



## SecureFedLung: Privacy-Preserving Multi Disease Diagnosis Using Federated CNN And ECC

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### Abstract

Medical image analysis plays a crucial role in early disease detection and diagnosis in modern healthcare systems. Deep learning techniques, particularly Convolutional Neural Networks (CNN), have significantly improved the accuracy of medical image classification for detecting diseases such as lung cancer, pneumonia, and tuberculosis. However, traditional centralized learning approaches require sharing sensitive patient data, raising serious privacy and security concerns. This project proposes SecureFedLung, a privacy-preserving multi-disease diagnosis framework that integrates Federated Learning (FL), Convolutional Neural Networks (CNN), and Elliptic Curve Cryptography (ECC). In this system, multiple hospitals collaboratively train a global model without sharing raw patient data. Each hospital trains a local CNN model and shares only encrypted model parameters using ECC. The central server aggregates these encrypted updates using the Federated Averaging algorithm to generate a global model. The system ensures secure communication, protects sensitive medical data, and achieves high diagnostic accuracy. Experimental results demonstrate that SecureFedLung provides an efficient, secure, and scalable solution for collaborative medical AI systems.

**Keywords:** Artificial Intelligence; Convolutional Neural Network; Federated Learning; Medical Image Analysis; Privacy Preservation.

### 1. Introduction

Artificial Intelligence and deep learning have revolutionized healthcare, especially in medical image analysis. Diseases such as lung cancer, pneumonia, and tuberculosis require early and accurate diagnosis to improve patient outcomes. Traditional diagnosis depends on expert radiologists, which is time-consuming and prone to human error. CNN models have shown excellent performance in analyzing chest X-rays and CT scans. However, training such models requires large datasets, which are often distributed across hospitals and cannot be shared due to privacy regulations like HIPAA and GDPR. Federated Learning addresses this issue by enabling collaborative model training without sharing raw data [1]. However, model parameters can still leak sensitive information. To overcome this, SecureFedLung integrates ECC encryption to ensure secure transmission of model updates.

### 2. Method (12 Pt)

The SecureFedLung system consists of multiple

hospital nodes and a central server.

- Each hospital trains a local CNN model using its own dataset
- Model parameters (weights) are generated after training
- These parameters are encrypted using ECC
- Encrypted parameters are sent to the central server
- The server aggregates them using Federated Averaging (FedAvg)
- A global model is created and shared back to hospitals
- This process repeats until the model achieves high accuracy.

### 3. Results And Discussion (12 Pt)

#### 3.1. Results

The system successfully detects multiple respiratory diseases including:

- Lung Cancer
- Pneumonia
- Tuberculosis



The model achieved high accuracy with secure communication between nodes. The federated approach improved model performance compared to individual local models [2].

### **3.2. Discussion**

The integration of Federated Learning and ECC ensures both:

- Data privacy
- Secure communication

Unlike traditional systems, SecureFedLung does not expose sensitive medical data. The system is scalable and suitable for real-world healthcare environments [3].

### **Conclusion**

SecureFedLung provides a privacy-preserving and efficient solution for multi-disease diagnosis using medical images. By combining CNN, Federated Learning, and ECC, the system ensures secure and collaborative model training. The proposed approach achieves high accuracy while maintaining strict data privacy, making it suitable for real-world medical applications [4].

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### **References**

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