Problem Definition with Example and Importance:

This project aims to classify chest X-ray images into six categories representing different pulmonary conditions: Normal, Pneumonia-Bacterial, Pneumonia-Viral, COVID-19, Tuberculosis, and Emphysema, using deep learning techniques.

One of the main challenges of this task is the visual similarity between certain diseases, such as Pneumonia-Viral and COVID-19, which may exhibit similar opacity patterns in chest X-ray images. This similarity makes accurate differentiation difficult for both human observers and automated models.

The importance of this problem lies in the fact that early and accurate diagnosis of pulmonary diseases can significantly improve treatment outcomes and reduce complications and mortality rates. Moreover, deep learning-based models can serve as supportive tools for clinicians, particularly in healthcare settings with limited medical resources or specialized expertise.

Dataset Description:

In this project, the dataset used was obtained from the Kaggle platform and is known as the **"Chest X-Ray 6-Class Dataset"**. This dataset was collected and reorganized from multiple publicly available medical sources to provide a diverse set of chest X-ray images representing various lung disease conditions. Such diversity makes the dataset suitable for studying **multi-class classification problems** in deep learning.

The dataset contains a total of **18,036 grayscale chest X-ray images**. All images were resized to a resolution of **224 × 224 pixels** to ensure compatibility with convolutional neural network (CNN) models.

The data was divided into three main subsets for training and evaluation purposes:

Training set: 14,551 images

Validation set: 1,748 images

Test set: 1,737 images

الفئة	Train	Validation	Test
Normal	2,671	300	300
Pneumonia-Bacterial	2,400	300	300
Pneumonia-Viral	2,413	300	300
COVID-19	2,417	300	300
Tuberculosis	2,600	298	287
Emphysema	2,050	250	250

Deep Learning Approach(es):

A **deep learning approach based on transfer learning** was used, utilizing the **DenseNet121** convolutional neural network pre-trained on **ImageNet**.
This model was selected because it can extract strong image features even with limited training data.

In the code, DenseNet121 is used as a feature extractor by removing the final classification layers and freezing its weights to preserve learned features and reduce overfitting. Custom classification layers were then added, including **Global Average Pooling**, **Dense** layers with **Dropout**, and a **Softmax** output layer for multi-class classification.

The model was trained using the **Adam optimizer**, with image preprocessing based on value rescaling to ensure stable training.
This approach is suitable because it provides good performance with reduced training time compared to training a deep model from scratch.

Evaluation Metrics:

To evaluate the performance of the chest X-ray image classification model, we used the following metrics:

Precision

Recall

F1-score

Support (number of actual samples per class)

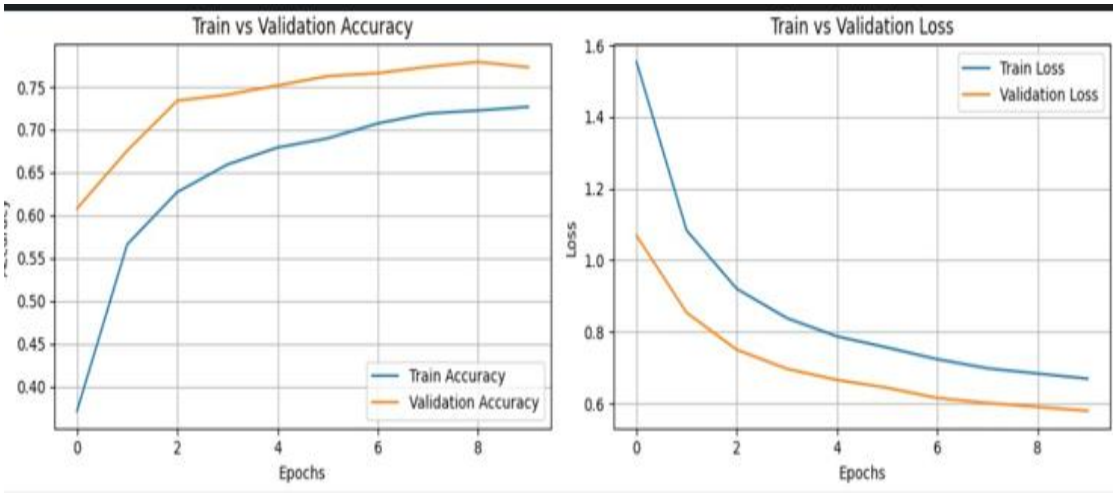
Confusion Matrix

These metrics were chosen because they provide a comprehensive view of the model's performance for each class, considering both the number of samples per category (support) and the model’s ability to distinguish between visually similar categories, such as Pneumonia-Viral and COVID-19. This is particularly important for applications where early and accurate diagnosis of pulmonary diseases is critical.

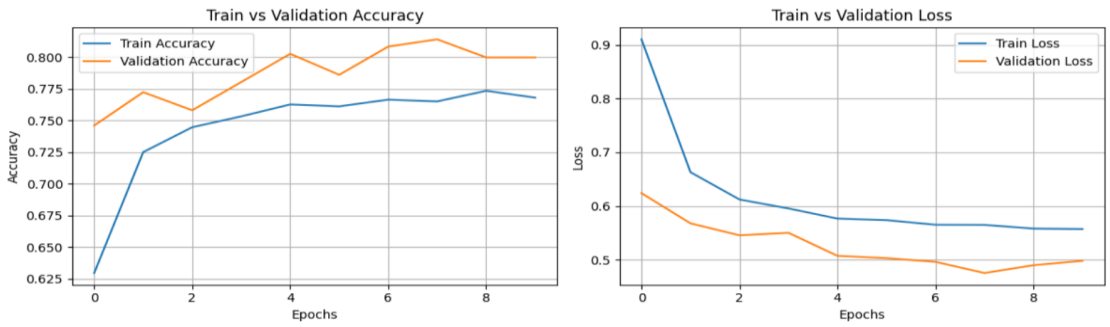
Hyperparameter Tuning Process:

To determine the optimal configuration for the chest X-ray classification model, several combinations of **learning rates (0.001, 0.0001, 0.00001)** and **epochs (5,10, 20)** were tested while keeping **batch size = 32** and **optimizer = Adam**. The goal of these experiments was to evaluate how different settings affect model performance and to prevent overfitting or underfitting

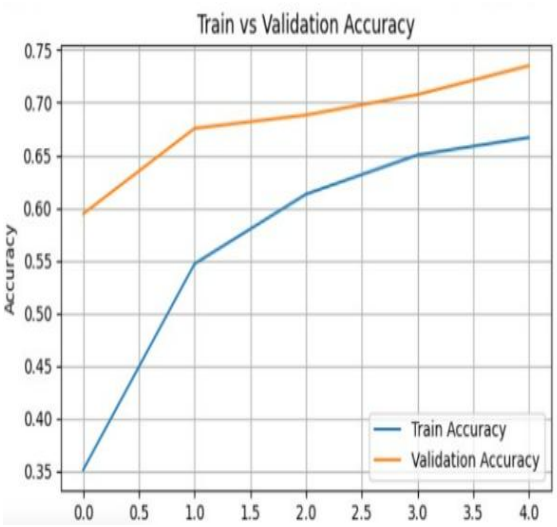
Learning rate = 0.0001 and Epochs = 10 was selected as the best configuration based on validation performance, providing a good balance between learning speed and stability.

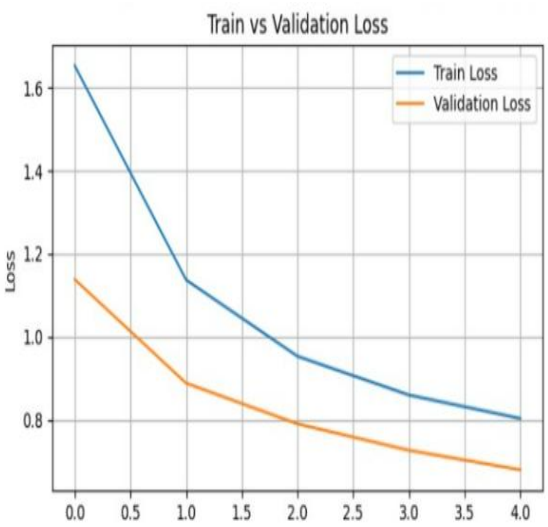


Learning rate = 0.001 **Epochs = 10**

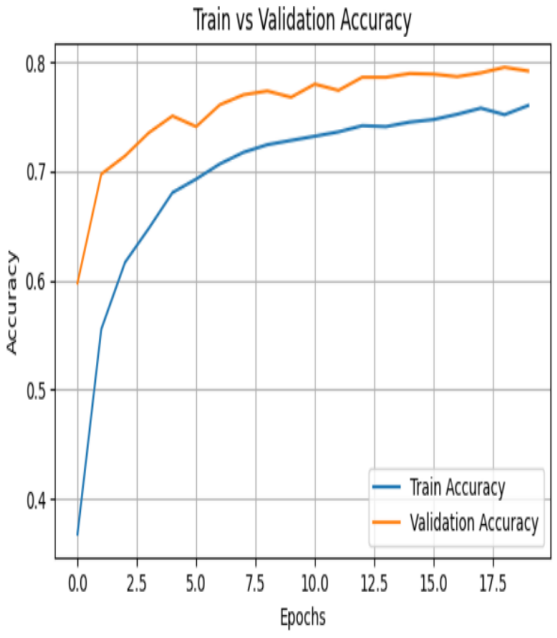


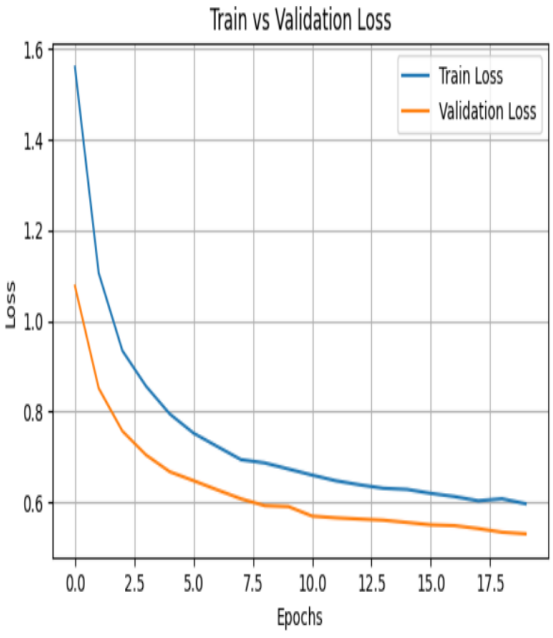
Learning rate = 0.0001 **Epochs = 5**



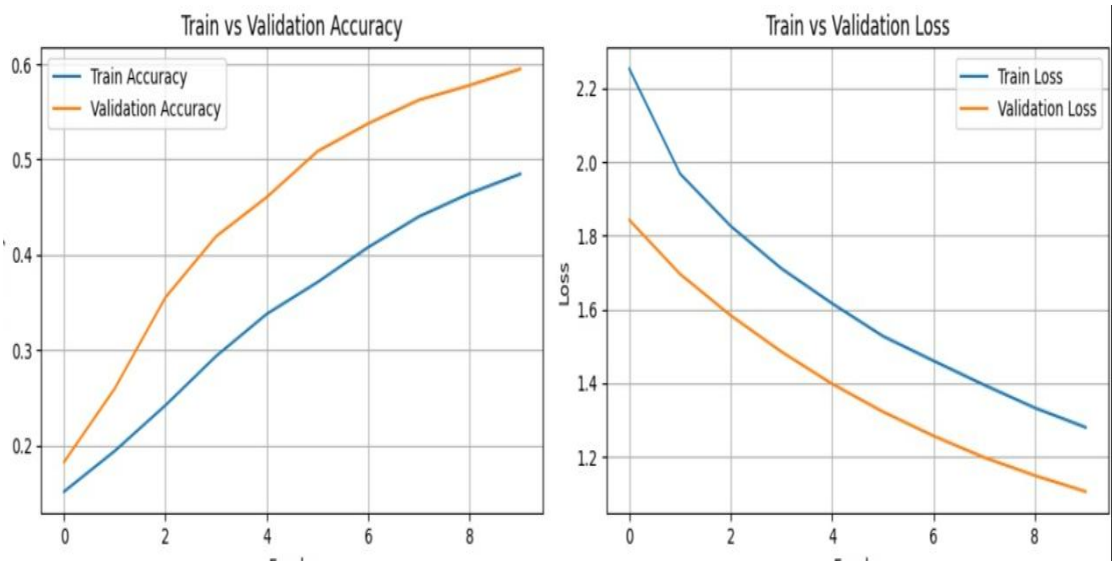


Learning rate = 0.0001 **Epochs = 20**





Learning rate = 0.00001 **Epochs = 10**



Observations from the experiments:

Very small learning rates (0.00001) resulted in slower learning and did not show significant improvement within the same number of epochs.

Hyperparameter Tuning Process:

Quantitative Results:

The chest X-ray classification model was evaluated on the final test set

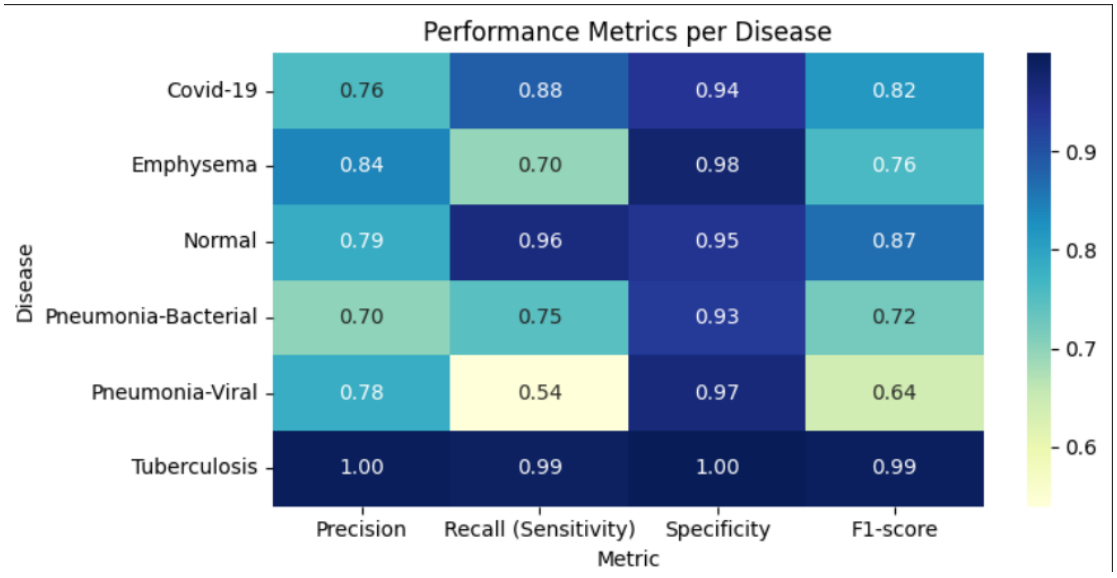
Test accuracy :0.8048

Test loss : 0.4310.

The class-wise metrics show the model's performance:

	Disease	TP	FP	FN	TN	Precision	Recall (Sensitivity)	Specificity	F1-score
0	Covid-19	265	85	35	1352	0.757143	0.883333	0.940849	0.815385
1	Emphysema	174	33	76	1454	0.840580	0.696000	0.977808	0.761488
2	Normal	289	79	11	1358	0.785326	0.963333	0.945024	0.865269
3	Pneumonia-Bacterial	224	96	76	1341	0.700000	0.746667	0.933194	0.722581
4	Pneumonia-Viral	162	45	138	1392	0.782609	0.540000	0.968685	0.639053
5	Tuberculosis	284	1	3	1449	0.996491	0.989547	0.999310	0.993007

The confusion matrix indicates that the model can distinguish most classes well, with some errors between Pneumonia-Bacterial and Pneumonia-Viral.



Qualitative Analysis:

- *The model performs excellently on the Tuberculosis and Normal classes the lower recall for Pneumonia Viral reflects the difficulty of distinguishing between visually similar conditions, specifically Pneumonia Bacterial and Pneumonia-Viral* Hyperparameter tuning experiments showed that learning rate = 0.001 and epochs = 10 provide the best balance between learning speed and stable performance.

Implications / Importance

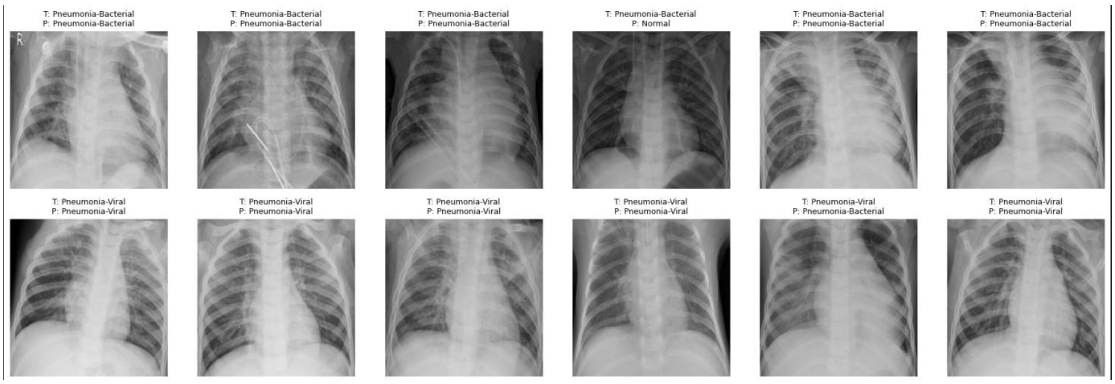
The results indicate that the model can serve as a supportive tool for **early diagnosis of chest diseases**.

High accuracy and good recall for critical classes show the model's potential to **assist doctors**, especially in **resource-limited environments**.

The model can help **detect severe diseases early**, including **COVID-19, Pneumonia-Bacterial, Pneumonia-Viral, and Tuberculosis**, which may improve patient outcomes and reduce complications.

Challenges:

Difficulty in distinguishing visually similar diseases, particularly **Pneumonia-Viral** and **Pneumonia-Bacterial**, which leads to lower recall for some classes



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Selecting optimal hyperparameters (learning rate and number of epochs) required **multiple experiments and careful tuning**.

Training the model is **time-consuming**, especially when trying to improve performance for the most critical diseases.

Numerous attempts were needed to enhance the model's performance for the **high-risk diseases**: **COVID-19, Pneumonia-Bacterial, Pneumonia-Viral, and Tuberculosis**, to achieve a balanced accuracy across classes.

Ensuring the model **generalizes well** while maintaining high precision and recall for critical cases was challenging due to **class imbalance** and visual similarities.

Dataset Citation (Public Dataset)

The dataset used in this project is publicly available and was obtained from Kaggle. It is titled **“Chest X-Ray 6-Class Dataset”** and contains labeled chest X-ray images for multiple pulmonary disease categories.

Dataset :
https://www.kaggle.com/datasets/mohamedasak/chest-x-ray-6-classes-dataset

Author / Contributor: mohamedasak (Kaggle user who uploaded and organized the dataset This dataset is publicly accessible and does not require special access permissions. Proper citation and link are provided here in accordance with the project submission requirements.