Chest X-Ray Image Classification

Project Report

Abstract

Chest X-ray imaging is an essential diagnostic tool for identifying respiratory conditions such as pneumonia, tuberculosis, and lung cancer. This project explores the use of deep learning and transfer learning techniques to classify chest X-ray images into distinct categories, aiming to assist clinicians in accurate and efficient diagnosis. The dataset was preprocessed by normalizing pixel values and converting labels into numerical formats using one-hot encoding. Models including DenseNet201, ResNet152V2, VGG19, and a custom CNN architecture were evaluated. Experimental results demonstrated that ResNet152V2 achieved the highest classification accuracy of 94%, closely followed by VGG19 at 93%. Simpler models like the custom CNN also performed well on this moderately complex dataset, showing the trade-off between model complexity and performance. The project underscores the potential of transfer learning in medical imaging and highlights the need for further exploration of ensemble methods, larger datasets, and integration into clinical workflows.

Introduction

Chest X-ray imaging plays a critical role in diagnosing various respiratory conditions. This project focuses on building a deep learning-based classification model to distinguish between normal and diseased chest X-ray images. By leveraging transfer learning techniques and advanced neural networks, the goal is to create a robust system that can assist clinicians in accurate diagnosis.

Background

Chest X-rays are a common diagnostic tool for detecting diseases such as pneumonia, tuberculosis, and lung cancer. However, manual analysis of these images can be time-consuming and prone to human error. This project explores the application of convolutional neural networks (CNNs) for automated classification to address these challenges.

Dataset

The dataset consists of labeled chest X-ray images categorized into different classes:

- **Normal**
- **Pneumonia**
- **Other Conditions**

Key Features:

- Preprocessed images resized to a uniform dimension.
- Grayscale and RGB formats used depending on the model.
- Splits: Training, Validation, and Test sets.

Data Preprocessing

1. **Normalization**: Pixel values were scaled to the range [0,1] by dividing each pixel by 255.
2. **Label Encoding**: One-hot encoding was used to convert categorical labels into numerical format.
3. **Image Format**:
   - Grayscale images for Models 1 and 2.
   - RGB images for Models 3 and 4.

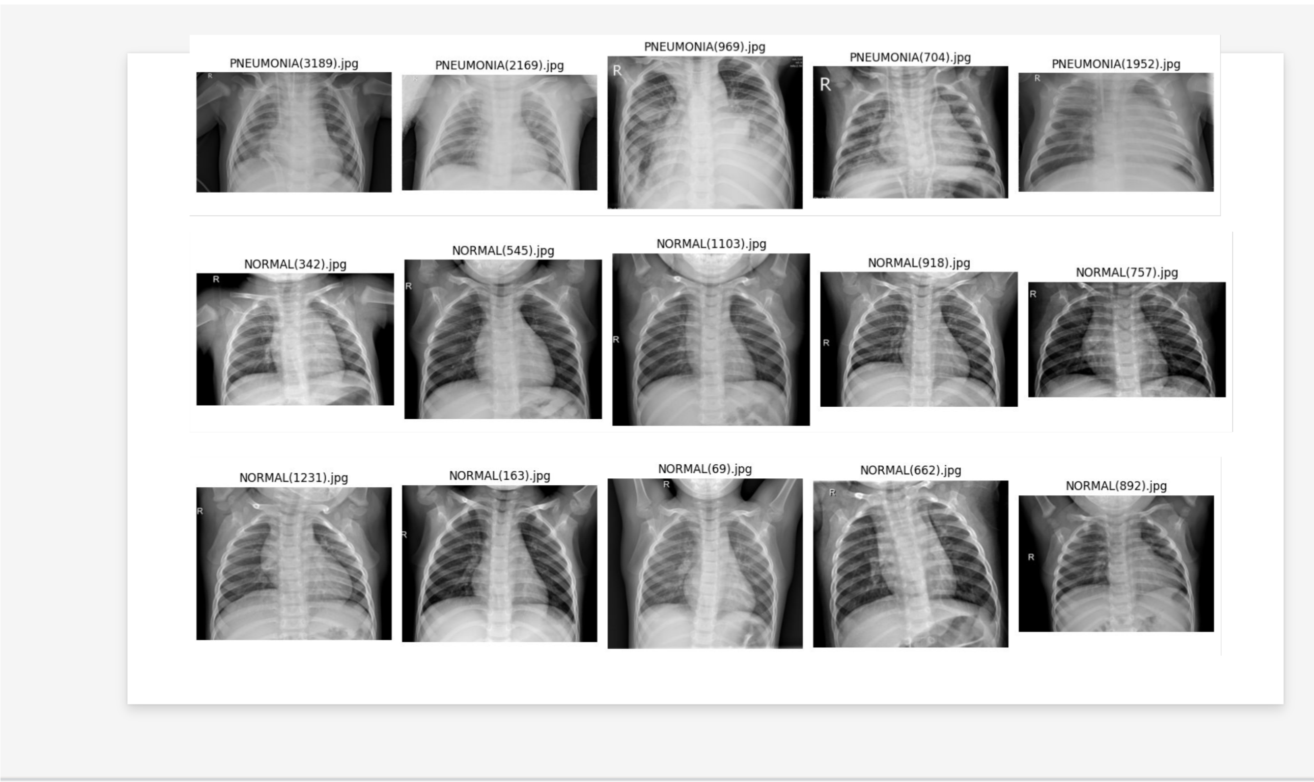

Figure 1: Enter Caption

Methodology

Models

Model 1

- Sequential architecture with Conv1, MaxPool1, Conv2, MaxPool2, Conv3, MaxPool3 layers.
- Flattening and two fully connected Dense layers.
- Trainable parameters: **319,350**.

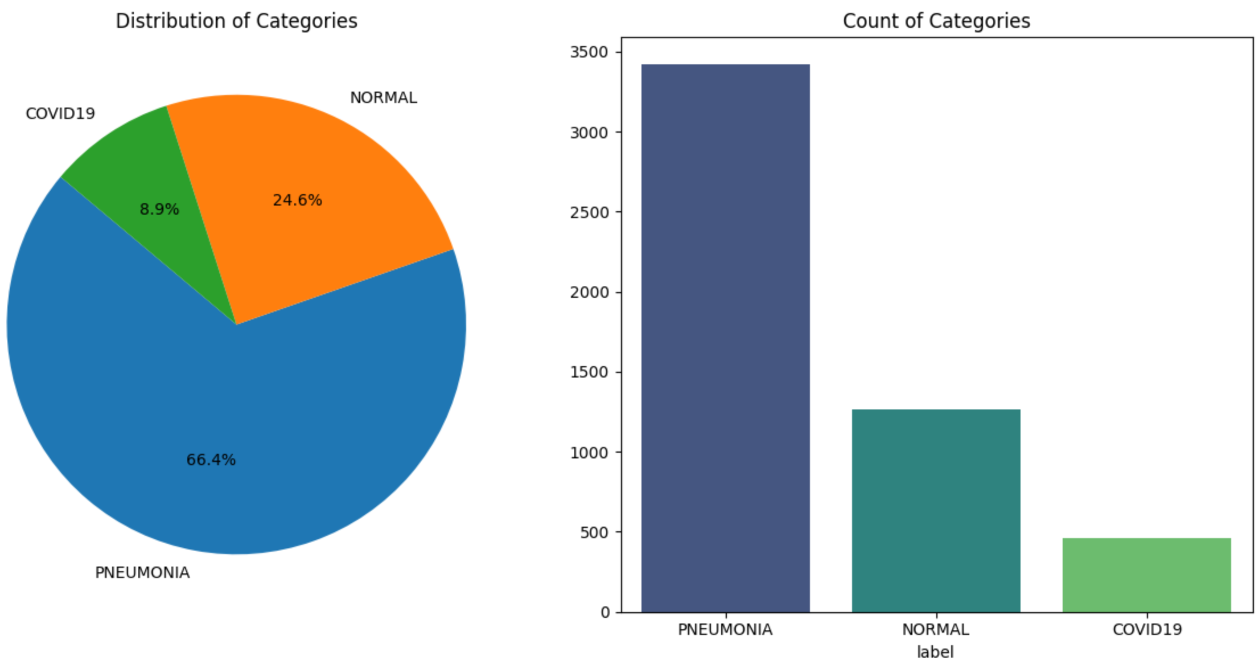

Figure 2: Enter Caption

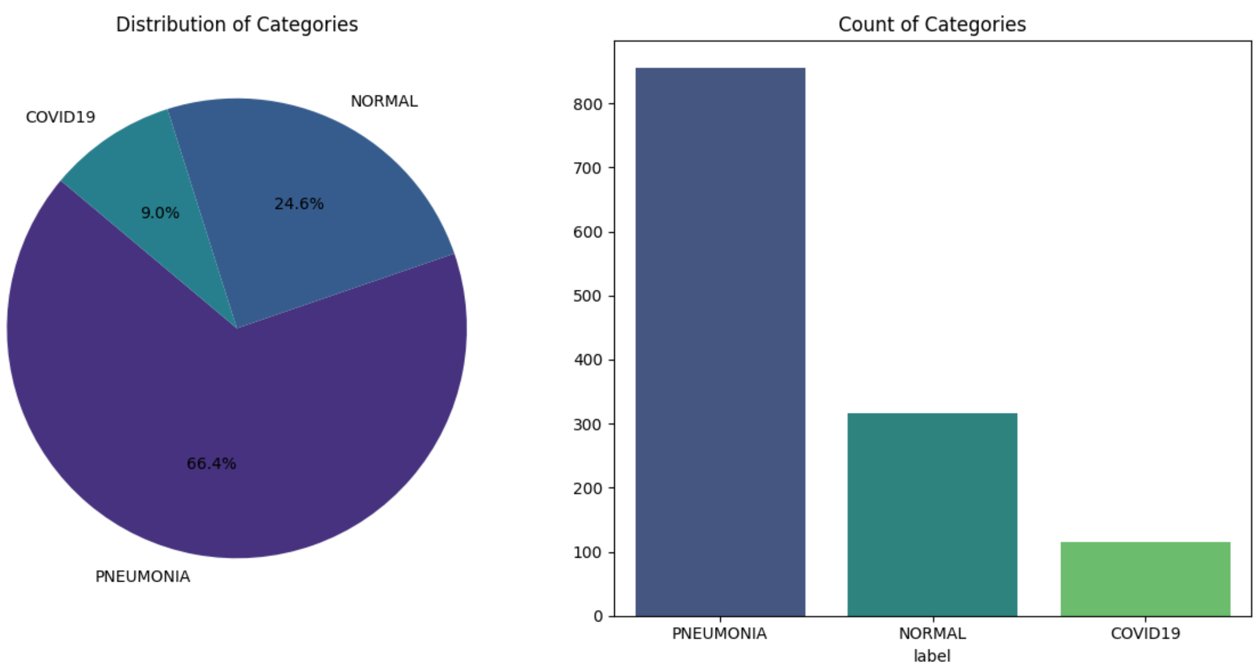

Figure 3: Enter Caption

Model 2

- Transfer learning using **DenseNet201** with pre-trained ImageNet weights.
- Custom additions: MaxPooling, Global Average Pooling, Dropout, Batch Normalization, and Dense layers.
- Fine-tuned last 10 layers.

- Trainable parameters: **12,000,348**.

Model 3

- Transfer learning with **ResNet152V2** as the base model.
- Added custom fully connected layers with Tanh activation for intermediate layers and softmax for the output layer.
- Trainable parameters: **25,877,712**.

Model 4

- Transfer learning with **VGG19** as the base model.
- Added three fully connected Dense layers with Tanh and softmax activation.
- Trainable parameters: **20,024,384**.

Experimental Results

	Epochs	Accuracy	Precision	Recall
Model1	30	.85	.83	.90
Model2	50	.92	.91	.95
Model3	50	.94	.93	.25
Model4	40	.93	.92	.94

Figure 4: Enter Caption

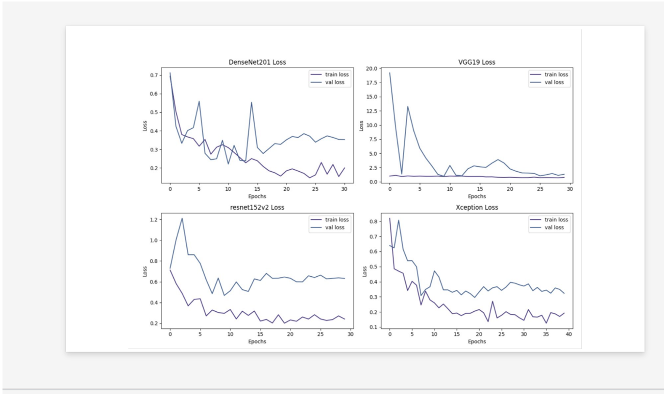

Figure 5: Enter Caption

Conclusion

The project demonstrated the effectiveness of transfer learning in classifying chest X-ray images. While simpler models like Model 1 were efficient, deeper architectures like ResNet152V2 and VGG19 offered better accuracy.

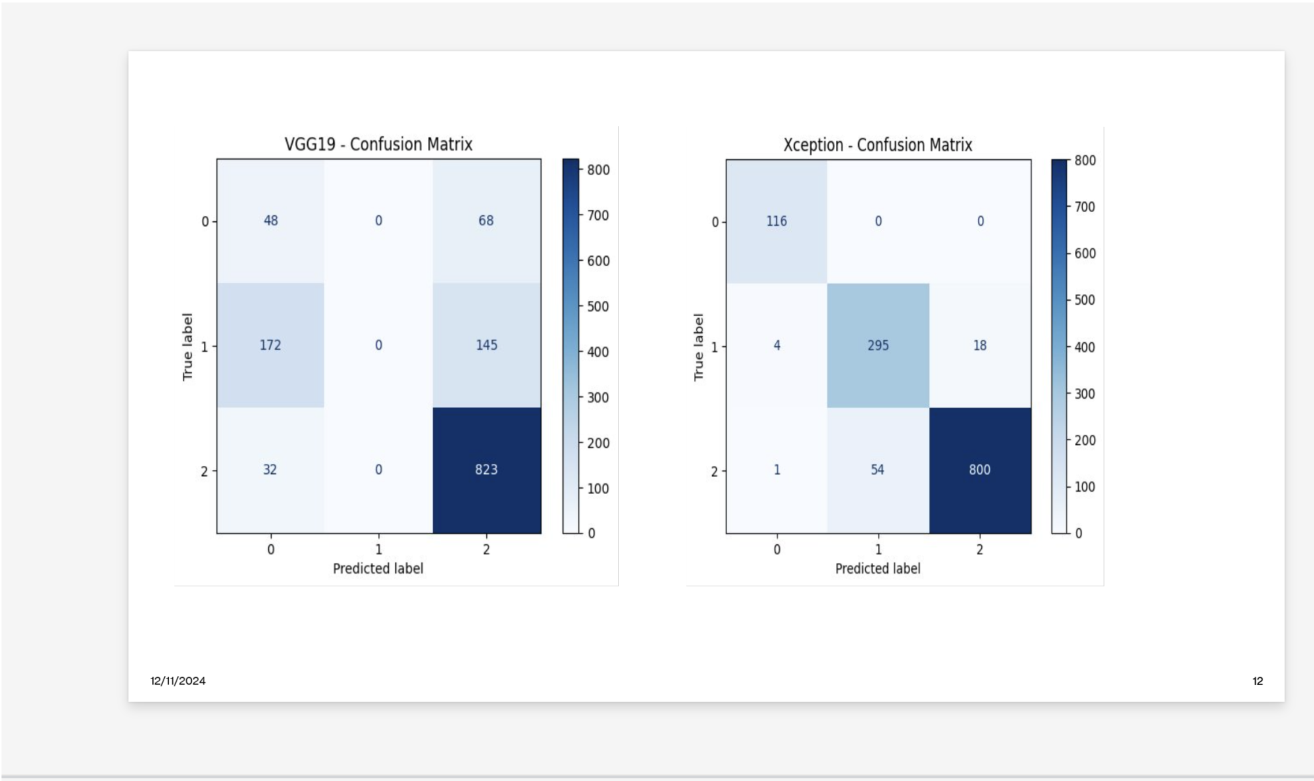

Figure 6: Enter Caption

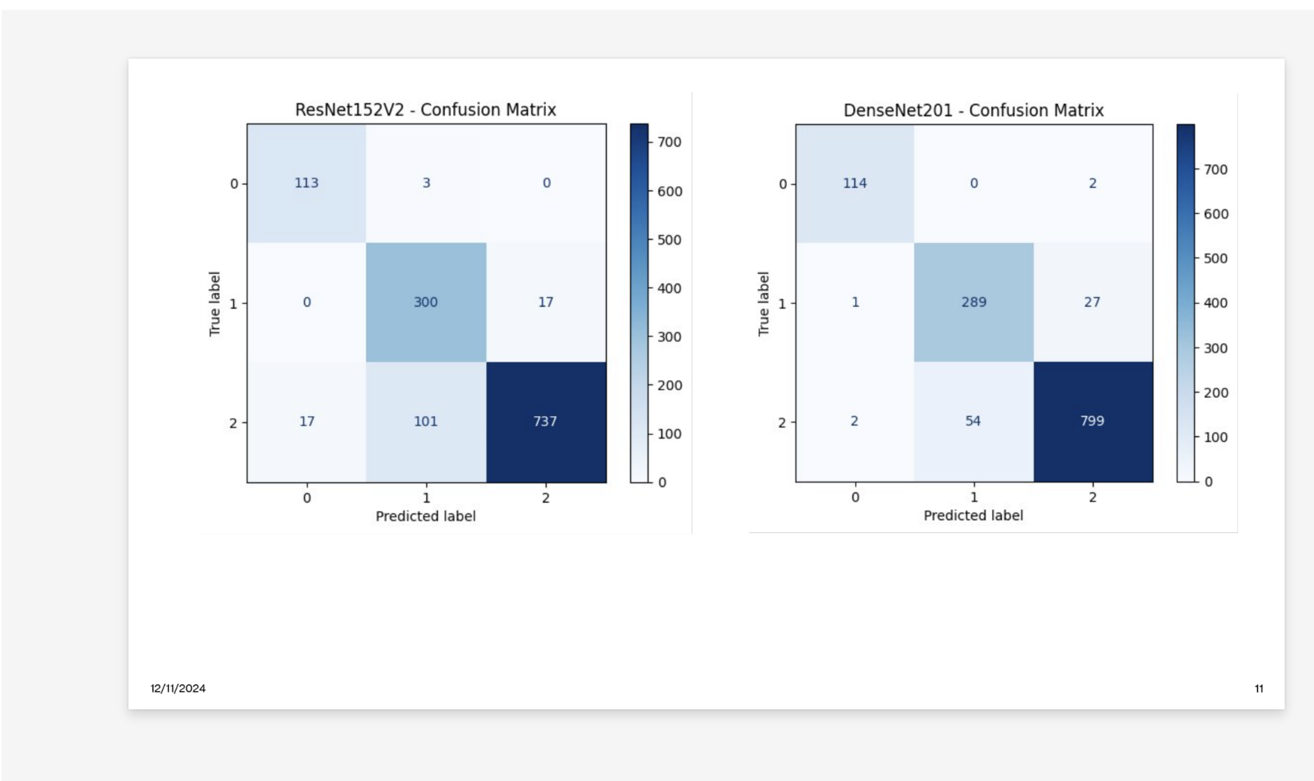

Figure 7: Enter Caption

Future Work

- Experiment with larger datasets to improve model generalization.
- Explore ensemble methods to combine the strengths of different models.
- Optimize hyperparameters to further enhance accuracy.
- Integrate the model into clinical workflows for real-time diagnostics.