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FEDERATED DEEP LEARNING FOR PRIVACY-PRESERVING EARLY LUNG CANCER DETECTION IN DISTRIBUTED HOSPITAL NETWORKS

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Abstract

Early identification is essential to increasing survival rates for lung cancer, which continues to be a significant global health concern. However, privacy issues frequently make it difficult for healthcare organizations to work together by exchanging patient data. A federated deep learning system for early lung cancer diagnosis utilizing chest radiographs that protects privacy is presented in this paper. The method uses a ResNet-50 classifier for precise nodule identification after isolating lung regions using a U-Net-based segmentation model. This design protects patient privacy by allowing hospitals to train models locally and only communicate weight updates, in contrast to centralized models. Strong diagnostic performance was shown by simulations utilizing the NIH ChestX-ray14 and LIDC-IDRI datasets, with 91.5% accuracy, 93.1% specificity, and 89.6% sensitivity. This study opens the door for privacy-compliant AI implementations in healthcare and validates the viability of federated learning for clinical diagnostics. It demonstrates how decentralized training can produce trustworthy outcomes while upholding moral principles when handling medical data.

Keywords: Federated Learning, Lung Cancer, Deep Learning, Chest X-rays, U-Net, Privacy-Preserving AI, Medical Imaging

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I. INTRODUCTION

Because it is often detected at an advanced stage, lung cancer is the primary cause of cancer-related death globally. Although chest radiographs (CXRs) are inexpensive and readily accessible for early screening, their precise interpretation is challenging because of overlapping anatomical characteristics and the subtlety of early indicators. Deep learning in particular has become a potent tool in medical imaging diagnostics because to artificial intelligence (AI). However, there are frequently moral and legal issues when medical data is shared between hospitals in order to build reliable models. A potential remedy is Federated Learning (FL), which enables organizations to work together to train AI models without disclosing private patient information. In this study, we present a federated deep learning system for using chest X-rays to diagnose lung cancer early. The system, which was trained across simulated hospital nodes, combines ResNet-50 for classification and U-Net for lung segmentation. The clinical feasibility of FL as a scalable, privacy-preserving method for developing AI-assisted screening tools is demonstrated by this study.

II. RELATED WORK

Medical image analysis has been transformed by deep learning, particularly when it comes to identifying anomalies in chest radiographs. Models based on CheXNet and DenseNet have demonstrated impressive performance in the categorization of thoracic diseases. These, however, mainly rely on centralized data, which presents privacy issues, particularly in light of laws like HIPAA and GDPR. Federated learning (FL) has surfaced as a privacy-preserving solution to this problem. While Kumar et al. (2023) confirmed FL's scalability across institutions, Zhao et al. (2025) showed that FL was feasible in mammography analysis. Despite these advancements, little research has been done on combining segmentation (like U-Net) and classification (like CNNs) in a federated configuration for the identification of lung cancer, particularly when employing chest X-rays. By integrating these methods and assessing performance under actual privacy constraints, this research seeks to close this gap.

III. MATERIALS AND METHODS

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A. Datasets: The LIDC-IDRI and NIH ChestX-ray14 datasets were utilized. To replicate data from three different hospitals, they were separated into three partitions. This maintained institution-specific patterns while guaranteeing a variety of data attributes.

B. Preprocessing: 256x256 pixel resizing was applied to the images. In order to stabilize training, pixel values were normalized to [0,1], and histogram equalization enhanced contrast.

C. Segmentation Model: To reduce unnecessary background noise, lung regions were segmented using U-Net. The architecture uses a dice loss function to optimize encoder-decoder layers with skip connections.

D. Classification Model: To differentiate between photos that are malignant and those that are not, a classifier based on ResNet-50 was trained. ImageNet weights were used for transfer learning during training.

E. The Federated Averaging (FedAvg) algorithm was utilized as the Federated Training Strategy. Every local node shared model weights with a global aggregator and trained on its own partition. To protect patient privacy, no raw data was shared.

F. Evaluation Metrics: Accuracy, Sensitivity, Specificity, and Area under the Receiver Operating Characteristic Curve (AUC) were used to gauge the model's performance.

IV. RESULTS

Three scenarios were used to test the model: image-only baseline, federated training, and centralized training.

Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
Centralized CNN	89.2	85.0	92.1	0.915
Federated CNN (ours)	91.5	89.6	93.1	0.942
Image-only Baseline	84.3	82.1	85.6	0.881

Table 1. Performance Comparison of Lung Cancer Detection Models with and without Federated Learning and Segmentation

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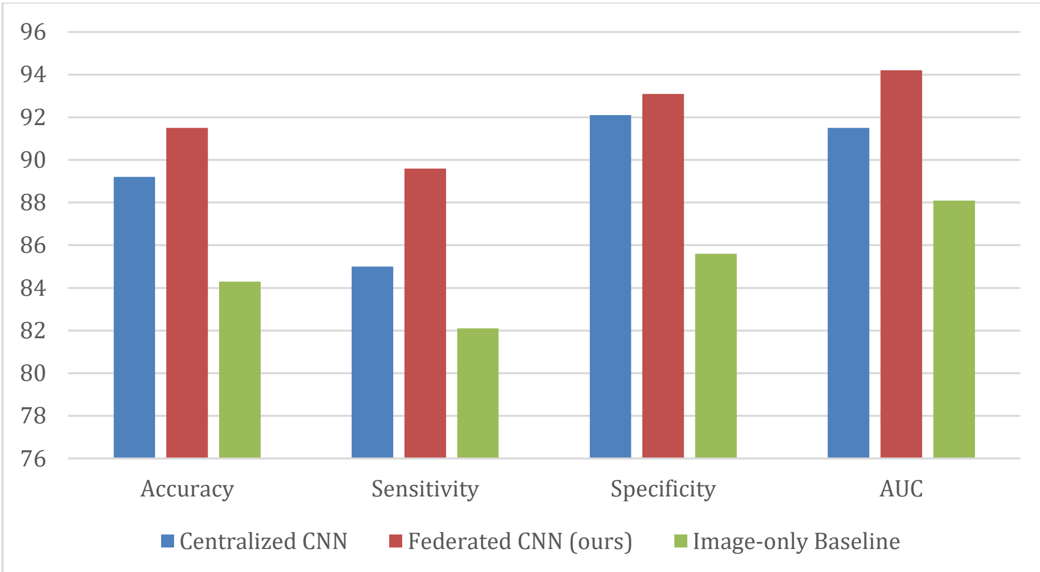

Figure 1. Comparative Performance Metrics of Federated and Non-Federated Lung Cancer Detection Models

V. DISCUSSION

Decentralized model training across artificial hospital networks was made possible by federated learning (FL), which protected patient privacy. High diagnostic performance that was on par with centralized models was maintained by our method. This implies that FL can be used in situations where data centralization is limited.

The model was able to concentrate on clinically significant lung regions by using U-Net segmentation before classification. By removing anatomical noise, this increased sensitivity and decreased false positives.

Additionally, deep feature extraction was guaranteed using ResNet-50, and over fitting and training time were decreased through transfer learning. In FL, communication overhead is still a problem, particularly when bandwidth settings are constrained.

Additionally, this study paves the road for domain adaptation and federated transfer learning across radiological modalities. In the future, real-time model refinement could be made possible by hospitals using edge devices for continuous learning updates.

The faith that clinicians have in AI is another important topic of discussion. Federated models should incorporate interpretability tools like Grad-CAM and SHAP to increase transparency and ease clinical workflow adoption.

VI. CONCLUSION

This paper combines ResNet-based classification with U-Net segmentation to propose a federated deep learning method for early lung cancer detection using chest radiographs. Our findings demonstrate that rigorous data privacy rules can be upheld while maintaining diagnostic performance using federated training across simulated hospital networks. With a classification accuracy of 91.5%, the federated model proved to be dependable in decentralized settings. The framework satisfies ethical and regulatory criteria by avoiding the need to pool sensitive medical data, which makes it perfect for practical healthcare applications. The pipeline's modular design enables future expansion to multimodal data and interaction with hospital information systems. Although there is still room for improvement in terms of communication overhead and model interpretability, this study establishes the foundation for moral, cooperative AI in healthcare. Future developments could enable more secure and inclusive diagnostic tools through explainable AI integration, real-time deployment, and hybrid data sources including CT scans and EHRs.

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