Computer Vision & Ai Project

AI-Driven Medical Imaging for Pneumonia Diagnosis Leveraging Transfer Learning and CNNs in Healthcare

A project report submitted to the award of degree of Practical Exam on
Computer Vision Course in
Faculty of Electronic Engineering CSE (Computer Science & Engineering)

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Introduction

Medical imaging is an essential tool in modern healthcare, enabling clinicians to diagnose and treat conditions effectively. Pneumonia, a severe respiratory infection, is one such condition that relies on accurate imaging for diagnosis. Despite its importance, traditional diagnostic methods face challenges such as high error rates and inefficiencies. This project explores how AI-driven solutions, specifically CNNs and transfer learning, can revolutionize pneumonia diagnosis, making it faster and more reliable.

Lung cancer remains one of the most lethal diseases globally, responsible for approximately 7.6 million deaths annually, according to the World Health Organization (WHO). Projections suggest this number could rise to 17 million by 2030. Early and accurate detection is critical for effective treatment and improved survival rates. However, traditional diagnostic techniques, such as MRI and X-ray, often fail to identify lung cancer in its nascent stages due to the complexity of visualizing subtle abnormalities and the risk of false negatives. This project also explores advanced machine learning techniques, specifically Mask R-CNN and U-Net architectures, to enhance lung cancer detection accuracy from CT scans.

Abstract

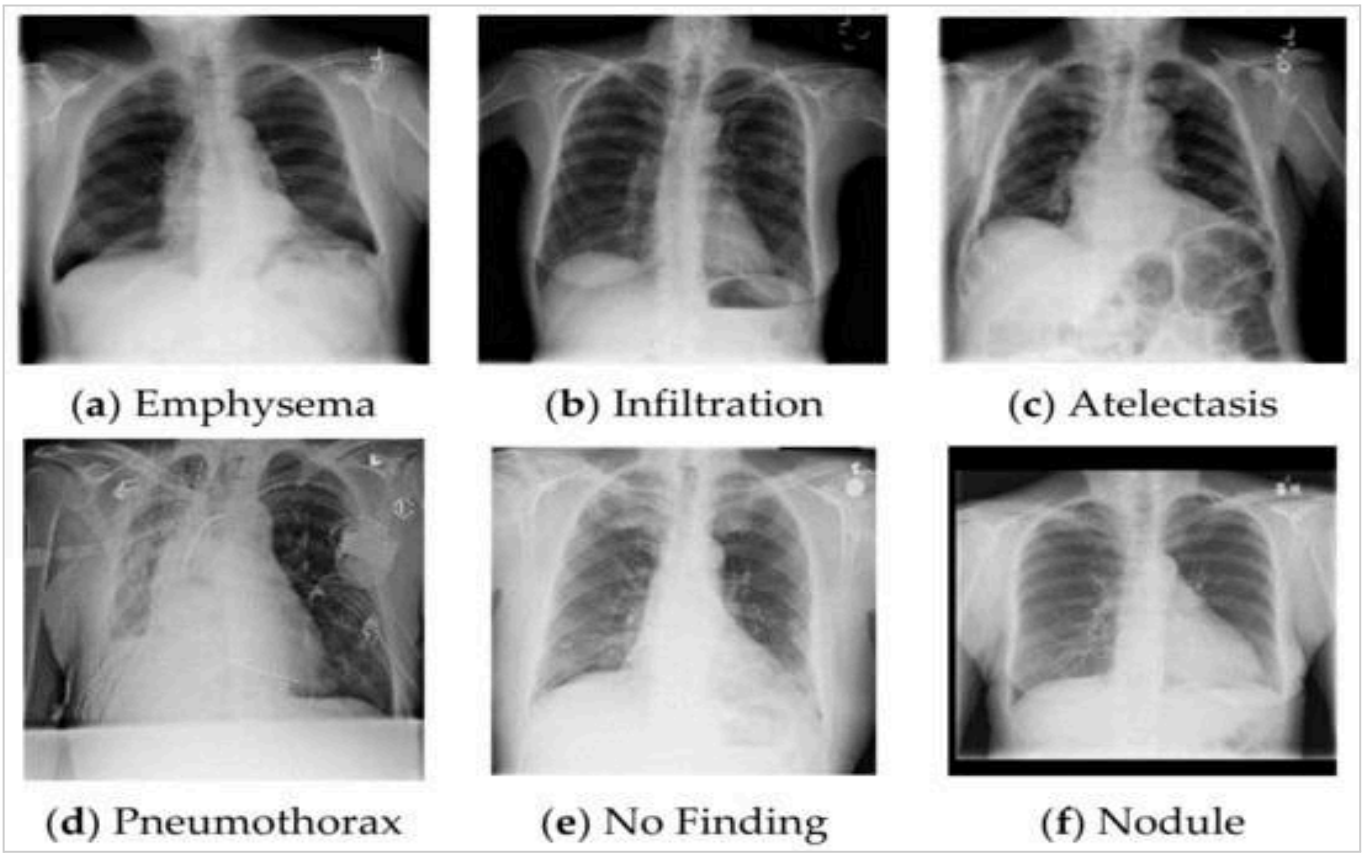
Pneumonia remains a significant global health challenge, causing millions of deaths annually, particularly in vulnerable populations. Early and accurate diagnosis is critical for effective treatment. This project leverages the power of Convolutional Neural Networks (CNNs) combined with transfer learning to develop a robust diagnostic framework for analyzing chest X-ray images. Using the Chest X-ray Pneumonia Dataset, we aim to preprocess and enhance medical images, implement data augmentation techniques, and fine-tune pre-trained models for domain-specific tasks. Our expected outcomes include improved diagnostic accuracy, reduced computational costs, and an accessible tool for healthcare providers. This research not only bridges gaps in current diagnostic methods but also advances the application of AI in medical imaging, promising significant benefits for clinical practice.

Problem Statement

Pneumonia diagnosis through manual analysis of chest X-rays is prone to errors and delays, especially in resource-constrained settings. Despite advancements in AI, existing diagnostic models often fail to generalize across diverse populations and datasets. Similarly, lung cancer detection faces challenges in early diagnosis, where subtle abnormalities in CT scans are often missed by traditional methods. This research seeks to address these limitations by creating a robust, accurate, and scalable AI-driven framework tailored for pneumonia and lung cancer detection.

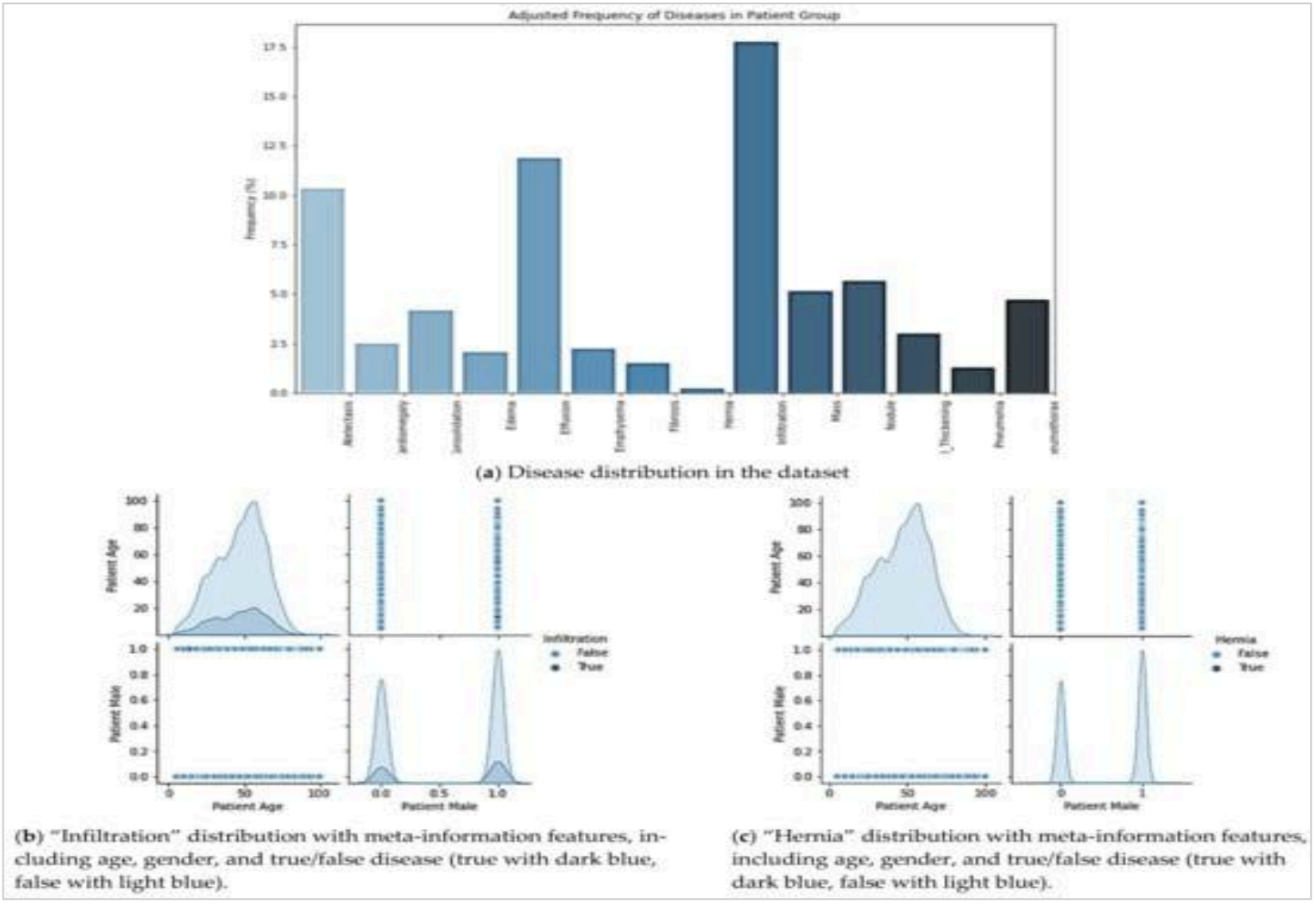
Dataset

The ChestX-ray14 database was used to develop deep learning algorithms. This database is currently one of the largest public X-ray databases, containing 112 back-to-front and front-to-back thoracic films from 30,805 unique patients. Each image was annotated with as many as 14 different thoracic pathological ethics, which were selected based on the frequency of observation and diagnosis in clinical practice. The label of each image was obtained with the automatic extraction method in the radiological report, and each image produced 14 binary values (Atelectasis, Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pleural Thickening, Pneumonia, Pneumothorax). Some of them are provided below, where 0 means that the pathology does not exist and 1 means that there are many pathologies in each image.



Six examples of the ChestX-ray14 dataset. ChestX-ray14 consists of 112,120 frontal chest X-rays from 30,805 patients. All images are labeled with up to 14 pathologies or "No Finding". The dataset does include acute findings, such as the "Nodule" (f), and also treated patients with a drain, such as "Pneumothorax" (d).

We show the distribution of each class illustrated in below. The prevalence of individual pathologies is generally low and varies between 0:2% and 17:74%, as shown in Table 2a, while the distribution of patient gender and view position is quite low. Even with a ratio of 1.3 and 1.5, respectively (see Table 2b), most of the data image samples were biased, as we got "Infiltration" as the most frequent with (9546) image samples, while the least frequent was "Hernia", with just 227 samples. "Emphysema"," Fibrosis"," Edema" Pneumonia", were close to each other, but were lower, with the number of samples between (322) and (727). For the other diseases, like in blow a, the frequency of classes was over 1093 and under 4214. This class imbalance issue will have had a huge impact on the result. Next, we create the data generator to do data augmentation and split the dataset into training, validation, and testing. b,c illustrates the distribution of the least frequent disease, "Hernia", and the most frequent, "Infiltration", with respect to the meta-information



(a) Disease distribution in the dataset

(b) "Infiltration" distribution with meta-information features, including age, gender, and true/false disease (true with dark blue, false with light blue).

(c) "Hernia" distribution with meta-information features, including age, gender, and true/false disease (true with dark blue, false with light blue).

The distribution of diseases in the dataset: the figures (a,b) represent the least frequent disease, "Hernia", and the most frequent disease, "Infiltration", and include (c) the meta-information which are age, gender, case positive or negative.

Aim & Objectives

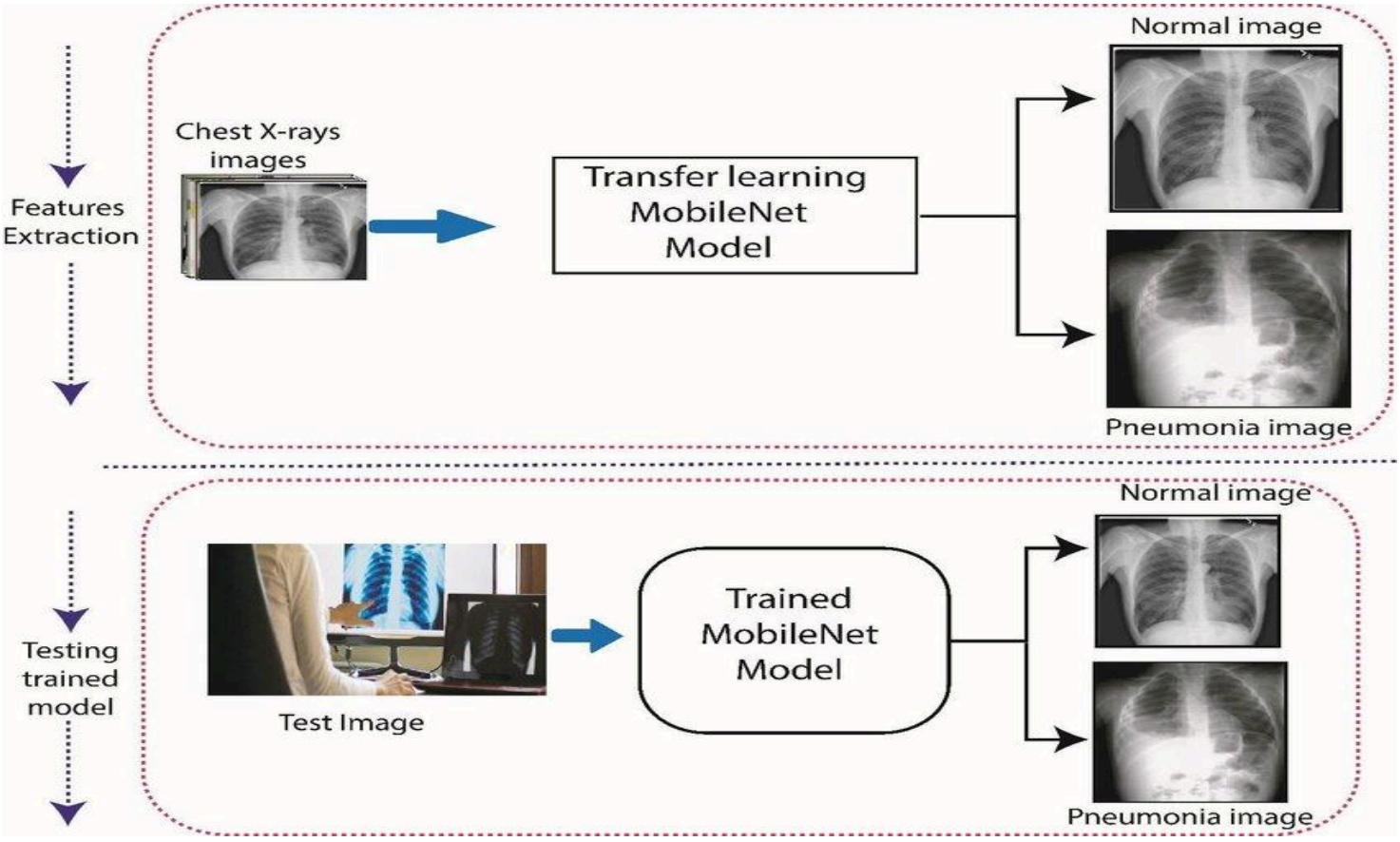
Aim :

- ★ To develop and implement a novel diagnostic framework combining CNNs and transfer learning for pneumonia detection in chest X-ray images and lung cancer detection in CT scans.

Objectives:

- ★ Preprocess chest X-ray and CT scan images to standardize input data.
- ★ Implement data augmentation techniques to enhance model generalization.
- ★ Fine-tune pre-trained CNN models (e.g., VGG16, ResNet50) for pneumonia diagnosis and U-Net models for lung cancer segmentation.
- ★ Optimize hyperparameters using the Taguchi method to improve accuracy and robustness.
- ★ Evaluate model performance using metrics such as accuracy, precision, recall, and F1-score.
- ★ Visualize results through confusion matrices, classified image examples, and segmentation maps.

Our Project Process



Methodology

Research Type (Quantitative): Employ statistical and computational methods to validate model performance.

we propose the listed model in both Figure 5 and Figure 6 to achieve the classification and prediction of 14 different lung diseases in chest X-rays using the Keras framework (which is an open-source software library that provides a Python interface for artificial neural networks) In this proposed work, we have identified and classified 112,120 chest X-ray images from the NIH dataset. The MobileNet V2 [26] model, and additionally the CNN layers, are employed in this work to predict and classify the chest thoracic diseases in the chest X-ray images.

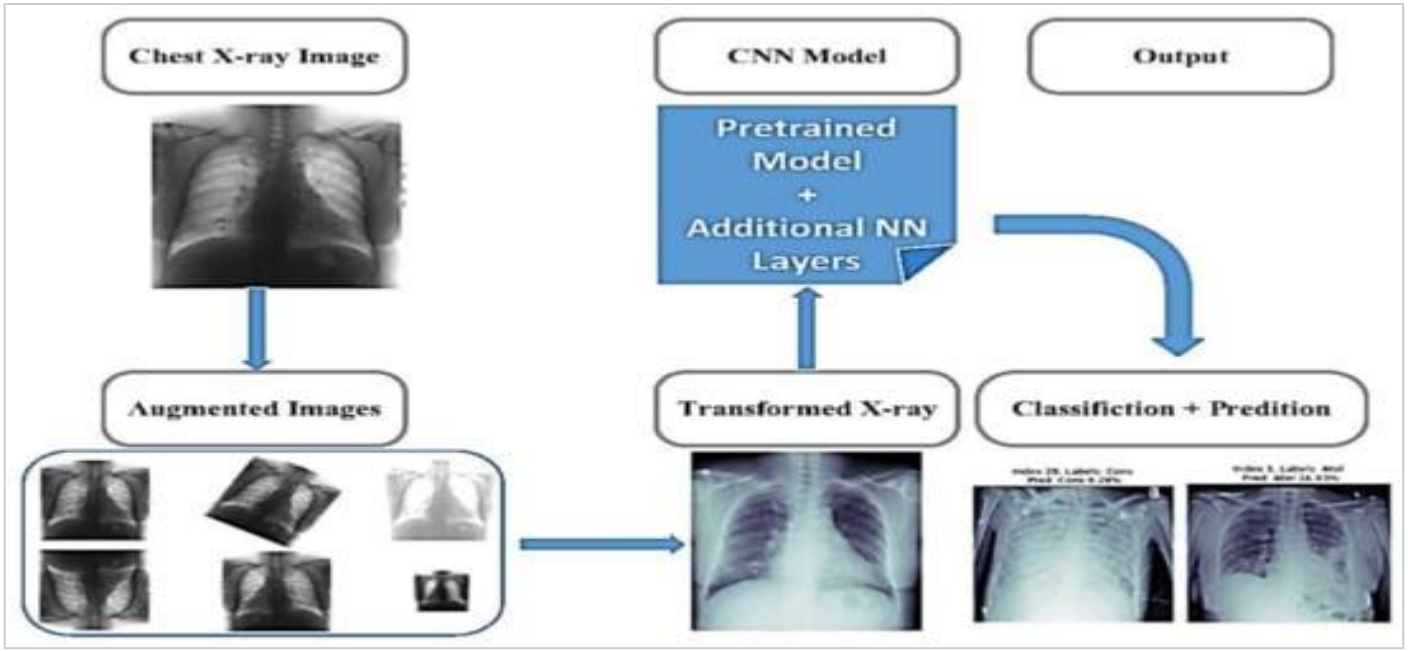


Figure 5. Diagram block for the proposed architecture: we started by loading the dataset and executed data sampling and image augmentation. Next, we loaded the CNN model and the pretrained MobileNet V2 on ImageNet plus and included additional layers on the train samples and the validation samples. Next, we loaded the new weight and started predicting the test samples. The result was a test image with a predicted label.

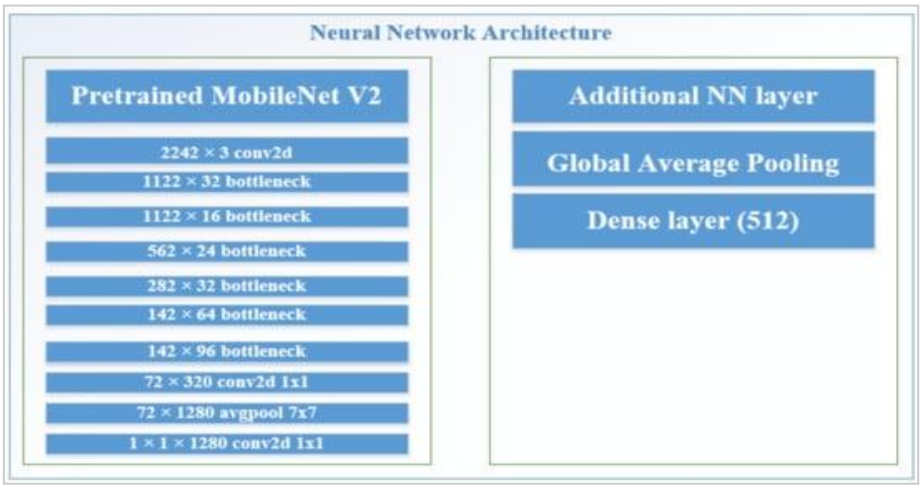


Figure 6. The convolutional neural network architecture: Constructed from an ImageNet [25] pretrained MobileNet V2 with an additional Global Average Pooling layer and one dense layer.

Methodological Approach

1. Data Collection and Preprocessing:

- ★ **Dataset:** *Chest X-ray Pneumonia Dataset* and lung CT scan datasets (e.g., LIDC-IDRI).
- ★ **Preprocessing Steps:** Image resizing, normalization, and enhancement.
- ★ **Segment lung regions and nodules based on radiologists' annotations**.

2. Data Augmentation:

- ★ **Techniques:** Rotation, flipping, zoom, cropping, and noise injection to simulate real-world variations.

3. Model Architecture:

- ★ Use pre-trained models (e.g., VGG16, ResNet50) for feature extraction in pneumonia detection.
- ★ Implement U-Net and Nested U-Net architectures for lung cancer segmentation.
- ★ Explore Attention U-Net to enhance focus on key areas in CT scans.

4. Training and Fine-Tuning:

- ★ Freeze initial layers to retain generic features.
- ★ Unfreeze deeper layers for domain-specific learning.
- ★ Optimize hyperparameters using the Taguchi method.

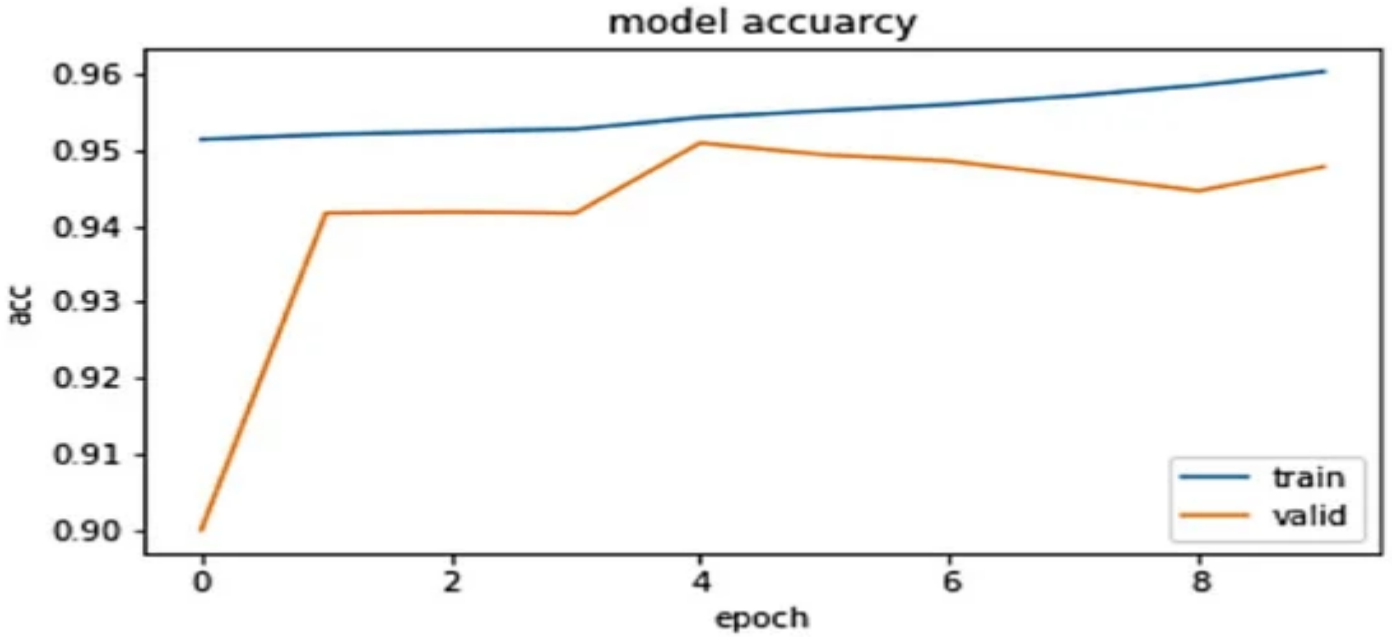
5. Evaluation:

- ★ **Metrics:** Accuracy, precision, recall, F1-score, sensitivity, and specificity.
- ★ **Tools:** Confusion matrices, ROC curves, and segmentation accuracy maps.

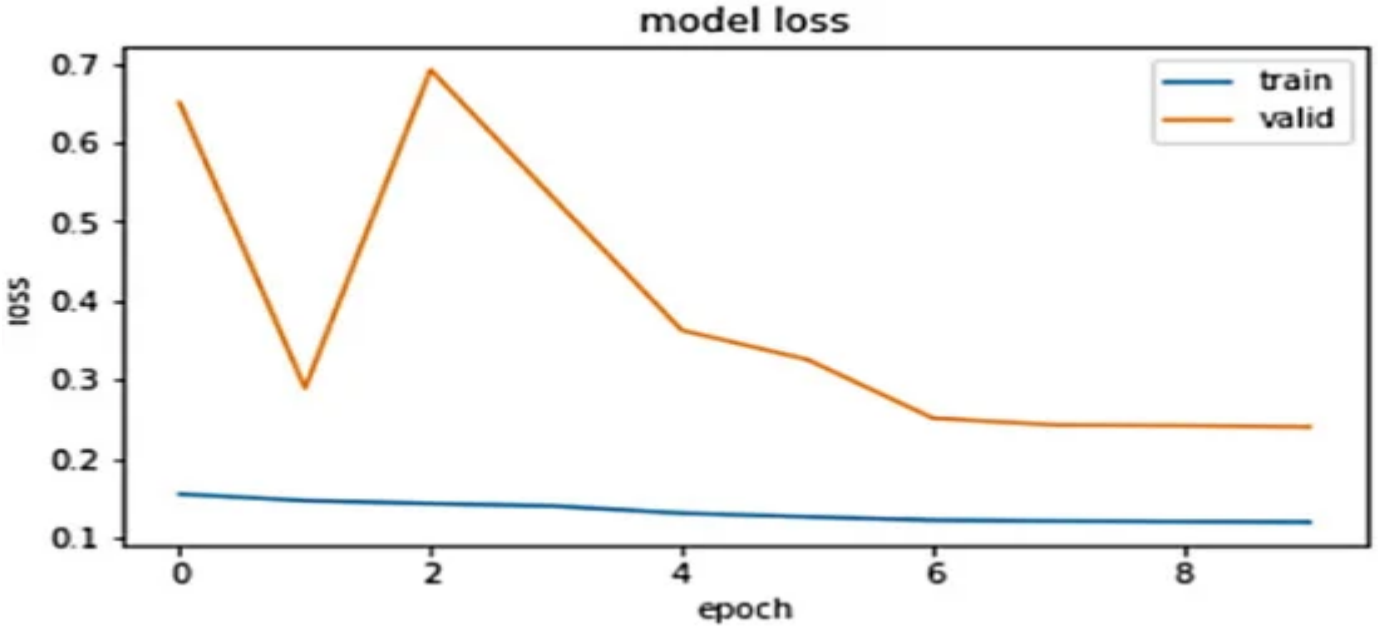
6. Integration:

- ★ Combine pneumonia classification and lung cancer segmentation into a unified diagnostic framework.

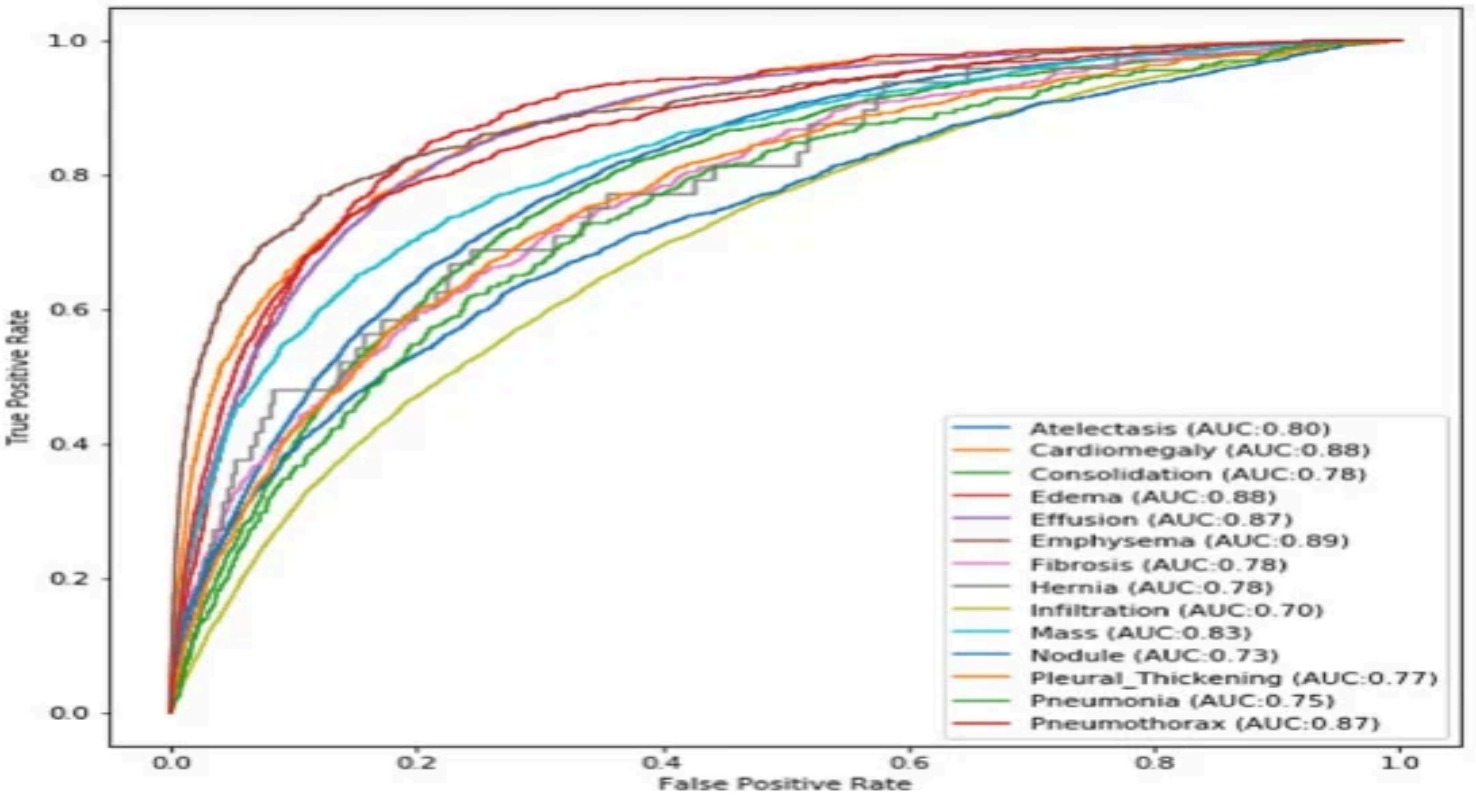
Model accuracy: a comparison between the training accuracy and the validation accuracy over a ten epoch.



Model loss: the difference between the loss under the training phase and loss under validation loss.



ROC curves for our model over ten epochs: AUC 0.89 for "Emphysema" and AUC 0.70 for "Infiltration".



Tools and Software

- ★ Python (3.x)
- ★ TensorFlow, Keras
- ★ NumPy, Pandas
- ★ Matplotlib, Seaborn
- ★ Jupyter Notebook

Acknowledgement

We express our deepest gratitude to Dr. Ahmed Ghozaih and Eng. Ahmed El Brawany for their invaluable guidance and mentorship throughout this project. Their expertise and encouragement have been instrumental in shaping the direction and success of our research. We also extend our thanks to the faculty of Computer Science & Engineering, Faculty of Electronic Engineering, for providing the resources and support needed to complete this work.

Justification for Choices

- ★ **Why Transfer Learning?** Reduces training time and improves performance on small datasets.
- ★ **Why CNNs ?** Proven effectiveness in image-based tasks for classification and segmentation.

Expected Results

- ★ Improved diagnostic accuracy (>90%) for pneumonia detection.
- ★ Enhanced segmentation precision for lung cancer nodules using U-Net and Nested U-Net architectures.
- ★ Visual outputs like confusion matrices, classification reports, segmentation maps, and sample predictions.
- ★ A deployable framework for clinical use in resource-limited settings.

References

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Team Details

- **Ahmed Hussien El Sayed Abd El Hamid:** (*Project Lead, Developer, Documentation Specialist, and Main Structure Creator.*)
- **Ahmed Ebrahim El Sayed Radwan:** (*Developer, Tester, Dataset Collector, and Traditional Machine Learning Creator.*)