When Accuracy Meets Privacy: Two-Stage Federated Transfer Learning Framework in Classification of Medical Images on Limited Data: A COVID-19 Case Study

Alexandros Shikun Zhang¹ and Naomi Fengqi Li²

¹Department of Computer Science, New Mexico State University, Las Cruces, NM, USA
²Independent Scholar, Las Cruces, NM, USA

ABSTRACT

COVID-19 pandemic has spread rapidly and caused a shortage of global medical resources. The efficiency of COVID-19 diagnosis has become highly significant. As deep learning and convolutional neural network (CNN) has been widely utilized and been verified in analyzing medical images, it has become a powerful tool for computer-assisted diagnosis. However, there are two most significant challenges in medical image classification with the help of deep learning and neural networks, one of them is the difficulty of acquiring enough samples, which may lead to model overfitting. Privacy concerns mainly bring the other challenge since medical-related records are often deemed patients’ private information and protected by laws such as GDPR and HIPPA. Federated learning can ensure the model training is decentralized on different devices and no data is shared among them, which guarantees privacy. However, with data located on different devices, the accessible data of each device could be limited. Since transfer learning has been verified in dealing with limited data with good performance, therefore, in this paper. We made a trial to implement federated learning and transfer learning techniques using CNNs to classify COVID-19 using lung CT scans. We also explored the impact of dataset distribution at the client-side in federated learning and the number of training epochs a model is trained. Finally, we obtained very high performance with federated learning, demonstrating our success in leveraging accuracy and privacy.

Keywords: COVID-19 Detection; Deep Learning; Transfer Learning

1 Introduction

Caused by severe acute respiratory syndrome coronavirus-2, coronavirus disease 2019 (COVID-19) has become an ongoing pandemic after it was found at the end of the year 2019, due to the fast spread and infection rate of the COVID-19 epidemic, the World Health Organization (WHO) designated it a pandemic [1]. It will be critical to find tools, processes, and resources to rapidly identify individuals infected.

According to several previous researches [2, 3, 4, 5, 6, 7], computed tomography (CT) offers a high diagnostic and prognostic value for COVID-19, CT scans of individuals with COVID-19 often revealed bilateral lung lesions comprised of ground-glass opacity [8] and in some cases, abnormalities and changes were observed [9]. Since CT scans are a popular diagnostic technique that is simple and quick to get without incurring the significant expense, incorporating CT imaging into the development of a sensitive diagnostic tool may expedite the diagnosis process while also serving as a complement to RT-PCR [10, 8, 11]. However, utilizing CT imaging to forecast a patient’s individualized prognosis may identify prospective high-risk individuals who are more likely to develop seriously and need immediate medical attention. Researchers have realized that developing effective methods to assist diagnosis has become critical to their success.

As a key machine learning method, deep learning has evolved in recent years and has achieved astonishing success in the field of medical image processing [12, 13, 14]. Because of the superior capability of convolutional neural networks (CNNs) in medical image classification, researchers have begun to concentrate their attention on the application of CNNs in order to address an increasing number of medical image processing issues using deep learning, and some previous researches have demonstrated the great capability of CNNs being implemented in computer-assisted diagnosis [15, 16, 17, 18, 19, 20, 21]. Some previous researches have also achieved exciting results in COVID-19 classification [22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32], however, since medical records of patients have always been deemed as privacy and protected by laws such as GDPR in the European Union (EU) and HIPPA in the US, collecting data needed for building high-quality classifiers such as CT scans becomes extremely difficult. In some other researches [33, 34, 35, 36, 37, 38, 39, 40], the authors built their covid detection or classification techniques utilizing federated learning. Federated learning is a decentralized computation approach for training a neural network [41, 42, 43, 44], which is able to address privacy concerns in training neural networks. In federated learning, rather than gathering data and keeping data in one place for centralized training, participating clients can process their own data and communicate model updates to the server, where the server collects and combines weights from clients to create a global model [41, 42, 43, 44]. Although federated learning can be used to handle privacy concerns, since data are distributed and located in clients’ devices, the data size that can be accessed by each client may be limited, which may compromise the overall model performance. Transfer learning is designed to address the issue caused by limited data, which transfers knowledge learned from source task to target task.
In this paper, the datasets used are obtained from the COVID-19 Radiography Database [60, 61] and Chest X-Ray Images (Pneumonia) [62]. From these two public databases, we obtained 10192 healthy CT scans, 4273 CT scans of bacterial or viral pneumonia that are not caused by covid, and 3616 covid CT scans, as are shown in Table 1, Figure 1 and Figure 2.

### 2 Our Contributions

We proposed a novel two-step federated transfer learning approach on classifying lung CT scans, with the first step classifying Pneumonia from Healthy and the second step differentiating Covid Pneumonia from Non-Covid Pneumonia, the achieved accuracy over limited data is worth being focused on.

We took the privacy concerns into consideration by performing model training in a decentralized way with a federated learning technique. Since federated learning requires data to remain on participated edges devices, combining federated learning and transfer learning further address the issue of limited data.

We thoroughly evaluated the model performance of centralized transfer learning and federated transfer learning by measuring sensitivity, specificity, as well as ROC curves, and AUC values and showed that our proposed approach has excellent capability to leverage between accuracy and privacy.

### 3 Theory and Methodology

#### 3.1 Deep Learning, CNNs and Transfer Learning

Deep learning techniques, such as convolutional neural networks (CNNs) [63], are used to generate predictions about future data. Convolutional neural networks (CNNs) contain several different layers such as convolutional layers, pooling layers, and fully connected layers [64, 65], each layer consists of many individual units known as neurons, which is a simulation of neurons in the human brain nervous system [66, 67]. Figure 3 shows a simple example architecture of CNNs; in CNNs, each neuron takes input and performs weights calculation, and passes calculation results to other neurons through activation function [65, 68]. To construct a decent classifier, CNNs are trained on previously collected data [69, 70, 71, 72], although a large amount of high-quality data is an essential factor in achieving better model training and testing performance, due to collecting and labeling data being always resource-consuming, the entire model training process could become less efficient until transfer learning [47, 45] can handle this issue. According to [47, 45, 18], transfer learning attempts to learn knowledge source tasks and apply it to a target task, in contrast to the conventional model training process, which attempts to learn each new task from scratch [47, 45, 18]. In this paper, we will utilize deep learning and transfer learning techniques to assist us in the classification task.

#### 3.2 Federated Learning

As a distributed machine learning technique, federated learning allows machine learning models to be trained using decentralized data stored on devices such as mobile phones and computers [41, 42, 43, 44], which solves the fundamental issues of privacy, ownership, and localization of data.

A neural model may be trained using federated learning, and weights from a large number of clients trained on their local datasets are aggregated by the server and integrated to build an accurate global model [41, 42, 43, 44].

In paper [41], the authors proposed FederatedAveraging, a method that is utilized on the server in order to aggregate clients’ local updated weights and generate weights for a global model. According to [41, 44], current global model weights are sent to a
As is shown in Algorithm 1, training round \( t \) starts from the same weights obtained from the server, which means all clients start from the same weights obtained from the server, which has either been randomly initialized or pre-trained on other data, depending on the configuration.

### 3.3 Two-Stage Federated Transfer Learning Framework

The two-stage transfer learning method was first proposed by the authors in [18], which achieved very high performance in classifying lung nodules. We further proposed our two-stage federated transfer learning framework, which highly references and is based on the algorithms proposed by the authors in [41, 44], as is shown in the following algorithm 1. In the first stage, CT scans are classified into Healthy and Pneumonia, while in the second stage, we further classify Pneumonia into Covid Pneumonia and Non-Covid Pneumonia. At the beginning of the framework, we first conducted stage one model training in a federated format, and weights are saved as a loadable file for transfer learning use in stage two.

As is shown in Algorithm 1, training round \( t \) is the number of global federated training rounds given by the user, and federated averaging \( \tau \) is the number of local training epochs of each client before sending local weights to the GlobalServer, for the federated averaged weights calculation in each training round. \( w(t) \) is the federated averaged weights obtained from calculation at the end of training round \( t \). Before the first training round, at \( t = 0 \), we initialize \( w(0) \) to vector containing random values for stage one, and for stage two, we initialize \( w(0) \) to the pre-trained weights obtained from stage one. At the beginning of each training round at GlobalServer, then federated averaged weights from previous training round \( w(t-1) \) is sent to all clients, each client \( i \) start local training on local data \( D_i \) based on the received weights in Procedure TrainClient. At training round \( t \), after finishing local training for \( \tau \) epochs, each client sends their weights \( w_i(\tau, t) \) to GlobalServer for federated averaged weights calculation. As is discussed in [41, 44], we also take the size of each client’s local dataset into consideration and performed a weighted average for the calculation of federated averaged weights \( w(t) \). If the currently running task is stage one, after all training rounds end, \( w(t_0) \) is saved as a loadable file to be used in stage two. Please note that for this two-stage federated transfer learning approach, the stage one must be run prior to the stage two in order to generate pre-trained weights for transfer learning in stage two.

### 4 Experiments and Results

#### 4.1 Dataset Preparation

As the proposed federated transfer learning framework contains two stages, two different datasets with overlapped data need to be prepared. To create the dataset for stage one, we combined the aforementioned 3616 covid CT scans and 4273 CT scans of non-covid bacterial or viral pneumonia into a new category named Pneumonia, which contains 7889 CT scans in total, and the other category is Healthy consists of 10192 CT scans. As for stage two, the 3616 covid CT scans are in the category named Covid Pneumonia and the other category Non-Covid Pneumonia contains 4273 CT scans of pneumonia that are not caused by covid, as is shown in Table 2, all CT scans are pre-processed into grayscale and resized to 28 by 28 pixels when creating datasets, in order to be utilized by LeNet model [63].

#### 4.2 CNN model: LeNet

In this paper, we utilize LeNet as the model to first classify CT scans into Healthy and Pneumonia in stage one, then classify Pneumonia into Covid Pneumonia and Non-Covid Pneumonia in stage two. LeNet is one of the most classic CNN architecture developed by Yann LeCun [63], which was used to classify data from the MNIST dataset [63]. The LeNet architecture we used contains two convolutional layers, two max-pooling layers, and two fully connected layers, with softmax [73] being used in the output layer.

#### 4.3 Experiment Results Analysis

In this paper, we conducted our experiments in simulation on a single computer with a GTX 1070 Ti GPU, tensorflow [74] and keras [75] were utilized to construct the CNN model during our experiments. We utilized 80% of the dataset as the training set and the remaining 20% as the testing set, which is shown in Table 3.

Before performing our proposed federated transfer learning, we first implement two-stage centralized transfer learning as is discussed in [18]. Centralized learning is the traditional training format where the dataset is located in only one device, and the model is trained on all data points. The results of the centralized learning format will be used as a baseline to be compared with
Algorithm 1: Two-Stage Federated Transfer Learning

1. **Input:** Total Training Round $t_e$, Federated Averaging Interval $\tau_c$, Number of Clients $N$, Stage Indicator $S$, Data $D$ with size $|D|$; Learning Rate $\eta$, Batch Size $b$.

2. **Variable:** Training Round Counter $t$, Local Training Epoch Counter $\tau$, Clients Index $i$;

3. **Loss Function:** $l$;

4. **Output:** $w(t)$.

5. **Procedure GlobalServer:**
   - if $S \leftarrow \text{stage\_one}$ then
     - Initialize $w(0)$ as a vector that contains random values;
   - else
     - if $S \leftarrow \text{stage\_two}$ then
       - Initialize $w(0)$ to pre-trained weights from stage\_one;
     - end
   - end
   - for $t \leftarrow 1, 2, \ldots, t_e$ do
     - Send $w(t-1)$ to all clients;
     - for $i \leftarrow 1, 2, \ldots, N$ do
       - $w^i_{\tau_c}(t) \leftarrow \text{TrainClient}(w(t-1), i)$;
     - end
     - $w(t) \leftarrow \frac{\sum_{i=1}^N |D_i| w^i_{\tau_c}(t)}{|D|}$; \(\triangleright\) calculate federated averaged weights in the end of this training round
   - end
   - if $S \leftarrow \text{stage\_one}$ then
     - Save the final federated averaged weights $w(t_e)$ as loadable file;
   - end

6. **Procedure TrainClient($w(t), i$):**
   - Receive $w(t)$ from GlobalServer;
   - $w^i_0(t+1) \leftarrow w(t)$; \(\triangleright\) set the initial local model weights of $t+1$ training round to the received federated averaged weights
   - Initialize $\tau \leftarrow 1$;
   - for $\tau \leftarrow 1, 2, \ldots, \tau_c$ do
     - $w^i_{\tau_c}(t+1) \leftarrow \text{Optimizer}(w^i_{\tau_c}(t+1), \eta, l, D_i, b)$ \(\triangleright\) update weights based on weights from previous epoch, learning rate, loss function, local dataset and batch size using the choosed optimizer, such as gradient decent, SGD, Adam
   - end
   - Send $w^i_{\tau_c}(t+1)$ to GlobalServer;

Note: This algorithm references and is based on algorithms proposed in [41, 44]

our proposed two-stage federated transfer learning framework. As for the model training configuration, to begin with, we train our model for stage one, the training epoch is set to 20, the batch size is set to 32, and the learning rate is set to 0.001, for stage two, since the previous weights from stage one are transferred, we reduce the training epochs to 10, while the batch size and learning rate remain unchanged.

After training models in the centralized setting, we then start the training model using the proposed federated transfer learning framework. In federated learning, weights of all clients are sent to GlobalServer for federated averaging [41] in each training round after being trained at the client side for certain local training epochs, then take the effect of federated averaging interval into consideration. As is shown in Algorithm 1, in our proposed framework, the federated averaging interval is controlling the number of epochs a local model is trained at the client-side; in our experiments, we create five clients, and we trained our models with the federated averaging interval being set from 1 to 10, in order to explore how it relates to the performance. Data distribution at each client may also become a key factor for overall performance; therefore, in our experiments, we explore the influences of data distribution by training model in two scenarios as is shown in Table 4: (1) distributing data in training set to each client evenly, with 20% of data for each client, which is marked as balanced and (2) distributing data to each client unevenly, with the five clients having access to 30%, 25%, 20%, 15%, 10% of data respectively, which is marked as unbalanced. Please note that in the federated model training process, the number of training rounds is set to 20 in stage one and 10 in stage two, the learning rate is set to 0.001, the batch size is set to 32 in both stages, which corresponds to the parameters in the aforementioned centralized training.

To evaluate the performance, we tested our models on the testing set. Due to data imbalance of different categories, traditional accuracy may be biased based on the size of the dataset, and we then decide to utilize the ROC curve and AUC value for a more robust model performance evaluation. ROC curves of models trained with balanced data distribution are shown in Figure 4, Figure 5, Figure 6 and Figure 7, and ROC curves of models trained with unbalanced data distribution are shown in Figure 8, Figure 9, Figure 10 and Figure 11. All AUC values are recorded, and we have also calculated precision, sensitivity, as well as specificity. When calculating AUC, precision, and sensitivity, we consider Pneumonia as positive and Healthy as negative in stage one, while in stage two, Covid Pneumonia is considered as positive and Non-Covid Pneumonia is considered as negative. Precision is calculated using the following Equation 1,

$$
\text{Precision} = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalsePositive}}
$$

(1)

while sensitivity is calculated as is shown in Equation 2,

$$
\text{Sensitivity} = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalseNegative}}
$$

(2)

and the following Equation 3 calculates specificity.

$$
\text{Specificity} = \frac{\text{TrueNegative}}{\text{TrueNegative} + \text{FalsePositive}}
$$

(3)

The recorded confusion matrix values are shown in Table 5, and AUC, precision, sensitivity and specificity are shown in Table 6. Please note that rounding has been applied to values in Table 6 in order to keep four decimals, resulting in identical values shown in Table 6, which may not be equal to each other before rounding.

The results of experiments show that our proposed two-stage federated transfer learning framework has achieved excellent
performance in both stages. By comparing balanced and unbalanced data distribution at the client-side, we can see that dataset distribution at the client-side may not affect the overall model performance in the current two-stage classification task. Additionally, we observed that the models achieved very high classification performance in stage two even with the federated averaging interval set to 1. However, the results of stage one classification showed that the increase of federated averaging interval might help the model achieve better performance, which could be observed from the sensitivity values. However, the performance may not always be positively correlated with the federated averaging interval, as too many local training epochs could result in overfitting.

5 Conclusion and Discussion

In this paper, we proposed the two-stage federated transfer learning framework to address privacy concerns while achieving high accuracy. We also explored the relationship between the performance and the number of epochs local models are trained. Experiments were conducted in both centralized setting and federated setting for comparison, and the results of our experiments showed that the performance of the proposed framework are surprisingly good.

In our current work, due to hardware limitations, the simulation experiments of our proposed framework were only run on
the LeNet model. Future endeavors may be focusing on running the proposed framework on other much more complicated CNNs, such as AlexNet [69], VGG [76], and ResNet [77]. In the future, we may further explore the time or other resources consumed when increasing the number of local training epochs at the client-side and focus on achieving high accuracy in a resource-constrained environment.

Please note that our research is not aimed to replace the diagnosis from doctors. We are only trying to provide a way to leverage privacy and accuracy as well as reduce the possible negative impact caused by limited data availability by utilizing both federated learning and transfer learning.

REFERENCES

[1] World Health Organization et al. Laboratory testing for coronavirus disease (covid-19) in suspected human cases: interim guidance, 19 march 2020. Technical report, World Health Organization, 2020.

[2] Marina Carotti, Fausto Salaffi, Piercarlo Sarzi-Puttini, Andrea Agostini, Alessandra Borgheresi, Davide Minorati, Massimo Galli, Daniela Marotto, Andrea Giovagnoni. Chest ct features of coronavirus disease-19 (covid-19) pneumonia: which findings on initial ct can predict an adverse short-term outcome? BJR Open, 2:20200016, 2020.

[3] Guillaume Herpe, Mathieu Lederlin, Mathieu Naudin, Mickael Ohana, Kathia Chaumoitre, Jules Gregory, Valerie Vilgrain, Cornelia Anna Freitag, Constance De Margerie-Mellon, Violaine Flory, et al. Efficacy of chest ct for covid-19 pneumonia in france. Radiology, 2020.

[4] Arshed Hussain Parry, Abdul Haseeb Wani, Naveed Nazir Shah, Mudasira Yaseen, and Majid Jehangir. Chest ct features of coronavirus disease-19 (covid-19) pneumonia: which findings on initial ct can predict an adverse short-term outcome? BJR Open, 2:20200016, 2020.

[5] Furkan Ufuk and Recep Savaş. Chest ct features of the novel coronavirus disease (covid-19). Turkish Journal of Medical Sciences, 50(4):664–678, 2020.

[6] Eric D Tenda, Mira Yulianti, M Asaf, R Yunus, Wita Sepiyanti, Vally Wu, Ceva W Putyo, Cleopas M Rumbene, and Siti Setiai. The importance of chest ct scan in covid-19: A case series. Acta med indones, 52(1):68–73, 2020.

[7] Marco Francone, Franco Iafrate, Giorgio Maria Masci, Simona Coco, Francesco Cilia, Lucia Manganaro, Valeria Panebianco, Chiara Andreoli, Maria Chiara Colaiacomo, Maria Antonella Zingaropoli, et al. Chest ct score in covid-19 patients: correlation with disease severity and short-term prognosis. European radiology, 30(12):6808–6817, 2020.

[8] Tao Ai, Zhenlu Yang, Hongyan Hou, Chenoa Zhan, Chong Chen, Wenzhi Lv, Qian Tao, Ziyong Sun, and Liming Xia. Correlation of chest ct and rt-pcr testing for coronavirus disease 2019 (covid-19) in china: a report of 1014 cases. Radiology, 296(2):E32–E40, 2020.

[9] Elaine YP Lee, Ming-Yen Ng, and Pek-Lan Khong. Covid-19 pneumonia: what has ct taught us? The Lancet Infectious Diseases, 20(4):384–385, 2020.

[10] Xingzhi Xie, Zheng Zhong, Wei Zhao, Chao Zheng, Fei Wang, and Jun Liu. Chest ct for typical coronavirus disease
Figure 11: Upper Left Zoom-In of ROC Curves of Stage Two with Unbalanced Data Distribution

2019 (covid-19) pneumonia: relationship to negative rt-pcr testing. *Radiology*, 296(2):E41–E45, 2020.

[11] Hester A Gietema, Noortje Zelis, J Martijn Nobel, Lars JG Lambriks, Lieke B Van Alphen, Astrid ML Oude Lashof, Joachim E Wildberger, Irene C Nelissen, and Patricia M Stassen. Ct in relation to rt-pcr in diagnosing covid-19 in the netherlands: a prospective study. *PloS one*, 15(7): e0235844, 2020.

[12] Dinggang Shen, Guorong Wu, and Heung-Il Suk. Deep learning in medical image analysis. *Annual review of biomedical engineering*, 19:221–248, 2017.

[13] Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi, Mohsen Ghafoorian, Jeroen Awm Van Der Laak, Bram Van Ginneken, and Clara I Sánchez. A survey on deep learning in medical image analysis. *Medical image analysis*, 42: 60–88, 2017.

[14] Grant Haskins, Uwe Kruger, and Pingkun Yan. Deep learning in medical image registration: a survey. *Machine Vision and Applications*, 31(1):1–18, 2020.

[15] Lourdes Duran-Lopez, Juan P Dominguez-Morales, Antonio Felix Conde-Martin, Saturnino Vicente-Diaz, and Alejandro Linares-Barranco. Prometeo: A cnn-based computer-aided diagnosis system for wsi prostate cancer detection. *IEEE Access*, 8:128613–128628, 2020.

[16] Hiroki Tanaka, Shih-Wei Chiu, Takeanori Watanabe, Setsuko Kaoku, and Takuhiro Yamaguchi. Computer-aided diagnosis system for breast ultrasound images using deep learning. *Physics in Medicine & Biology*, 64(23):235013, 2019.

[17] Takumi Okamoto, Masayuki Odagawa, Tetsushi Koide, Shinji Tanaka, Toru Tamaki, Bissar Raytchev, Kazufumi Kaneda, Shigeto Yoshida, and Hiroshi Mieno. Feature extraction of colorectal endoscopic images for computer-aided diagnosis with cnn. In 2019 2nd International Symposium on Devices, Circuits and Systems (ISDCS), pages 1–4, IEEE, 2019.

[18] Shikun Zhang, Fengrong Sun, Naishun Wang, Cuicui Zhang, Qianlei Yu, Mingqiang Zhang, Paul Babyn, and Hai Zhong. Computer-aided diagnosis (cad) of pulmonary nodule of thoracic ct image using transfer learning. *Journal of digital imaging*, 32(6):995–1007, 2019.

[19] Adrian Barbu, Le Lu, Holger Roth, Ari Seff, and Ronald M Summers. An analysis of robust cost functions for cnn in computer-aided diagnosis. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, 6(3):253–258, 2018.

[20] Yuchen Qiu, Shiju Yan, Rohith Reddy Gundreddy, Yunzhi Wang, Samuel Cheng, Hong Liu, and Bin Zheng. A new approach to develop computer-aided diagnosis scheme of breast mass classification using deep learning technology. *Journal of X-ray Science and Technology*, 25(5):751–763, 2017.

[21] Wenqing Sun, Bin Zheng, and Wei Qian. Computer aided lung cancer diagnosis with deep learning algorithms. In *Medical imaging 2016: computer-aided diagnosis*, volume 9785, pages 241–248. SPIE, 2016.

[22] Dina M Ibrahim, Nada M Elshennawy, and Amany M Sarhan. Deep-chest: Multi-classification deep learning model for diagnosing covid-19, pneumonia, and lung cancer chest diseases. *Computers in biology and medicine*, 132:104348, 2021.

[23] Abdullahi Umar Ibrahim, Mehmet Ozsoz, Sertan Serte, Fadi Al-Turjman, and Polycarp Shizawaliyi Yakoi. Pneumonia classification using deep learning from chest x-ray images during covid-19. *Cognitive Computation*, pages 1–13, 2021.

[24] Emtyaz Hussain, Mahmudul Hasan, Md Anisur Rahman, Ickjai Lee, Tasmi Tamanna, and Mohammad Zavid Parvez. Corodet: A deep learning based classification for covid-19 detection using chest x-ray images. *Chaos, Solitons & Fractals*, 142:110495, 2021.

[25] Sadman Sakib, Taharat Tazrin, Mostafa M Fouda, Zubair Md Fadullah, and Mohsen Guizani. Di-crc: deep learning-based chest radiograph classification for covid-19 detection: a novel approach. *Ieee Access*, 8:171575–171589, 2020.

[26] Joy Iong-Zong Chen. Design of accurate classification of covid-19 disease in x-ray images using deep learning approach. *Journal of ISMAC*, 3(02):132–148, 2021.

[27] Anunay Gupta, Shreyansh Gupta, Rahul Katarya, et al. Instacovnet-19: A deep learning classification model for the detection of covid-19 patients using chest x-ray. *Applied Soft Computing*, 99:106859, 2021.

[28] Omar M Elzeki, Mahmoud Shams, Shahenda Sarhan, Mohamed Abd Elfattah, and Aboul Ella Hassanien. Covid-19: a new deep learning computer-aided model for classification. *PeerJ Computer Science*, 7:e358, 2021.

[29] Tuan D Pham. A comprehensive study on classification of covid-19 on computed tomography with pretrained convolutional neural networks. *Scientific reports*, 10(1):1–8, 2020.

[30] Daphna Keidar, Daniel Yaron, Elisha Goldstein, Yair Shachar, Ayelet Blass, Leonid Charbinsky, Israel Aharony, Liza Lifshitz, Dimitri Lumelsky, Ziv Neeman, et al. Covid-19 classification of x-ray images using deep neural networks. *European radiology*, 31(12):9654–9663, 2021.

[31] Ali Nari, Ceren Kay, and Ziynet Pamuk. Automatic detection of coronavirus disease (covid-19) using x-ray...
images and deep convolutional neural networks. *Pattern Analysis and Applications*, 24(3):1207–1220, 2021.

[32] Ghulam Gilanie, Usama Ijaz Bajwa, Mustansar Mahmood Waraich, Muttyba Asghar, Rehana Kousar, Adnan Kashif, Rabab Shereen Aslam, Muhammad Mohsin Qasim, and Hamza Rafique. Coronavirus (covid-19) detection from chest radiology images using convolutional neural networks. *Biomedical Signal Processing and Control*, 66: 102490, 2021.

[33] Ines Feki, Sourour Ammar, Yousri Kessentini, and Khan Muhammad. Federated learning for covid-19 screening from chest x-ray images. *Applied Soft Computing*, 106: 107330, 2021.

[34] Bingjie Yan, Jun Wang, Jieren Cheng, Yize Zhou, Yixian Zhang, Yifan Yang, Li Liu, Haojiang Zhao, Chunjuan Wang, and Boyi Liu. Experiments of federated learning for covid-19 chest x-ray images. In *International Conference on Artificial Intelligence and Security*, pages 41–53. Springer, 2021.

[35] Ittai Dayan, Holger R Roth, Aoxiao Zhong, Ahmed Harouni, Amilcare Gentili, Anas Z Abidin, Andrew Liu, Anthony Beardsworth Costa, Bradford J Wood, Chien-Sung Tsai, et al. Federated learning for predicting clinical outcomes in patients with covid-19. *Nature medicine*, 27(10):1735–1743, 2021.

[36] Rajesh Kumar, Abdullah Aman Khan, Jay Kumar, Noorbakhsh Amiri Golilazar, Simin Zhang, Yang Ting, Chengyu Zheng, Wenyong Wang, et al. Blockchain-federated learning and deep models for covid-19 detection using ct imaging. *IEEE Sensors Journal*, 21(14):16301–16314, 2021.

[37] Dinh C Nguyen, Ming Ding, Pubudu N Pathirana, Aruna Seneviratne, and Albert Y Zomaya. Federated learning for covid-19 detection with generative adversarial networks in edge cloud computing. *IEEE Internet of Things Journal*, 2021.

[38] Alper Emin Cetinkaya, Murat Akin, and Serer Sagiorglu. A communication efficient federated learning approach to multi chest diseases classification. In *2021 6th International Conference on Computer Science and Engineering (UBMK)*, pages 429–434. IEEE, 2021.

[39] Weishan Zhang, Tao Zhou, Qinghua Lu, Xiao Wang, Chunsheng Zhu, Haoyun Sun, Zhipeng Wang, Sin Kit Lo, and Fei-Yue Wang. Dynamic-fusion-based federated learning for covid-19 detection. *IEEE Internet of Things Journal*, 8(21):15884–15891, 2021.

[40] Adnan Quayyum, Kashif Ahmad, Muhammad Ahhtazaz Ahsan, Ala Al-Fuqaha, and Junaid Qadir. Collaborative federated learning for healthcare: Multi-modal covid-19 diagnosis at the edge. *arXiv preprint arXiv:2101.07511*, 2021.

[41] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Agueray Arcas. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*, pages 1273–1282. PMLR, 2017.

[42] Keith Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloe Kiddon, Jakub Konečný, Stefano Mazzocchi, Brendan McMahan, et al. Towards federated learning at scale: System design. *Proceedings of Machine Learning and Systems*, 1:374–388, 2019.

[43] Andrew Hard, Kanishka Rao, Rajiv Mathews, Swaroop Ramaswamy, Françoise Beaufays, Sean Augenstein, Hubert Eichner, Chloé Kiddon, and Daniel Ramage. Federated learning for mobile keyboard prediction. *arXiv preprint arXiv:1811.03604*, 2018.

[44] Shiqiang Wang, Tiffany Tuor, Theodoros Salondis, Kin K Leung, Christian Makaya, Ting He, and Kevin Chan. When edge meets learning: Adaptive control for resource-constrained distributed machine learning. In *IEEE INFOCOM 2018-IEEE Conference on Computer Communications*, pages 63–71. IEEE, 2018.

[45] Karl Weiss, Taghi M Khoshgoftaar, and DingDing Wang. A survey of transfer learning. *Journal of Big data*, 3(1):1–40, 2016.

[46] Lisa Torrey and Jude Shavlik. Transfer learning. In *Handbook of research on machine learning applications and trends: algorithms, methods, and techniques*, pages 242–264. IGI global, 2010.

[47] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2009.

[48] Yadunath Pathak, Prashant Kumar Shukla, Akhilesh Tiwari, Shalini Stalin, and Saurabh Singh. Deep transfer learning based classification model for covid-19 disease. *Irbm*, 2020.

[49] Muhammet Fatih Aslan, Muhammed Fahri Unlersen, Irbm Sabanci, and Akif Durdu. Cnn-based transfer learning–bilstm network: A novel approach for covid-19 infection detection. *Applied Soft Computing*, 98:106912, 2021.

[50] Aayush Jaiswal, Neha Gianchandani, Dilbag Singh, Vijay Kumar, and Manjit Kaur. Classification of the covid-19 infected patients using densenet201 based deep transfer learning. *Journal of Biomolecular Structure and Dynamics*, 39(15):5682–5689, 2021.

[51] Fouzia Altaf, Syed Islam, and Naeem Khalid Janjua. A novel augmented deep transfer learning for classification of covid-19 and other thoracic diseases from x-rays. *Neural Computing and Applications*, 33(20):14037–14048, 2021.

[52] Ariyo Oluwasanmi, Muhammad Umar Aftab, Zhiguang Zhang, Wenyong Wang, et al. Blockchain-federated learning–bilstm network: A novel approach for covid-19 infection detection. *Applied Soft Computing*, 98:106912, 2021.

[53] Michael J Horry, Subrata Chakraborty, Manoranjan Paul, Anwar Ulhaq, Biswajeet Pradhan, Manas Saha, and Nagesh Shukla. Covid-19 detection through transfer learning using multimodal imaging data. *Ieeec Access*, 8:149808–149824, 2020.

[54] Shui-Hua Wang, Deepak Ranjan Nayak, David S Guttery, Xin Zhang, and Yu-Dong Zhang. Covid-19 classification by cshnet with deep fusion using transfer learning and discriminant correlation analysis. *Information Fusion*, 68: 131–148, 2021.
[55] Chun Li, Yunyun Yang, Hui Liang, and Boying Wu. Transfer learning for establishment of recognition of covid-19 on ct imaging using small-sized training datasets. Knowledge-Based Systems, 218:106849, 2021.

[56] Oussama El Gannour, Soufiane Hamida, Bouchaib Chernadi, Abdelhadi Raihani, and Hicham Moujahid. Performance evaluation of transfer learning technique for automatic detection of patients with covid-19 on x-ray images. In 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), pages 1–6. IEEE, 2020.

[57] N Narayan Das, Naresh Kumar, Manjit Kaur, Vijay Kumar, and Dilbag Singh. Automated deep transfer learning-based approach for detection of covid-19 infection in chest x-rays. Irbn, 2020.

[58] Iason Katsamenis, Effychios Protopapadakis, Athanasios Voulodimos, Anastasios Doulamis, and Nikolaos Doulamis. Transfer learning for covid-19 pneumonia detection and classification in chest x-ray images. In 24th Pan-Hellenic Conference on Informatics, pages 170–174, 2020.

[59] Ruochi Zhang, Zhehao Guo, Yue Sun, Qi Li, Zijian Xu, Zhaomin Yao, Meiyu Duan, Shuai Liu, Yanjiao Ren, Lan Huang, et al. Covid19xraynet: a two-step transfer learning model for the covid-19 detecting problem based on a limited number of chest x-ray images. Interdisciplinary Sciences: Computational Life Sciences, 12(4):555–565, 2020.

[60] Muhammad EH Chowdhury, Tawsifur Rahman, Amit Khandakar, Rashid Mazhar, Muhammad Abdul Kadir, Zaid Bin Mahbub, Khandakar Reajul Islam, Muhammad Salman Khan, Atif Iqbal, Nasser Al Emadi, et al. Can ai help in screening viral and covid-19 pneumonia? Image recognition based on deep learning model for the covid-19 detecting problem based on a limited number of chest x-ray images. IEEE Access, 8:132665–132676, 2020.

[61] Tawsifur Rahman, Amit Khandakar, Yazan Qiblawey, Anas Tahir, Serkan Kiranyaz, Saad Bin Abul Kashem, Mohammad Tariqul Islam, Somaya Al Maadeed, Susu M Zughai, Muhammad Salman Khan, et al. Exploring the effect of image enhancement techniques on covid-19 detection using chest x-ray images. Computers in biology and medicine, 132:104319, 2021.

[62] Daniel S Kermany, Michael Goldbaum, Wenjia Cai, Carolina CS Valentim, Huiying Liang, Sally L Baxter, Alex McKeown, Ge Yang, Xiaoang Wu, Fangbing Yan, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell, 172(5):1122–1131, 2018.

[63] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278–2324, 1998.

[64] Quan Zhang. Convolutional neural networks. In Proceedings of the 3rd International Conference on Electromechanical Control Technology and Transportation, pages 434–439, 2018.

[65] Zewen Li, Fan Liu, Wenjie Yang, Shouheng Peng, and Jun Zhou. A survey of convolutional neural networks: analysis, applications, and prospects. IEEE Transactions on Neural Networks and Learning Systems, 2021.

[66] Warren S McCulloch and Walter Pitts. A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5(4):115–133, 1943.

[67] Ji He, Hongwei Yang, Lei He, and Lina Zhao. Neural networks based on vectorized neurons. Neurocomputing, 465:63–70, 2021.

[68] Sagar Sharma, Simone Sharma, and Anidhya Athaiya. Activation functions in neural networks. Towards data science, 6(12):310–316, 2017.

[69] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25, 2012.

[70] Ernst Kussul and Tatiana Baidyk. Improved method of handwritten digit recognition tested on mnist database. Image and Vision Computing, 22(12):971–981, 2004.

[71] Meiyin Wu and Li Chen. Image recognition based on deep learning. In 2015 Chinese Automation Congress (CAC), pages 542–546. IEEE, 2015.

[72] Rasim Caner Çalik and M Fatih Demirci. Cifar-10 image classification with convolutional neural networks for embedded systems. In 2018 IEEE/ACIS 15th International Conference on Computer Systems and Applications (AICCSA), pages 1–2. IEEE, 2018.

[73] John Bridle. Training stochastic model recognition algorithms as networks can lead to maximum mutual information estimation of parameters. Advances in neural information processing systems, 2, 1989.

[74] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevedo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dandelion Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. URL https://www.tensorflow.org/. Software available from tensorflow.org.

[75] François Chollet et al. Keras. https://keras.io, 2015.

[76] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

[77] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.
Table 5: Confusion Matrix Values of All Models

| Stage   | Training Setting | Data Dist. | Fed. Averaging Interval | TP   | TN   | FP   | FN   |
|---------|------------------|------------|-------------------------|------|------|------|------|
| stage one | centralized     | N/A        | N/A                     | 1423 | 1925 | 159  | 110  |
| stage two | centralized     | N/A        | N/A                     | 700  | 858  | 7    | 13   |
| stage one | federated      | balanced   | 1                       | 1260 | 1964 | 120  | 273  |
|          |                 |            | 2                       | 1316 | 2005 | 79   | 217  |
|          |                 |            | 3                       | 1381 | 1980 | 104  | 152  |
|          |                 |            | 4                       | 1359 | 2005 | 79   | 174  |
|          |                 |            | 5                       | 1377 | 2010 | 74   | 156  |
|          |                 |            | 6                       | 1436 | 1959 | 125  | 97   |
|          |                 |            | 7                       | 1383 | 2006 | 78   | 150  |
|          |                 |            | 8                       | 1402 | 1992 | 92   | 131  |
|          |                 |            | 9                       | 1388 | 1978 | 106  | 145  |
|          |                 |            | 10                      | 1412 | 1976 | 108  | 121  |
| stage two | federated      | balanced   | 1                       | 698  | 850  | 15   | 15   |
|          |                 |            | 2                       | 701  | 857  | 8    | 12   |
|          |                 |            | 3                       | 699  | 857  | 8    | 14   |
|          |                 |            | 4                       | 696  | 859  | 6    | 17   |
|          |                 |            | 5                       | 697  | 861  | 4    | 16   |
|          |                 |            | 6                       | 703  | 853  | 12   | 10   |
|          |                 |            | 7                       | 698  | 857  | 8    | 15   |
|          |                 |            | 8                       | 700  | 858  | 7    | 13   |
|          |                 |            | 9                       | 700  | 854  | 11   | 13   |
|          |                 |            | 10                      | 700  | 861  | 4    | 13   |
| stage one | federated      | unbalanced | 1                       | 1287 | 1972 | 112  | 246  |
|          |                 |            | 2                       | 1335 | 2002 | 82   | 198  |
|          |                 |            | 3                       | 1409 | 1989 | 95   | 124  |
|          |                 |            | 4                       | 1397 | 1978 | 106  | 136  |
|          |                 |            | 5                       | 1393 | 1989 | 95   | 140  |
|          |                 |            | 6                       | 1385 | 1974 | 110  | 148  |
|          |                 |            | 7                       | 1400 | 1980 | 104  | 133  |
|          |                 |            | 8                       | 1425 | 1981 | 103  | 108  |
|          |                 |            | 9                       | 1413 | 1976 | 108  | 120  |
|          |                 |            | 10                      | 1419 | 1986 | 98   | 114  |
| stage two | federated      | unbalanced | 1                       | 689  | 857  | 8    | 24   |
|          |                 |            | 2                       | 697  | 857  | 8    | 16   |
|          |                 |            | 3                       | 704  | 861  | 4    | 9    |
|          |                 |            | 4                       | 699  | 859  | 6    | 14   |
|          |                 |            | 5                       | 698  | 858  | 7    | 15   |
|          |                 |            | 6                       | 697  | 861  | 4    | 16   |
|          |                 |            | 7                       | 695  | 859  | 6    | 18   |
|          |                 |            | 8                       | 697  | 860  | 5    | 16   |
|          |                 |            | 9                       | 702  | 859  | 6    | 11   |
|          |                 |            | 10                      | 702  | 858  | 7    | 11   |
Table 6: AUC, Pre. (Precision), Sen. (Sensitivity) and Spe. (Specificity) Values of All Models

| Stage     | Training Setting | Data Dist. | Fed. Averaging Interval | AUC   | Pre.   | Sen.   | Spe.   |
|-----------|------------------|------------|-------------------------|-------|--------|--------|--------|
| stage one | centralized      | N/A        | N/A                     | 0.9801| 0.8995 | 0.9282 | 0.9237 |
| stage two | centralized      | N/A        | N/A                     | 0.9992| 0.9901 | 0.9818 | 0.9919 |
|           |                  |            |                         | 0.9626| 0.9130 | 0.8219 | 0.9424 |
|           |                  |            |                         | 0.9761| 0.9434 | 0.8584 | 0.9621 |
|           |                  |            |                         | 0.9790| 0.9300 | 0.9008 | 0.9501 |
|           |                  |            |                         | 0.9812| 0.9451 | 0.8865 | 0.9621 |
|           |                  |            |                         | 0.9829| 0.9490 | 0.8982 | 0.9645 |
|           |                  |            |                         | 0.9807| 0.9199 | 0.9367 | 0.9400 |
|           |                  |            |                         | 0.9836| 0.9466 | 0.9022 | 0.9626 |
|           |                  |            |                         | 0.9818| 0.9384 | 0.9145 | 0.9559 |
|           |                  |            |                         | 0.9793| 0.9290 | 0.9054 | 0.9491 |
|           |                  |            |                         | 0.9820| 0.9289 | 0.9211 | 0.9482 |
| stage one | federated        | balanced   |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
| stage two | federated        | balanced   |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
| stage one | federated        | unbalanced |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
| stage two | federated        | unbalanced |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |
|           |                  |            |                         |       |        |        |        |