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Federated Multi-Modal Deep Learning with Feature Fusion for Lung Disease Classification

S.Nandhinidevi[1]; G.Rajendran[2]

[1]Department of Computer Science, Thiruvalluvar Government Arts College, Rasipuram, Namakkal, Affiliated to Periyar University, Salem – 636 011, Tamil Nadu, India
[2]Department of Computer Science, Government Arts and Science College, Modakkurichi, Erode, Affiliated to Bharathiar University, Coimbatore –641046, Tamil Nadu, India
[1] nandhiniugc@gmail.com; [2] gururajendran@yahoo.com

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Abstract: Lung diseases like COVID-19 and Pneumonia represent a significant global health challenge which need the accurate and timely diagnostic system. Even traditional machine learning and deep learning methods provides a solution using medical images, it depends on consolidating large amounts of data into a centralized location. The centralized data collection process deals different problems such as privacy concern, data cracks and unauthorized access of data due to the medical data are more sensitive. In this proposed work, these problems are addressed by integrating federated learning framework to provide a privacy-preserving distributed learning environment that allows the model to train without sharing medical data. This proposed work introduces a federated learning framework utilizing existing deep learning architectures such as InceptionV3, ResNet50, and DenseNet121. To simulate the distributed environment, the dataset is distributed across three clients and every model is trained in each client. After local models are trained independently, the weights of global model are updated using FedAvg algorithm. Finally, the performance of the three proposed models is evaluated with various metrics such as accuracy, precision, recall, and F1-score. Experimental results shows that DenseNet121 achieves highest performance with the highest classification accuracy as 90%, owing to its dense connectivity and efficient feature reuse capability.

Keywords: Lung Disease, Deep Learning, InceptionV3, Resnet50, DenseNet121 and Federated Learning

I. INTRODUCTION

The lungs are important components of the respiratory system. The lungs are involved in various processes in the human body such as breathing, sustaining oxygen levels in the body, getting out carbon dioxide and maintaining blood pH balance. Respiratory system complications can have a cascading effect, potentially impairing the function of other organs. Environmental influences, such as air pollution, along with personal behaviours such as smoking and inadequate dietary habits, can harm the respiratory system, potentially leading to a range of lung diseases in individuals of all ages. Lung conditions, including pneumonia, COVID-19, and cancer, are among the primary causes of death in the country.

Traditionally, the diagnosis of pulmonary diseases was based on clinical examination, laboratory testing, and assessments of pulmonary function. Medical imaging has emerged as a prominent tool for enhancing early detection, diagnostic precision, and disease monitoring. The only aim of radiological scans processing is to advance the interpretability of the information provided. However radiological images play a vital role in disease prediction and the manual interpretation of radiological images, regularly requires substantial effort and is susceptible to variations between observers, potentially causing delays in essential care procedures. Artificial Intelligence. The main processes in medical image analysis are segmentation, classification, localisation, and detection.

Traditionally radiological images are interpreted manually which requires significant effort and are vulnerable to differences in interpretation among observers potentially creating delays in critical care processes. Artificial intelligence has become a revolutionary element in medical imaging, providing the capability to automate the prediction and classification of lung diseases. Deep learning has been deployed as a transformative technology in medical image classification, enabling significant advancements in automated disease detection and diagnostic accuracy [1]. The integration of deep learning specifically convolutional neural networks, has demonstrably improved the accuracy and efficiency of clinical procedures by separately learning features from multidimensional medical images such as MRI, CT, and X-ray scans [2]. The implementation of the deep learning process, which shifts from manual interpretation to automated analysis significantly minimize the possibility of human error and substantially enhances diagnostic throughput [3]. Deep learning models, predominantly Convolutional Neural Networks, attain high accuracy in the process of disease detection, segmentation, and classification, often outperforming traditional methods by 10-15% in certain detection tasks [4].

However, despite notable performance of deep learning approach in medical image analysis, traditional centralised deep learning approaches have major constraints such as requiring large volumes of training data, data privacy and security, and large memory for centralised training, especially in healthcare applications. These limitations can be overcome by implementing a distributed learning approach [5]. Federated learning is one of the approaches to train a model with a distributed dataset [6]. Federated Learning provides a privacy-preserving framework through distributed learning that empowers collaborative model training without sharing medical data. Therefore, integrating federated learning into lung disease classification systems can improve the robustness, scalability, and clinical applicability of the models.

Multimodal learning supports healthcare professionals for a comprehensive decision-support system by combining patient data, including imaging, medical records, and laboratory results. This integration improves diagnostic accuracy, reduces uncertainty, and assist to prepare the treatment plans.

In this study, a federated multi-modal deep learning framework is introduced which integrates chest X-ray and CT scan images using feature fusion. By leveraging pretrained convolutional neural networks and distributed data, the framework enhances the performance of classification and ensures the patient data privacy. Federated learning empowers collaborative model training across distributed environments without sharing sensitive medical information.

The rest of this paper is structured as follows. Section 2 describes previous and related research on federated learning in medical image classification. Section 3 elaborates the proposed methodology, and Section 4 presents the experiments conducted on the models. Section 5 discusses the attained results during the experiment of the proposed work. Finally, Section 6 concludes the study.

II. LITERATURE REVIEW

The application of deep learning advanced the domain of medical image analysis, especially in the classification of lung diseases, as a result of its special capability to unconventionally extract complete features from complex datasets. [7]. Deep learning models, especially Convolutional Neural Networks are expert to interpret the complex images and also to identify the subtle indicators of disease that might be overlooked by human readers or traditional image analysis techniques [8], [9].Ther are several systems which are particularly valuable for differentiating between various lung diseases, including distinguishing COVID-19 pneumonia from other types of pneumonia and healthy lung tissue, thereby guiding timely and appropriate medical interventions [10], [11]. Transfer learning techniques such as VGG, ResNet, DenseNet, Inception Net, EfficientNet were employed in medical image classification to enhance the performance of classification, regularly trained on extensive public datasets [12]. Even, Deep learning has extensive advancements in medical image classification, it faces some significant challenges like privacy concerns, the requirement of large centralised datasets, and high computational costs to train complex models. Collecting of medical data and aggregating in a central location often raises ethical and legal issues. Also, centralised training leads to bottlenecks and vulnerability to data breaches. To address these challenges, federated learning approach is introduced which facilitate collaborative learning without compromising the data privacy. In federated learning approach, the model is trained in distributed manner using the data residing in distributed environment. It reduces the risk of data leakage and uses the distributed computational resources.

Kumar et al. [13] proposed a multimodal Federated Learning framework for the early diagnosis of pulmonary diseases. The proposed work employed the Flower framework for decentralised training and the FedAvg aggregation method. This proposed architecture incorporates Convolutional Neural Networks for feature extraction and different classifiers, such as Gated Recurrent Units, Long Short-Term Memory with autoencoders, and transfer learning models, such as VGG-19 for classification. Among these classifiers, the FL model with a GRU backbone achieved 98.79% and 97.19% training and validation accuracies respectively.

Durga et al. [14] introduced the FLEM-XAI model, a federated learning model integrated with an explainable AI such as SHAP and Grad-CAM to classify COVID-19, Pneumonia, and Tuberculosis using chest X-ray images. The model architecture includes a comparative analysis of four deep learning models: InceptionV3, Convolution2D, VGG16, and ResNet-50. Among these four, ResNet-50 achieved an accuracy of 97.72% which was higher than that of the other models.

Sawant et al. [15] proposed a federated deep learning model that included the Canis-collie algorithm and bio-inspired optimisation to distinguish between tuberculosis, common pneumonia, and COVID-19. The Canis-collie algorithm addressed the challenge of overlapping features in infected lung images and optimisation enhanced the prediction performance. The model achieved a maximum accuracy of 93.02%.

Srinivasu et al. [16] developed a federated learning framework which incorporated a pre-trained EfficientNet with global aggregation using gRPC protocols for efficient communication of trainable parameters. The performance of this model was assessed using two different datasets: the BR35H dataset and the SARS-CoV-2 CT scan dataset. The proposed global federated model achieved an accuracy of 97.4% for CT scan classification, which is higher than that of the individual local models.

Usharani and Selvapandian [17] proposed FedLRes, an automated system to diagnose lung cancer. The model combined federated learning with the ResNet50 architecture. The Adam optimizer and data augmentation techniques were applied to normalise the variations in the input data. The model influences ResNet50's residual blocks to extract features from 3D CT. The model was evaluated by using the IQ-OTH/NCCD lung cancer dataset, which includes 1,190 CT scan slices categorized into malignant, benign, and normal cases. The framework achieved classification accuracy, precision, and sensitivity of 99.40%, 98.92% and 99.03% respectively.

Liu et al. [18] proposed FedBG, an effective federated learning framework with an Enhanced Classification-GAN algorithm for medical image classification. The methodology used joint optimisation where the generator receives feedback from the classifier through a cross-entropy-based loss function, generating balanced synthetic images that reduce the risk of mode collapse. The model was validated using the Covid-19 Radiography dataset and ChestCOVID datasets which contained images of normal lungs, COVID-19, and viral pneumonia. FedBG achieved 96.23% classification accuracy on the Covid-19 Radiography dataset, with 97% precision 96% recall, and 96% F1-score. On Chest-COVID, it maintained a precision, 94% recall, and F1-score of 95%,94%, and 94% F1-score. Karmakar et al. [19] developed a decentralised diagnostic system for detecting lung diseases. The model is a combination of Federated Learning and customised Convolutional Neural Networks. The model was evaluated with Chest X-ray images and lung masks with three clients and achieved an accuracy of 93.66%, a precision of 92.45%, and recall of 92.87%.

Liu et al. [20] proposed a semi-supervised federated learning framework to address class imbalance and labelled data insufficiency in medical image classification. This method merges regularisation constraints with pseudo-label representations, using a data selector to identify stable unlabelled samples during decentralised training. The model employed a DenseNet121 backbone with dropout layers and random data augmentation to enhance the input representations. The authors utilised the ISIC 2018 dataset for skin lesion analysis, which included 10,015 dermoscopic images in seven diagnostic groups. The model achieved 95.75%, 73.88%, 72.92%, and 72.90% F1-score. The 95.47% specificity and 95.75% AUC showed that regularisation and pseudo-labelling enhanced the diagnostic stability and outperformed traditional federated methods.

Saha et al. [21] designed Lung-AttNet, a compact attention-driven deep learning framework for timely detection of lung cancer within a federated learning environment to retain the privacy of patient data. The model incorporates a standard convolution block with a Lightweight Global Attention Module which comprises 3.749 million parameters and 43 MB size. The authors employed Explainable AI techniques, Grad-CAM and LIME, for visual interpretability. The framework was evaluated with CT-Scan images and achieved 92% global accuracy, 92.27% precision, 92.03% F1-score, and 99% AUC which is higher than ResNet50 and InceptionV3.

A. Heidari et al. [22] proposed a model FBCLC-Rad to recognize the lung cancer from CT-scan images. The model was proposed by combining federated learning and block chain technology to ensure the data privacy and data authenticity. In the evaluation of performance, FBCLC-Rad showed impressive effectiveness in detecting lung cancer, outperforming existing state-of-the-art methods.

In clinical practice, clinician depends on multiple sources of patient data which includes imaging, laboratory results, and medical history, to make accurate diagnoses. To imitate this approach, Multimodal Learning has emerged to combine the heterogeneous data sources to improve the diagnostic accuracy and robustness

Multimodal Federated Learning (MMFL) models [23][24] were proposed for COVID-19 diagnosis by incorporating Electronic Health Records (EHR), CT scans, chest X-ray images, and biochemical data which demonstrate improved performance over unimodal approaches.

Borazjani et al. [25] proposed a federated multimodal learning framework that integrates diverse data types, including mRNA sequences, clinical information and histopathological images. This study proved that combining heterogeneous modalities improves the accuracy and reliability of cancer staging.

Based on the reviewed literature, Federated Learning (FL) occupies a prominent place in analysing medical images such as CT, X-ray and MRI by allowing model training to occur in a decentralised manner, thereby ensuring data privacy. Several studies have effectively utilized existing deep learning frameworks, such as ResNet, EfficientNet, and GAN-based models and achieved notable classification accuracy rates in both centralized and decentralized model training.

However, most existing works focused on single-modality data for multi class classification of disease. Limited research has explored the integration of multiple imaging modalities within a federated learning framework for lung disease classification. This highlights a potential research gap, underscoring the necessity for a federated multi-modal approach to improve diagnostic performance.

III. METHODOLOGY

This section elucidates the proposed federated learning framework implemented for classifying various lung disease using X-ray images and CT-scan images from different hospitals. This methodology includes data preprocessing, data splitting, Local Model training, global model updating, validation and performance evaluation. The work flow of the proposed method is shown in Figure 1.

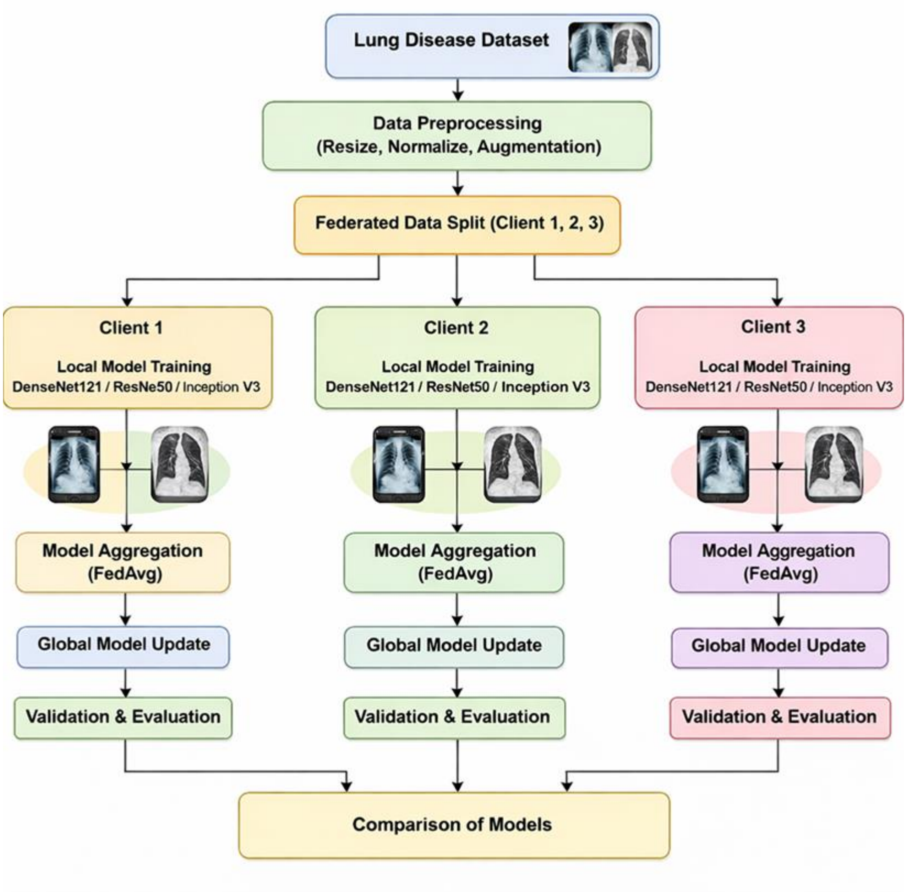

Fig.1. Proposed work Flow

A. *Data Preprocessing*

This proposed study uses a chest X-ray image and CT-image dataset which consists of four different disease classes COVID-19, Bacterial Pneumonia, Viral Pneumonia, Normal. The dataset is separated into training and validation subsets. A conventional data loading pipeline was implemented to confirm robustness. Error handling for corrupted or missing images is performed by substituting them with placeholder images. The images were converted to RGB format before processing. Data augmentation was performed using transformation techniques such as random resized cropping, horizontal flipping, slight rotation, and colour jittering methods to enhance generalisation. All images were normalised using the ImageNet mean and standard deviation values. Figure 2,3,4, and 5 show X-rays of the affected lungs with various diseases and normal lungs and Figure 7,8,9 and 10 show CT-images of affected lungs.

Fig. 2. X-Ray of Covid 19

Fig. 3.X-Ray of Bacterial Pneumonia

Fig.4. X-Ray of Viral Pneumonia

Fig. 5. X-Ray of Normal

Fig. 6. CT of Covid 19

Fig. 7. CT of Bacterial Pneumonia

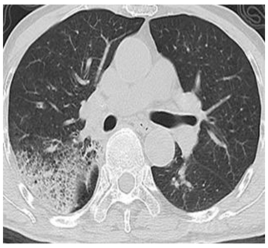

Fig. 8. CT of Viral Pneumonia

Fig. 9. CT of Normal

B. *Models Architecture*

DenseNet-121

A customized DenseNet-121 model was employed as the feature extractor. Transfer learning was applied by freezing the preliminary layers and fine-tuning the advanced layers. Specifically, 50% of the network parameters were unfrozen to adapt to the target domain. Additionally, a channel attention module is combined to enhance the feature representation. It employs both global average pooling and max pooling operations, followed by a shared network to compute channel-wise attention weights. Finally, a customised classifier was added which includes a Global Average Pooling (GAP) layer, fully connected layer with batch normalisation, ReLU activation, and dropout regularization. The final layer outputs the predictions corresponding to the four classes.

Inception-v3

A modified Inception v3 network is employed as the backbone architecture using a transfer learning approach. A partial fine-tuning approach is implemented where the former layers were kept frozen to preserve low-level feature extraction and 40% of the deeper layers were unfrozen. Continuously, Convolutional Block Attention Module (CBAM) is added for enhancing feature representation. The fully connected layer of Inception v3 was replaced by a custom classification head which consist of global average pooling followed by fully connected layers of sizes 1024, 512, 256, and 5, along with batch normalization, ReLU activation, and dropout for regularization. Additionally, the auxiliary classifier of Inception v3 was retained during training to improve gradient flow and stabilize convergence.

ResNet-50

An enhanced ResNet-50 architecture was adopted as the foundation network using a transfer learning approach. ResNet-50 was fine-tuned by freezing the earlier layers and unfreezing the deeper layers to retain low-level feature extraction and adapt higher-level representations to the target dataset. A Convolutional Block Attention Module (CBAM) was inserted after the final convolutional block, incorporating both channel attention (squeeze-and-excitation) to emphasise important feature channels and spatial attention to focus on relevant spatial regions. Additionally, a multi-scale feature extraction mechanism is introduced by applying parallel convolutional layers with kernel sizes 1 x *1, 3 x 3, 5 x *5 and 7 x *7 and concatenating the resulting feature maps to capture information at different receptive fields. Global average pooling and global max pooling were then applied to extract complementary features, which were combined with the multi-scale representations and fed into a fully connected classification head consisting of layers with size of 1024,512,256 and 5, along with batch normalisation, ReLU activation, and dropout for effective regularisation.

C. Loss Function

To address the class imbalance and to improve the model performance during minority classes, the Focal Loss function was employed. It is expressed as Equation (1), where pt refers to the predicted probability of the true class, α_t refers to the balancing parameter, and γ refers to the focussing parameter.

$$FL(p_t) = -\alpha_t\,(1-p_t)^{\gamma} log(p_t) \qquad (1)$$

D. Federated Learning

Federated learning is a decentralized machine learning method in which models are trained in edge devices or servers without transforming local data, ensuring high data privacy. Instead of collecting raw data, devices train a global model locally with their local data and send only encrypted updates to a central server for aggregation.

E. Federated Data split

To simulate the federated learning environment, the dataset was partitioned across three clients. Each client receives a subset of the dataset using a stratified distribution approach to maintain class balance.

F. Local Training

Each model is distributed to clients and trained with the dataset available for the particular clients. The training process includes forward propagation, loss computation using the Focal Loss function, and backpropagation for weight updates. Data augmentation and regularisation techniques were also applied locally to improve generalisation. At the end of the training, each client had updated weights based on the data distribution. The updated weights are transferred to the central server to update the weights in the global model.

G. Model Aggregation

After the completion of local training at each client, the updated model parameters are transmitted to a central server for aggregation. In this study, the Federated Averaging (FedAvg) algorithm is used to aggregate locally trained models into a global model. This approach empowers collaborative learning by maintaining data privacy, as only model weights are shared instead of patient data are shared. The function of FedAvg is expressed in Equation (2) where w_t refers to the global model weight in iteration t, η refers to the learning rate, nk refers to the number of data available at the k^{th}client, n refers to the total number of samples available at the kth client, and g_k refers to the gradient of the loss function computed

$$w_{\{t+1\}} = w_t - \eta \sum_{\{k=1\}}^{\{k\}} \frac{n_k}{n}\, g_k \qquad (2)$$

IV. Experimental Result

All the models are trained for a total of 30 epochs with a batch size of 12 for training and 24 for validation using the AdamW optimizer with a differential learning rate strategy to effectively fine-tune the model. A lower learning rate of $5 \times 10^{-6}$is assigned to the pretrained backbone layers to retain previously learned feature representations and a higher learning rate of $1 \times 10^{-4}$is used for the newly added layers to enable faster adaptation to the target dataset. Learning rate is dynamically adjusted during the training with the help of ReduceLROnPlateau scheduler to achieve better convergence. And also, early stopping approach with a patience of 15 epochs is implemented to prevent from overfitting by halting training when there is no significant improvement in validation performance. The three models are validated using four performance metrics such as accuracy, precision, Recall and F1-Score. Every model's performance in every epoch is represented in Figure 6, 7 and 8 respectively.

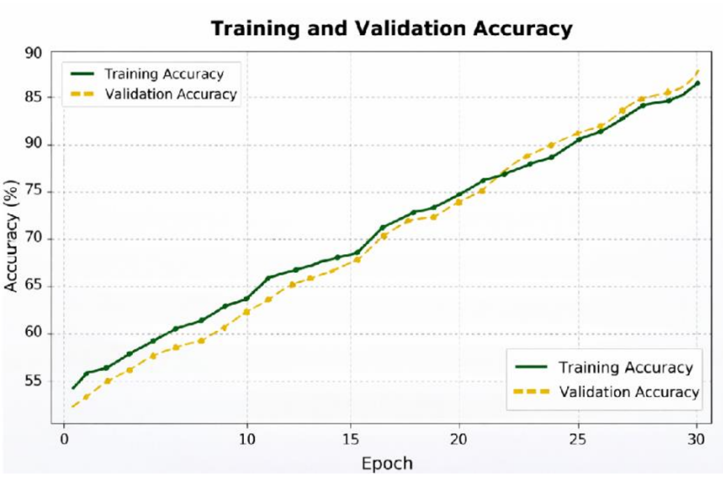

Fig.6. Inception-v3 Accuracy

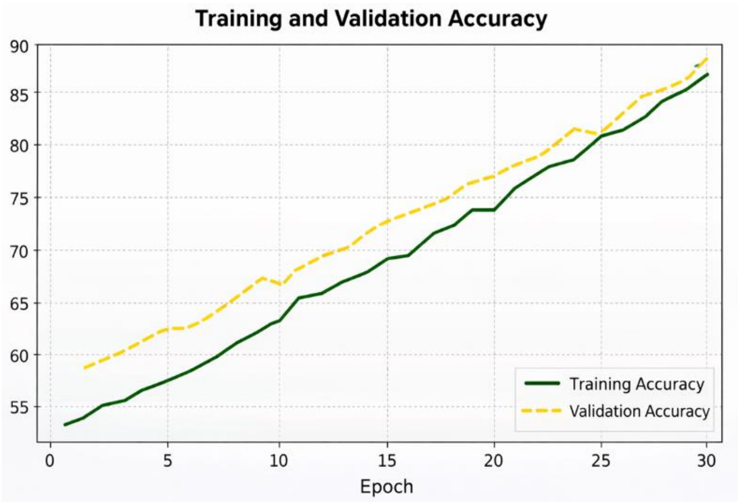

Fig.7. Resnet50 Accuracy

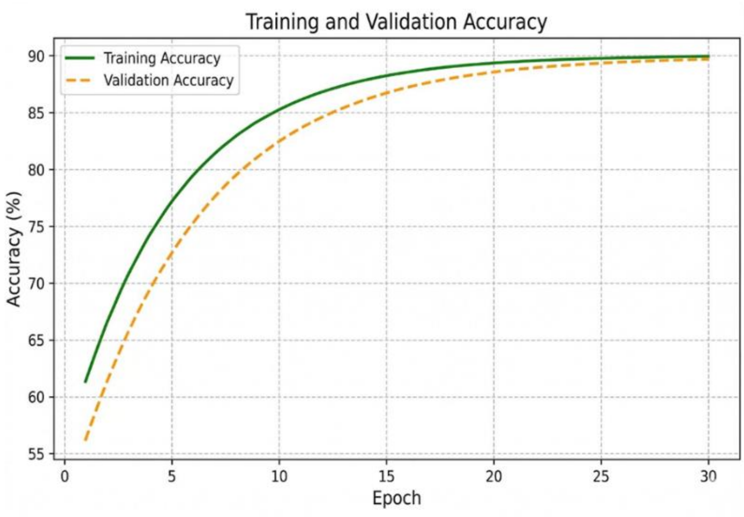

Fig.8. DenseNet121 Accuracy

V. Result and Discussion

The performance of the three deep learning models—DenseNet121, ResNet50, and Inception-V3 was evaluated in a federated learning environment across four primary metrics: Accuracy, Precision, Recall, and F1-score. The comparative results are detailed in the chart below and summarised in Figure 9.

According to the experimental findings, DenseNet121 yielded the best results across all assessed metrics. It achieves a training accuracy of 90% and a, validation accuracy of 90% which is greater than those of ResNet50 and InceptionV3 by approximately 2% and 3%, respectively. Additionally, DenseNet121 demonstrated the most balanced performance, with a precision of 90.21% and recall of 90.05%, resulting in an impressive F1-score of 90.13%. The results confirm that federated learning allows for high-accuracy lung disease classification (reaching 90% with DenseNet121) without storing patient data in a central repository and sharing the data.

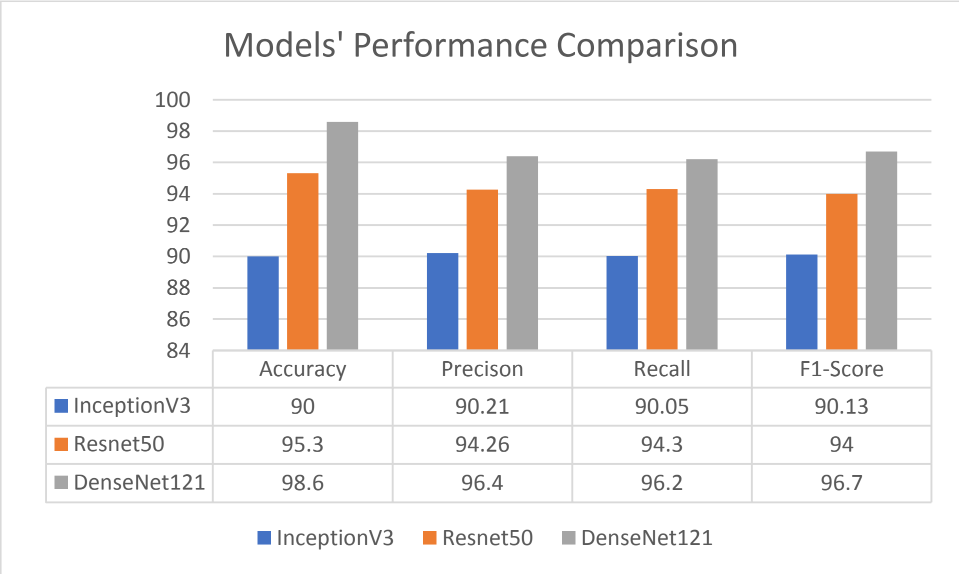

Fig.9. Models' Performance Comparison

VI. Conclusion

This study has introduced a federated learning framework using a transfer learning approach with three deep learning models, InceptionV3, ResNet50 and DenseNet121 for lung diseases classification. Unlike conventional approaches that rely on a single imaging modality, this work incorporates a multi-modal framework by utilizing both X-ray and CT-scan images, enabling the model to learn complementary features from different diagnostic sources. Experiments are conducted in a federated learning setup with three clients, where each client trained the models locally with their dataset to avoid the exchange of sensitive data. Among the three models, Densnet121 provided the best results for all assessed metrics. The results, confirm that the federated learning framework with the densnet121 architecture can handle large amounts of distributed data and is well suited for real world deployment in healthcare applications.

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