the advancement of computer-aided diagnosis in many healthcare domains. The Deep Learning-based CNN classification models have previously diagnosed diseases like cancer and pneumonia. Thus, these models have a lot of promising results and hold hope for predicting COVID-19 using CXR images. However, this is quite challenging to achieve as data is not sufficiently available for use, and there is a significant concern about data privacy.

The proposed methodology does not necessitate storing patient data, thereby keeping users' data private and secure. The patients' data used is confidential enough to be shared with the research scientists for their work. Internet of Medical Things (IoMT) refers to a connected infrastructure of medical hardware, software, health systems, and services. The widespread adoption of IoT technology has already benefited numerous other industries. The IoMT ecosystem is unique as it combines connected devices with patient monitoring data that are in the context of medicine, healthcare, and other related services. IoMT is in the ideal position to grow within the sector. It serves not only as a boon for doctors and industry but also for the patients. The penetration of healthcare into society has now reached new heights. In the scope of the present work, the more tests performed, the faster it is. Researchers working on this architecture aimed to use federated learning rather than primitive machine learning in situations where data privacy is of significant concern. Moreover, the authors aimed to reduce the computational complexity by distributing the training among various clients. The paper explains all the details of this proposed work. Figure 1 presents a glimpse of the suggested

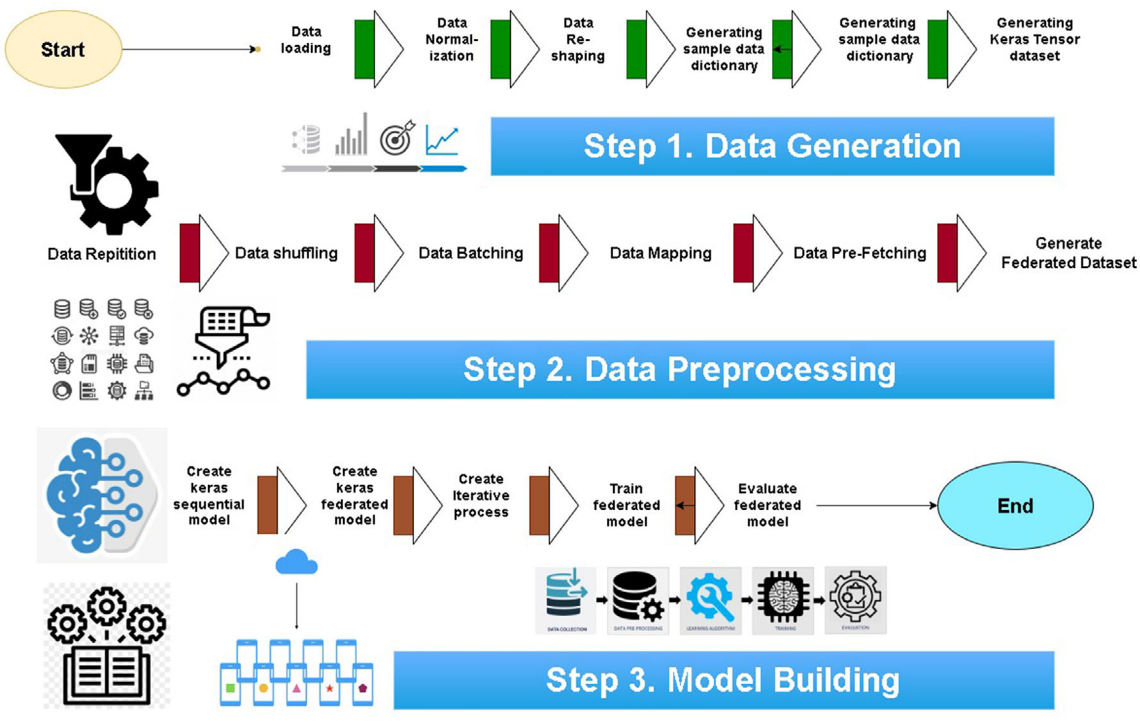

FIGURE 1 Algorithm/work-flow of proposed methodology

methodology. The remaining paper is organized as follows: Section 2 showcases the Vision of the work; Section 3 presents the Related works while Section 4 is the Proposed Methodology; Section 5 presents the Results and Discussion; and Section 6 is the Conclusion.

2 | THE VISION

A fast and accurate result is crucial to stop the further spread of COVID-19. The authors have developed a web application based on federated and deep learning for rapid detection of COVID-19. The deep learning-aided diagnosis gives accurate results identifying COVID-19 using a chest X-ray. It takes a few seconds to provide results, and tests can be done quickly since almost all health centres contain X-ray machines. On the other hand, the authors used federated learning for user data privacy. The system helps users detect COVID-19 results without consuming much time. Users will be able to check their present condition by uploading chest X-ray images. The authors have implemented federated learning through a sequential model in this paper. The proposed model takes images as input, and then after comparing with features, it gives COVID results as output. The result will help users to make instant decisions and get proper care and medication.

3 | RELATED WORKS

In recent months, there has been an increase in the number of analyses on basic deep learning models to detect COVID-19 by analysing chest X-ray images. Several solutions have been considered for this problem, and much of the research conducted was based on deep learning. They focused on image processing functions such as feature extraction and classification. The model developed by the authors does the same thing by using deep learning and federated learning. The results have been promising, but more work on the design is required. Apart from these, computer vision has also proven to be useful in medical diagnosis. It can be used as a tool to detect abnormalities present in human bodies. Some of the related works are discussed hereafter.

Wu et al. (2021) developed a model based on a deep active learning framework named COVID-AL. This proposed model consisted of lung region segmentation with 2D U-Net and diagnosis of COVID-19 with a hybrid active learning strategy. Their model could diagnose COVID-19 efficiently and be validated on a sizeable CT-Scan dataset. Their proposed model achieved an accuracy of 95%. Yang et al. (2021) developed a model based on an algorithm named FLOP. They used FLOP to share a partial model between clients and the server. The suggested algorithm reduced the privacy and security risks up-to a great extent. Experimental results portray the algorithm's acceptance in real-world medical and benchmark datasets with an accuracy rate of 98.04%.

Ucar and Korkmaz (2020) developed 'COVIDDiagnosis-Net', achieving a predictive performance of 98.26% for the three classes. Das, Samal, et al. (2021) proposed an AI-based HEALTHCARE CYBER-PHYSICAL System. Their model helps the user to determine COVID-19 by uploading a chest X-ray image. They proposed a convolutional neural network model of X-ray images compacted into an X-ray device for automated detection of COVID-19. Their proposed model achieved an accuracy of 99%. Another work by He et al. (2020) proposed a model based on federated learning.

Tabik et al. (2020) developed the COVIDGR DATASET AND COVID SDNET methodology to predict COVID-19 using CXR. The model used a smart data-based networking approach to improve the generalization capacity for the classification of COVID-19. Their proposed model achieved an accuracy of 97.72% $+-0.95$%, 86.90% $+-3.20$%, 61.80% $+-5.49$% in severe, moderate, and mild COVID-19 security levels, respectively. Ozturk et al. (2020) proposed DarkCovidNet, which achieved an accuracy of 98.08%. The dataset used for training had 1125 images, among which only 125 images were of COVID-19. In another work, Mahmud et al. (2020) developed a CNN model named CovxNet. Their suggested model achieved an accuracy rate of 97.4%. A deep learning-based model for COVID-19 detection using CXR was created by Minaee et al. (2020). Here, they transformed images of the CXR plates using data augmentation. Their model had a sensitivity and specificity of 98% and 90%, respectively.

Das, Ghosh, et al. (2021) founded a model using ensemble learning and a DCNN for detecting COVID-19. The dataset used for training their model contained 468 COVID-19 negative images and 538 COVID-19 positive images. Their suggested model had a 91.62% accuracy rate. In another work by Khan and Aslam (2020), a new architecture to identify X-ray images was introduced. They employed VGG16, ResNet-50, and VGG19. Greater accuracy was achieved by VGG 16 and VGG 19. An accuracy rate of 99.3% was attained by their suggested model. Similarly, Che Azemin et al. (2020) created a model based on the ResNet-101 CNN model. To find patterns in the model, they considered thousands of images. However, the accuracy of their suggested model was only 71.9%.

Using digital chest X-ray images, Taresh et al. (2020) created a pre-trained algorithm to distinguish COVID-19 from induced pneumonia automatically. In the dataset, there were 274 COVID-19 cases, 380 viral pneumonia cases, and 380 healthy cases. The main driving force behind their research is to appreciate the performance of advanced neural architectures. The accuracy of their model was higher, at 98.72%.

Tammina (2019) proposed transfer learning using VGG-16. They used a deep convolutional neural network to classify images. VGG16 model was employed to achieve higher accuracy. Their proposed model achieved an accuracy of 95.40%. Khalifa et al. (2019) established a deep transfer

TABLE 1 Related works comparison

Author	Dataset used	Client algo. used	Global model acc. (%)	Federated transfer learning	Android app
Yang et al. (2021)	13,954 Images	ResNet50 and MobileNet-v2 based Federated Learning	98.04	✓	×
Liu et al. (2020)	15,282 Images	ResNet18 based Federated Learning	98.06	✓	×
Feki et al. (2021)	468 Images	VGG-16 and ResNet50 based Federated Learning	97.00	✓	×
Abdul Salam et al. (2021)	5144 Images	Tensorflow Federated based Framework	98.72	✓	×
Wu et al. (2021)	617,775 Images	2D U-Net	95	×	×
Loey et al. (2020)	307 Images	GAN and Deep Transfer Learning	99.9	×	×
This Work	1823 Images	Xception based Federated Learning	99.59	✓	✓

learning model to detect medical diabetic retinopathy. In this study, they deployed APTOS 2019 dataset for training with AlexNet, ResNet18, SqueezeNet, GoogleNet, VGG16, and VGG19 models. Their suggested model achieved a 97.9% accuracy rate.

Apostolopoulos and Mpesiana (2020) proposed a model based on automatic detection of COVID-19 using chest X-ray images. They used transfer learning and a convolutional neural network for automated identification of COVID-19. Their primary dataset consisted of 224 images of COVID-19 disease, 700 images of common bacterial pneumonia, and 504 images of normal conditions. Additionally, a dataset including 224 images of COVID-19 disease, 714 images of bacterial and viral pneumonia, and 504 images of normal conditions was utilized for training the model. Their proposed model achieved an accuracy, sensitivity, and specificity of 96.78%, 98.66%, and 96.46%, respectively. Likewise, Loey et al. (2020) suggested a methodology using a transfer learning approach along with three pertained models to detect COVID-19. There were 70 images of COVID-19 among 300 images in their dataset. Their proposed model achieved an accuracy of 85.20%.

Liu et al. (2020) used federated learning for the detection of COVID-19 data. They extended their experiments to verify their effectiveness and compared their work with four popular models (MobileNet, ResNet18, MobileNet, and CovidNet). Their suggested model had a 98.06% accuracy rate. Differential privacy was introduced using the design (dPbD) framework by Ulhaq and Burmeister (2020). Here they mainly focused on the data privacy of COVID-19 imaging. They considered using computer vision and deep learning techniques to diagnose the illness. Abdul Salam et al. (2021) developed a model based on COVID-19 detection using federated machine learning. They had developed two machine learning models and compared the efficiency of federated learning with the traditional learning. Their proposed model achieved an accuracy of 98.72%. Feki et al. (2021) proposed a collaborative federated learning framework for screening COVID-19 in chest X-ray images. They used deep learning without revealing any patient information. Their proposed model had a 97.0% accuracy.

Table 1 shows the comparison of our work with the existing state art.

4 | PROPOSED METHODOLOGY

This section will discuss the approach used to achieve the objectives of the proposed work. Here the system architecture, the dataset used, and so forth, are covered.

4.1 | System architecture

The authors have developed this model to improve the accuracy levels achieved in present COVID-19 detection approaches and preserve users' privacy. It aims to eradicate or lower other problematic issues in general ML-assisted COVID-19 detection techniques. The implemented model in this paper takes chest X-ray images from users as input and gives the test result based on it as COVID positive or negative. First, users have to visit the website created and click the browse option to upload their chest X-ray images from their devices. After uploading the image, results are derived from a locally stored pre-trained model. To specify, a local copy of the global model is sent to the client and trained locally. If the accuracy achieved is better or has improved over training, then the global model weights are updated, thus increasing the global model's accuracy. This process of accessing the universal model, training it locally, and pushing revised weights into the global model happens at regular intervals. Thus, accuracy is enhanced with the client–server calls without hindering information privacy or having to perform data breaches. As per the architecture, the uploaded image is then used for classification or deriving other desired results, which is done using the locally trained model. The locally trained model is economical enough to be stored locally for faster yet accurate evaluation unless an updated feature is added to the global model.

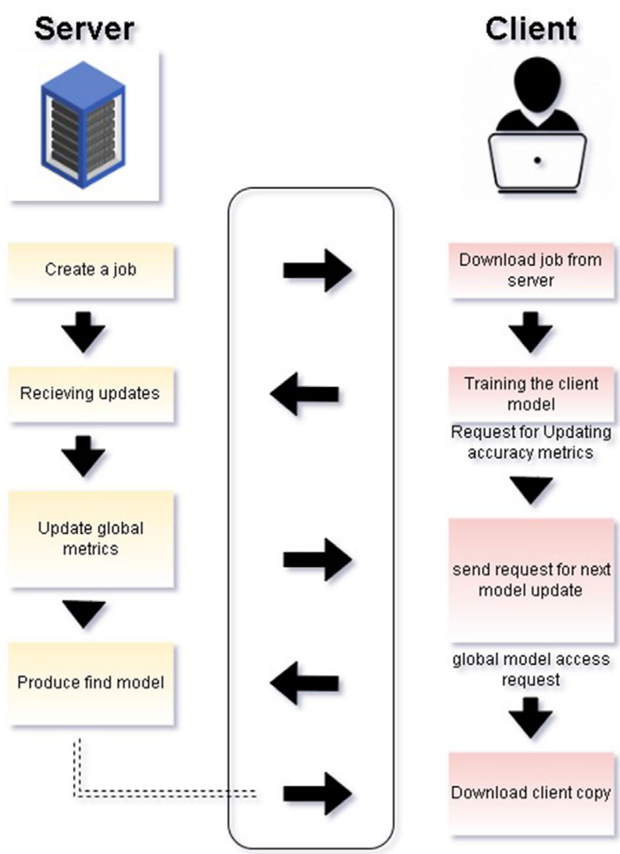

FIGURE 2 Server/client architecture depiction

No uploaded data has to be sent to the server, preventing all privacy threats. The front-end of this web app has been developed using the StreamLit Library, and the backend has been curated using Flower Framework—a modern tool that handles both client and server calls seamlessly. The Flower framework has been adopted by big tech giants recently since it is simple to use and also effective. It is regularly updated to meet the current industrial standards. While developing this architecture, the authors decided to utilize the Flower framework in the project architecture because of its effectiveness.

To summarize the entire mechanism of the architecture, the discussion about the proposed methodology is broken down into several modular sub-parts like dataset, input pre-processing, transfer learning models, federated learning approach, and model generation. The discussion focuses on each sub-part to derive a clear overview of the architecture in this paper (as seen in Figure 2).

4.2 | Dataset used

The dataset used in this paper, named COVID19ACTION-RADIOLOGY-CXR (Sheet et al., 2020), is a collection of chest X-ray images in a dataset. The total number of classes is 3. There are 1823 images in the dataset. Out of them, 536 images are of COVID-19, 668 of healthy individuals, and the rest of 619 chest X-ray images are of viral pneumonia. The dataset consists of image from various age groups, ranging from 18 to 75 years. The dataset is divided into two categories: 80% training and the rest (20%) testing images.

4.3 | Input preprocessing

To achieve accurate results, input data preprocessing is a vital step. Different sizes of images ranging from (512 $\times$ 512) pixels to (1024 $\times$ 1024) pixels are present in the dataset. Therefore, all the images were resized to (224 $\times$ 224) pixels and converted from the Grayscale channel to RGB. Then the images were ready as input to the system. The images were labelled accordingly using a label list. Here, 'healthy' images and COVID-19 images were labelled as '0' and '1', respectively. The image list was then converted into a NumPy array, and the dimensions were reduced to the range of 0–1 by dividing by 255. Finally, the whole dataset was divided into training and testing images and sent for training the model.

4.4 | Transfer learning models

4.4.1 | ResNet50

ResNet-50, abbreviated for Residual Networks, is a widely used convolutional neural network with 50 layers that forms the basis for many computer vision applications. The architecture has 48 convolutional layers along with 1 MaxPool and 1 Average Pooling layer. ResNet's key breakthrough was the ability to train extremely complex neural networks with 150 layers or more. Since the value of the gradient rapidly decreases during backpropagation, the neural network encounters the 'Vanishing Gradient Problem', which results in essentially little change to the weights. To solve this problem, ResNet uses 'skip connections'. The pre-trained version of ResNet50 is trained over ImageNet dataset, consisting of over a million images across 200 classes.

4.4.2 | DenseNet121

DenseNet (Dense Convolutional Network) tries to enhance the depth of deep learning networks while maintaining enhanced training effectiveness by using shorter connections between the layers. The Dense convolutional neural network is composed of several layers, each of them is linked to all the layers below it. This is done in order to maximize the information flow between network layers. Each layer receives inputs from all the layers that came before it and send them on to all the levels that will follow it to maintain the feed-forward nature. Thus, it requires fewer parameters than traditional convolutional neural network.

4.4.3 | InceptionV3

The major goal of InceptionV3 is to consume fewer computing resources by altering the Inception architecture from earlier versions. Inception Networks (GoogleNet/InceptionV1) have proven to be more computationally effective than VGGNet in terms of both the number of parameters produced by the network and the associated costs involved (memory and other resources). Due to the unknown effectiveness of the new network, it becomes difficult to modify an Inception network for various use cases. Several methods for improving the network have been proposed in the InceptionV3 model to ease the restrictions for simpler model adaption. Some symmetric and asymmetric building blocks that make up the model itself include convolutions, max pooling, average pooling, dropouts, fully connected layers, and concatenations. The activation inputs are subjected to batch normalization as well; which is heavily utilized by the model. Using Softmax, the loss is calculated. It has attained greater than 78.1% overall accuracy on the ImageNet dataset.

4.4.4 | Xception

Xception is a deep convolutional neural network that consists of Depthwise separable convolutional units. Introduced by Google researchers, Xception is another name for an 'extreme' interpretation of the Inception model. Xception consists of 71 convolutional layers, and these layers take part in forming the feature extraction basis of the network. It works on depth-separable convolution, and it forms skip connections between convolutional layers, which makes it useful in image recognition challenges. With an improved training procedure, the Xception architecture outperforms ResNet, VGG16, and Inception architectures with less computational complexity in classical classification challenges. One can load a network that has been pre-trained using images in the ImageNet database.

4.5 | Federated learning

Google first proposed the idea and concept of federated learning in 2016 as a new era of machine learning. Their objective was to build an ML model based on a scattered dataset without sharing users' raw data, thus preserving data privacy. In federated learning, every client has a dataset and a local ML model, whether it is a server or a mobile device. Apart from that, a centralized global server with a centralized ML model (also known as the global model) acquires and aggregates the scattered model's weights and parameters. Each client shares the trained model parameters in each iteration without sharing the raw user data. The Federated Learning Flowchart has been visualized in Figure 3.

So why Federated Learning:

- The global model remains decentralized, and there is no need to transfer data for training, unlike primitive machine learning models.
- There is complete data privacy as it employs multiple devices' computations for training the model, and no user data is shared with the global model.

- Less computational work has to be done as model training occurs on distributed clients, and the centralized model aggregates the weights for updating itself.
- There is no need for massive data to train the federated learning model.

4.6 | Model for federated learning

4.6.1 | Batched clients creation

The authors needed to split the data from the given dataset into training and testing data. Then the data and label list were zipped and randomized within a tuple. Finally, data shards were created from the tuple based on the desired number of clients. A dictionary containing each client's name along with their data was returned as a key-value pair. The next big deal was to process individual clients' data into a TensorFlow dataset and batch them accordingly.

4.6.2 | Model creation and compilation

The authors have implemented federated learning through a Transfer Learning Pretrained Model in this paper. The pre-trained model allows one to create a model easily by adding a sequence of layers to the output of the base model. It is the easiest way to build a deep learning model in Keras. Each model layer has weights that communicate with the layer that follows it. This paper has added five consecutive layers: a convolutional 2D layer with ReLu activation, a Dropout layer, a MaxPooling layer as the next communication layer, a Flattening layer, and a sigmoid-activated dense layer as the final output layer. Next, the model was compiled, which required two main parameters: optimizer and loss. The framework works on binary classification, so Binary CrossEntropy was used as the loss function. The authors found that the RMSprop optimizer provided better results when the learning rate was set at 0.0001.

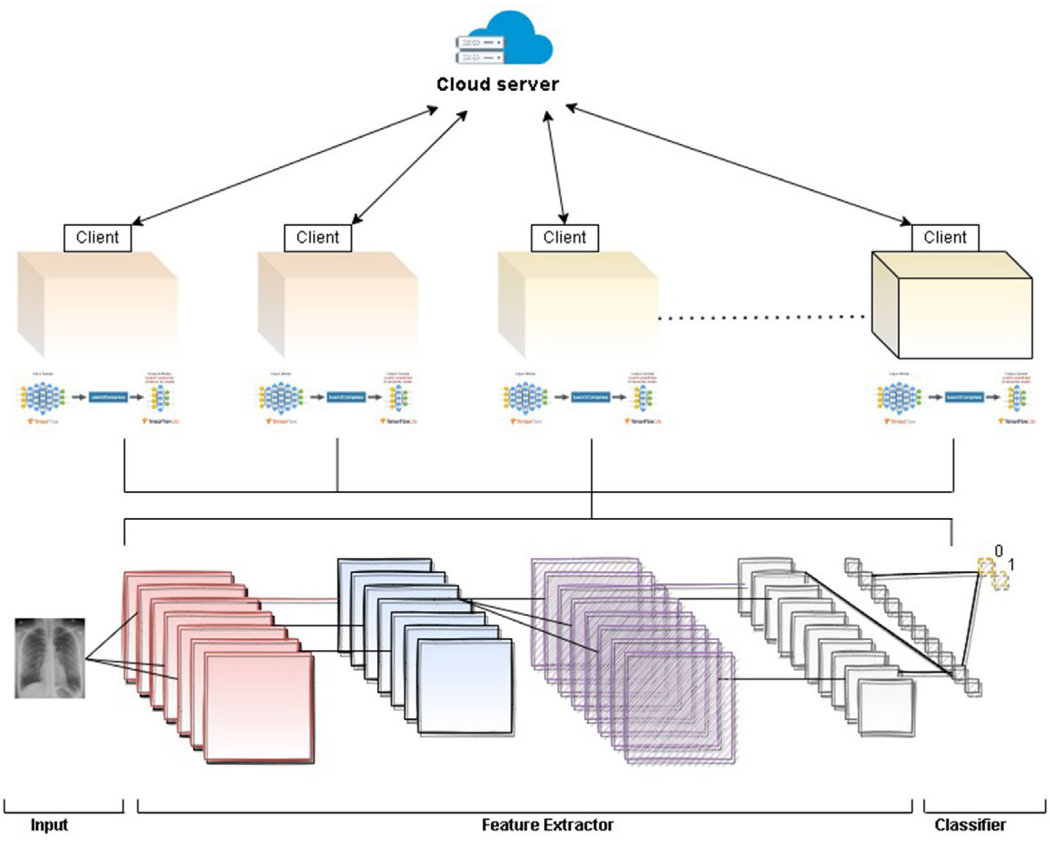

FIGURE 3 Flowchart of proposed methodology

4.6.3 | Model training

Finally, the model was trained on the batch of clients created at an earlier stage with the help of datasets. The model was trained for 10 communication rounds, each of which had 20 epochs. That is how the accuracy increases in a federated learning model. Therefore, the global and local models were built, and weights were initialised. The local weights were uploaded to the global weights after every communication round to improve the accuracy of further prediction.

5 | RESULTS AND DISCUSSION

This section discusses all the essential information regarding the experimental setup used in this paper. In addition, the authors have assessed the accuracy of the Global and Client Models, which are periodically updated. The authors examined the model's performance with various loss functions and values of hypertunable parameters and came up with an efficient one. Finally, the Flower backend framework is implemented in a Web application, which will be discussed further in this section.

5.1 | Experimental setup

The Sequential CNN model has been trained for about 10 communication rounds, in which each communication round had 20 epochs. The main aim was to update the global model weights with each communication round. RMSProp optimizer and a learning rate of 0.0001 were used to compile the client model. The time taken for model training on Google Colab was about 300–400 ms/step in each epoch.

5.2 | Analysis of results

In this section, the results achieved from training four different transfer learning models based on federated learning are analysed. The authors have discussed the accuracy or performance metrics of the model along with its training time. Moreover, this paper includes visualizations of various graphs, which would further help infer the best model of the lot.

5.2.1 | Training time

The experiments involved three communication rounds, each of which contained 20 epochs for training. Hence, the client model weights were updated after each communication round. The training time was recorded for each communication round to evaluate the training efficiency of each model. Since federated learning models tend to lower the training time by a huge factor, the average training time was quite low for all the models. The best training time was for about 8 min. The average time taken in milliseconds for each step in each epoch is tabulated for all the models in Table 2.

5.2.2 | Accuracy

The models used during the experimentation were ResNet50, DenseNet121, InceptionV3, and Xception. These models were pre-trained using the ImageNet dataset and performed very well when used for binary classification. The authors have compared the results from the Accuracy

TABLE 2 Computational time

Classifier	Training time (ms/step)
ResNet50	350
DenseNet121	335
InceptionV3	390
Xception	320

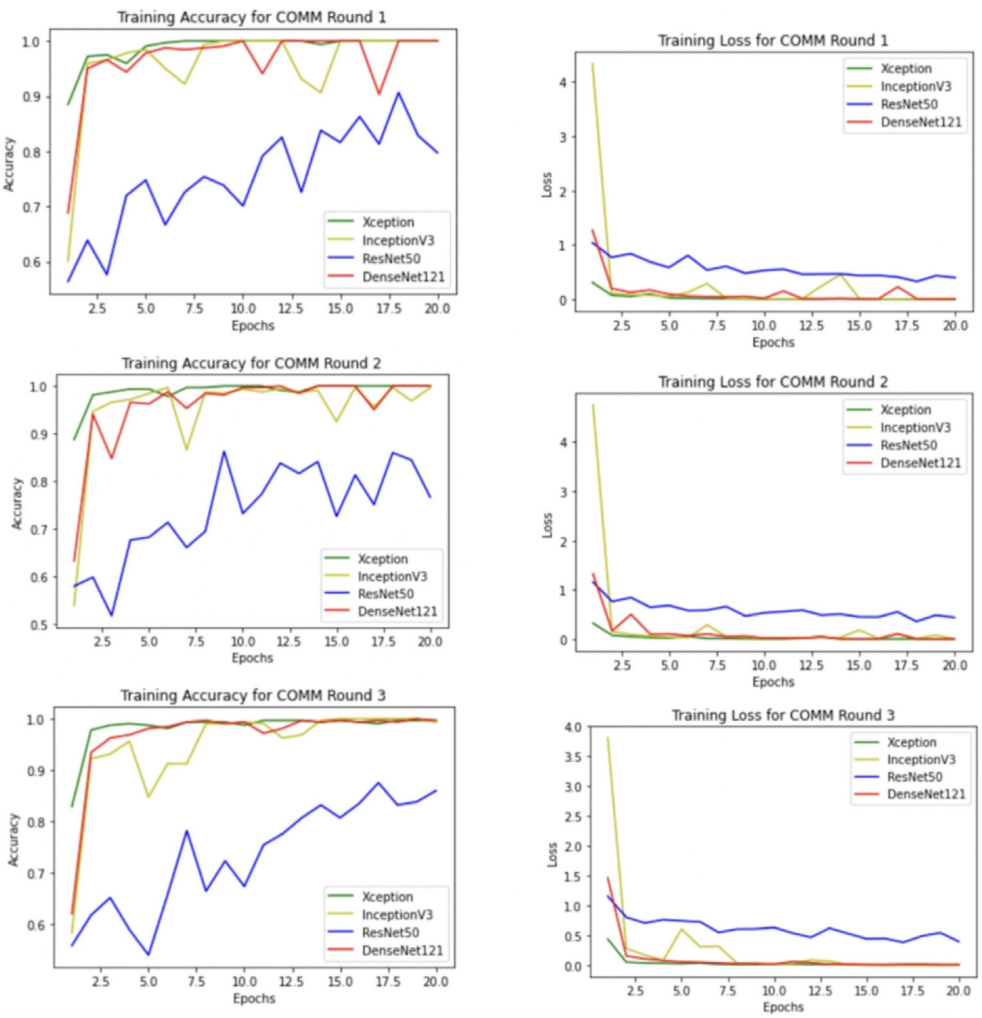

FIGURE 4 Accuracy & loss curve

TABLE 3 Performance metrics

Classifier	Accuracy	Sensitivity	Specificity	*F*-1 score
Xception	0.9959	0.9911	1.000	0.9955
InceptionV3	0.9917	1.0000	0.9845	0.9922
DenseNet121	0.9751	1.0000	0.9535	0.9762
ResNet50	0.9087	0.8125	0.9922	0.8934

versus Epoch Graphs for different COMM Rounds, which are visualized in Figure 4. Other reports include the Loss versus Epoch graph and the AUC-ROC curve.

In addition to graphs, the authors calculated the performance metrics such as accuracy, precision, recall, and *F*-1 score, which are tabulated below in Table 3. After training for three communication rounds, results show that the Xception model outperforms the other general models. Other models were trained using the same hyperparameters as well. However, the ResNet50 model occasionally displayed overfitting, and the testing accuracy was also subpar. On the other hand, the InceptionV3 model and the DenseNet121 model were close to the Xception model with decent accuracy. Due to the deployment of federated learning, the loss was reduced by a considerable factor, leading to increased accuracy and precision. The results for each model are presented in Figures 5 and 6.

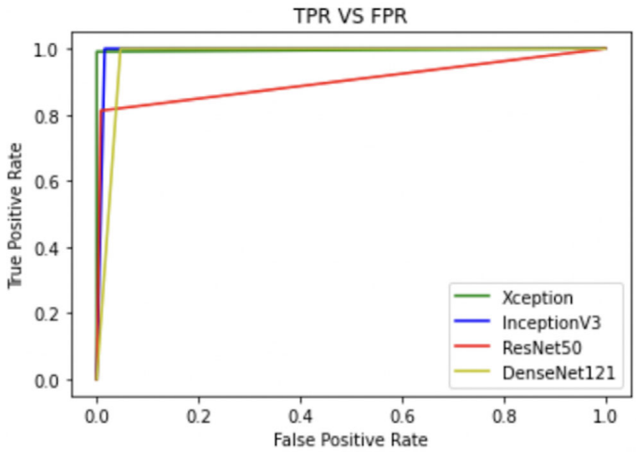

FIGURE 5 AUC-ROC curve for fed-DNNs

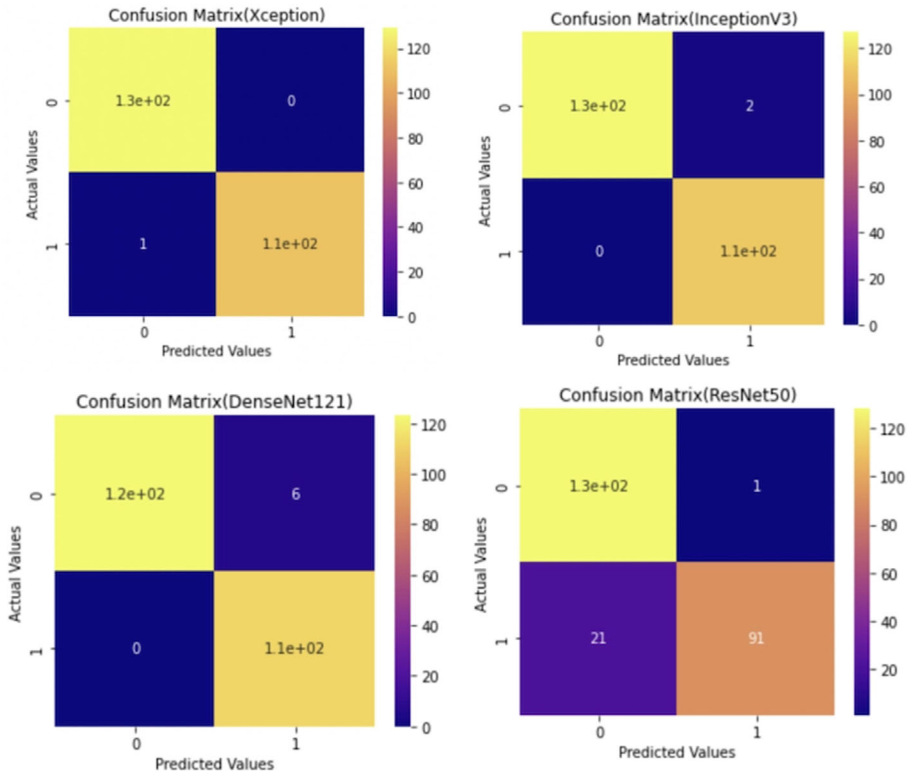

FIGURE 6 Confusion matrix of fed-DNNs

5.3 | The prototype WebApp

A web application has been developed based on the StreamLit framework. The serverless web app can be accessed within a few seconds with a couple of clicks. This web application has a Flower-based Server that manages the client devices where the local model would be trained as well as the global federated model. The user can upload an image of their chest X-ray to detect whether they are affected by COVID-19 or not. The best part of the Web Application is that the user's data never gets uploaded to the server. Rather, the model is replicated on the client's device for evaluation, thus preserving user privacy.

6 | CONCLUSION

A readily available and reliable examination technique is crucial to prevent the further spread of COVID-19. In this research work, the authors have developed a basic sequential CNN model for federated learning implementation after analysing multiple previous papers. Federated learning has been used to yield highly accurate results while keeping users' privacy at the focal point. The proposed model achieved a global accuracy of 99.59% after training for three federated communication rounds. The StreamLit-based web application is relatively easy to use, where users would be able to take COVID tests from their local devices using only a single chest X-ray image. The accuracy of the model will improve in classifying COVID-19 and other X-ray images as more people use it. In the future, the paper can be expanded upon and integrated into various IoT architectures, such as IoTpi (Shao et al., 2022), as well as various fog and cloud computing architectures, such as FogDLearner (Iftikhar et al., 2022) and HealthCloud (Desai et al., 2022). Additionally, a smart embedded device like a smartwatch can be incorporated with this work (Saleem et al., 2022).

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in COVID19ACTION-RADIOLOGY-CXR at https://ieee-dataport.org/open-access/covid19action-radiology-cxr.

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