Pneumonia Detection Using Deep Learning

This notebook explores the **PneumoniaMNIST** dataset from MedMNIST, containing chest X-ray images labeled as either **pneumonia-positive** or **normal**.

Task Overview

- **Objective:** Detect pneumonia in lung X-ray images
- **Dataset:** PneumoniaMNIST (from MedMNIST)
- **Approach:** Experiment with different deep learning models

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Dataset Visualization

Load & Explore the Dataset

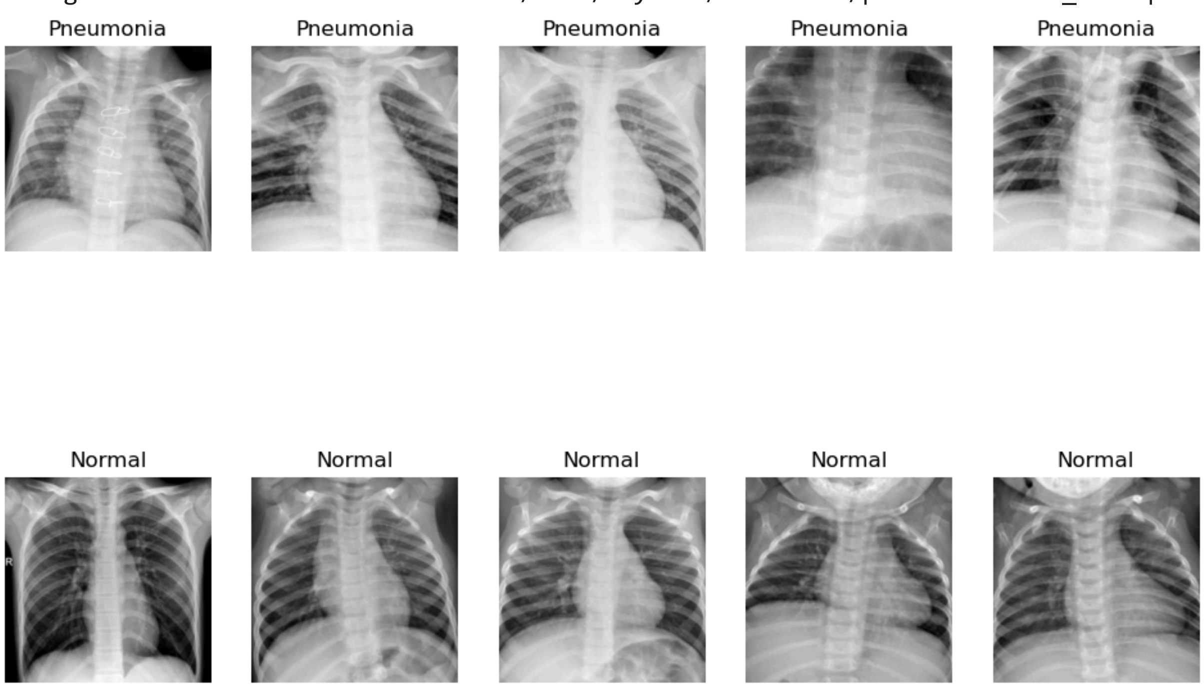
- Load **training, validation, and test datasets**
- **Visualize Normal vs Pneumonia lung X-rays** for better understanding

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import tensorflow as tf
from medmnist import PneumoniaMNIST
import torch
import torch.nn as nn
from torch.utils.data import DataLoader, Dataset
import torchvision.transforms as transforms
from PIL import Image
import torch.optim as optim
```

```
2025-03-14 02:39:37.557022: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.c
c:9261] Unable to register cuDNN factory: Attempting to register factory for plugin
cuDNN when one has already been registered
2025-03-14 02:39:37.557067: E external/local_xla/xla/stream_executor/cuda/cuda_fft.c
c:607] Unable to register cuFFT factory: Attempting to register factory for plugin c
uFFT when one has already been registered
2025-03-14 02:39:37.558414: E external/local_xla/xla/stream_executor/cuda/cuda_blas.
cc:1515] Unable to register cuBLAS factory: Attempting to register factory for plugi
n cuBLAS when one has already been registered
2025-03-14 02:39:37.569840: I tensorflow/core/platform/cpu_feature_guard.cc:182] Thi
s TensorFlow binary is optimized to use available CPU instructions in performance-cr
itical operations.
To enable the following instructions: AVX2 AVX512F FMA, in other operations, rebuild
TensorFlow with the appropriate compiler flags.
```

In [2]:
```
if 'dataset_train' not in globals():
    dataset_train = PneumoniaMNIST(split="train", download=True, size=224)
    dataset_val = PneumoniaMNIST(split="val", download=True, size=224)
    dataset_test = PneumoniaMNIST(split="test", download=True, size=224)

# Visualizing Pneumonia vs Normal Lungs
pneumonia_images = [dataset_train[i][0] for i in range(len(dataset_train)) if datas
normal_images = [dataset_train[i][0] for i in range(len(dataset_train)) if dataset_

fig, axes = plt.subplots(nrows=2, ncols=5, figsize=(12, 8))
for i in range(5):

    # Pneumonia images
    image_pneumonia = np.array(pneumonia_images[i]) if isinstance(pneumonia_images[
    axes[0][i].imshow(image_pneumonia, cmap='gray')
    axes[0][i].axis('off')
    axes[0][i].set_title("Pneumonia")

    # Normal images
    image_normal = np.array(normal_images[i]) if isinstance(normal_images[i], Image
    axes[1][i].imshow(image_normal, cmap='gray')
    axes[1][i].axis('off')
    axes[1][i].set_title("Normal")
plt.show()
```

```
Using downloaded and verified file: /home/chynson/.medmnist/pneumoniamnist_224.npz
Using downloaded and verified file: /home/chynson/.medmnist/pneumoniamnist_224.npz
Using downloaded and verified file: /home/chynson/.medmnist/pneumoniamnist_224.npz
```



Preprocessing & DataLoader

- Converts images to **grayscale format** `(1, 224, 224)`
- Applies transformations like **resizing** and **normalization**

- Wraps the dataset in a **PyTorch `Dataset` class** for easy use with DataLoaders

In [3]:

```
class PneumoniaDataset(Dataset):
    def __init__(self, dataset, transform=None):
        self.dataset = dataset
        self.transform = transform

    def __len__(self):
        return len(self.dataset)

    def __getitem__(self, idx):
        image, label = self.dataset[idx]
        image = np.array(image, dtype=np.float32) / 255.0

        # ensure grayscale images have a single channel (1, H, W)
        if len(image.shape) == 2:  # if (H, W), convert to (1, H, W)
            image = np.expand_dims(image, axis=0)

        # convert to PIL Image only if a transformation is applied
        if self.transform:
            image = Image.fromarray((image.squeeze(0) * 255).astype(np.uint8))  # c
            image = self.transform(image)  # transformations

        else:
            image = torch.tensor(image)  # convert NumPy array to Tensor manually

        label = torch.tensor(label, dtype=torch.long).squeeze()  # check label is a

        return image, label




# transformations
transform = transforms.Compose([
    transforms.Resize((224, 224)),  # Resize before tensor conversion
    transforms.ToTensor(),  # Converts to tensor and keeps grayscale format (1, H,
    transforms.Normalize(mean=[0.5], std=[0.5])  # Normalize grayscale image
])


# Create PyTorch datasets
train_dataset = PneumoniaDataset(dataset_train, transform=transform)
val_dataset = PneumoniaDataset(dataset_val, transform=transform)
test_dataset = PneumoniaDataset(dataset_test, transform=transform)
print("Training Set Size:", len(train_dataset))
print("Validation Set Size:", len(val_dataset))
print("Test Set Size:", len(test_dataset))

BATCH_SIZE = 32
train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=BATCH_SIZE, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=BATCH_SIZE, shuffle=False)

USE_GPU = True
```

```
device = torch.device("cuda" if USE_GPU and torch.cuda.is_available() else "cpu")
print('Using device:', device)
```

```
Training Set Size: 4708
Validation Set Size: 524
Test Set Size: 624
Using device: cuda
```

Baseline Model: Simple Neural Network

Purpose

- This is our **first very simple model** to establish a **baseline accuracy**
- Uses a **fully connected network** with basic linear layers

Approach

- **Architecture:**
  - **Flatten Input:** Converts image into a **1D vector**
  - **Fully Connected Layers:** Two dense layers process the data
  - **Output:** Binary classification (**Pneumonia vs. Normal**)
- **Training Strategy:**
  - Loss Function: **CrossEntropyLoss**
  - Optimizer: **Adam**
  - Runs for a **small number of epochs** to establish a baseline

In [4]:
```
from files.models import nn1
model = nn1()
print(model)
```

```
nn1(
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (fc1): Linear(in_features=50176, out_features=128, bias=True)
  (fc2): Linear(in_features=128, out_features=2, bias=True)
)
```

In [5]:
```
dummy_input = torch.randn(1, 1, 224, 224)
output = model(dummy_input)
# print output shape (should be [1, 2] for binary classification)
print("Output shape:", output.shape)
```

```
Output shape: torch.Size([1, 2])
```

In [6]:
```
# loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# sample label (batch size = 1, class index 0 or 1)
label = torch.tensor([1])  # pneumonia
```

```
# forward pass
output = model(dummy_input)

# loss
loss = criterion(output, label)
print("Loss:", loss.item())

# backpropagation
loss.backward()
optimizer.step()

print("Backpropagation successful!")
```

```
Loss: 0.7577195167541504
Backpropagation successful!
```

In [7]:
```
from files.train import train_model

model = nn1().to(device)

# loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# train the model
train_model(model, train_loader, val_loader, criterion, optimizer, device, epochs=1
```

```
Epoch 1/10, Train Loss: 0.3478, Train Acc: 0.9174, Val Loss: 0.2279, Val Acc: 0.9046
Epoch 2/10, Train Loss: 0.1260, Train Acc: 0.9541, Val Loss: 0.1129, Val Acc: 0.9618
Epoch 3/10, Train Loss: 0.1077, Train Acc: 0.9616, Val Loss: 0.1181, Val Acc: 0.9542
Epoch 4/10, Train Loss: 0.0914, Train Acc: 0.9673, Val Loss: 0.1167, Val Acc: 0.9599
Epoch 5/10, Train Loss: 0.0809, Train Acc: 0.9705, Val Loss: 0.1421, Val Acc: 0.9370
Epoch 6/10, Train Loss: 0.0608, Train Acc: 0.9764, Val Loss: 0.1175, Val Acc: 0.9561
Epoch 7/10, Train Loss: 0.0649, Train Acc: 0.9730, Val Loss: 0.1635, Val Acc: 0.9466
Epoch 8/10, Train Loss: 0.0763, Train Acc: 0.9711, Val Loss: 0.1232, Val Acc: 0.9504
Epoch 9/10, Train Loss: 0.0421, Train Acc: 0.9845, Val Loss: 0.1445, Val Acc: 0.9561
Epoch 10/10, Train Loss: 0.0569, Train Acc: 0.9781, Val Loss: 0.2197, Val Acc: 0.940
8
Training Complete!
```

In [8]:
```
from files.evaluate import test_model

# test evaluation
test_acc, report = test_model(model, test_loader, device)
```

```
Test Accuracy: 83.01%

Classification Report:
              precision    recall  f1-score   support

      Normal       0.97      0.56      0.71       234
   Pneumonia       0.79      0.99      0.88       390

    accuracy                           0.83       624
   macro avg       0.88      0.78      0.80       624
weighted avg       0.86      0.83      0.82       624
```

Optimizing Model Performance

Analyzing Baseline Test Results

- The baseline model achieved **83.01% test accuracy**, but let's break down the classification report

Metric	Normal (0)	Pneumonia (1)
Precision	97%	79%
Recall	56%	99%
F1-score	71%	88%

Class Imbalance in Performance

- The **Normal class** has high **precision (97%)**, but **low recall (56%)**
- The model is biased towards predicting **Pneumonia** (99% recall)

Potential Overfitting

- **Training accuracy = 98.45%**, but **test accuracy = 83.01%**
- The model is **memorizing the training set** rather than generalizing well

Weighted Average F1-score = 0.82

- The model performs well overall, but **misclassifications in Normal cases need to be addressed**

Next Steps: Improve Model Performance

Now that we have a baseline, let's improve it using different strategies:

Method 1: Convolutional Neural Network (CNN)

- The baseline model is a **fully connected neural network**, which doesn't capture **spatial features** so implementing a **CNN** will be able to detect **edges, textures, and shapes**, which are critical for **X-ray analysis**

CNN Architecture

Layers Breakdown

Layer	Details
Conv2D(16 filters, 3x3)	Extracts **low-level features** like edges & textures
ReLU Activation	Applies non-linearity for better feature extraction
MaxPooling(2x2)	Reduces spatial dimensions by half (downsampling)
Conv2D(32 filters, 3x3)	Extracts more complex patterns
ReLU Activation	Another non-linear activation
MaxPooling(2x2)	Further reduces spatial dimensions
Flatten	Converts the **feature map** into a **1D vector**
Fully Connected (128 neurons)	Learns global patterns from extracted features
Fully Connected (2 neurons, Softmax Output)	Outputs **class probabilities** (Pneumonia vs Normal)

In [10]:
```
from files.models import CNNModel

model_cnn = CNNModel().to(device)

# loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model_cnn.parameters(), lr=0.001)

# train
print("Training CNN Model...")
train_model(model_cnn, train_loader, val_loader, criterion, optimizer, device, epoc
```

```
Training CNN Model...
Epoch 1/10, Train Loss: 0.1823, Train Acc: 0.9344, Val Loss: 0.1345, Val Acc: 0.9427
Epoch 2/10, Train Loss: 0.0855, Train Acc: 0.9673, Val Loss: 0.1188, Val Acc: 0.9561
Epoch 3/10, Train Loss: 0.0623, Train Acc: 0.9783, Val Loss: 0.1266, Val Acc: 0.9580
Epoch 4/10, Train Loss: 0.0432, Train Acc: 0.9841, Val Loss: 0.1871, Val Acc: 0.9485
Epoch 5/10, Train Loss: 0.0286, Train Acc: 0.9877, Val Loss: 0.1084, Val Acc: 0.9656
Epoch 6/10, Train Loss: 0.0205, Train Acc: 0.9938, Val Loss: 0.1545, Val Acc: 0.9599
Epoch 7/10, Train Loss: 0.0085, Train Acc: 0.9970, Val Loss: 0.1451, Val Acc: 0.9599
Epoch 8/10, Train Loss: 0.0028, Train Acc: 0.9992, Val Loss: 0.1514, Val Acc: 0.9676
Epoch 9/10, Train Loss: 0.0005, Train Acc: 1.0000, Val Loss: 0.1503, Val Acc: 0.9618
Epoch 10/10, Train Loss: 0.0002, Train Acc: 1.0000, Val Loss: 0.1546, Val Acc: 0.963
7
Training Complete!
```

In [11]:
```
# test evaluation
test_acc, report = test_model(model_cnn, test_loader, device)
```

```
Test Accuracy: 82.69%

Classification Report:
              precision    recall  f1-score   support

      Normal       0.97      0.56      0.71       234
   Pneumonia       0.79      0.99      0.88       390

    accuracy                           0.83       624
   macro avg       0.88      0.77      0.79       624
weighted avg       0.86      0.83      0.81       624
```

CNN vs Baseline Model: Performance Comparison

Test Results

Metric	Baseline	CNN Model
Test Accuracy	**83.01%**	**82.69%**
Precision (Normal)	**97%**	**97%**
Recall (Normal)	**57%**	**56%**
F1-score (Normal)	**72%**	**71%**
Recall (Pneumonia)	**99%**	**99%**

- **CNN shows higher training & validation accuracy** but still favors Pneumonia
- **No significant test accuracy improvement**—overfitting remains an issue.

Next Steps: Improving Model Performance with ResNet-18

After implementing a **CNN**, we can further enhance performance by leveraging **deeper architectures**. **ResNet-18** utilizes **skip connections** to allow deeper networks to train effectively ultimately leading to better feature extraction and mitigating the vanishing gradient problem.

- **Two Approaches**:
  1. **Train ResNet from scratch** (no pre-trained weights): Trained entirely from **random initialization**
  2. **Use a Pretrained ResNet** (leveraging Transfer Learning): Uses **pretrained ImageNet weights** for faster convergence

Method 2: ResNet-18 Architecture

Layers Breakdown

Layer	Details
Conv2D(64 filters, 7x7, stride=2, padding=3)	Extracts **low-level features** like edges & textures
Batch Normalization & ReLU Activation	Improves stability and non-linearity
MaxPooling(3x3, stride=2)	Reduces spatial dimensions by half
ResNet Blocks (Basic Blocks)	Deep feature extraction via residual connections
Adaptive Avg Pooling	Reduces dimensions for final classification
Fully Connected Layer (2 neurons, Softmax Output)	Outputs class probabilities (Pneumonia vs Normal)

In [13]:
```
from files.models import ResNetScratch, ResNetPretrained

model_scratch = ResNetScratch().to(device)
model_pretrained = ResNetPretrained().to(device)

criterion = nn.CrossEntropyLoss()
optimizer_scratch = optim.Adam(model_scratch.parameters(), lr=0.001)
optimizer_pretrained = optim.Adam(model_pretrained.parameters(), lr=0.001)

print("Training ResNet from Scratch...")
train_model(model_scratch, train_loader, val_loader, criterion, optimizer_scratch,

print("\n Training Pretrained ResNet...")
train_model(model_pretrained, train_loader, val_loader, criterion, optimizer_pretra
```

```
Training ResNet from Scratch...
Epoch 1/10, Train Loss: 0.2523, Train Acc: 0.9034, Val Loss: 0.1916, Val Acc: 0.9218
Epoch 2/10, Train Loss: 0.1364, Train Acc: 0.9452, Val Loss: 0.1159, Val Acc: 0.9618
Epoch 3/10, Train Loss: 0.1090, Train Acc: 0.9533, Val Loss: 0.2398, Val Acc: 0.8989
Epoch 4/10, Train Loss: 0.1040, Train Acc: 0.9603, Val Loss: 0.0891, Val Acc: 0.9695
Epoch 5/10, Train Loss: 0.0904, Train Acc: 0.9664, Val Loss: 0.0684, Val Acc: 0.9714
Epoch 6/10, Train Loss: 0.0935, Train Acc: 0.9679, Val Loss: 0.1617, Val Acc: 0.9294
Epoch 7/10, Train Loss: 0.0809, Train Acc: 0.9711, Val Loss: 0.1237, Val Acc: 0.9542
Epoch 8/10, Train Loss: 0.0707, Train Acc: 0.9707, Val Loss: 0.0726, Val Acc: 0.9733
Epoch 9/10, Train Loss: 0.0594, Train Acc: 0.9777, Val Loss: 0.4221, Val Acc: 0.8607
Epoch 10/10, Train Loss: 0.0560, Train Acc: 0.9781, Val Loss: 0.0692, Val Acc: 0.975
2
Training Complete!

 Training Pretrained ResNet...
Epoch 1/10, Train Loss: 0.1460, Train Acc: 0.9486, Val Loss: 0.1130, Val Acc: 0.9695
Epoch 2/10, Train Loss: 0.0929, Train Acc: 0.9654, Val Loss: 0.3969, Val Acc: 0.8511
Epoch 3/10, Train Loss: 0.0856, Train Acc: 0.9684, Val Loss: 0.1371, Val Acc: 0.9580
Epoch 4/10, Train Loss: 0.0594, Train Acc: 0.9796, Val Loss: 0.0557, Val Acc: 0.9828
Epoch 5/10, Train Loss: 0.0501, Train Acc: 0.9805, Val Loss: 0.1388, Val Acc: 0.9637
Epoch 6/10, Train Loss: 0.0472, Train Acc: 0.9819, Val Loss: 0.0699, Val Acc: 0.9790
Epoch 7/10, Train Loss: 0.0358, Train Acc: 0.9853, Val Loss: 0.0856, Val Acc: 0.9695
Epoch 8/10, Train Loss: 0.0438, Train Acc: 0.9839, Val Loss: 0.1191, Val Acc: 0.9618
Epoch 9/10, Train Loss: 0.0388, Train Acc: 0.9845, Val Loss: 0.0790, Val Acc: 0.9771
Epoch 10/10, Train Loss: 0.0343, Train Acc: 0.9879, Val Loss: 0.0593, Val Acc: 0.979
0
Training Complete!
```

In [14]:

```python
from files.evaluate import test_model

print("Evaluating ResNet from Scratch...")
test_model(model_scratch, test_loader, device)

print("\nEvaluating Pretrained ResNet...")
test_model(model_pretrained, test_loader, device)
```

```
Evaluating ResNet from Scratch...
Test Accuracy: 84.94%

Classification Report:
               precision    recall  f1-score   support

      Normal       0.99      0.61      0.75       234
   Pneumonia       0.81      0.99      0.89       390

    accuracy                           0.85       624
   macro avg       0.90      0.80      0.82       624
weighted avg       0.88      0.85      0.84       624


Evaluating Pretrained ResNet...
Test Accuracy: 86.86%

Classification Report:
               precision    recall  f1-score   support

      Normal       1.00      0.65      0.79       234
   Pneumonia       0.83      1.00      0.90       390

    accuracy                           0.87       624
   macro avg       0.91      0.82      0.85       624
weighted avg       0.89      0.87      0.86       624
```

Out[14]:
```
(0.8685897435897436,
 '              precision    recall  f1-score   support\n\n      Normal       1.00
0.65      0.79       234\n   Pneumonia       0.83      1.00      0.90       390\n
\n    accuracy                           0.87       624\n   macro avg       0.91
0.82      0.85       624\nweighted avg       0.89      0.87      0.86       624
\n')
```

ResNet-18 Performance Analysis

After training both **ResNet from Scratch** and **Pretrained ResNet**, let's compare their performance.

ResNet from Scratch

Epoch	Train Acc	Val Acc	Train Loss	Val Loss
1	90.3%	92.2%	0.2523	0.1916
5	96.6%	97.1%	0.0904	0.0684
10	97.8%	97.5%	0.0560	0.0692

- **Consistent performance** with stable validation accuracy
- **Slight overfitting** noticed at **Epoch 9** (val loss spiked to **0.4221**)

Pretrained ResNet (Transfer Learning)

Epoch	Train Acc	Val Acc	Train Loss	Val Loss
1	94.9%	96.9%	0.1460	0.1130
5	98.0%	96.4%	0.0501	0.1388
10	98.8%	97.9%	0.0343	0.0593

- **Faster convergence**, reaching high validation accuracy early
- **Val loss spiked** at **Epoch 2** (**0.3969**, 85.1%), indicating some instability

Key Observations:

Model	Training Time	Final Test Accuracy	Stability	Overfitting Risk
ResNet from Scratch	Longer	**84.94%**	More stable	Moderate
Pretrained ResNet	Faster	**86.86%**	Some instability	Slightly higher

- **Pretrained ResNet converged faster** but had minor **instability in early epochs**
- **ResNet from Scratch** had **more stable training** but required **longer training time**
- **Test Accuracy: 86.9%**
  - **Precision (Normal): 100%**, but **recall = 65%** (still misclassifying Normal cases)
  - **Recall (Pneumonia): 100%**, indicating **model bias toward Pneumonia**

Next Steps: Enhancing Feature Extraction

After implementing **ResNet-18**, we now experiment with **even deeper architectures** that **capture more complex patterns in X-rays**.

- **Two Approaches**:
  1. **CNN with Batch Norm & Dropout**: Improves generalization and prevents overfitting
  2. **ResNet-50 (Transfer Learning)**: A **deeper residual network** leveraging **pretrained ImageNet weights**

Method 3: Advanced Model Architectures

CNN with Batch Normalization & Dropout

Layer	Details
Conv2D(32 filters, 3x3, padding=1)	Extracts **low-level features** like edges & textures
BatchNorm & ReLU Activation	Stabilizes training and improves feature extraction
MaxPooling(2x2)	Reduces spatial dimensions
Conv2D(64 filters, 3x3, padding=1)	Extracts higher-level features
BatchNorm & ReLU Activation	Improves non-linearity
MaxPooling(2x2)	Further reduces spatial dimensions
Fully Connected (256 neurons, Dropout 0.5)	Prevents overfitting
Fully Connected (2 neurons, Softmax Output)	Outputs class probabilities

ResNet-50

Layer	Details
Conv2D(64 filters, 7x7, stride=2, padding=3)	Extracts **low-level features**
Batch Normalization & ReLU Activation	Improves stability and non-linearity
MaxPooling(3x3, stride=2)	Reduces spatial dimensions
Deeper ResNet Blocks (50 layers)	Extracts advanced features with **skip connections**
Adaptive Avg Pooling	Reduces dimensions for classification
Fully Connected Layer (2 neurons, Softmax Output)	Outputs class probabilities

In [26]:
```
from files.models import CNNModelAdvanced, ResNet50Pretrained

model_cnn = CNNModelAdvanced().to(device)
model_resnet50 = ResNet50Pretrained().to(device)

criterion = nn.CrossEntropyLoss()
optimizer_cnn = optim.Adam(model_cnn.parameters(), lr=0.001)
optimizer_resnet50 = optim.Adam(model_resnet50.parameters(), lr=0.001)

print("Training CNN with Batch Normalization & Dropout...")
train_model(model_cnn, train_loader, val_loader, criterion, optimizer_cnn, device,

print("\nTraining ResNet-50...")
train_model(model_resnet50, train_loader, val_loader, criterion, optimizer_resnet50
```

```
Training CNN with Batch Normalization & Dropout...
Epoch 1/10, Train Loss: 1.7324, Train Acc: 0.9212, Val Loss: 0.0940, Val Acc: 0.9637
Epoch 2/10, Train Loss: 0.1242, Train Acc: 0.9567, Val Loss: 0.1085, Val Acc: 0.9695
Epoch 3/10, Train Loss: 0.1154, Train Acc: 0.9588, Val Loss: 0.1035, Val Acc: 0.9580
Epoch 4/10, Train Loss: 0.1344, Train Acc: 0.9573, Val Loss: 0.0800, Val Acc: 0.9676
Epoch 5/10, Train Loss: 0.0982, Train Acc: 0.9652, Val Loss: 0.1828, Val Acc: 0.9389
Epoch 6/10, Train Loss: 0.1218, Train Acc: 0.9558, Val Loss: 0.1689, Val Acc: 0.9580
Epoch 7/10, Train Loss: 0.1041, Train Acc: 0.9605, Val Loss: 0.1064, Val Acc: 0.9637
Epoch 8/10, Train Loss: 0.1238, Train Acc: 0.9522, Val Loss: 0.0997, Val Acc: 0.9523
Epoch 9/10, Train Loss: 0.1302, Train Acc: 0.9518, Val Loss: 0.1440, Val Acc: 0.9618
Epoch 10/10, Train Loss: 0.1198, Train Acc: 0.9533, Val Loss: 0.0920, Val Acc: 0.969
5
Training Complete!

Training ResNet-50...
Epoch 1/10, Train Loss: 0.1642, Train Acc: 0.9367, Val Loss: 0.2202, Val Acc: 0.9275
Epoch 2/10, Train Loss: 0.0773, Train Acc: 0.9713, Val Loss: 0.1501, Val Acc: 0.9561
Epoch 3/10, Train Loss: 0.0778, Train Acc: 0.9732, Val Loss: 0.0662, Val Acc: 0.9714
Epoch 4/10, Train Loss: 0.0556, Train Acc: 0.9809, Val Loss: 1.4315, Val Acc: 0.6794
Epoch 5/10, Train Loss: 0.0432, Train Acc: 0.9845, Val Loss: 0.0611, Val Acc: 0.9733
Epoch 6/10, Train Loss: 0.0374, Train Acc: 0.9875, Val Loss: 0.0691, Val Acc: 0.9714
Epoch 7/10, Train Loss: 0.0410, Train Acc: 0.9847, Val Loss: 0.1499, Val Acc: 0.9542
Epoch 8/10, Train Loss: 0.0375, Train Acc: 0.9866, Val Loss: 0.0914, Val Acc: 0.9676
Epoch 9/10, Train Loss: 0.0229, Train Acc: 0.9919, Val Loss: 0.1110, Val Acc: 0.9733
Epoch 10/10, Train Loss: 0.0130, Train Acc: 0.9955, Val Loss: 0.1405, Val Acc: 0.961
8
Training Complete!
```

In [27]:
```python
print("Evaluating CNN with Batch Normalization & Dropout...")
test_acc_cnn, report_cnn = test_model(model_cnn, test_loader, device)

print("\nEvaluating ResNet-50...")
test_acc_resnet50, report_resnet50 = test_model(model_resnet50, test_loader, device
```

```
Evaluating CNN with Batch Normalization & Dropout...
Test Accuracy: 87.18%

Classification Report:
              precision    recall  f1-score   support

      Normal       0.96      0.68      0.80       234
   Pneumonia       0.84      0.98      0.91       390

    accuracy                           0.87       624
   macro avg       0.90      0.83      0.85       624
weighted avg       0.89      0.87      0.87       624


Evaluating ResNet-50...
Test Accuracy: 85.10%

Classification Report:
              precision    recall  f1-score   support

      Normal       0.99      0.61      0.75       234
   Pneumonia       0.81      1.00      0.89       390

    accuracy                           0.85       624
   macro avg       0.90      0.80      0.82       624
weighted avg       0.88      0.85      0.84       624
```

Final Model Comparison: CNN with Batch Norm & Dropout vs. ResNet-50

Key Observations

CNN with BatchNorm & Dropout:

- Achieved the **highest test accuracy (87.18%)**
- More **balanced recall** between **Normal (68%)** and **Pneumonia (98%)**
- **Stronger generalization**, with **better performance across both classes**

ResNet-50:

- Achieved **85.10% test accuracy** but has **higher precision (99%)** for Normal cases
- **Poor recall (61%)** for Normal cases—**over-predicts Pneumonia**
- **Signs of overfitting**: Training accuracy reached **99.55%**, but validation fluctuated
- A **sudden validation loss spike (Epoch 4: 1.43)** suggests instability

Model	Test Accuracy	Normal Precision	Normal Recall	Pneumonia Precision	Pneumonia Recall	F1-Score (Weighted)
CNN (BatchNorm + Dropout)	**87.18%**	96%	**68%**	**84%**	**98%**	**87%**
ResNet-50 (Transfer Learning)	85.10%	**99%**	61%	81%	100%	84%

Potential Architecture Improvements

To further enhance model performance and mitigate **recall imbalance**, several architectural modifications could be introduced:

Increase Model Depth & Capacity

- **Add more convolutional layers** to capture deeper spatial features
- **Use larger kernel sizes (5x5 or 7x7)** for broader feature extraction

Implement Squeeze-and-Excitation (SE) Blocks

- Introduces **attention mechanisms** to focus on pneumonia-affected lung regions

---

Transitioning to Vision Transformers (ViT)

After experimenting with multiple architectures, it was determined what was needed inorder to develop an effective pneumonia classifier. CNNs and ResNets rely on **localized feature extraction**, but **X-rays require global context** for better classification. Our **recall imbalance** and **ResNet's instability** suggested:

1. **We need a model that captures long-range dependencies**
2. **Self-attention can help learn subtle differences** between pneumonia and normal cases
3. **A shift away from CNN-based architectures** might improve generalization