Deep Learning Project Documentation

Intoduction

Deep learning has revolutionized the field of medical imaging, enabling the development of highly accurate and efficient diagnostic tools. This project focuses on solving a binary classification problem involving chest X-ray images to distinguish between two classes: NORMAL (healthy individuals) and PNEUMONIA (individuals diagnosed with pneumonia). Early and accurate detection of pneumonia from chest X-rays is crucial for timely treatment and improving patient outcomes

To address this problem, we utilize three state-of-the-art convolutional neural network (CNN) architectures: Xception, DenseNet, and ResNet. These models have demonstrated exceptional performance in image recognition tasks and are well-suited for analyzing the intricate features of chest X-ray images

- **Xception** (Extreme Inception): A model built on depthwise separable convolutions, which reduces computational cost while maintaining high performance. It excels in capturing complex image patterns.
- **DenseNet** (Densely Connected Convolutional Network): A unique architecture where every layer is connected to all subsequent layers, enhancing feature reuse and gradient flow, making it highly efficient for medical image analysis.
- **ResNet** (Residual Network): A groundbreaking model that introduced skip connections to address the vanishing gradient problem, enabling the training of very deep networks and achieving state-of-the-art results in many classification tasks.

The goal of this project is to evaluate the effectiveness of these models in classifying chest X-rays. We compare their performance in terms of accuracy, precision, recall, and other relevant metrics, both with and without data augmentation techniques. Through this study, we aim to identify the most suitable model for the early detection of pneumonia, providing a foundation for deploying automated diagnostic systems in clinical settings

The Topics that we will Cover:

1.Xception Model Explanation

- ✓ Introduction
- ✓ Architecture of Xception
- ✓ Pretrained Xception
- ✓ How it works
- ✓ Pros and Cons of Xception

2.DenseNet Model Explanation

- ✓ Introduction
- ✓ Versions of DenseNet Models
- ✓ Architecture of DenseNet121
- ✓ Pretrained DenseNet121
- ✓ How it works
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3.ResNet Model Explanation

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4.Xception Model Evaluation and Results

- ✓ Accuracy
- ✓ Classification Report
- ✓ ROC ,AUC Graph
- ✓ Confusion Matrix
- ✓ Training and Validation Accuracy Graph
- ✓ Training and Validation Loss Graph
- ✓ Advantages
- ✓ Disdvantages
- ✓ Model analysis

5. DenseNet Model Evaluation and Results

- ✓ Accuracy
- ✓ Classification Report
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- ✓ Confusion Matrix
- ✓ Training and Validation Accuracy Graph

Xception Model Explanation

Introduction

Xception (Extreme Inception) is a deep learning architecture that builds upon the principles of the Inception model but replaces the standard Inception modules with depthwise separable convolutions. It was introduced by François Chollet in 2017.

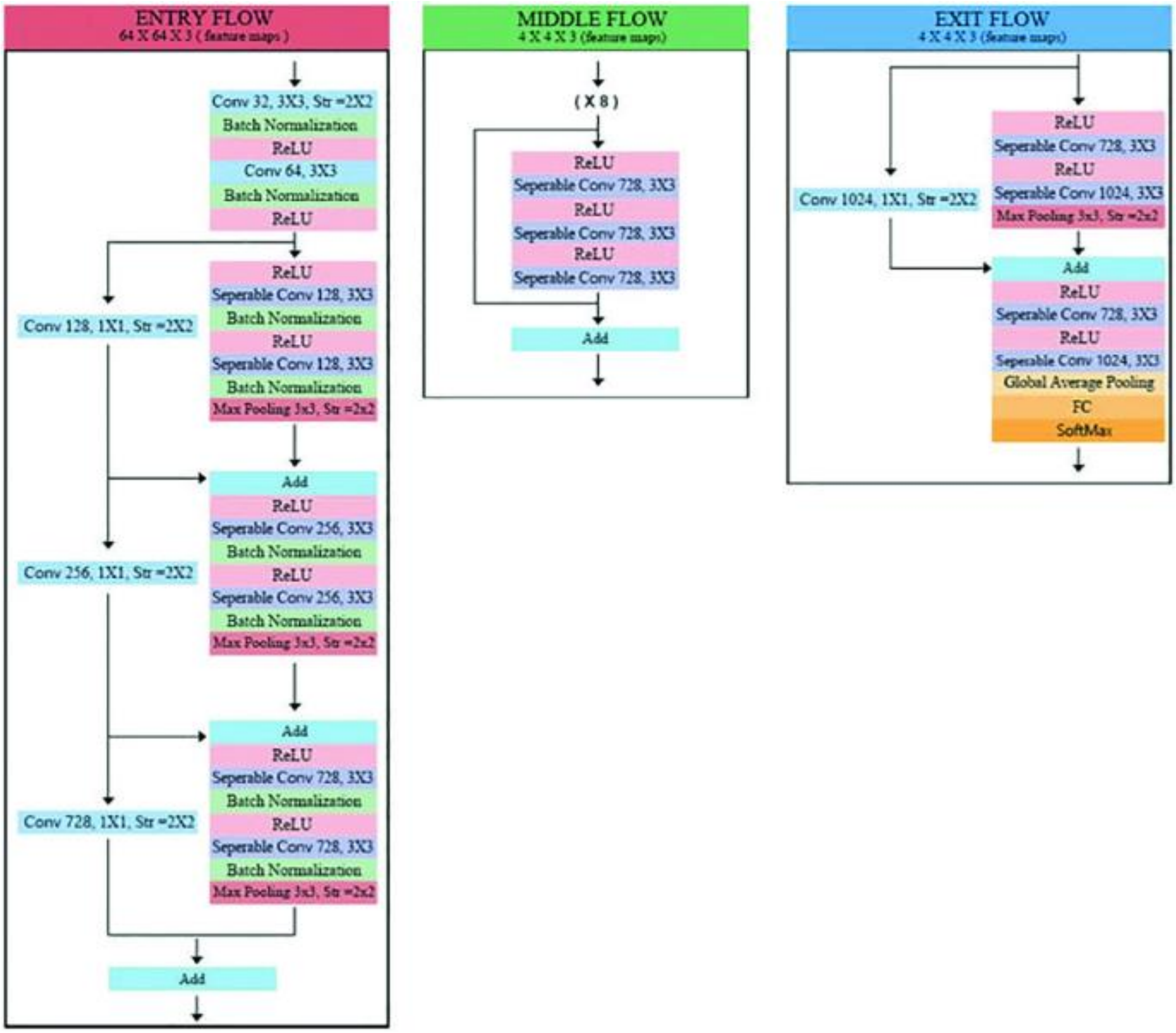
The Xception model represents a significant advancement over traditional convolutional networks and the Inception model. It achieves a balance between computational efficiency and performance, making it a popular choice for tasks requiring pretrained models, such as transfer learning. However, its effectiveness depends on task-specific requirements and resource availability.

Xception has one version (Xception-71 with 71 layers) of deep convolutional neural networks. It utilizes depthwise separable convolutions, which factorize standard convolutions into two parts:

1. Depthwise Convolutions: Perform spatial convolutions (per channel).
2. Pointwise Convolutions: Use 1x1 convolutions to combine channel information.

These operations make Xception more computationally efficient compared to models with traditional convolutions while maintaining high accuracy.

Architecture of Xception



The Xception model is organized into three main stages, consisting of 71 layers in total:

- Entry Flow:
  - Initial feature extraction using standard convolution.
  - Includes three convolutional blocks with ReLU activation and batch normalization.
  - Downsamples the input image by reducing its spatial dimensions.
- Middle Flow:
  - Repeats 8 identical blocks of depthwise separable convolutions.
  - Focuses on learning complex and abstract patterns.
  - The bulk of the 71 layers is in this section.
- Exit Flow:
  - Refines and aggregates high-level features.
  - Includes depthwise separable convolutions, followed by global average pooling and a fully connected layer for classification.

Pretrained Xception

Key Features:

1. Pretrained on ImageNet:
   - Xception models are often pretrained on large datasets like ImageNet.
   - This makes them suitable for transfer learning, where their learned weights can be fine-tuned for specific tasks.
2. Fine-Tuning:
   - The fully connected (classification) layer can be replaced with task-specific layers during transfer learning.

Number of Layers and Their Responsibilities:

- Total Layers: 71, structured as:
  - Entry Flow (12 layers): Extracts basic image features (e.g., edges, textures).
  - Middle Flow (48 layers): Learns hierarchical and abstract features.
  - Exit Flow (11 layers): Aggregates and prepares features for classification.

How It Works

- **Entry Flow**:
  - Starts with standard convolution and max-pooling to downsample the input.
  - Features are extracted while reducing spatial dimensions.
- **Middle Flow**:
  - Repeats a set of depthwise separable convolutional layers 8 times.
  - Focuses on learning complex and abstract patterns in the data.
- **Exit Flow**:
  - Final depthwise separable convolutions and global average pooling.
  - Outputs predictions for classification tasks through a fully connected layer.

Pros and Cons of Xception

Pros:

- **Efficiency**:
  - Depthwise separable convolutions reduce computational complexity compared to standard convolutions.
- **High Accuracy**:
  - Achieves state-of-the-art results on image classification benchmarks.
- **Scalability**:
  - Flexible architecture adapts to various input sizes and tasks.
- **Residual Connections**:
  - Enhances gradient flow, making the model more stable during training
- **Transfer Learning**:
  - Pretrained Xception models are effective for transfer learning, reducing the need for large datasets.

Cons:

- **Computational Cost**:
    - While efficient for high-end GPUs, it can still be computationally intensive for embedded systems.
- **Overfitting Risk**:
    - A large number of parameters can lead to overfitting on small datasets if not properly regularized.

DenseNet Model Explanation

Introduction

DenseNet (Dense Convolutional Network) developed by researchers Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger in 2017

is a type of deep learning architecture that focuses on efficiency and feature reuse. It connects each layer to every other layer in a dense block, which means the output of each layer is concatenated with the outputs of all previous layers. This dense connectivity improves gradient flow, reduces the number of parameters, and promotes feature reuse.

Types of DenseNet Models (Versions)

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112×112	7×7 conv, stride 2			
Pooling	56×56	3×3 max pool, stride 2			
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv			
	28×28	2×2 average pool, stride 2			
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv			
	14×14	2×2 average pool, stride 2			
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer (3)	14×14	1×1 conv			
	7×7	2×2 average pool, stride 2			
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Classification Layer	1×1	7×7 global average pool			
		1000D fully-connected, softmax			

Table 1: DenseNet architectures for ImageNet. The growth rate for all the networks is $k = 32$. Note that each "conv" layer shown in the table corresponds the sequence BN-ReLU-Conv.

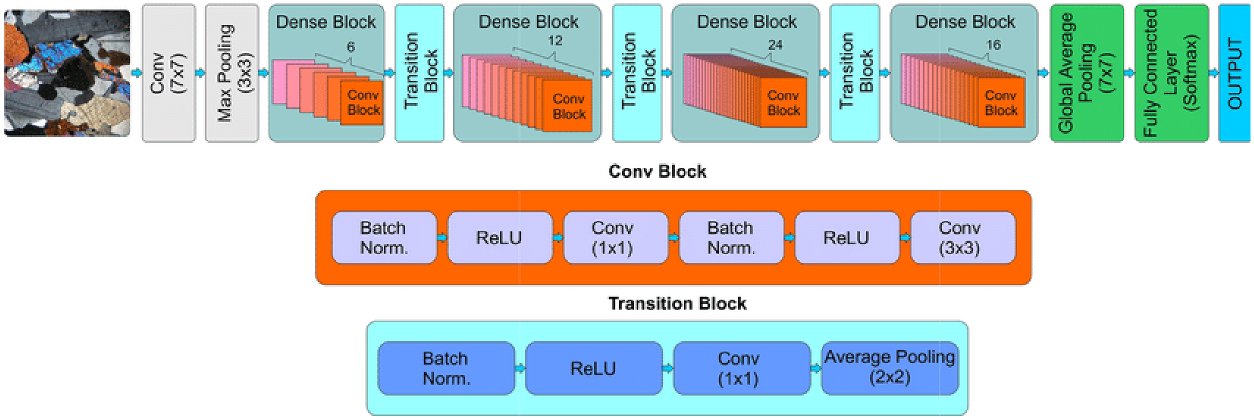
DenseNet has multiple variants, differentiated by the number of layers:

1. **DenseNet-121**: 121 layers.
2. **DenseNet-169**: 169 layers.
3. **DenseNet-201**: 201 layers.
4. **DenseNet-264**: 264 layers.

Comparison with Other DenseNet Variants

- **DenseNet-121**: Lightweight and efficient, suitable for general tasks and transfer learning.
- **DenseNet-169, 201, 264**: Deeper networks with better accuracy on complex tasks but require more computational resources.

DenseNet-121



Number of Layers and Their Responsibilities in DenseNet-121

The 121 layers include:

- **Convolutional and Pooling Layers**:
  - Initial convolutional layer and max-pooling layer extract low-level features (e.g., edges, textures).
- **Dense Blocks**:
  - Each dense block consists of **multiple layers**, where the output of each layer is concatenated with the outputs of previous layers. This promotes feature reuse.
  - Dense Block 1: 6 layers.
  - Dense Block 2: 12 layers.
  - Dense Block 3: 24 layers.
  - Dense Block 4: 16 layers.
- **Transition Layers**:
  - Between dense blocks, transition layers downsample the spatial dimensions using 1x1 convolutions and average pooling.
- **Final Layers**:
  - Global average pooling and a fully connected layer for classification.

How DenseNet-121 Works

1. **Feature Reuse**:
    - Unlike traditional CNNs where each layer learns features independently, DenseNet-121 concatenates outputs of all preceding layers. This leads to efficient feature reuse and reduces redundancy.
2. **Improved Gradient Flow**:
    - Dense connections ensure gradients flow smoothly during backpropagation, mitigating the vanishing gradient problem.
3. **Compact Model**:
    - Fewer parameters compared to other architectures with similar depth due to the feature concatenation.

Pretrained DenseNet-121

Features:

1. **Pretrained on ImageNet**:
    - DenseNet-121 is often pretrained on large datasets like ImageNet, which provides robust feature representations for transfer learning.
2. **Fine-Tuning**:
    - The final fully connected layer can be replaced and fine-tuned for specific tasks.

Benefits of Pretrained DenseNet-121:

- Avoids the need for training from scratch.
- Effective on smaller datasets.

Pros and Cons of DenseNet-121

Pros:

- **Efficient Feature Use**:
  - Reduces redundancy by reusing features across layers.
- **Fewer Parameters**:
  - Despite its depth, DenseNet-121 has fewer parameters compared to similar architectures like ResNet.
- **Good Gradient Flow**:
  - Dense connections prevent gradient vanishing, making training deeper networks feasible.
- **Effective Transfer Learning**:
  - Pretrained versions perform well on diverse tasks after fine-tuning.

Cons:

- **Computational Overhead**:
  - Dense concatenations can increase memory usage and computational cost during training.
- **Overfitting Risk**:
  - May overfit small datasets if regularization techniques (like dropout) are not applied.

ResNet Model Explanation

Introduction

ResNet (Residual Network) was introduced in 2015 by Kaiming He et al. It solved the vanishing gradient problem and allowed for training very deep neural networks by introducing residual connections (or shortcuts). These connections enable the model to learn identity mappings and preserve information across layers, making it easier to optimize very deep networks.

ResNet Versions (Types)

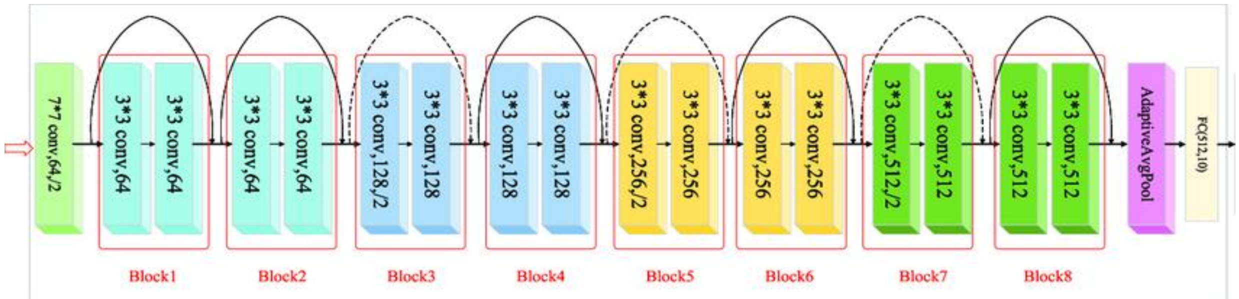
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		[3×3, 64 3×3, 64] ×2	[3×3, 64 3×3, 64] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3
conv3_x	28×28	[3×3, 128 3×3, 128] ×2	[3×3, 128 3×3, 128] ×4	[1×1, 128 3×3, 128 1×1, 512] ×4	[1×1, 128 3×3, 128 1×1, 512] ×4	[1×1, 128 3×3, 128 1×1, 512] ×8
conv4_x	14×14	[3×3, 256 3×3, 256] ×2	[3×3, 256 3×3, 256] ×6	[1×1, 256 3×3, 256 1×1, 1024] ×6	[1×1, 256 3×3, 256 1×1, 1024] ×23	[1×1, 256 3×3, 256 1×1, 1024] ×36
conv5_x	7×7	[3×3, 512 3×3, 512] ×2	[3×3, 512 3×3, 512] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

:ures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of block

Comparison with Other ResNet Versions

Model	Layers	Parameters	Main Use Case
ResNet18	18 Layers	11.7M	Small datasets, low compute.
ResNet34	34 Layers	21.8M	Deeper feature extraction.
ResNet50	50 Layers	25.6M	High-level feature extraction.
ResNet101	101 Layers	44.5M	Complex datasets.
ResNet152	152 Layers	60.2M	Large-scale datasets.

ResNet18 From Scratch



- Total Layers: 18.
- Architecture: Uses Basic Blocks with residual connections.
- Structure:
  - Conv1: Initial 7x7 convolution, followed by max pooling (reduces spatial dimensions).
  - Four Residual Stages:
    - Stage 1: Two Basic Blocks, operating at a smaller spatial size.
    - Stage 2: Two Basic Blocks, downsampling the input.
    - Stage 3: Two Basic Blocks.
    - Stage 4: Two Basic Blocks.
  - Fully Connected Layer: A dense layer at the end for classification.

Number of Layers and Responsibilities

ResNet18's 18 layers can be grouped into the following components:

1. Conv1 (1 layer): Extracts low-level features (edges, textures).
2. Residual Blocks (16 layers):
   - Basic Blocks, each containing:
     - Two 3x3 convolutions.
     - Batch Normalization and ReLU activations.
     - Residual connections (shortcut paths).
   - Responsibilities:

- First blocks: Learn low- to mid-level features.
- Later blocks: Learn high-level abstract features.

3. Fully Connected Layer (1 layer): Outputs final class probabilities.

How ResNet18 Works

1. **Basic Block Design**:
   - Each block performs:
     1. A convolution.
     2. Batch normalization and ReLU.
     3. A second convolution, batch normalization, and addition of the residual (shortcut) connection.
   - Residual connections add the input directly to the output, allowing gradients to flow backward effectively.
2. **Training**:
   - The model focuses on learning the "residual" (difference) between the input and output of a block, which simplifies the learning task.
3. **Forward Pass**:
   - Data passes through the convolutional layers and residual blocks, progressively extracting hierarchical features.
   - At the end, the fully connected layer maps features to the desired number of classes.

Pros and Cons of ResNet18

Pros:

- **Efficient Gradient Flow**:
  - Residual connections mitigate the vanishing gradient problem, enabling deeper models.
- **Simple Architecture**:
  - Easy to implement and train due to its modular structure.
- **Good for Transfer Learning**:
  - ResNet18 is less complex compared to deeper variants, making it faster for fine-tuning.
- **High Accuracy**:
  - Achieves competitive performance on benchmarks like ImageNet.

Cons:

- **Overfitting Risk**:
  - On small datasets, it may overfit without proper regularization.
- **Computational Cost**:
  - Although lighter than deeper ResNets, it still requires substantial computational resources for training from scratch.

Xception Model Evaluation and Results

1. Model Overview

The Xception model was selected for its efficiency in capturing complex patterns in image data through its use of depthwise separable convolutions. It has demonstrated strong performance in similar image classification tasks, making it a suitable choice for this project

2. Model Accuracy

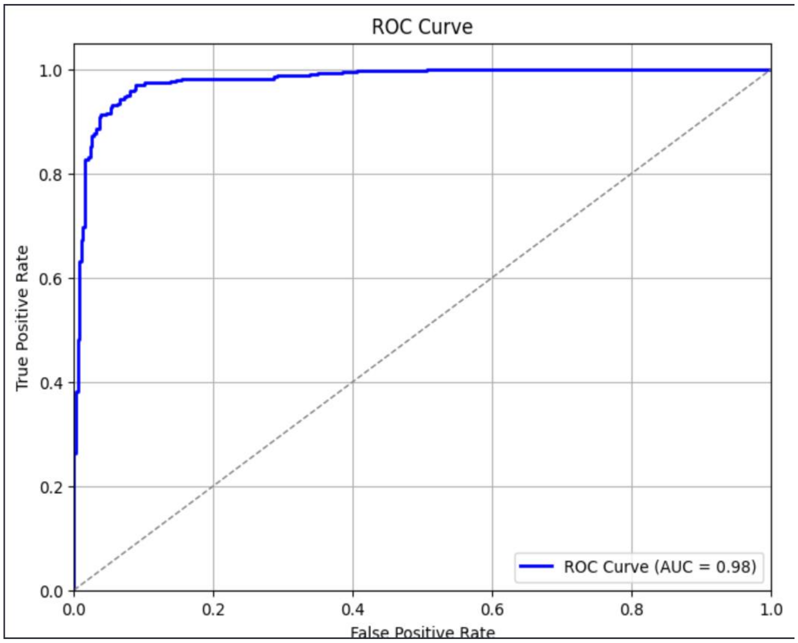
Accuracy: The model achieved a classification accuracy of **93.6%**, indicating its robustness in distinguishing between the two classes.

3.Classification Report:

Class	**Precision**	**Recall**	**F1-Score**	**Support**
NORMAL	0.94	0.93	0.94	384
PNEUMONIA	0.94	0.94	0.94	390
Accuracy			0.94	774
Macro Avg	0.94	0.94	0.94	774
Weighted Avg	0.94	0.94	0.94	774

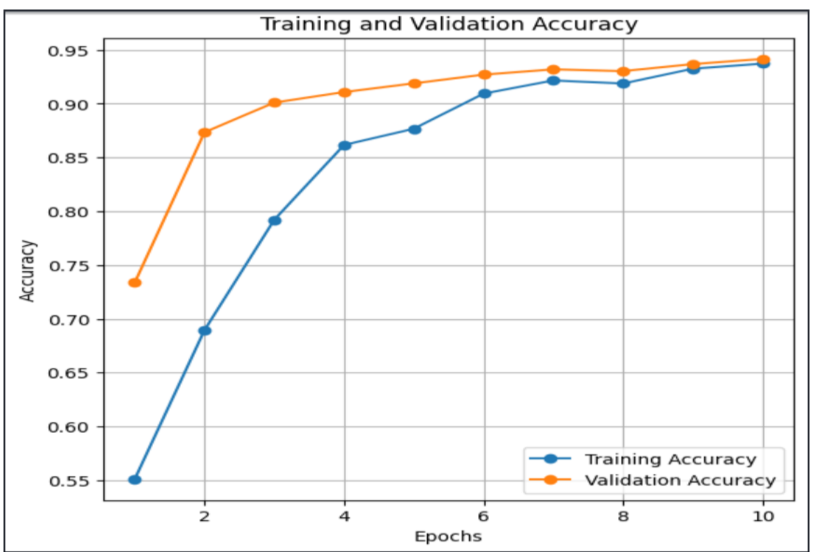
The classification report demonstrates excellent performance for both classes. The **NORMAL** class achieved a perfect precision of **0.94** but slightly lower recall (**0.93**), indicating some false negatives. Conversely, the **PNEUMONIA** class achieved a recall of **0.94** with a precision of **0.94**, showing no missed positive cases but a few false positives. Overall, the model achieved a strong accuracy of **93.6%**, with consistent macro and weighted average scores (**0.94**), reflecting balanced performance across both classes.

3.ROC Curve



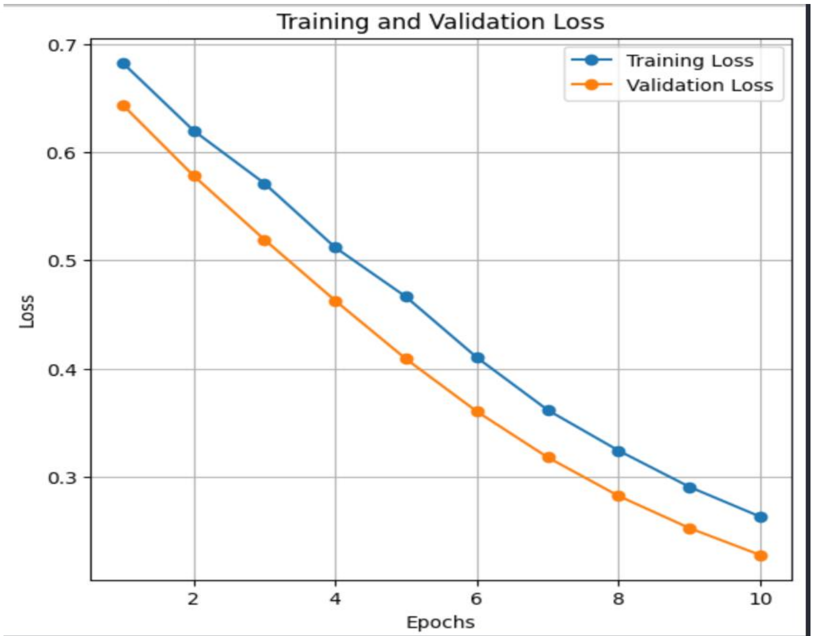
The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.98**

4.Training and Validation Accuracy Graph:



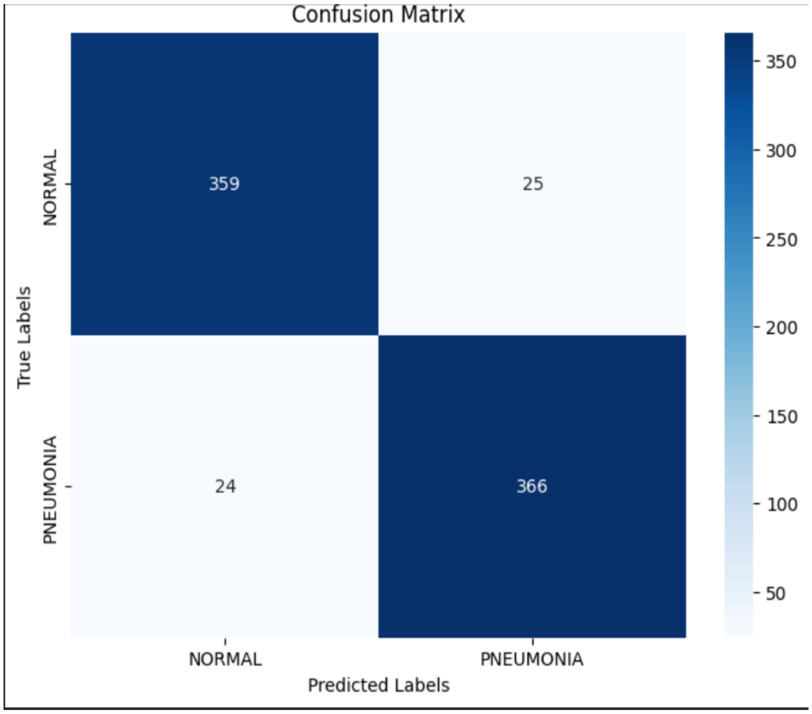
The graph demonstrates a steady increase in accuracy over epochs, with the validation accuracy closely following the training accuracy, indicating no overfitting.

5.Training and Validation Accuracy Graph:



The loss curve shows a consistent decrease during training, and the validation loss stabilizes at a low value, further confirming the model's effective learning without overfitting

6.Confusion Matrix



The confusion matrix shows:

- **True Positives (PNEUMONIA correctly classified)**: **366**
- **True Negatives (NORMAL correctly classified)**: **359**
- **False Positives (NORMAL misclassified as PNEUMONIA)**: **24**
- **False Negatives (PNEUMONIA misclassified as NORMAL)**: **25**
  This indicates the model's overall reliability, with minimal misclassifications.

7.Advantages:

- Achieved an accuracy of 93.6% and F1-scores of 0.94 for both classes, reflecting balanced performance.
- Lower false positives and false negatives compared to other models, indicating relatively high precision and recall.
- Smooth training and validation loss curves with no overfitting, confirming robust generalization.
- ROC-AUC of 0.98, showcasing excellent discriminatory ability.
- Lightweight compared to DenseNet, resulting in lower computational overhead.

8.Disadvantages:

- Accuracy and F1-scores are slightly lower than DenseNet and ResNet, indicating a possible gap in learning finer details of the data.
- May not be the best choice when extremely high precision or recall is required for certain classes.

9. Model Analysis

The Xception model successfully captured the intricate features of the chest X-ray images, enabling accurate classification. While the model shows excellent performance metrics, the slight misclassifications (24 false positives and 25 false negatives) highlight areas where further fine-

DenseNet Model Evaluation and Results

1. Model Overview

The **DenseNet** model was selected for its efficiency in capturing complex patterns in image data through its innovative architecture, which involves dense connections between layers. Unlike traditional convolutional networks, DenseNet ensures maximum feature reuse by connecting each layer to all preceding layers. This design facilitates the flow of information and gradients throughout the network, addressing issues like vanishing gradients and improving learning efficiency. DenseNet's ability to capture fine-grained details makes it particularly suitable for image classification tasks involving medical imagery, such as chest X-rays.

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2. Model Accuracy

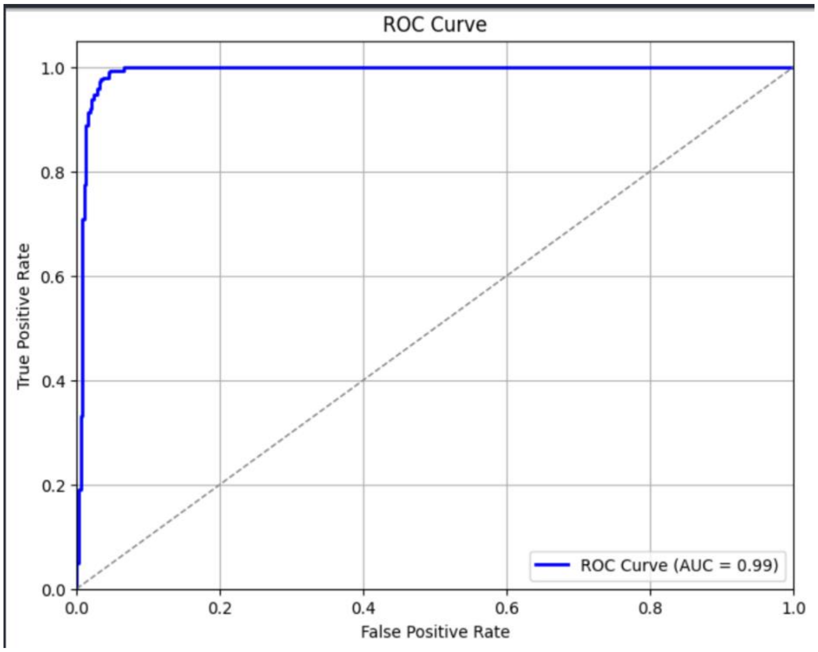
Accuracy: The model achieved a classification accuracy of **95.7%**, indicating its robustness in distinguishing between the two classes.

3.Classification Report:

Class	**Precision**	**Recall**	**F1-Score**	**Support**
NORMAL	1.00	0.91	0.96	384
PNEUMONIA	0.92	1.00	0.96	390
Accuracy			0.96	774
Macro Avg	0.96	0.96	0.96	774
Weighted Avg	0.96	0.96	0.96	774

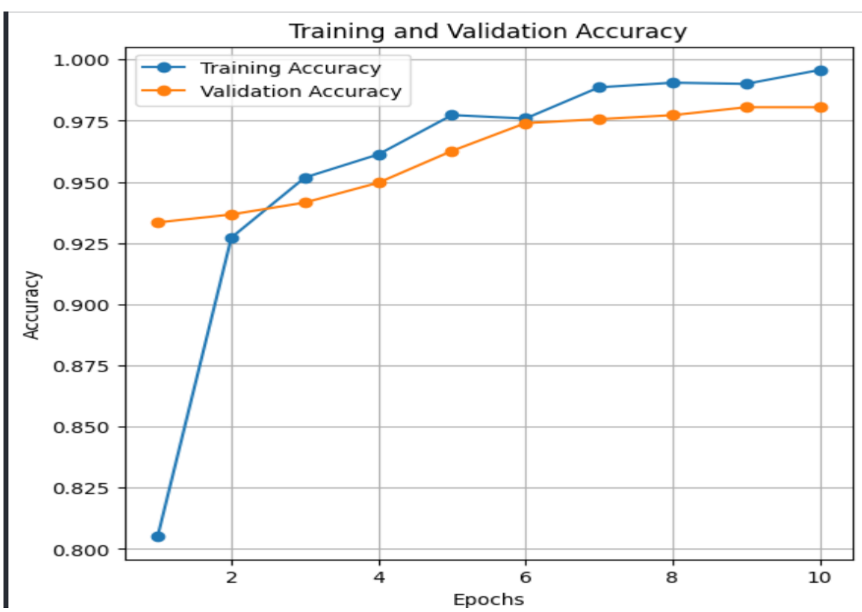
The classification report demonstrates excellent performance for both classes. The **NORMAL** class achieved a perfect precision of **1.00** but slightly lower recall (**0.91**), indicating some false negatives. Conversely, the **PNEUMONIA** class achieved a recall of **1.00** with a precision of **0.92**, showing no missed positive cases but a few false positives. Overall, the model achieved a strong accuracy of **95.7%**, with consistent macro and weighted average scores (**0.96**), reflecting balanced performance across both classes

3.ROC Curve



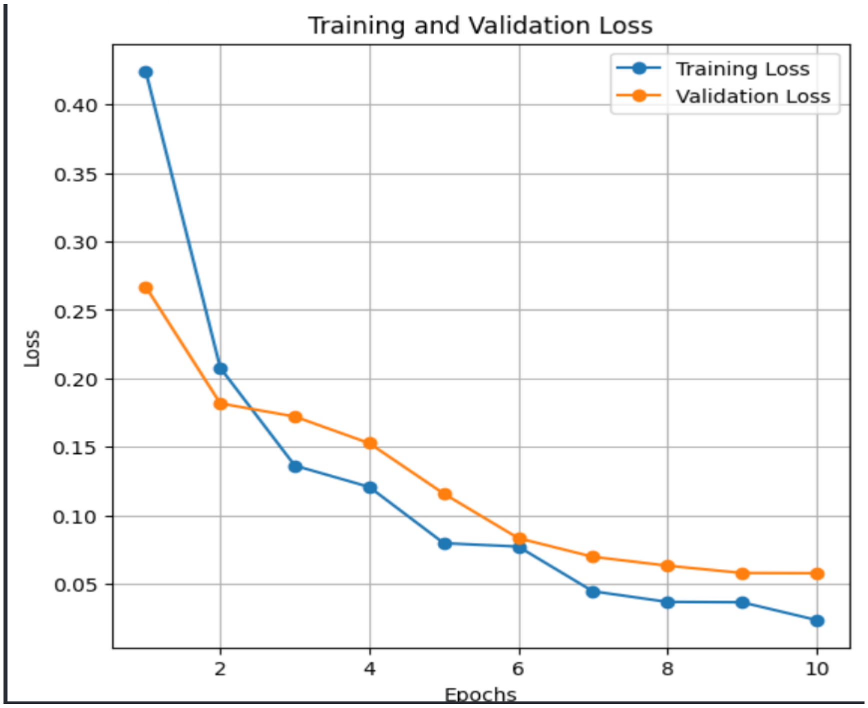
The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.99**

4.Training and Validation Accuracy Graph:



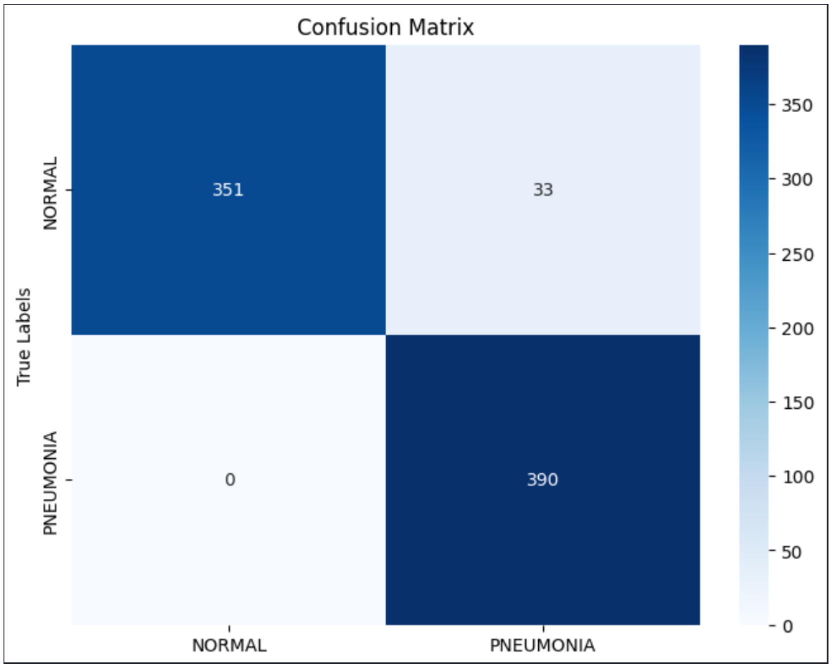
The graph demonstrates a steady increase in accuracy over epochs, with the validation accuracy closely following the training accuracy, indicating no overfitting.

5.Training and Validation Accuracy Graph:



The loss curve shows a consistent decrease during training, and the validation loss stabilizes at a low value, further confirming the model's effective learning without overfitting

6.Confusion Matrix



The confusion matrix shows:

- **True Positives (PNEUMONIA correctly classified)**: **390**
- **True Negatives (NORMAL correctly classified)**: **351**
- **False Positives (NORMAL misclassified as PNEUMONIA)**: **33**
- **False Negatives (PNEUMONIA misclassified as NORMAL)**: **0**
  This indicates the model's overall reliability, with minimal misclassifications

7.Advantages:

- Achieved the highest accuracy (95.7%) among the models.
- Perfect recall for PNEUMONIA (1.00), making it highly effective in ensuring no positive cases are missed.
- F1-scores of 0.96 for both classes, indicating robust and balanced predictions.
- ROC-AUC of 0.99, showing excellent model performance in distinguishing between the classes.
- Dense connectivity enables better gradient flow and feature reuse, leading to efficient learning.

8.Disadvantages:

- Higher number of false positives for the NORMAL class (33), which may lead to unnecessary interventions.
- More computationally intensive due to its dense architecture, requiring higher memory and training time.
- Overhead from using a deeper architecture may not always justify the marginal increase in performance for smaller datasets.

9. Model Analysis

The DenseNet model successfully captured the intricate features of the chest X-ray images, enabling accurate classification. While the model shows excellent performance metrics, the slight misclassifications (33 false positives and 0 false negatives) highlight areas where further fine-tuning

ResNet Model Evaluation and Results

1. Model Overview

The **ResNet** model was selected for its ability to efficiently capture complex patterns in image data through its deep residual learning framework. ResNet, or Residual Network, introduces skip (shortcut) connections that mitigate the vanishing gradient problem, enabling the training of very deep networks. These skip connections allow gradients to flow directly through the network, improving learning efficiency and convergence

ResNet's innovative architecture makes it particularly suitable for medical image classification tasks, such as chest X-rays, where capturing intricate details is critical for accurate diagnosis

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2. Model Accuracy

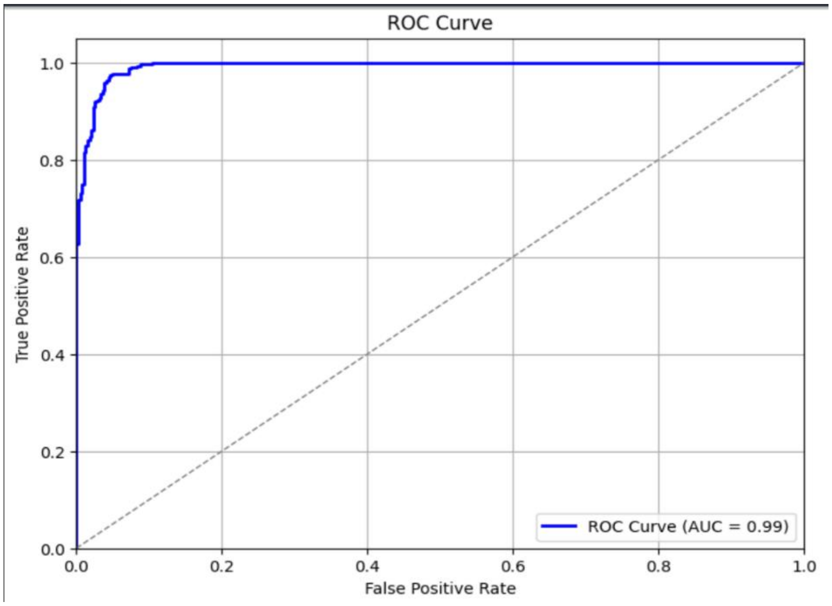
Accuracy: The model achieved a classification accuracy of **95.4%**, indicating its robustness in distinguishing between the two classes.

3.Classification Report:

Class	**Precision**	**Recall**	**F1-Score**	**Support**
NORMAL	0.99	0.92	0.95	384
PNEUMONIA	0.92	0.99	0.96	390
Accuracy			0.95	774
Macro Avg	0.96	0.95	0.95	774
Weighted Avg	0.96	0.95	0.95	774

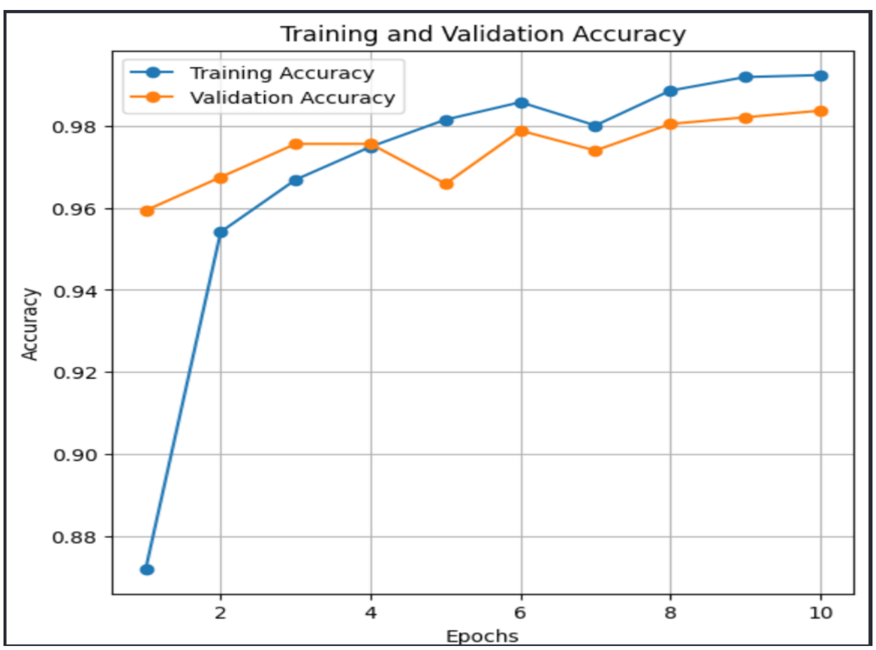
The classification report demonstrates excellent performance for both classes. The **NORMAL** class achieved a perfect precision of **0.99** but slightly lower recall (**0.92**), indicating some false negatives. Conversely, the **PNEUMONIA** class achieved a recall of **0.92** with a precision of **0.99**, showing no missed positive cases but a few false positives. Overall, the model achieved a strong accuracy of **95.4%**, with consistent macro and weighted average scores (**0.96**), reflecting balanced performance across both classes

3.ROC Curve



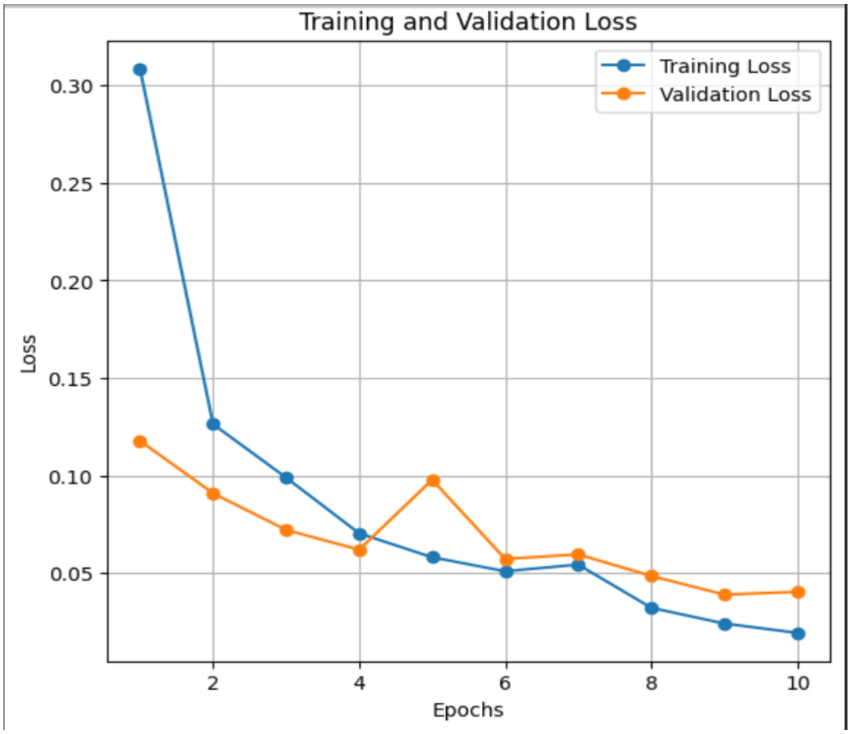
The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.99**

4.Training and Validation Accuracy Graph:



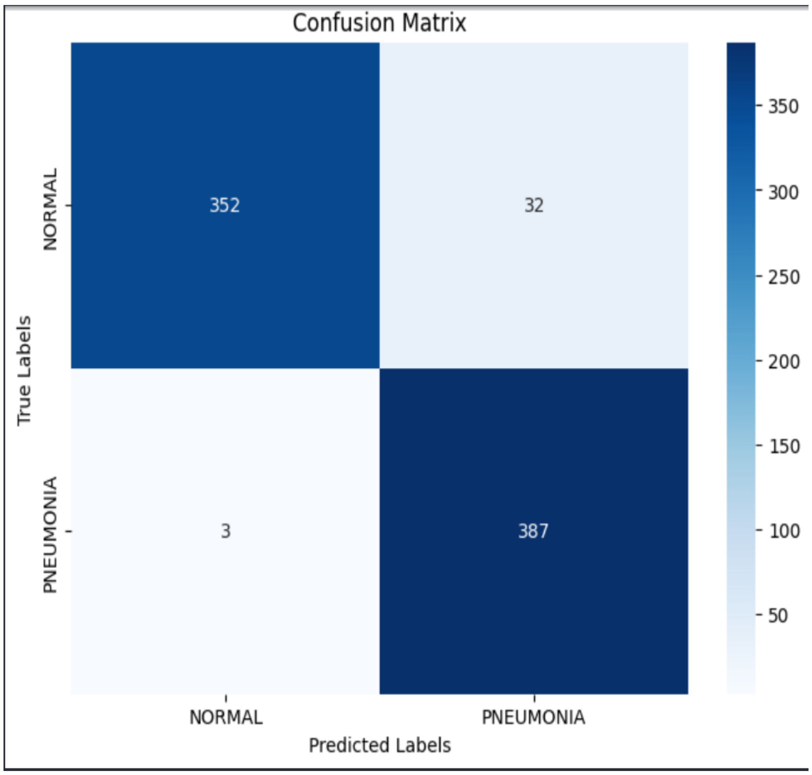
The graph demonstrates a steady increase in accuracy over epochs, with the validation accuracy closely following the training accuracy, indicating no overfitting

5.Training and Validation Accuracy Graph:



The loss curve shows a consistent decrease during training, and the validation loss stabilizes at a low value, further confirming the model's effective learning without overfitting

6.Confusion Matrix



The confusion matrix shows:

- **True Positives (PNEUMONIA correctly classified)**: **387**
- **True Negatives (NORMAL correctly classified)**: **352**
- **False Positives (NORMAL misclassified as PNEUMONIA)**: **32**
- **False Negatives (PNEUMONIA misclassified as NORMAL)**: **3**
  This indicates the model's overall reliability, with minimal misclassifications.

7.Advantages:

- Achieved an accuracy of 95.4% and an ROC-AUC of 0.99, comparable to DenseNet.
- F1-scores are robust (NORMAL: 0.95, PNEUMONIA: 0.96), with high precision for both classes.
- Simple and lightweight architecture compared to DenseNet, making it suitable for smaller datasets and lower computational resources.
- Smooth loss and accuracy curves indicate effective learning and no overfitting.

8.Disadvantages:

- Slightly lower accuracy and F1-scores than DenseNet, indicating less effective feature extraction.
- The recall for the PNEUMONIA class is slightly lower (0.92), leading to a few missed positive cases (false negatives).

9. Model Analysis

The ResNet model successfully captured the intricate features of the chest X-ray images, enabling accurate classification. While the model shows excellent performance metrics, the slight misclassifications (32 false positives and 3 false negatives) highlight areas where further fine-tuning

Comparison of the Three Architectures Based on Results

Metric	Xception	DenseNet121	ResNet18
Accuracy	93.6%	95.7%	95.4%
Precision (Normal)	0.94	1.00	0.99
Recall (Normal)	0.93	0.91	0.92
Precision (Pneumonia)	0.94	0.92	0.99
Recall (Pneumonia)	0.94	1.00	0.92
AUC	0.98	0.99	0.99
True Positives (Pneumonia)	366	390	387
False Positives	24	33	32
False Negatives	25	0	3

Best Model For the DataSet

For this dataset, **DenseNet121** stands out as the most effective architecture and the most robust mode due to its superior accuracy, perfect recall for PNEUMONIA, and efficient feature learning

Its Advantages:

- Excellent for medical imaging, especially when sensitivity **(recall)** for PNEUMONIA is critical
- DenseNet is advantageous when minimizing **false negatives** (critical in diagnosing pneumonia) is the top priority
- Dense connections improve feature propagation and mitigate the vanishing gradient problem
- Suitable for datasets requiring high feature extraction quality.
- DenseNet requires fewer parameters, making it suitable for tasks with limited labeled data like this chest X-ray dataset

All Models Comparison

Model	Without Data Augmentation	With Data Augmentation	Difference (Accuracy Drop)
DenseNet121	**95.7%**	91.5%	-4.2%
Xception	93.6%	91.1%	-2.5%
ResNet18	95.4%	**77.4%**	-18.0%
VGG16	95.4%	91.1%	-4.3%

Best Overall Model:

DenseNet121 is the most robust model, consistently delivering the highest accuracy in both scenarios.

Resourses

Data Agumentation:

https://link.springer.com/article/10.1007/s10462-023-10453-z

Xception paper:

https://arxiv.org/abs/1610.02357

DenseNet paper:

https://arxiv.org/abs/1608.06993

ResNet paper:

https://arxiv.org/abs/1512.03385

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