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Automated Multi-Class Lung Disease Classification Using Deep Learning with Transfer Learning Approach

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ABSTRACT: Lung diseases such as Pneumonia and Tuberculosis are major health concerns worldwide, and early detection is essential for effective treatment. Manual analysis of chest X-ray images can be time-consuming and may lead to diagnostic errors. This project proposes an automated lung disease classification system using deep learning and transfer learning techniques. A pretrained ResNet18 Convolutional Neural Network (CNN) model is used to classify chest X-ray images into three categories: Normal, Pneumonia, and Tuberculosis. The model is implemented using the PyTorch framework with transfer learning, where the final layers are fine-tuned for improved classification performance. Image preprocessing techniques such as resizing, normalization, random horizontal flipping, and random rotation are applied to improve model generalization and reduce overfitting.

A Streamlit-based web application is developed to provide real-time chest X-ray image upload, disease prediction, confidence score display, and visualization of training results. Experimental results show that the proposed system achieves a test accuracy of 96.15% with high precision, recall, and F1-score values, demonstrating the effectiveness of the ResNet18 model for automated lung disease detection.

I. INTRODUCTION

Lung diseases such as Pneumonia and Tuberculosis are major health problems affecting millions of people worldwide. Early diagnosis is essential for effective treatment and reducing mortality rates. Chest X-ray imaging is one of the most widely used techniques for detecting lung diseases because it is fast, cost-effective, and easily accessible. However, traditional diagnosis mainly depends on radiologists to manually analyze X-ray images, which can sometimes be time-consuming and prone to human error.

Recent advancements in Artificial Intelligence (AI) and Deep Learning have enabled automated disease detection with high accuracy. In this project, a ResNet18 deep learning model with transfer learning is used to classify chest X-ray images into three categories: Normal, Pneumonia, and Tuberculosis. The system is implemented using the PyTorch framework and integrated with a Streamlit-based web application for real-time prediction, confidence score display, and visualization of training results.

II. EXISTING SYSTEM

Traditional lung disease diagnosis is mainly performed manually by radiologists using chest X-ray images to identify abnormalities related to diseases such as Pneumonia and Tuberculosis. Earlier automated systems used traditional machine learning algorithms such as Support Vector Machine (SVM), k-Nearest Neighbour (kNN), and Random Forest, which required manual feature extraction and often achieved lower accuracy compared to modern deep learning-based approaches.

Disadvantages:

- Time-consuming manual diagnosis.
- Requires experienced radiologists.
- Possibility of human error and misdiagnosis.
- Traditional machine learning methods require manual feature extraction.
- Lower accuracy compared to deep learning approaches.

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III. RESEARCH GAP

Many existing lung disease detection systems mainly focus on binary classification, such as distinguishing only Normal and Pneumonia cases, while very few systems perform multi-class classification involving Normal, Pneumonia, and Tuberculosis together. Some deep learning models such as ResNet50 and VGG16 require high computational resources and longer training time. In addition, many existing systems do not provide a simple graphical interface for real-time prediction. Therefore, there is a need for a lightweight, accurate, and user-friendly deep learning system that can efficiently classify multiple lung diseases.

IV. PROPOSED SYSTEM

The proposed system is an automated multi-class lung disease classification system that uses deep learning and transfer learning techniques to classify chest X-ray images into three categories: Normal, Pneumonia, and Tuberculosis. The system uses the pretrained ResNet18 Convolutional Neural Network (CNN) model as the feature extractor. Transfer learning is applied by fine-tuning the final residual block (Layer 4) and the fully connected classification layer, while earlier layers retain pretrained ImageNet features. The model is trained using the PyTorch framework with image preprocessing and data augmentation techniques to improve performance and generalization. A Streamlit-based web application is integrated to provide real-time disease prediction, confidence scores, and visualization of training results.

Key Features

- Uses pretrained ResNet18 with transfer learning for efficient classification.
- Performs three-class classification: Normal, Pneumonia, and Tuberculosis.
- Applies selective layer fine-tuning for reduced training cost and improved accuracy.
- Uses Adam optimizer, Cross-Entropy Loss, batch size 16, and 20 training epochs.
- Includes data augmentation techniques such as random horizontal flip and random rotation.
- Provides real-time prediction and confidence score display through a Streamlit GUI.
- Displays training accuracy, loss graphs, and evaluation metrics.

Advantages:

- Achieves high classification accuracy with efficient training performance.
- Provides accurate detection of Tuberculosis and Pneumonia from chest X-ray images.
- Reduces dependency on manual diagnosis by radiologists.
- Offers a user-friendly interface for healthcare applications.
- Supports deployment on standard CPU or GPU systems.

V. SYSTEM ARCHITECTURE

The proposed lung disease classification system follows a sequential pipeline for detecting diseases from chest X-ray images. Initially, the chest X-ray dataset containing Normal, Pneumonia, and Tuberculosis images is collected and preprocessed using image resizing (224 × 224), normalization, and data augmentation techniques such as random rotation and horizontal flipping. The dataset is then divided into training, validation, and testing sets. The preprocessed images are passed to the ResNet18 deep learning model using transfer learning with pretrained ImageNet weights, where only Layer4 and the fully connected layer are fine-tuned for classification. The extracted features are passed through the classification layer with Softmax activation to predict one of the three classes: Normal, Pneumonia, or Tuberculosis. Finally, the prediction result along with the confidence score is displayed through a Streamlit-based graphical user interface.

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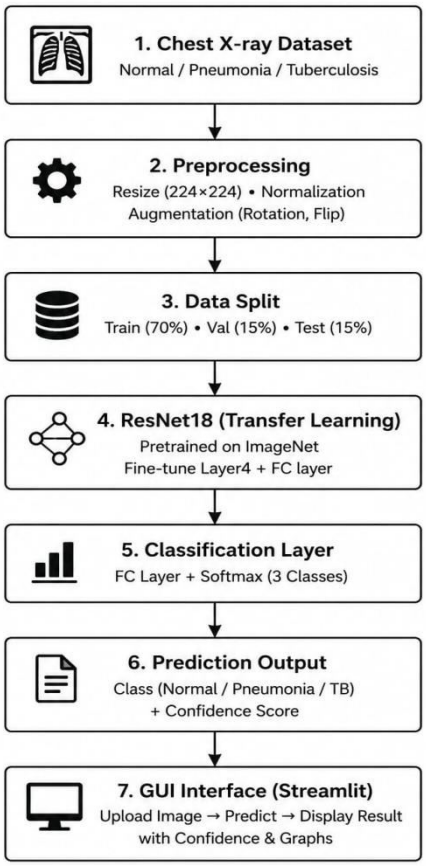

Figure 5.1.1 System Architecture (ResNet18)

VI. METHODOLOGY

A. Data Collection

Chest X-ray images are collected and organized into three classes: Normal, Pneumonia, and Tuberculosis. The dataset is obtained from publicly available sources including the NIH Chest X-ray Dataset, Kaggle Chest X-ray Pneumonia Dataset, and Tuberculosis datasets from Montgomery County and Shenzhen Hospital. The dataset is divided into training (~2,100 images), validation (~300 images), and test sets (675 images with 225 images per class) to ensure balanced model evaluation.

B. Data Preprocessing

Before training, all images are resized to 224 × 224 pixels, converted into tensors, and normalized using ImageNet mean and standard deviation values. Data augmentation techniques such as Random Horizontal Flip and Random Rotation (±5°) are applied to improve model generalization and reduce overfitting. These preprocessing steps help the model learn better feature representations from chest X-ray images.

C. Model Architecture — ResNet18

ResNet18 is used as the deep learning model for lung disease classification. It uses residual (skip) connections to improve training efficiency and overcome the vanishing gradient problem. The architecture consists of convolution layers, residual blocks, global average pooling, and a fully connected classification layer. In this project, the original ImageNet classification layer is replaced with a Linear(512, 3) layer to classify Normal, Pneumonia, and Tuberculosis images.

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Transfer Learning
The model uses pretrained ImageNet weights (ResNet18_Weights.DEFAULT) for transfer learning. Most convolution layers are frozen, while Layer4 and the final fully connected layer are trained for the classification task. This approach reduces training time, improves accuracy, and minimizes overfitting.

D. Training Process
The model is trained using the Adam optimizer with a learning rate of 0.001 and Cross-Entropy Loss. A batch size of 16 is used for training and 32 for testing. The model is trained for 20 epochs using either CUDA GPU or CPU. The best model is saved as best_model.pth, while the latest trained model is stored as model.pth. During training, the model achieved a peak training accuracy of 95.08% at Epoch 18 with stable loss reduction.

E. Prediction System
The trained ResNet18 model is integrated with a Streamlit web application for real-time prediction. Users can upload chest X-ray images in JPG, JPEG, or PNG format. The application preprocesses the image, performs prediction, and displays the predicted disease class, confidence score, probability values for each class, training graphs, and evaluation metrics dashboard. This provides an easy-to-use interface for lung disease detection and visualization.

VII. MODULE DESCRIPTION

1. Dataset Collection Module
Loads and organizes chest X-ray images into Normal, Pneumonia, and Tuberculosis classes using PyTorch ImageFolder and DataLoader.

2. Data Preprocessing Module
Performs image resizing, normalization, tensor conversion, and data augmentation techniques such as horizontal flip and rotation.

3. Model Training Module
Implements the ResNet18 deep learning model with transfer learning. The model is trained using Adam optimizer and Cross-Entropy Loss for multi-class classification.

4. Disease Predicton Module
Processes uploaded chest X-ray images and predicts the disease category with confidence scores and probability values.

5. GUI Modul
Provides a Streamlit-based web interface for image upload, prediction display, probability visualization, training graphs, and evaluation metrics.

VIII. RESULTS AND DISCUSSION

The proposed ResNet18-based system is evaluated on a balanced test set of 675 images (225 per class) using standard classification metrics: accuracy, precision, recall, and F1-score. The results are summarized in Table 1.

Table 8.1 Test Evaluation Metrics

Metric	Value
Accuracy	96.15%
Precision (weighted)	0.96
Recall (weighted)	0.96
F1-Score (weighted)	0.96

The model achieves a peak training accuracy of 95.08% in Epoch 18, with the training loss decreasing from 0.4698 (Epoch 1) to 0.1365 (Epoch 20), confirming steady convergence. Class-wise evaluation reveals that the Tuberculosis class achieves perfect scores (precision = recall = F1 = 1.00 at support 225), reflecting the clear radiological differences of TB. The Normal and Pneumonia classes achieve precision and recall in the range 0.94–0.95. The confusion matrix [213, 11, 1 | 13, 212, 0 | 0, 1, 224] indicates that the primary misclassification occurs between Normal and Pneumonia,

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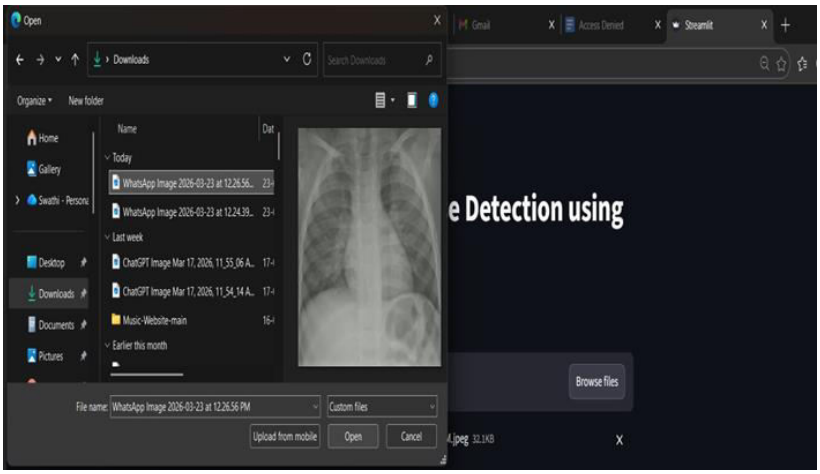
which is clinically expected given their overlapping early-stage radiological features. The model demonstrates stable, consistent performance across all three classes with no significant overfitting.

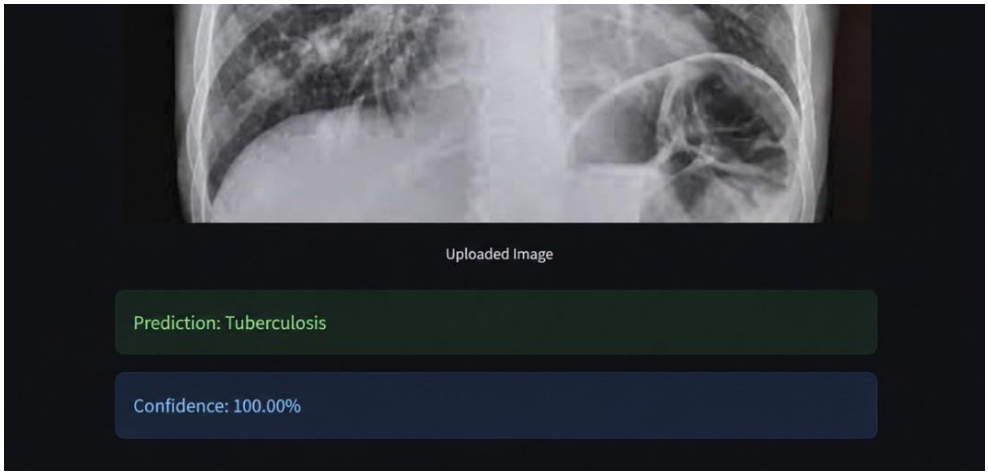
The following screenshots illustrate the step-by-step workflow of the Streamlit-based GUI:

1. UPLOAD THE IMAGE

2. SELECTING THE IMAGE



3. PREDICTION RESULT WITH CONFIDENCE



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4. TEST EVALUATION METRICS

IX. CONCLUSION

This project successfully developed a lung disease classification system using the ResNet18 deep learning model with transfer learning to classify chest X-ray images into three categories: Normal, Pneumonia, and Tuberculosis. The model achieved a test accuracy of 96.15% with strong precision, recall, and F1-score values, demonstrating that the proposed system can effectively classify lung diseases from chest X-ray images. The Streamlit web application provides an easy-to-use interface for real-time disease prediction along with confidence scores and evaluation metrics, helping support faster and more reliable medical diagnosis.

In future work, the system can be further improved by using larger datasets, adding more disease categories, and implementing advanced deep learning models to enhance overall performance and clinical applicability.

X. FUTURE ENHANCEMENTS

- Expand the system to detect additional lung diseases such as COVID-19, Lung Cancer, Atelectasis, and Pleural Effusion.
- Integrate Grad-CAM visualization to highlight important regions in chest X-ray images and improve prediction interpretability.
- Experiment with advanced deep learning models such as EfficientNet and Vision Transformers for improved classification accuracy.
- Develop a mobile application for portable and real-time disease prediction.
- Add DICOM image support for better compatibility with hospital radiology systems.
- Deploy the application on cloud platforms for scalable multi-user access.
- Improve the system using larger medical datasets to enhance model generalization and robustness.
- Integrate the system with healthcare management platforms for clinical assistance and automated reporting.

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