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FLNCVD-net: COVID-19 Detection Using Chest X-rays

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Abstract

This research work proposes faster alternative ways of predicting the Coronavirus Disease 2019 (COVID-19) infection in the patient's body. Firstly, this research work proposes a transfer learning-based solution methodology that trains the following models, VGG16, VGG19, MobileNetV2, NASnet Moblie and ResNet-50 to find out an efficient base model for Novel Corona Virus Detect-net (NCVD-net) to detect COVID-19 infected patients using chest X-rays. Among these, VGG-19 is chosen as the best base model as it outperforms the other models. Afterward, the chosen VGG-19 is transformed to VGG-19 based NCVD-net by replacing its fully connected layer with an average max pooling layer, flattened layer, three dense layers (1 x 256, 1x128, 1 x 64) with leaky ReLU activation function and one output dense layer (1 x 2) with softmax activation. Following that, VGG-19-based NCVD-net is tested against unseen chest X-rays and successfully detects COVID-19-infected patients with 99.91% accuracy. Secondly, this paper employs Federated Learning-based Novel Corona Virus Detect-net (FLNCVD-net) by considering VGG-16, VGG-19 and ResNet101 as its base model. Later, these models are distributed securely to each hospital and trained on the chest X-rays available in that hospital. Finally, the model parameters from each FLNCVD-net are securely transmitted and combined to build a global FLNCVD-net. The proposed FLNCVD-net using the above-said three base models are validated against unseen COVID-19 +ve and COVID-19 –ve chest X-ray images from Dr. Joseph Cohen's GitHub repository and Kaggle respectively. Surprisingly, it is observed that the VGG-16-based FLNCVD-net marginally outperforms VGG-19-based FLNCVD-net.

Keywords: COVID-19, Federated Learning, Federated Learning-based Novel Corona Virus Detect-net, Novel Corona Virus Detect-net.

Introduction

The novel coronavirus is a new kind of virus that originated in Wuhan, China, gaining lots of attention presently (1). Coronaviruses are a large family of viruses named after their shape protruding spikes that look like crown. SARS and MERS are a part of the coronavirus family that causes common diseases among humans from common cold to mild or severe respiratory illnesses. The WHO mentions that COVID-19 has pandemic potential because this virus can cause flu-like symptoms that range from cough, to fever and shortness of breath. Since the infection can include symptoms similar to pneumonia influenza and common cold, only a diagnostic test can confirm whether or not an individual is positive for the virus. During the periods of previous pandemics, i.e. almost either decades or centuries back, large issues arose due to a lack of technical advancements. Currently, the fact is that the world is medically much more sophisticated and has better technology to handle this pandemic. As per the studies carried out by several doctors, there is a difference between the chest X-ray images of COVID-19-infected and the normal patients. Presently, the countries are unclear in diagnosing methods of COVID-19 as its structure and infecting pattern varies according to race, demography, weather, age, sex, pre-existing diseases and genetic information. It is mandated to detect the COVID-19-infected as early as possible and isolate them to avoid the spread. Henceforth, there is a high demand for AI-based methods to assist doctors to predict COVID-19-infected patients as early as possible. This research work proposed a solution with which a secured privacy-preserved detection of COVID-19 can be achieved using chest X-rays without uploading them from each hospital to a centralized testing center. The research work incorporates transfer learning, fog computing and federated learning in the proposed solution to predict COVID-19 using chest X-rays. Transfer

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learning is a method of using a machine learning model developed for one application to solve another application. This research work explores VGG16, VGG19, MobileNetV2, NASnetMoblie and ResNet-50 for the training process to find out the efficient base model for the prediction of COVID-19- infected patients using chest X-ray radiographs. Finally, it identifies VGG-19 as the best base model and re-engineers the VGG19 architecture to develop the NCVD-net model. Federated learning is utilized by the proposed model to develop a high-quality global model using the parameters of local models trained over the X-ray images that are available in the respective hospital premises. This approach eliminates the mass uploading of X-ray images from several hospitals to a central server thereby preserving their autonomy on their own data. Also, it only demands the model parameters need to be communicated between central server to all the clients' devices and vice-versa. Fog computing is used in the proposed solution to enable safe and secured communication between the central server where the global model resides and the local fog nodes available in the hospitals which are responsible for administering the chest X-rays as well as the execution of local models over these chest X-rays. Besides, the integration of fog computing assures the secure communication of local and global model parameters among the authenticated participants. The major contributions and the salient features of the proposed FLNCVD-net are as follows:

VGG-19-based NCVD-net

The proposed NCVD-net chooses VGG19 as its base model because of its low loss and high accuracy based on the results of transfer learning. To improve the prediction accuracy, the proposed NCVD-net replaces the fully connected layer of VGG19 with an average max pooling layer, flattened layer, three dense layers (1 x 256, 1x128, 1 x 64) with leaky ReLU activation function and one output dense layer (1 x 2) with softmax activation function.

FLNCVD-net

Then the proposed NCVD-net is distributed over two worker nodes as a local model and is trained over the chest X-rays available in the respective hospital site and the local model parameters are securely sent back to the global FLNCVD-net model. Then the aggregation of local model parameters is accomplished by FLNCVD-net, sending back the updated model parameters to the local model securely.

Secured Communication of Model Parameters

Before transferring local or global model parameters, the proposed approach mandates the authentication between the central server and a fog node present in the hospital. Besides the model parameters are encrypted using Elliptic Curve Cryptography (ECG).

Validation of FLNCVD-net

The proposed FLNCVD-net model is tested against unseen COVID-19 +ve and COVID-19 –ve chest X-ray images and showcases an accuracy of 99.7% thereby outperforming the existing state-of-the-art COVID-19 detection architectures. Then the rest of the paper is organized as follows: Section 2 consolidates the research works that are developed with similar objectives. Subsequently, the NCVD-net, a proposed method for detecting COVID-19 infection using X-ray radiographs, FLNCVD-net, a global model for detecting COVID-19 infection using X-ray radiographs in a federated way and a secured way of communicating between the central server and fog nodes to update the local and global model parameters are narrated in section 3. Later, section 4 clearly outlines the validation of the proposed NCVD-net and FLNCVD-net by testing against the X-ray images of normal as well as COVID-19-infected patients. Additionally, this section discusses the accuracy and losses of different base models that we used for transfer learning. Finally, section 5 concludes the salient features of the proposed work together with the methods for improving the accuracy of the model. In the literature, Deep Convolutional Neural Networks (CNN) are majorly applied for the image classification and segmentation process as it outperforms many other existing segmentation and classification approaches. An efficient convolutional neural network for extracting features from the X-Ray images is proposed and also demonstrated that CNN showcases a superior performance against other classifiers as it preserves the spatial correlation information of an image which is utilized to extract important features (2). The features of the preceding layers are convolved with the succeeding layer and the activation function is applied to the resultant values. Further, the down-sampling of images is achieved via Max Pooling. After conducting a reasonable number of convolutions and sub-samplings, the output layer is flattened and given as an input to the fully connected layer which applies the softmax function for the classification process. In the recent past, Deep learning and computer vision have been predominantly used to detect Coronavirus by analyzing the key features from the CT scan images (3). The proposed solution utilizes 1,119 CT images for the training process of the Inception transfer learning model and yields 89.5% and 79.3% accuracy. For better computational efficiency the solution uses Region of Interest (ROI) extracted from the input CT scan images in the initial stage. The pre-input segment produces a 1D feature vector that is utilized by a fully connected section to accomplish the forecasting of the data. To improve the prediction accuracy, Adaboost and decision tree classification approaches are applied. The Area under the Curve, AUC of the proposed model is 0.90 and 0.78 on internal and external validation respectively (3). Several researchers proposed better solutions for the prediction of COVID-19 in the literature. Nearly, 46,096 CT scan images are employed to train the Unet++ model thereby prediction boxes of suspicious lesions are marked out as an output of the model (4). To minimize the false positives, the legitimate bounding boxes are considered for prediction. The legitimate regions are decided by training the model with 289 random CT scan images and tested on 600 random unseen images. The trained model showcases 100% accuracy while identifying the legitimate regions from the unseen data while using 512 x 512 resolution images as input. The efficacy of the obtained model is pretty much closer to the decisions of expert radiologists. A new deep CNN named COVID-net is proposed to detect COVID-19 from the chest radiography images (5). Four types of predictions are made using this network: No Infection (normal case), Infection caused by Bacteria, Viral Infection which is not caused by COVID-19, and COVID-19 Infection. 224 x 224 x 3 image is used as input to the network.

Many lightweight residual Projection-Expansion-Projection-Extensions (PEPX) are used in the network. For computational efficiency and effective learning of spatial characteristics, depth-wise representation is used. A two-stage projection process is implemented to project input features to a smaller dimension. A total of 5941 images are used as a dataset. A deep learning model which detects COVID-19-causing pneumonia has been proposed in past study (6). CT images are used for the training and detection process. To avoid noises caused by lung contours in the CT images, the main regions of the lungs are extracted and the blank parts in the lung segmentation are filled with lungs. To extract the top details from the CT scan images, Detail Relation Extraction neural network (DRE-net) is used. ResNet 50 is used as the base model upon which the Feature pyramid network (FPN) is added to obtain the important features. This model demonstrated an accuracy of 86% and outperformed other models like VGG16, DenseNet and ResNet. DeCoVNet uses CT Volume and corresponding 3D lung mask to predict the COVID-19. U-net is used to generate 3D lung masks (7). These masks are used to reduce the background information and increase the accuracy of prediction. The input image undergoes vanilla 3D convolution of 5 x 7 x 7 Kernel size, batch normalization and pooling. Later, these 3D feature maps undergo 3D convolution with batch normalization for 3 residual blocks. Classification is done using progressive classifiers. This consists of three 3D convolutional layers, a fully connected layer and a softmax activation function. Random affine transformation and color jittering are used for augmenting the data. The Bayesian convolutional neural network is used to measure the uncertainty in the prediction of COVID-19 (8). The VGG16 base network is used for the training process. The input to the final fully connected layer is the output that is obtained from the added average maxpool layer. Final softmax activation is used for the prediction process. Bayesian DNN is used to generate predictive distributions. Kernel density is estimated with a Gaussian kernel. The variations of predictions at different drop weight rates have been shown. Uncertainty is high for false predictions. The relation between uncertainty predictions, drop weights and accuracy has been explained clearly. The development of a two-stage COVID-19 detection model has been described in past study (9). The first stage is a four-different subset classification process without extracting features using a support vector machine (SVM). The next stage extracts features and then uses SVM for the classification process. Discrete wavelet transform (DWT), Grey level run length matrix (GLRLM), Grey level size zone matrix (GLSZM), Local directional patterns (LDP), and Grey level co-occurrence matrix (GLCM) are used for classification. SVM maps feature vectors to a high dimensional space by using a non-linear method and later data is separated using a hyper plane. A deep learning model is developed to segment and quantify the infected portions in the lungs (10). The proposed algorithms VB-net help to overcome the contrast problem which generally occurs in the CT scan images. In the contracting path, down sampling is performed followed by three-dimensional convolutions to extract the important features. Later, up sampling is performed and the features are integrated by convolution. Three additional layers are added to the V-net model. The first layer reduces the number of channels, the second layer is used for general kernel processing and the final layer restores the channels of feature maps. A deep learning model to predict the host of viruses which cause COVID-19 has been developed (11). The DNA sequence is used as input for the model. It is observed that various other vertebrate-infectious coronaviruses influence the chances of spreading infection to humans. The dataset includes genomes and coding sequences of DNA and RNA viruses respectively. From their study, it is observed that bat-coronaviruses are similar to the nCoV viruses which are spread among humans. Phylogenetic trees have been developed to understand the sequences of different coronaviruses among different species. The approach proposed used the logistic, Bertlanffy and Gompertz model to predict and analyze COVID-19 (12). It is observed that the Logistic model outperformed the other two models for the prediction process. A logistic model helps to understand the risk factors of a particular disease and predict the chances of occurrences of a disease by considering different risk factors. To observe the growth of a disease and identify the factors to control the increase in the spread Bertlanffy model is used to identify different factors and measures. The Gompertz model is used to identify the spread of infection. The performances of different models have been explained clearly in the paper. The COVID-19 chest X-ray image dataset, created by Joseph Paul Cohen and colleagues, supported AI research in detecting COVID-19 using medical imaging (13). The dataset is publicly available on GitHub. The Kaggle dataset with labeled chest X-ray images for pneumonia detection, including cases of bacterial and viral pneumonia, was designed to aid in training diagnostic models (14). Besides, a summary of several federated learning frameworks proposed in the literature for the COVID-19 prediction is given in Table 1.

Table 1: Federated Learning Frameworks in the Literature for COVID-19 prediction

Title	Authors	Year	Key Points	Reference
Federated learning for COVID-19 screening from Chest X-ray images	Ines Feki *et al.*,	2021	Collaborative federated learning framework is developed to help medical institutions screen covid-19.	(15)
FedDPGAN: Federated Differentially Private GAN for COVID-19 Pneumonia Detection	Zhang *et al.*,	2021	Differentially Private GANs (DP-GAN) model with differential privacy to detect pneumonia COVID-19 from X-ray images.	(16)
A COVID-19 Auxiliary Diagnosis Based on Federated Learning and Blockchain	Wang *et al.*,	2022	Federated learning and blockchain concepts are used to help medical institutions in diagnosing covid-19	(17)

FedSGDCOVID: Federated SGD COVID-19 Detection Using Chest X-Ray Images	Ho *et al.*,	2022	Employs federated learning with differential privacy using chest X-rays and symptom data for COVID-19 detection.	(18)
An Adaptive Federated Learning Scheme with Differential Privacy for COVID-19 Detection	Wu *et al.*,	2022	Differential privacy approach is used here to protect the patient's sensitive data	(19)
CCTCOVID: COVID-19 Detection from Chest X-Ray Images Using Compact Convolutional Transformers	Marefat *et al.*,	2022	Use a transformer-based architecture for COVID-19 detection with federated learning.	(20)
Privacy-Preserving Model Training for Disease Prediction Using Federated Learning	Khanna *et al.*,	2022	Machine learning model is built on distributed data to predict breast cancer breast from gene expression data	(21)
Federated Learning with Adaptive Differential Privacy Protection in Medical IoT	Ni *et al.*,	2021	Examine adaptive differential privacy in federated learning, applied to medical IoT and COVID-19 detection.	(22)
Hybrid Differential Privacy-Based Federated Learning for IoT	Liu *et al.*,	2022	Combines differential privacy with federated learning for disease detection in IoT, including COVID-19 scenarios.	(23)
Kalman Filter-Based Differential Privacy Federated Learning Method	Yang *et al.*,	2022	Differential privacy federated learning method is proposed, noise on data is reduced using Kalman filtering	(24)
Cov-Fed: Federated learning-based framework for COVID-19 diagnosis using chest X-ray scans	Isaac *et al.*,	2024	Multi-Efficient Channel Attention Network and a multi-model user-server weight update mechanism used for data privacy to improve x-ray classification	(25)
COVID-19 Detection Through Transfer Learning Using Multimodal Imaging Data	Michael J. Horry *et al.*,	2020	Transfer learning with a deep learning model is used to detect COVID-19 from X-ray	(26)
Architecture for	Ahmed	2024	AI, big data analytics, and blockchain to	(27)

COVID-19 analysis and detection using big data, AI, and data architectures.	Mohammed Alghamdi *et al.*,		analyze and detect COVID-19 cases, ensuring data security and decentralized access for better management.	
Federated Deep Learning Models for COVID-19 and Pneumonia Detection	Deepraj *et al.*,	2024	A hybrid deep learning model using federated learning for COVID-19 and pneumonia detection. Features enhanced security measures.	(28)
A comparative study of federated learning methods for COVID-19 detection	Darzi E *et al.*,	2024	Implements federated models across different hospital datasets to perform real-time detection and aggregation for COVID-19 cases.	(29)

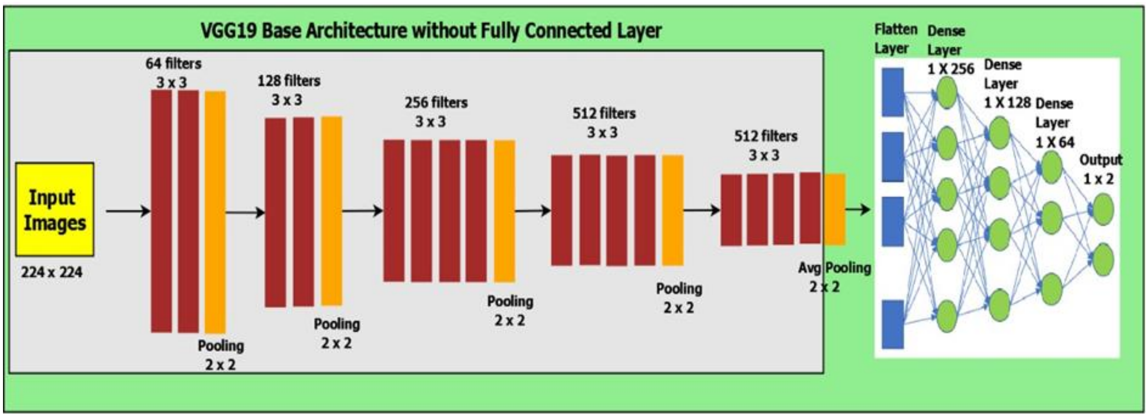

Figure 1: Architecture of VGG-19-based NCVD-net

Methodology

The Architecture of Proposed FLNCVD-net

The proposed FLNCVD-net has the following two stages: VGG-19-based NCVD-net, FLNCVD-net.

VGG-19-based NCVD-net: Transfer learning is an approach of applying the knowledge of an existing machine learning model that showcases a proven solution for one application to solve a completely different application. This research work applies transfer learning to assess the suitability of existing state-of-the-art deep learning models for COVID-19 training process such as VGG16, VGG19, MobileNetV2, NASnetMoblie and ResNet-50. For that, each of the above-said models is trained and tested using COVID-19-infected patients' chest X-ray radiographs. For this experiment, COVID-19-positive X-ray images are taken from Dr. Joseph Cohen's GitHub repository (13) and normal chest X-ray images are extracted from publicly available Chest X-Ray Images, Kaggle (14). We used 1380 images (690 COVID-19 positive and 690 normal) in total for the training process. After carefully analyzing the different aspects of the obtained results, it is concluded that the VGG-19 is the best-performing model among the others and has been chosen as a base model for the problem of COVID-19 prediction using chest X-rays. Afterward, the original architecture of the VGG-19 was re-engineered to improve accuracy. To improve the prediction accuracy, the fully connected layers of VGG19 in NCVD-net are replaced with an Average Pooling layer, Flattened layer, Three Dense Layers with LeakyReLU activation and a final dense layer with softmax activation that is going to classify the input chest X-rays as corona infected or normal (refer to Figure 1). Additionally, the binary cross entropy loss is estimated by the Adam optimizer with 0.0001 learning rate.

Execution of proposed VGG-19-based NCVD-net: The NCVD-net utilizes VGG-19 as the primary model in which the chest X-rays are given as input. However, three mandatory preprocessing phases must be accomplished before stacking the input chest X-rays into VGG19: swapping of BGR channels into RGB channels, resizing of input images of varying sizes into fixed 224 x 224 and converting the intensities of pixel size into a range of 0 to 255. The sample COVID-19 +ve and COVID-19 –ve images of the dataset that are used in this research work are shown in Figure 2. Afterward, one hot encoding is performed on the labels that are used to categorize the data. For the training process, the data is split into 80:20 partitions of training and testing data and the training data is augmented with rotations. The final fully connected layers are modified with a few more layers. 224 x 224 x 3 input images are fed to the VGG-19 base network, Average pooling of size 2 x 2 is applied to the output from the base model. The output is flattened and passed through a series of three dense layers with LeakyReLU activation and dropout after each dense layer. The final fourth dense layer undergoes softmax activation which is used for the classification process (corona or normal). Keeping the base model constant (freezing the layers in the base model), the added layers will be trained. A detailed analysis of the results is given in the subsequent section.

FLNCVD-net: FL is a machine learning technique. The model learns from data at different places like hospitals, without sharing the actual data. This keeps patient data safe and helps meet laws. In FLNCVD-net which is described in Figure 3, there is a global model at a server. Local models at the hospitals train on X-ray images. The global model grows by averaging the local model's parameters. The process uses SGD for local training, FedAvg to combine model parts, and ECC for secure data transfer. Communication is secure with SSL/TLS.

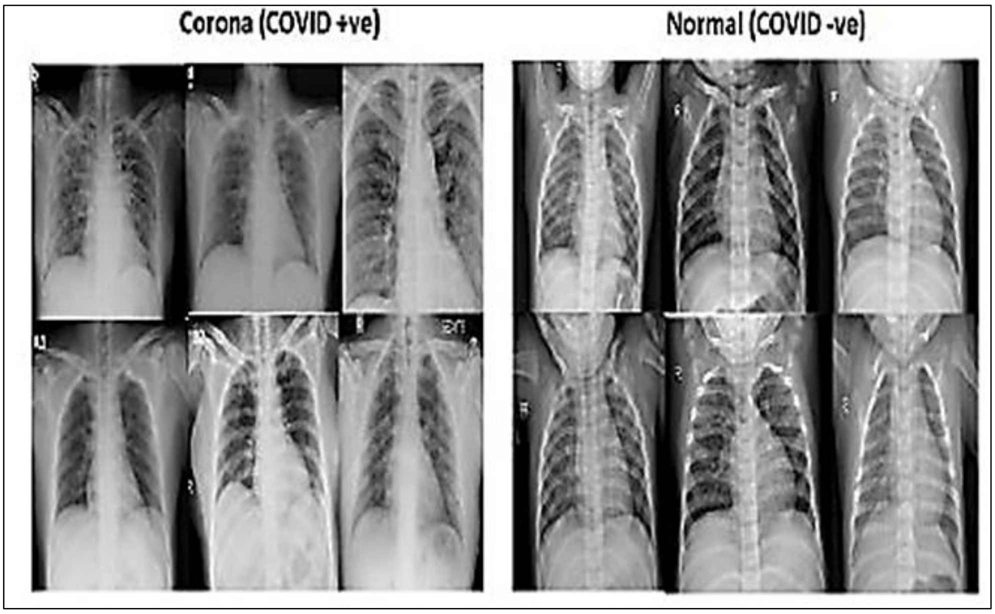

Figure 2: Sample Dataset Contains COVID-19 +ve and COVID-19 –ve

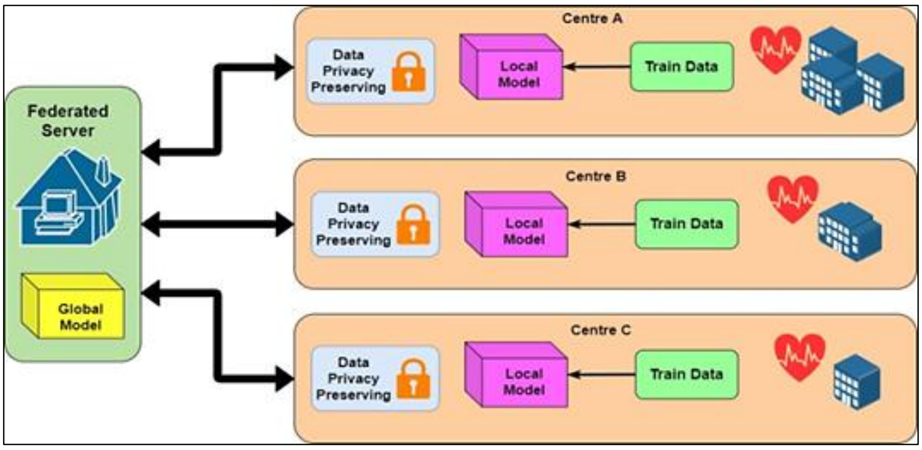

Figure 3: Architecture of FLNCVD-net

Initialization and Model Distribution: The central server initializes a global model of NCVD-net and disseminates its initial parameters to the participating fog nodes through Center A, Center B, and Center C. Interaction amongst the central server (global model) and the local fog nodes (local models) during communication undergoes a mutual authentication step to guarantee secure data transfer. The authentication step uses Elliptic Curve Cryptography (ECC) for encryption and validation through which each local node (hospital fog node) receives the initial global model securely.

Local Model Training: At each fog node (hospital site), the local NCVD-net model is trained on the local dataset (chest X-ray images) that employs a Stochastic Gradient Descent (SGD) optimizer given in equation [1] to minimize the loss function. Also, local models perform mini-batch training for improved performance and convergence.

$w^i_{t+1}=w^i_t-\eta\cdot\nabla f_i(w^i_t\cdot D_i)$ [1]

w^i_t: Local model parameters at hospital 'i' during training round't'

η: Learning rate

∇f_i: Gradient computed from the local dataset D_i

Parameter Aggregation at the Central Server: After receiving encrypted parameters from Center A, Center B, and Center C, the central server securely decrypts them and aggregates them to update the global NCVD-net model. The Federated Averaging (FedAvg) algorithm shown in equation [2] is utilized for parameter aggregation. In the FLNCVD-net framework, data privacy is a crucial issue as chest X-ray images used in decentralized model training are sensitive. The potential risk includes inference attacks that refer to the reconstruction of sensitive data from model updates and membership inference attacks, which identify the specific data used in training. Elliptic Curve Cryptography (ECC) is used to encrypt model updates and mutual authentication protocols are used for communication between fog nodes and the central server. Moreover, differential privacy (DP) introduces noise to protect data integrity, while secure aggregation protocols are used to ensure that only combined updates are accessible to the central server. Communication security is further developed using SSL/TLS encryption and access control mechanisms that minimize access risks due to unauthorized users.

FedAvg Formula:

$w_{global}^{t+1}=\sum_{i=1}^{N} n_i/n\ w_i^{t+1}$ [2]

w_{global}^{t+1}: Updated global model parameters.

N: Number of participating hospitals (fog nodes).

n_i: Number of data samples at hospital iii.

n: Total number of data samples across all hospitals.

w_i^{t+1}: Local model parameters from hospital 'i'.

Challenges and Limitations of FLNCVD-net: Data heterogeneity, where varying imaging protocols and patient demographics affect model performance, and infrastructure limitations, as smaller hospitals may lack the computational resources required for local training and secure communication, are practical challenges. Compliance with the GDPR and HIPAA, as well as the communication overheads that are particularly troubling in resource-limited areas, are also formidable obstacles. Gaining the trust of stakeholders and addressing fears about data governance, leadership, and responsibility are vital; proving that the algorithms are reliable, trustworthy, and secure is another key factor in building clinician trust together with ensuring the validation and interpretability of models. Issues like underfunded facilities, especially, cost, and maintenance are problematic in this regard, as well as a lack of interoperability that arises from inconsistent data formats. The use of advanced domain adaptation techniques, and links to cloud service providers, as well as other things such as the establishment of custom protocols, can help conquer challenges facilitate adoption and guarantee the success of the system in real-world situations. In the future, research work will address these challenges incrementally.

Results and Discussion

Performance Evaluation of NCVD-net

The proposed solution for COVID-19 disease prediction using chest X-rays is implemented in two stages: predicting the base model for the solution using a transfer learning approach; re-engineering the base model by removing and adding some additional layers to the proposed NCVD-net.

Base Model Selection: This phase assesses the performance of the following five different base architectures, VGG16, VGG19, MobileNetV2, NASnetMoblie and ResNet-50s on COVID-19 and normal data to choose the best base model. During training, 1380 X-Ray images are used wherein 690 images are corona +ve and the remaining 690 images are corona –ve. After the training and testing, the VGG-19 model is chosen as base model as it showcases high accuracy and low error.

Performance of VGG-19-based NCVD-net During Training and Testing: Then the base model is re-engineered as specified to realize the proposed NCVD-net for COVID-19 prediction. Afterward, all four models (except VGG-19) together with VGG-19-based NCVD-net are trained for 25 epochs with a batch size of 8. The training and validation accuracy, train and validation loss for different base architecture are depicted in Figure.4. Subsequently, all these models are tested against unseen data and the VGG-19 based NCVD-net showcases the highest training and validation accuracy and lowest training and validation loss. Additionally, it is observed that the training accuracy and the validation accuracy are close from the 8th epoch onwards. Further, the validation loss and the training loss gradually decreased to a very small value. It is evident that the VGG-16 showcases competing performances in terms of training and validation accuracy as well as training and validation errors (refer to Figure 4). However, the VGG-19 outperforms VGG-16 when tested against unseen data. Further, MobileNet V2 architecture exhibits extreme validation loss against other models. Hence, it is evident that the MobileNet V2 suffers from overfitting as it showcases smaller training loss compared to validation loss. Following that, as the validation loss is lesser than the training loss in the NasNetMobile base model, it suffers from underfitting the data with inconsistent accuracy value. Finally, ResNet50 (5) also suffers from overfitting as it unveils larger validation loss. The accuracy of the model is calculated by using the following formula:

Accuracy = (TP + TN) / (TP + TN + FN + FP) [3]

Where TP: true positive, TN: true negative, FP: False positive, FN: False negative. The results of the final prediction are shown in Figure 5.

Performance of VGG-19-based NCVD-net on Unseen Data

Subsequently, these trained models are tested by giving the unseen chest X-rays as an input to assess their precision accuracy as per their prediction. Towards that, 16 unseen chest X-rays are stacked as input X-rays to all the five models, wherein 8 images are corona images and 8 are normal images. In the end, all the models except ResNet 50 and MobileNetV2 can predict the unseen X-ray images accurately. From Figure 4, the proposed VGG-19-based NCVD-net is capable enough to distinguish the corona +ve chest X-rays from corona –ve images precisely with the demonstrated precision accuracy of 100%. In other words, the VGG-19 interpreted 16 out of 16 chest X-rays correctly. On the contrary, the ResNet50 wrongly predicts the entire unseen corona -ve images as corona +ve images thereby exhibiting the precision accuracy of 50% meaning that 8 out of 16 predictions are wrong. Similarly, the MobileNetV2 model predicts 10 images are corona and 6 images as normal with a precision accuracy of 71% meaning that 2 normal images are wrongly predicted as corona images. The precision, recall, f1-score, and support of different models are shown in Table 2.

Table 2: Performance Comparison of Five Different Base Models on Unseen Chest X-Rays

	Model	Precision	Recall	F1 Score	Support	Accuracy	Sensitivity	Specificity	Time
VGG16	COVID	0.99	1.00	1.00	138	99.64	1.00	0.9928	277min 54 secs
	NORMAL	1.00	0.99	1.00	138				
ResNet 50	COVID	0.50	1.00	0.67	138	50.00	1.00	0.00	329 min 45secs
	NORMAL	0.00	0.00	0.00	138				
Mobile NetV2	COVID	0.99	0.94	0.97	138	96.74	0.9420	0.9928	135min
	NORMAL	0.94	0.99	0.97	138				
VGG19	COVID	1.00	1.00	1.00	138	99.91	1.00	1.00	343min 45 secs
	NORMAL	1.00	1.00	1.00	138				
NASNet Mobile	COVID	0.94	1.00	0.97	138	96.73	1.00	0.9348	172min 30 secs
	NORMAL	1.00	0.93	0.97	138				

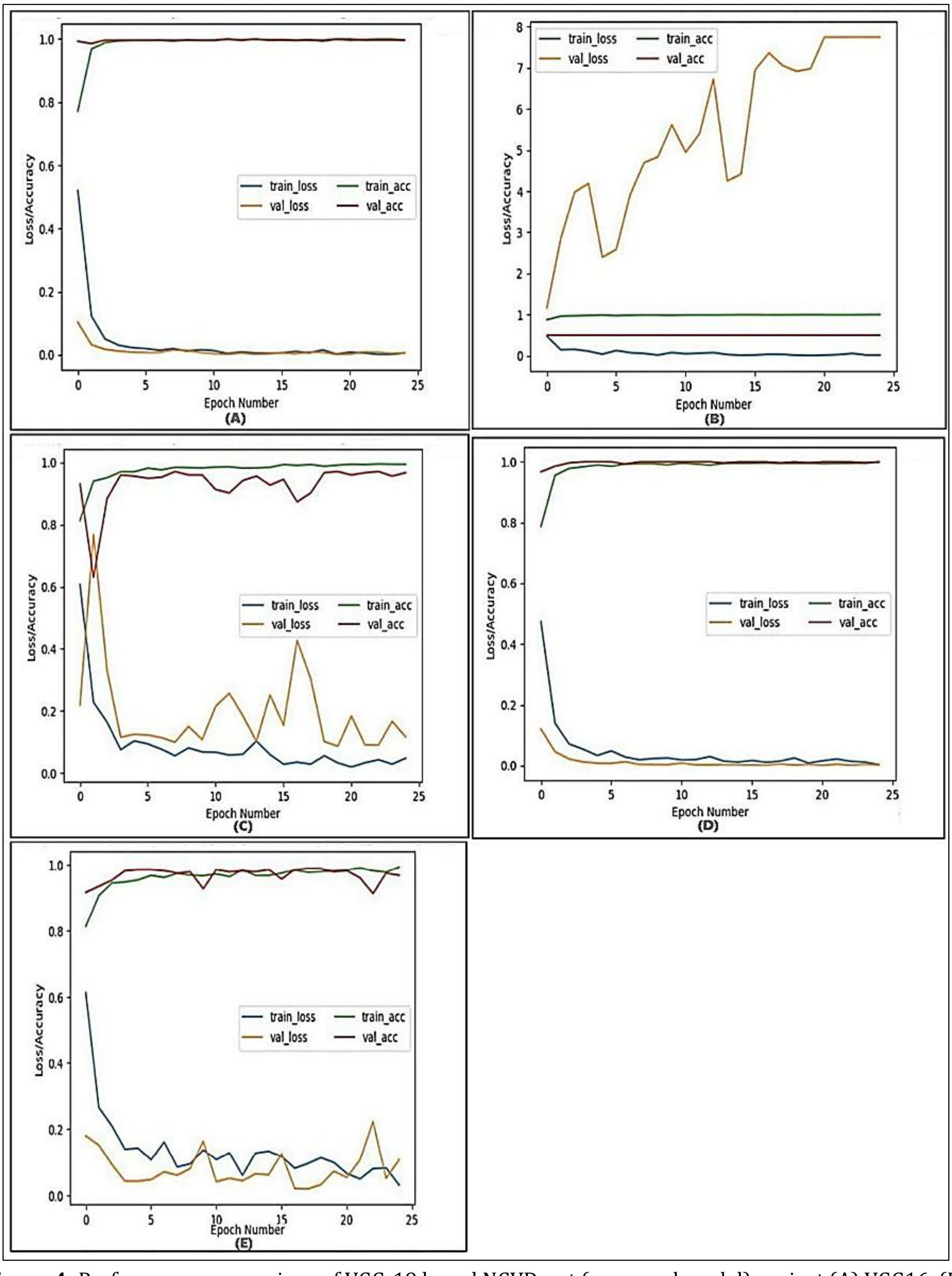

Figure 4: Performance comparison of VGG-19 based NCVD-net (proposed model) against (A) VGG16, (B) ResNet50, (C) NasNet, (D) VGG19, and (E) Mobilenet V2

The sensitivity, specificity, precision, recall, F1 score of the model is calculated as follows:

Sensitivity = TP / (TP + FN) [4]

Specificity = TN / (TN + FP) [5]

Precision = TP / (TP + FP) [6]

Recall = TP / (TP + FN) [7]

F1-score = (2 x Precision x Recall) / (Precision + Recall) [8]

Where, TP: True positive, TN: True negative, FP: False Positive, FN: False Negative.

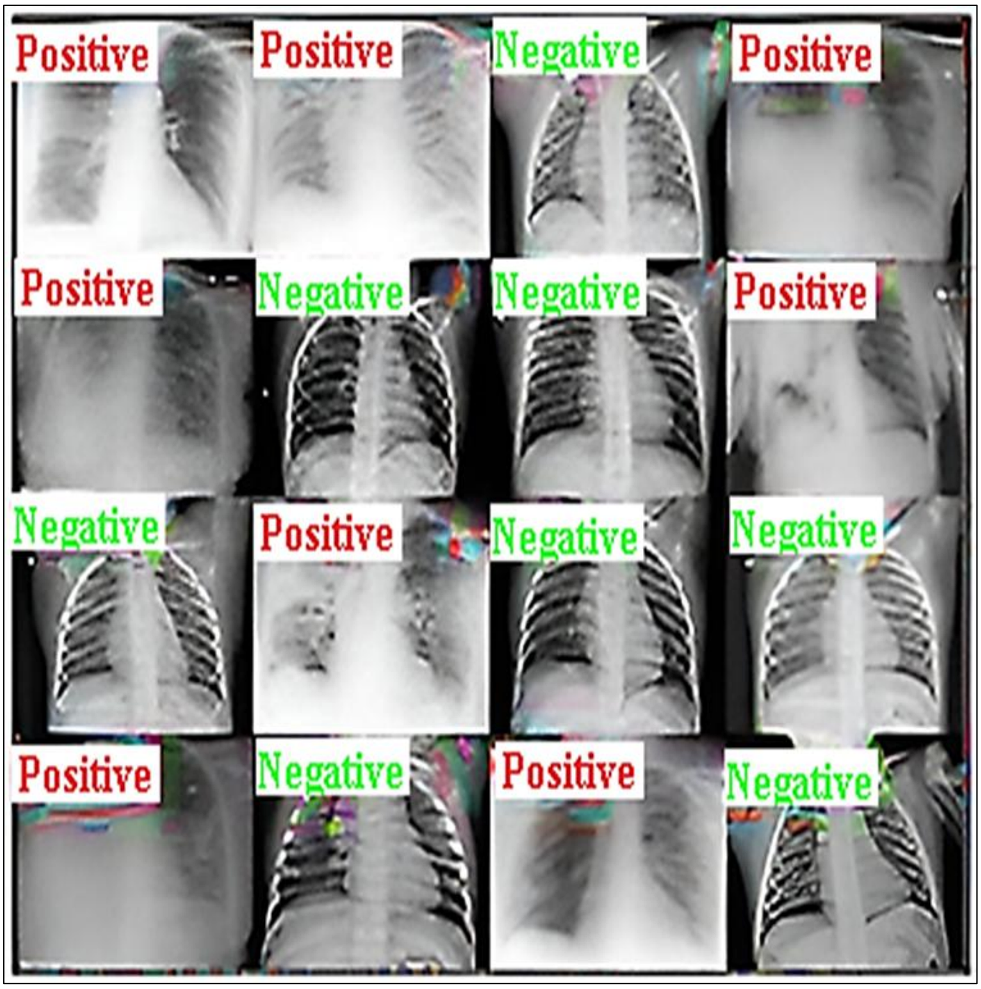

Figure 5: Prediction of Proposed NCVD-net (with 100% precision) on Unseen Data

Performance Evaluation of FLNCVD-net

To assess the performance of the proposed FLNCVD-net, a global model is implemented at the central server, and two worker/fog nodes Fog-A (at Hospital A) and Fog-B (at Hospital B) implemented in two different machines that are executing local models. Further, Hospital A contains 800 images in total (400 COVID +ve and 400 COVID –ve images) and Hospital B contains 580 images in total (290 COVID +ve and 290 COVID –ve images) respectively. This research work uses VGG-19 based NCVD-net, VGG-16 based NCVD-net and ResNet101 based NCVD-net as global as well as local models. In the beginning, the chosen global model (VGG-19-based NCVD-net or GG-16 based NCVD-net or ResNet101-based NCVD-net) was distributed to fog nodes Fog-A and Fog-B after the successful authentication. Each fog node trains the appropriate model on its own local data (800 for Fog-A and 580 for Fog-B). However, the model does not converge immediately. It trains some and sends back the encrypted model parameters (ECC-based) to the central server after successful authentication. Then the appropriate global model updated the model parameters by averaging after decryption. These sequences of operations are repeated for several iterations until global model parameters achieve an acceptable amount of accuracy and error. E proposed FLNCVD-net is validated using 16 unseen chest X-rays of which 8 are COVID +ve, and 8 are COVID -ve. During training in the federated set-up, a batch size of 8 is used together with a cross-entropy loss function. VGG-19-based NCVD-net, VGG-16-based NCVD-net and ResNet101-based NCVD-net are trained with stochastic gradient descent (SGD) and Adam optimizer for 25 epochs. The values of accuracy, train loss, validation loss, and test loss are given in Table 3.

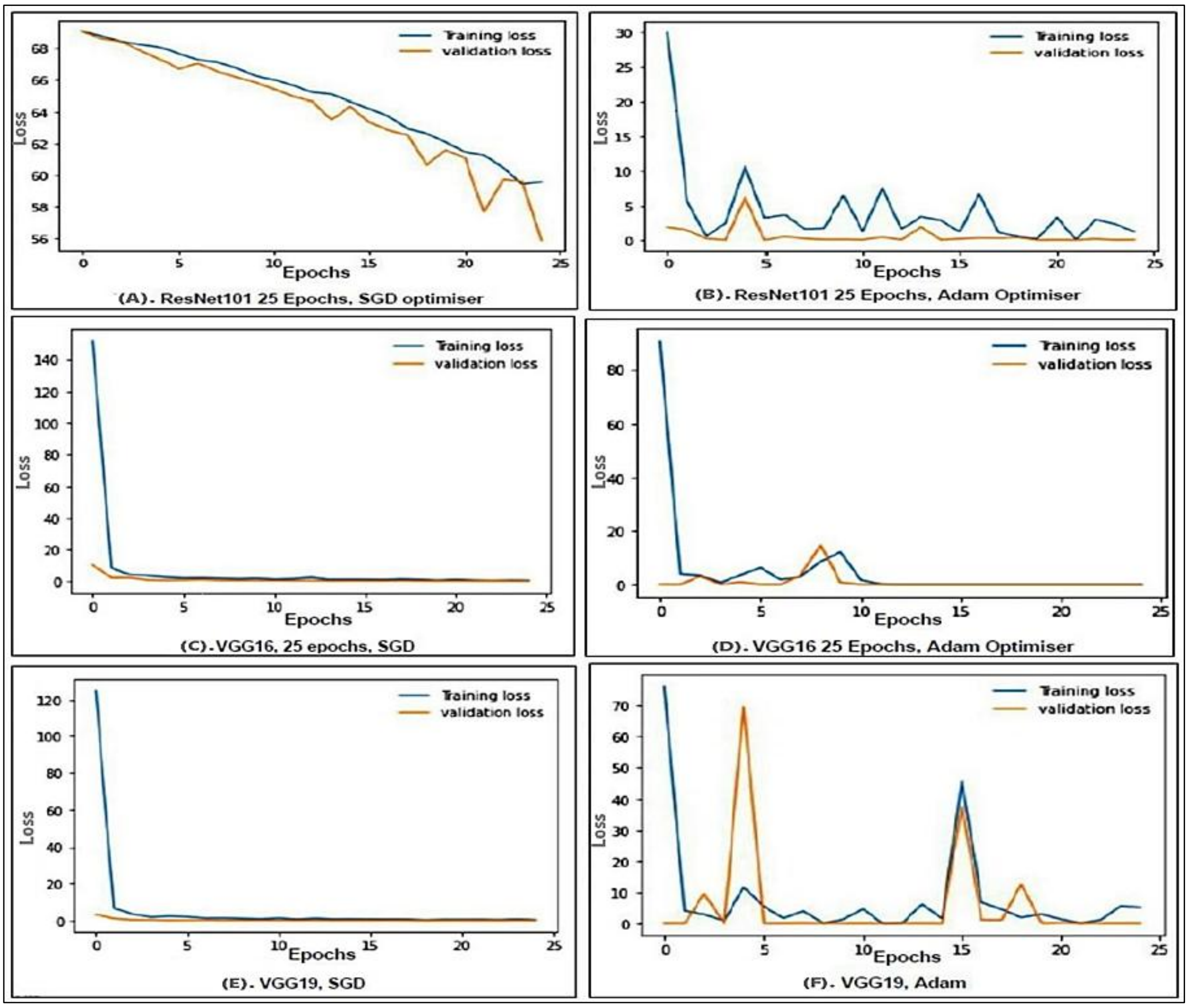

Figure 6: Training and Validation loss of FNCVD-Net with ResNet101 ((A) and (B)), FNCVD-Net with VGG-16 (C) and (D) and FNCVD-Net with VGG19 ((E) and (F)) Base Architectures

Table 3: Federated Learning Using VGG-19, VGG-16 and Resnet101 Base Models

Base Model	Epochs	Optimizer	Training Time	Accuracy	Train Loss	Validation Loss	Test Loss
ResNet 101	25	SGD	64min 30 secs	95	0.595771	0.558778	1.698424
		Adam	64min 46 sec	100	0.012745	0.000451	0.000023
VGG16	25	SGD	63min 25 sec	100	0.004697	0.000577	0.000515
		Adam	68min 20 secs	100	0	0	0
VGG19	25	SGD	69 min 47 sec	100	0.004532	0.000516	0.000414
		Adam	91 min 10 sec	100	0.051240	0.000050	0.0000

From Table 3, it is evident that the VGG16 base model with Adam optimizer outperformed VGG19 base model with SGD optimizer and ResNet101 base model with Adam and SGD optimizer. The accuracy of VGG-19-based FLNCVD-Net model is 100 in most of the epochs and the losses are also slightly lesser than VGG-16-based FLNCVD-net. The training and validation loss of ResNet101, VGG-19 and VGG16 base architectures are shown in Figure 6.

Conclusion

This research work initially discusses a transfer learning-based NCVD-net model to detect COVID-19 using X-ray images. Subsequently, the performance of several models is compared and concluded that the proposed VGG-19-based NCVD-net model superior to other architectures like MobilenetV2, VGG19, ResNet50, and NasNet-mobile. The accuracy of the NCVD-net and FLNCVD-net can be improved by enlarging the dataset. This method can further be trained with more data and later can be used as a tool to predict coronavirus in real scenarios after getting confirmation from medical physicians. Besides, as the VGG-19 and VGG-16 demonstrated closer performance, our future work majorly focusing on the re-engineering of these architectures to improve the accuracy.

Abbreviations

COVID-19: Coronavirus Disease 2019,NCVD-net: Novel Corona Virus Detect-net, FLNCVD-net: Federated Learning-based Novel Corona Virus Detect-net, CNN: Convolutional Neural Networks, DWT: Discrete Wavelet Transform , GLRLM: Grey Level Run Length Matrix , GLSZM: Grey Level Size Zone Matrix ,LDP: Local Directional Patterns ,GLCM: Grey Level Co-occurrence Matrix ,ECC: Elliptic Curve Cryptography, DRE-net: Detail Relation Extraction Neural Network.

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Author Contributions

PB conceived the idea; RM and VM implemented the idea and prepared the initial draft. Finally, AL rewrote the entire draft.

Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this paper.

Ethics Approval

The dataset on which this research work is carried out is taken from https://github.com/ieee8023/covid-chestxray-dataset which is already approved by the University of Montreal's Ethics Committee #CERSES-20-058-D.

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