# Categorization Of Healthcare Images Using Federated Learning with Pre-Trained Model

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**Abstract:**
Classification of medical images is crucial in healthcare, especially for disease diagnosis and treatment planning. However, privacy concerns regarding patient information hinder the use of centralized machine learning models. Federated learning (fl) provides a promising solution by enabling collaborative model training across distributed data while ensuring information confidentiality. This study evaluates the use of Models trained beforehand in fl for categorization of healthcare images, specifically using ct scan images. The local models, based on resnet, contribute to the construction of a global model. Pre-trained models, trained on extensive datasets, improve the operational efficiency and classification effectiveness of fl models without compromising data confidentiality.

Keywords: categorization of healthcare images, Federated learning, Models trained beforehand, EfficientNet, Resnet ,CNN2D, COVID-19, sophisticated neural networks.

## I.Introduction:

categorization of healthcare images (MIC) is critical for disease diagnosis, treatment planning, and drug formulation. It plays a vital role in localizing abnormalities in images, such as covid and enables early disease detection, improving patient outcomes. Traditional machine learning (ML) models face privacy concerns when working with medical data. Federated learning(FL) offers a solution by enabling decentralized model training without sharing sensitive patient data.

The present investigation explores the use of pre-trained sophisticated neural networks models in FL for categorization of healthcare images, particularly using computed tomography images. Models trained beforehand, trained on large datasets, help accelerate training and improve operational efficiency in FL systems and privacy concerns.

The study also examines key research questions, including the feasibility of using Models trained beforehand in FL, their impact on classification classification effectiveness, and the effectiveness of combining multiple local models to create a global model.

The objectives of the study include implementing local models based on CNN and EfficientNet, utilizing Models trained beforehand for feature extraction, and evaluating the operational efficiency of the global model.

The results highlight the advantages of Federated learning in preserving information confidentiality while improving classification outcomes.

### 1.1 Motivation

Traditional centralized machine learning models face significant challenges in the medical field, primarily due to **information confidentiality concerns** and **inefficiencies** in handling **heterogeneous data** from multiple institutions. Centralized machine learning often requires gathering vast amounts of sensitive patient data into a single location, raising concerns about **data security**, **privacy violations**. Furthermore, the centralized nature of these systems can be inefficient in terms of data access, and it does not take into account the diverse nature of data across different healthcare institutions, which may use different imaging equipment, protocols, and patient demographics.

In response to these limitations, **Federated learning(FL)** has emerged as a promising solution for **collaborative model training** without compromising **information confidentiality**. By enabling training on decentralized data while keeping the data stored locally, FL allows institutions to maintain control over their sensitive data, which is critical in healthcare.

In parallel, sophisticated neural networks models such as Convolutional Neural Networks (CNNs) and EfficientNet have revolutionized categorization of healthcare images by automatically learning complex, high-level features from medical images. These models, particularly Models trained beforehand, have demonstrated significant potential in medical image analysis by leveraging large-scale datasets and applying transfer learning techniques. EfficientNet, in particular, has shown strong operational efficiency in image classification tasks by efficiently scaling up model parameters while maintaining computational efficiency. The application of Models trained beforehand to medical images, however, still requires fine-tuning to adapt to domain-specific tasks, and training these models on decentralized data adds further complexity.

Our motivation stems from the need to combine the advantages of **Federated learning** with **advanced sophisticated neural networks models** to create a robust, scalable, and privacy-preserving system for **categorization of healthcare images**. While FL ensures information confidentiality, its integration with state-of-the-art models like **EfficientNet** can address operational efficiency issues in heterogeneous data environments.

### 1.2 Objectives

Apply EfficientNet or resnet as a pre-trained local model.

Aggregate local models' parameters using FL to form a robust global classifier.

Evaluate operational efficiency on CT Scan datasets.

Analyze security, efficiency, and diagnostic potential.

**II.Literature survey** categorization of healthcare images (MIC) has undergone significant advancements with the integration of both traditional and sophisticated neural networks techniques. Earlier approaches relied on conventional machine learning models like K-Nearest Neighbor (KNN), Decision Trees (DT), Support Vector

Machines (SVM), and Gaussian Process Regression (GPR) for tasks such as tumor and anomaly detection. These models offered satisfactory operational efficiency on smaller datasets but lacked scalability and robustness when confronted with the complexity of medical images. The advent of sophisticated neural networks architectures, particularly Convolutional Neural Networks (CNN), EfficientNet, ResNet, and Recurrent CNNs, addressed many of these limitations by automating high-level feature extraction and achieving improved classification classification effectiveness. However, these models typically require large volumes of centralized, labeled data, posing a challenge, particularly in the healthcare domain, where privacy regulations and the decentralized nature of medical data make it difficult to use centralized training approaches.

To overcome these challenges, researchers have turned to decentralized, privacy-preserving. Among these, Federated learning(FL) has emerged as a promising solution, enabling collaborative model training without the need to expose sensitive patient data. Federated learning facilitates model development across multiple institutions while keeping data decentralized, making it especially relevant for healthcare applications. Studies by Tripathy et al., Sai et al., and Subashchandrabose et al. have demonstrated the potential of FL in various healthcare contexts. However, much of the existing research on Federated learning in medical image analysis has focused on relatively simple models and has yet to fully exploit the potential of transfer learning using Models trained beforehand.

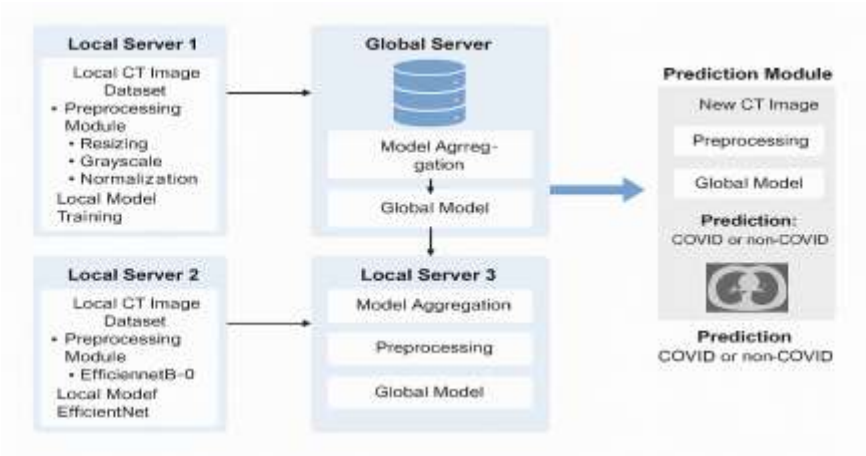
## III.Methodology

### Proposed System

The proposed system leverages a Federated Learning (FL) framework to train local models at distributed nodes, such as healthcare institutions, hospitals, clinics, or edge devices. Each local model is trained on its decentralized dataset, using advanced deep learning techniques like Convolutional Neural Networks (CNN) .The feature extraction enhance the classification process by capturing texture and spatial features that are critical for analyzing medical images. In addition, EfficientNet, a pre-trained deep learning model, is fine-tuned using transfer learning to improve performance, especially when working with small datasets common in medical image classification.

### System Architecture

The system utilizes Federated learning(FL) to train local models at distributed healthcare institutions (e.g., hospitals or clinics) using their private medical data. Each institution trains its own model and shares only model updates (not raw data) with a central server. The server aggregates these updates and creates a global model, which is then sent back to the institutions for further refinement. This iterative process continues until the model reaches optimal operational efficiency.




**1. Data Preprocessing:**

**Local Data Preparation**:
Each healthcare institution (or local node) preprocesses its own medical image data (e.g., CT scans, X-rays). Common preprocessing steps include:

**Image Resizing**: Adjusting the dimensions of the medical images to a uniform size to fit the model input requirements.

**Normalization**: Scaling pixel values to a standard range (typically 0-1) to aid in model convergence.

**Data Augmentation**: Techniques like rotation, flipping, zooming, and shifting to artificially expand the dataset and prevent overfitting.

**Feature Extraction**:
Local models perform feature extraction using CNNs, GLCM (Gray Level Co-occurrence Matrix), and LBP (Local Binary Patterns). These techniques help extract key texture and spatial features from medical images, enhancing the ability to classify medical conditions accurately.

**2. Local Model Training:**

**Model Configuration**:
Each node trains its own local model using the prepared dataset. The local model can be a combination of:

**CNN**: For automatic feature extraction from images.

**EfficientNet**: A pre-trained model fine-tuned using **transfer learning** on the local data for improved operational efficiency.

**Model Training**:
The local models are trained on their datasets independently, without sharing any data with other nodes. During this step, the models learn to recognize medical patterns, such as identifying anomalies in CT scans or distinguishing between COVID and non-COVID images.

**3. Model Updates to the Global Server:**

**Weight Updates**:
After training, only the **model weights and gradients** (not the raw data) are sent to the central global server. This ensures the privacy and security of sensitive patient data.

**SecureTransmission**:
The model updates are transmitted securely using encryption to protect the integrity and privacy of the communication.

**4. Global Model Aggregation:**

**FederatedAveraging**:
The global server aggregates the model updates from all local nodes using the **Federated Averaging (FedAvg)** algorithm. This algorithm averages the weights of the models to create an updated global model. The aggregation step ensures that the global model incorporates knowledge from all local datasets, improving its generalization capabilities.

**Global Model Update**:
Once the global model is updated with the aggregated weights, it is ready for the next iteration of training.

**5. Model Refinement at Local Nodes:**

**Global Model Deployment**:
The updated global model is sent back to the local nodes for further training. Each local node fine-tunes the global model on its own data, allowing the model to adapt to the unique characteristics of the local dataset.

**Iterative Process**:
This process of model update and refinement continues iteratively until the global model converges to an optimal state, achieving the best possible classification effectiveness in categorization of healthcare images tasks.

**6. Model Evaluation:**

**Global Model Evaluation**:
Once the model has been updated and trained through several rounds, the global model is examined on a separate validation dataset to assess its **generalization operational efficiency**. Metrics such as **classification effectiveness**, **sensitivity**, **specificity**, and **F1-score** are used to evaluate the effectiveness of the model.

**operational efficiency Validation**:
If the model performs well across all metrics, it is deemed ready for deployment.

**Algorithms** :

Convolutional Neural Networks (CNN) :

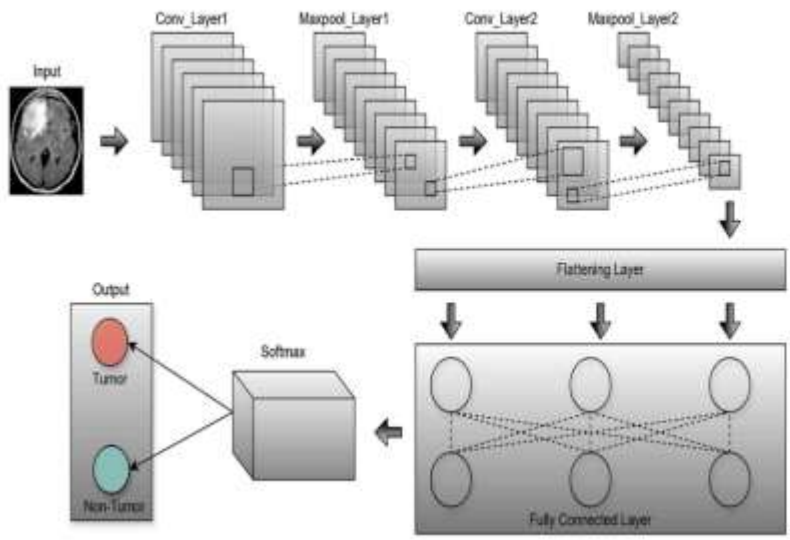
Convolutional Neural Networks (CNNs) are a class of sophisticated neural networks models specifically designed for analyzing visual data, making them highly effective for categorization of healthcare images tasks such as detecting COVID-19 from CT scans. In the context of Federated learning(FL), CNNs are deployed locally at each healthcare institution to process and learn from their private image datasets.

Each CNN extracts hierarchical spatial features from the input images. The early layers detect simple features like edges and gradients, while deeper layers learn more complex structures like organs, lesions, or abnormalities. This makes CNNs well-suited for identifying disease patterns and differentiating between COVID and non-COVID cases.

In FL, CNNs are trained locally on each node's data without sharing patient images. After local training, only the learned model parameters (weights) are sent to a central server, which aggregates them using algorithms like Federated Averaging. This approach ensures information confidentiality while allowing CNNs to contribute to a collaborative global model that benefits from diverse medical data sources.

**CNN for Medical Image Classification :**

This is a simplified Convolutional Neural Network (CNN) designed to classify medical images—such as brain scans—into two categories: **covid**or **Non-covid**. In a Federated learningsystem, this model is trained across multiple hospitals or institutions without sharing any patient images, ensuring privacy. Only the model's learned parameters (like weights) are exchanged.




**Input Layer**

Takes in medical images (e.g., grayscale brain scans).

Each image is a grid of pixel values.

**Convolutional Layers (Conv_Layer1 & Conv_Layer2)**

Extract features from the image using filters.

**Conv_Layer1** detects basic features like edges and lines.

**Conv_Layer2** detects more complex features like textures, shapes.

**Max-Pooling Layers (Maxpool_Layer1 & Maxpool_Layer2)**

Shrink the feature maps to make the model faster.

Retain only the most important features by keeping the maximum values in small sections.

**Flattening Layer**

Converts the 2D data into a 1D vector.

Prepares the data for the next stage—fully connected layers.

**Fully Connected Layer**

Acts like a regular neural network.

Combines all the extracted features to decide whether the scan shows a covid or not.

**Softmax Layer**

Turns the output into probability scores.

EfficientNet :

EfficientNet is a family of convolutional neural networks optimized for both classification effectiveness and efficiency. It uses a compound scaling method that balances depth, width, and resolution, allowing it to achieve high operational efficiency with fewer parameters and computations. In a Federated learningsetup, EfficientNet serves as a pre-trained backbone model at each local node. It is fine-tuned on each institution's dataset (e.g., CT scans), enabling it to adapt to specific features in the medical images while retaining general knowledge. This pre-trained structure speeds up convergence and enhances operational efficiency even with limited local data.

ResNet :

ResNet (Residual Network) is known for its use of skip connections or identity shortcuts, which allow the model to bypass certain layers. This addresses the vanishing gradient problem and enables training of very deep networks. In Federated learning, ResNet can be used locally to capture fine-grained features from medical images, particularly useful for complex patterns like those in lung abnormalities. Its ability to maintain operational efficiency in deeper architectures makes it suitable for enhancing local model robustness, especially when local data varies in complexity.

Federated Averaging (FedAvg):

FedAvg is the core algorithm used to aggregate model updates in Federated learning. After each round of local training, nodes send their updated model weights to the global server. The server then computes a weighted average of these models, typically based on the size of each node's dataset. This updated global model is then redistributed to all nodes for the next round. FedAvg enables collaborative learning without sharing raw data, thus maintaining information confidentiality while progressively improving the global model's classification effectiveness across all participating institutions.

**Prediction :**

To evaluate the practical applicability of the proposed Federated learning-based categorization of healthcare images system, we integrated a prediction module capable of analyzing unseen computed tomography images and identifying COVID or non-COVID cases. The final aggregated global model, trained across multiple decentralized clients, accepts preprocessed grayscale CT images resized to 224×224 pixels. Each input image undergoes normalization and reshaping before being passed to the model. The model returns a class label along with a confidence score, which can assist healthcare professionals in making informed decisions. This prediction functionality was tested using a separate validation set not seen during training, ensuring unbiased operational efficiency assessment.

For demonstration, we deployed the trained global model in a simulated hospital setting, where CT images from local sources were uploaded for real-time inference. A sample prediction on an unseen image yielded the result “COVID”. This output not only confirms the reliability of the model but also showcases its potential for real-world deployment in screening environments.

**Results:**

**1. Precision**

Precision is the proportion of positive predictions that are actually correct. It measures how many of the predicted positive cases are true positives.

**Formula**:

Precision=TP/(TP+FP)

Where:

**TP**: True Positives (correctly predicted positive cases)

**FP**: False Positives (incorrectly predicted as positive)

**2. Recall (Sensitivity or True Positive Rate)**

Recall is the proportion of actual positive cases that are correctly identified by the model. It tells you how good the test is at identifying true positives.

**Formula**:

Recall=TP/TP+FN

Where:

**TP**: True Positives (correctly predicted positive cases)

**FN**: False Negatives (actual positive cases predicted as negative)

**3. F1-Score**

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The F1-Score is the harmonic mean of precision and recall. It gives a balance between the two metrics. It's especially useful when you have an imbalanced dataset.

**Formula**:

F1-Score=2×(Precision×Recall/Precision+Recall)

**4. Confusion Matrix**

A confusion matrix is a table that helps evaluate the operational efficiency of a classification model by showing the counts of true positives, true negatives, false positives, and false negatives.

**Matrix format**:

**TP FP**

**FN TN**

Where:

**TP**: True Positives (correctly predicted positive cases)

**FP**: False Positives (incorrectly predicted as positive)

**FN**: False Negatives (actual positive cases predicted as negative)

**TN**: True Negatives (correctly predicted negative cases)

| | accuracy | precision | recall | F1-score |
|---|---|---|---|---|
| Local server 1 | 0.9076 | 0.9896 | 0.8120 | 0.8920 |
| Local server 2 | 0.9317 | 0.9032 | 0.9573 | 0.9295 |
| Local server 3 | 0.8956 | 0.8321 | 0.9744 | 0.8976 |

**Conclusions:**

The present investigation highlights how combining Federated learning(FL) with pre-trained sophisticated neural networks models can significantly improve the classification of medical images. With FL, hospitals and clinics can train models locally without sharing sensitive patient data—making privacy a top priority. Using Models trained beforehand like CNN and EfficientNet not only speeds up the training process but also boosts the overall operational efficiency of both local and global models. Our findings show that this approach can accurately detect conditions such as tumors or COVID-19 from CT scans, all while keeping patient information secure. In essence, this research shows how privacy-aware AI can be both practical and powerful in real-world healthcare environments.

In the current study, the baseline models of CNN are being used along with some feature engineering techniques, which can be further improvised by advanced sophisticated neural networks techniques like Cross Stage Partial Networks, RepVGG, Normalizer-Free Networks, and other pre trained learning models. The image fusion mechanism over the single classification model could also drive a better global model in Federated learning.

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