Federated Learning for Enhanced Classification of Covid, Pneumonia, and Normal Lung X-Ray Images

Abstract:

The ongoing global health crisis underscored by the COVID-19 pandemic has intensified the need for advanced diagnostic tools that are both efficient and privacy-preserving. This study investigates the application of federated learning (FL) to classify lung X-ray images into COVID-19, pneumonia, and normal categories. We developed a federated network that aggregates learning models trained on an open Kaggle dataset divided into four distinct partitions. Each partition was securely distributed to separate devices to simulate real world applications of this technique wherein sharing of data across devices is not only costly but can potentially violate patient privacy law. Utilizing ResNet-50, a convolutional neural network (CNN), as a base model in a federated approach ensures data privacy and accesses diverse data features.

Index Terms: Federated Learning, COVID-19, Pneumonia, Deep Learning, Convolutional Neural Network (CNN), ResNet-50 model.

Introduction:

COVID-19, the disease caused by the novel coronavirus SARS-CoV-2, first emerged in Wuhan, China, in late 2019 and quickly escalated into a global pandemic by March 2020. It is primarily transmitted through respiratory droplets and has symptoms ranging from mild respiratory issues to severe acute respiratory syndrome, often leading to death, particularly in older adults and those with underlying health conditions. The ongoing COVID-19 pandemic has posed unprecedented challenges to global healthcare systems, highlighting the critical need for rapid, accurate, and efficient diagnostic tools that can maintain patient privacy. In response to this challenge, using Deep Learning and machine learning techniques in medical imaging has gained significant attention. Among the various imaging modalities, chest X-ray imaging stands out due to its availability, cost-effectiveness, and speed, making it a vital tool in the early detection and management of COVID-19. However, traditional machine learning models in healthcare often necessitate centralized data pools, creating significant concerns over privacy, data security, and governance. Federated learning (FL) emerges as a revolutionary approach to overcome these challenges by allowing multiple participants or institutions to collaboratively train a shared prediction model while keeping all the training data on isolated devices, decoupling the ability to do machine learning from the need to store the data in centralized storage. This approach not only helps protect patient privacy but also leverages diverse datasets across different regions and populations, enhancing the robustness and generalizability of the models.

Federated Learning:

Federated learning (FL) is a decentralized machine learning approach that empowers multiple devices or servers to collaboratively train a shared predictive model while keeping the training data localized, thus eliminating the need for data centralization. This method is crucial in environments where data privacy is critical, such as healthcare, financial services, and personal data applications. The training process is coordinated by a central server that initializes a global model and distributes it to the participating devices. Each device then trains this model on its local data and sends back only the model updates—such as weights or gradients—to the central server, which aggregates these updates to enhance the global model iteratively. This system not only enhances privacy and security but also mitigates risks associated with data breaches, complies with strict data protection regulations, reduces communication costs, and harnesses the power of diverse datasets to improve the robustness and generalizability of models across various populations and conditions. Federated learning is a potent tool in the era of big data, where the need for privacy standards is becoming increasingly stringent, particularly in domains like healthcare and finance, where data is distributed and highly sensitive.

Related Work:

The first research paper that sparked the inspiration for this project is "Centralized CNN-GRU model by federated learning for COVID-19 prediction in India" (Pandianchery, Mredulraj, et al.). The proposed Fed-CNN–GRU model in the study combines convolutional neural networks (CNN) and gated recurrent units (GRU) to analyze the active cases per day dataset for 36 provinces in India using transfer and federated learning techniques. The use of transfer learning in Stage 1 of the approach involves training a pre-trained model on the dataset of Maharashtra and then testing it on the rest of the provinces in India. This approach helps provinces with limited data dynamics by leveraging the knowledge captured in the pre-trained model. It enables the model to adapt to different transmission trends of COVID-19 cases across various regions. In Stage 2 of the approach, federated learning is employed to update the parameters of the model based on locally updated parameters from selected provinces. This approach allows for decentralized data from different provinces to be aggregated and used to enhance the prediction results of the centralized model. By leveraging federated learning, the model can capture new trends and patterns present in remote data, leading to improved accuracy in predicting COVID-19 cases.

The second research paper titled "Ensemble learning for multi-class COVID-19 detection from big data" (Kaleem, Sarah, et al.) presents a novel architecture for detecting COVID-19 from chest X-ray images using ensemble learning techniques. The study leverages novel machine learning techniques to propose new methods of detection for the global health crisis caused by the COVID-19 pandemic. The study utilizes ensemble learning methods, integrating architectures like VGG-16, VGG-19, and ResNet-50.

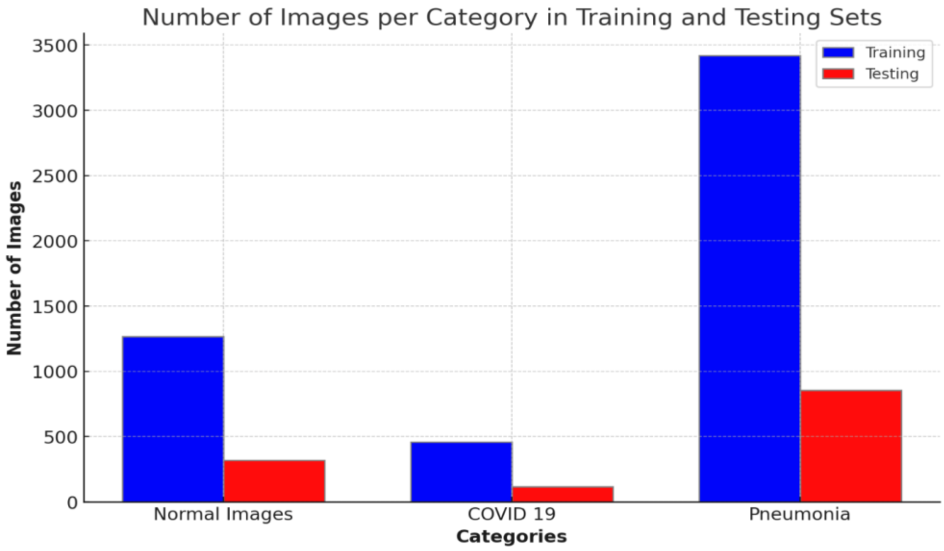
The proposed architecture incorporates a parallel and distributed framework in Spark to facilitate parallel processing, improving both training and execution times for COVID-19 detection from chest X-ray images. The proposed architecture offers a promising solution for early detection and management of COVID-19, with implications for improving diagnostic accuracy and resource optimization in healthcare settings.

The third paper titled "CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images" (Khan et al.), presents the development and evaluation of a Deep Convolutional Neural Network model called CoroNet for the automated detection of COVID-19 infection from chest X-ray images. The paper addresses the urgent need for effective screening methods for COVID-19, highlighting the potential of chest radiography images in detecting the virus. The study proposes the CoroNet model, based on the Xception architecture pre-trained on the ImageNet dataset. The model is trained end-to-end on a dataset comprised of COVID-19, pneumonia bacterial, pneumonia viral, and normal chest X-ray images collected from public databases. CoroNet achieved an overall accuracy of 89.6% in classifying chest X-ray images into four categories. Notably, the model demonstrates high precision and recall rates for COVID-19 cases, underscoring its effectiveness in identifying positive instances compared to other state-of-the-art deep learning models designed for COVID-19 detection. The study highlights the potential clinical utility of CoroNet in aiding radiologists and clinicians in the detection, quantification, and follow-up of COVID-19 cases. The model's automated screening capabilities can streamline the triage process and optimize resource allocation in medical settings.

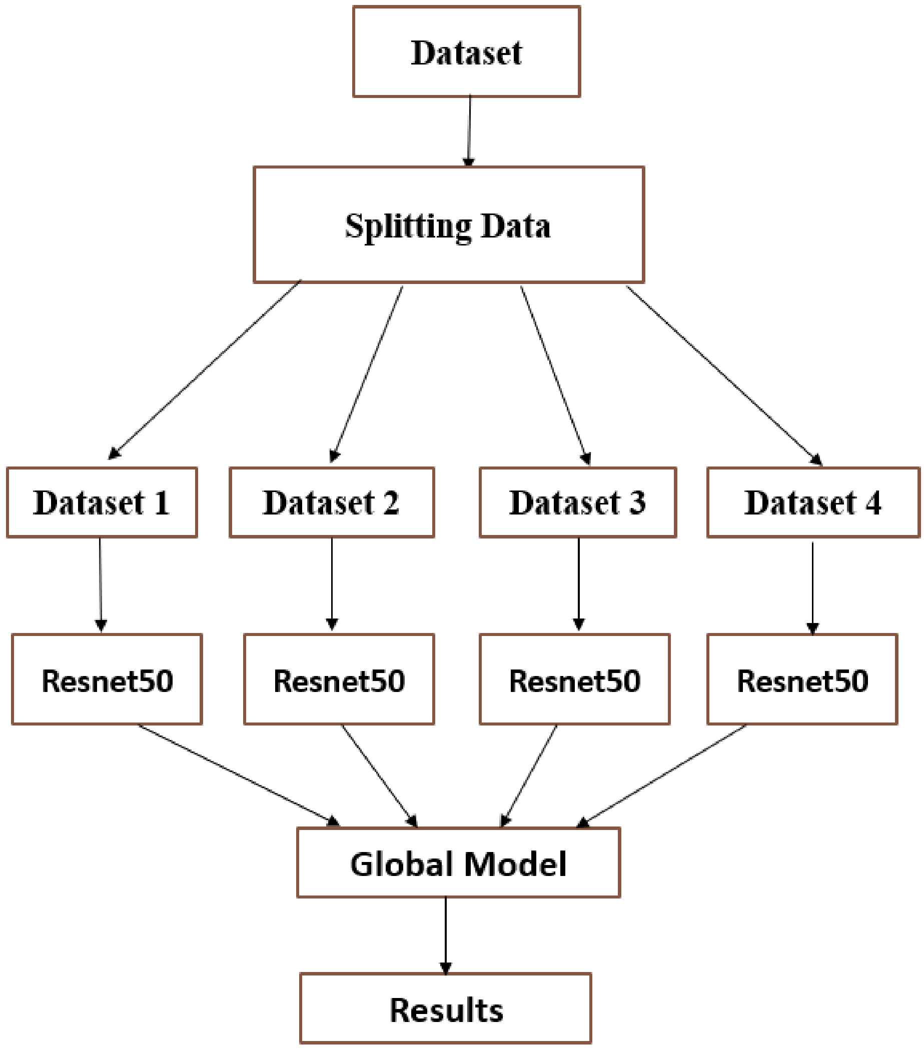
Dataset:

The Chest X-ray (CXR) images of COVID-19, Pneumonia and Normal is a publicly available image dataset on Kaggle and is a collection of multiple public datasets of CXR images (Cohen et al.; Kermany, Zhang and Goldbaum). It contains a significant collection of X-ray images categorized explicitly into three distinct groups: COVID-19, pneumonia, and routine. The dataset was collected from multiple public sources online, such as Twitter posts, and indirect collection from hospitals and physicians, with most data collected in 2020. This dataset is structured into two main folders for training and testing purposes. Each folder is divided into three subfolders corresponding to the different classifications of X-ray images: COVID-19, pneumonia, and normal. The dataset comprises a total of 6432 X-ray images. Specifically, 20% of these images are used for testing purposes, which ensures a substantial amount of data is available for validating the accuracy and effectiveness of machine learning models trained using this dataset. This structured organization and substantial data volume make the dataset highly suitable for training deep learning models to automate the detection and differentiation of COVID-19 and pneumonia from normal X-ray images, providing a valuable resource for researchers and healthcare professionals working on diagnostic algorithms.

COVID-19 PNEUMONIA NORMAL



Structure of the project:



This project was executed in python on the KSU HPC.

1. Dataset: The dataset comprises image data categorized into three groups: COVID-19, Normal, and Pneumonia.

2. Data Split: The dataset is strategically divided into four subsets. Each subset serves a specific purpose in the training and validation process, allowing for comprehensive testing and optimization of the models across various data scenarios.

3. Model: For each of the four subsets of the dataset, a ResNet50 model is employed. ResNet50 is a convolutional neural network that is 50 layers deep. It is widely used in deep learning for image classification tasks because it can learn rich feature representations for a wide range of images.

4. Global Model: After training, the results from the ResNet50 models on each subset are collected. These results are then aggregated to form a global model by taking the average of the four model's weights. This aggregation process combines the insights gained from each subgroup to enhance the overall accuracy and performance of the final model. This global model effectively synthesizes the findings from each separate model, providing a unified outcome that predicts the presence of COVID-19, pneumonia, or normal conditions in unseen chest X-ray images.

Methodology:

In our research project we proposed federated learning with a CXR dataset on Normal, Covid, and Pneumonia infected lungs. The dataset of a total of 6432 x-ray images of Normal, Covid and Pneumonia infected lungs were split each into four equal parts. Each of the four parts has combination of x-ray images of Normal, Covid and Pneumonia infected lungs. There was no crossover between these four parts. In each part we split the data into train, test and validation sets. We proposed ResNet50 architecture in each part as the base model, with pre-trained weights from the ImageNet dataset. By using the transfer learning approach, the final layer of these four models were locally trained independently on four servers. We then took the average of the locally updated weights and inserted them into our global model.

Result and Discussion:

Individual and Global Model Results			
	Loss	Train Accuracy	Test Accuracy
Model A	0.1354	0.9848	0.9510
Model K	0.1136	0.9872	0.9717
Model C	0.1200	0.9983	0.9568
Model P	0.1381	0.9845	0.9527
Global Model	0.5449	NA	0.7741

Table 1

Table 1 summarizes the performance metrics of four individual machine learning models (Model A, Model K, Model C, Model P) and a combined Global Model. Each row represents a different model, and the columns provide details on three key performance indicators: Loss, Train Accuracy, and Test Accuracy.

- **Model A** shows a loss of 0.1354, a high training accuracy of 98.48%, and a test accuracy of 95.10%.
- **Model K** has a lower loss of 0.1136 compared to Model A, a slightly lower training accuracy of 98.72%, and a higher test accuracy of 97.17%.
- **Model C** reports the lowest loss among the individual models at 0.1200, the highest training accuracy at 99.83%, and a test accuracy of 95.68%.
- **Model P** exhibits a loss of 0.1381, training accuracy of 98.45%, and test accuracy of 95.27%.

The Global Model combines the insights from the individual models and indicates a significantly higher loss of 0.5449. No data is available for training accuracy (NA), which suggests that this figure was not calculated or not applicable in this context. The test accuracy for the Global Model is 77.41%, which is notably lower than any of the individual models. This summary suggests that while individual models perform well on training and test data, the aggregation method combined with the Global Model may be less effective, as indicated by the higher loss and lower test accuracy. This could be due to several factors, such as overfitting in individual models, differences in data distribution across datasets, or a need for further tuning of the aggregation method to effectively combine the models' predictions.

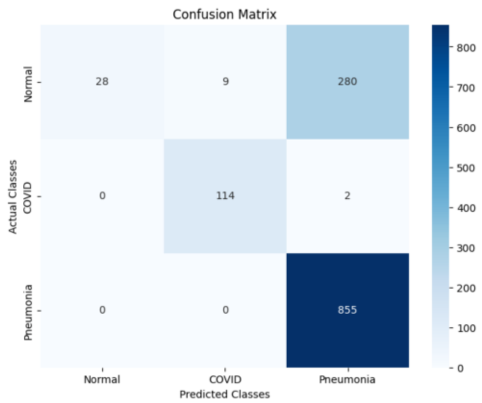


Fig 1

Figure 1 presents a confusion matrix; it compares the actual classes of data points against the classes predicted by the model. The actual classes are displayed along the y-axis, and the predicted classes are shown along the x-axis. This confusion matrix includes three classes: Normal, COVID, and Pneumonia.

The matrix shows many true positives for the Pneumonia class, with 855 correct predictions. The Normal class had 28 true positives and nine false negatives, indicating that 9 Normal cases were incorrectly predicted as Pneumonia. The COVID class had 114 true positives, with two false negatives where the model incorrectly predicted them as Pneumonia.

The colour gradient represents the frequency of predictions, with darker shades typically indicating higher numbers. In this case, the darkest shade corresponds to the Pneumonia predictions, which is the most frequent correct prediction made by the model. Overall, the model is highly accurate in predicting Pneumonia cases, with many true positives and very few false negatives for the COVID class. However, there is a relatively small number of Normal cases, which could be a point of focus for further improving the model's performance.

Conclusion:

We found Federated learning is effective but introduces new challenges that are not present in other deep learning methods. One advantage of federated learning is that it minimizes data transmission, which is critical for data privacy and is important with big data. However, ensuring all models are trained well, and aggregated correctly is an issue encountered in this study, and further work is necessary to investigate the cause of the drop in performance during model aggregation. If aggregation does in this case cause a decrease in accuracy, the cause of this decline is important to determine for wide application of federated learning.

Recommendation:

There is a large data imbalance present in this dataset which could be corrected with data augmentation techniques to create additional, altered images for training. Additionally, in aggregating the local models to the final, global model, the four local model’s weights were averaged without consideration for variance in accuracy or loss. Accounting for this variance could improve model performance by a method like weighted averaging, such that models with higher performance are more influential to the global model. Finally, federated learning is usually an iterative process where models are updated repeatedly over time, this was not considered as a part of this work, and in future work would be incorporated into the methods by way of augmented data for additional training, or repartitioning the data set multiple times to provide different training sets for each local model to learn on.

References:

Dataset: [Chest X-ray (Covid-19 & Pneumonia) (kaggle.com)]

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