notebook12d9ded5ac

January 1, 2026

[3]:
```
# ========================================
# PNEUMONIA DETECTION FROM CHEST X-RAYS
# ========================================
# A Complete Deep Learning Pipeline
# Models: Baseline CNN, ResNet50, EfficientNetB0

# ========================================
# CELL 1: Setup and Imports
# ========================================

import os
import gc
import warnings
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from PIL import Image
import cv2
from pathlib import Path
import pickle

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import (
    Conv2D, MaxPooling2D, Flatten, Dense, Dropout,
    BatchNormalization, GlobalAveragePooling2D
)
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,␣
↪ModelCheckpoint
from tensorflow.keras.regularizers import l2
from tensorflow.keras.applications import ResNet50, EfficientNetB0

from sklearn.model_selection import train_test_split
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```python
from sklearn.utils.class_weight import compute_class_weight
from sklearn.metrics import (
    confusion_matrix, classification_report,
    roc_curve, auc, roc_auc_score,
    precision_score, recall_score, f1_score, accuracy_score
)

warnings.filterwarnings('ignore')
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")

print(f"TensorFlow version: {tf.__version__}")
print(f"GPU Available: {tf.config.list_physical_devices('GPU')}")

# Configuration
IMG_SIZE = 224
BATCH_SIZE = 32
SEED = 42
np.random.seed(SEED)
tf.random.set_seed(SEED)

# Create directories
os.makedirs('models', exist_ok=True)

print("  Setup complete!")
```

```
TensorFlow version: 2.20.0
GPU Available: []
 Setup complete!
```

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# ========================================
# CELL 2: Download Dataset
# ========================================

import kagglehub

# Download dataset
path = kagglehub.dataset_download("paultimothymooney/chest-xray-pneumonia")
print(f"Dataset downloaded to: {path}")

# Set data path
base_path = path
data_path = os.path.join(base_path, 'chest_xray')

print(f"  Data path: {data_path}")
```

```
Dataset downloaded to: /kaggle/input/chest-xray-pneumonia
 Data path: /kaggle/input/chest-xray-pneumonia/chest_xray
```

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```python
# ========================================
# CELL 3: Dataset Statistics
# ========================================

def count_images(directory):
    """Count images in each directory"""
    counts = {}
    for root, dirs, files in os.walk(directory):
        if 'NORMAL' in root or 'PNEUMONIA' in root:
            class_name = os.path.basename(root)
            split_name = os.path.basename(os.path.dirname(root))
            key = f"{split_name}/{class_name}"
            counts[key] = len([f for f in files if f.endswith(('.jpeg', '.jpg', '.png'))])
    return counts

# Count all images
image_counts = count_images(data_path)

# Display results
print("="*60)
print("DATASET STATISTICS")
print("="*60)
for key, count in sorted(image_counts.items()):
    print(f"{key:30s}: {count:5d} images")

# Calculate totals
train_normal = image_counts.get('train/NORMAL', 0)
train_pneumonia = image_counts.get('train/PNEUMONIA', 0)
val_normal = image_counts.get('val/NORMAL', 0)
val_pneumonia = image_counts.get('val/PNEUMONIA', 0)
test_normal = image_counts.get('test/NORMAL', 0)
test_pneumonia = image_counts.get('test/PNEUMONIA', 0)

print("\n" + "="*60)
print("CLASS DISTRIBUTION")
print("="*60)
print(f"Training: {train_normal + train_pneumonia} images")
print(f"  Normal: {train_normal} ({train_normal/(train_normal+train_pneumonia)*100:.2f}%)")
print(f"  Pneumonia: {train_pneumonia} ({train_pneumonia/(train_normal+train_pneumonia)*100:.2f}%)")
print(f"  Imbalance Ratio: 1:{train_pneumonia/train_normal:.2f}")

print(f"\nValidation: {val_normal + val_pneumonia} images   Very small!")
print(f"Test: {test_normal + test_pneumonia} images")
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============================================================
DATASET STATISTICS
============================================================
test/NORMAL                    :   234 images
test/PNEUMONIA                 :   390 images
train/NORMAL                   :  1341 images
train/PNEUMONIA                :  3875 images
val/NORMAL                     :     8 images
val/PNEUMONIA                  :     8 images

============================================================
CLASS DISTRIBUTION
============================================================
Training: 5216 images
  Normal: 1341 (25.71%)
  Pneumonia: 3875 (74.29%)
  Imbalance Ratio: 1:2.89

Validation: 16 images   Very small!
Test: 624 images
```

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# ========================================
# CELL 4: Visualize Distribution
# ========================================

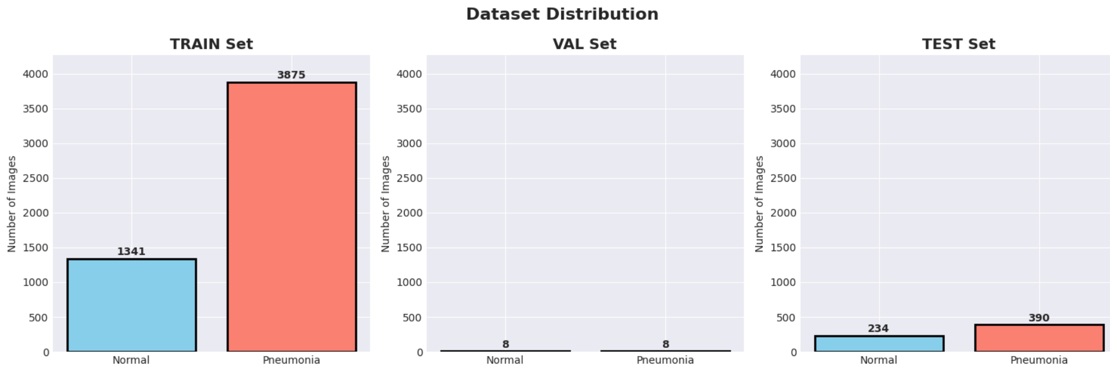
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

splits = ['train', 'val', 'test']
for idx, split in enumerate(splits):
    normal = image_counts.get(f'{split}/NORMAL', 0)
    pneumonia = image_counts.get(f'{split}/PNEUMONIA', 0)

    axes[idx].bar(['Normal', 'Pneumonia'], [normal, pneumonia],
                  color=['skyblue', 'salmon'], edgecolor='black', linewidth=2)
    axes[idx].set_title(f'{split.upper()} Set', fontsize=14, fontweight='bold')
    axes[idx].set_ylabel('Number of Images')
    axes[idx].set_ylim(0, max(train_normal, train_pneumonia) * 1.1)

    for i, v in enumerate([normal, pneumonia]):
        axes[idx].text(i, v + 50, str(v), ha='center', fontweight='bold')

plt.suptitle('Dataset Distribution', fontsize=16, fontweight='bold')
plt.tight_layout()
plt.show()
```



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# ========================================
# CELL 5: Display Sample Images
# ========================================

def display_sample_images(data_path, split='train', samples_per_class=6):
    """Display sample X-ray images"""
    fig, axes = plt.subplots(2, samples_per_class, figsize=(20, 8))

    classes = ['NORMAL', 'PNEUMONIA']

    for class_idx, class_name in enumerate(classes):
        class_path = os.path.join(data_path, split, class_name)
        image_files = [f for f in os.listdir(class_path) if f.endswith(('.
↪jpeg', '.jpg', '.png'))]

        selected_samples = np.random.choice(image_files,
                                          size=min(samples_per_class,␣
↪len(image_files)),
                                          replace=False)

        for img_idx, img_file in enumerate(selected_samples):
            img_path = os.path.join(class_path, img_file)
            img = Image.open(img_path)

            axes[class_idx, img_idx].imshow(img, cmap='gray')
            axes[class_idx, img_idx].axis('off')

            if img_idx == 0:
                axes[class_idx, img_idx].set_title(f'{class_name}\n{img_file}',
                                                   fontsize=12,␣
↪fontweight='bold', loc='left')
            else:
                axes[class_idx, img_idx].set_title(img_file, fontsize=10)
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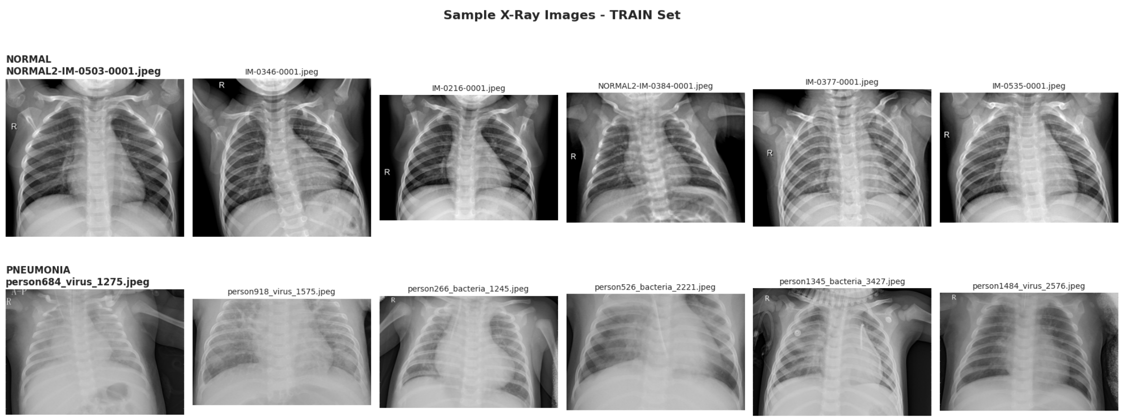
    plt.suptitle(f'Sample X-Ray Images - {split.upper()} Set',
                 fontsize=16, fontweight='bold', y=1.02)
    plt.tight_layout()
    plt.show()

print("Displaying sample images from training set...")
display_sample_images(data_path, split='train', samples_per_class=6)
```

Displaying sample images from training set…



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# ========================================
# CELL 6: Analyze Image Properties
# ========================================

def analyze_image_properties(data_path, split='train', num_samples=300):
    """Analyze dimensions, aspect ratios, and pixel statistics"""
    properties = {
        'widths': [], 'heights': [], 'aspect_ratios': [],
        'mean_intensities': [], 'std_intensities': [], 'classes': []
    }

    classes = ['NORMAL', 'PNEUMONIA']

    for class_name in classes:
        class_path = os.path.join(data_path, split, class_name)
        image_files = [f for f in os.listdir(class_path) if f.endswith(('.
↪jpeg', '.jpg', '.png'))]
        sampled_files = np.random.choice(image_files,
                                         size=min(num_samples, len(image_files)),
                                         replace=False)
```

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        for img_file in sampled_files:
            img_path = os.path.join(class_path, img_file)
            try:
                img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
                if img is not None:
                    h, w = img.shape
                    properties['widths'].append(w)
                    properties['heights'].append(h)
                    properties['aspect_ratios'].append(w / h)
                    properties['mean_intensities'].append(np.mean(img))
                    properties['std_intensities'].append(np.std(img))
                    properties['classes'].append(class_name)
            except Exception as e:
                print(f"Error reading {img_file}: {e}")

    return pd.DataFrame(properties)

print("Analyzing image properties...")
df_properties = analyze_image_properties(data_path, split='train',␣
 ↪num_samples=300)

print("\n" + "="*60)
print("IMAGE PROPERTIES SUMMARY")
print("="*60)
print(f"Dimensions:")
print(f"  Width  - Min: {df_properties['widths'].min()}, Max:␣
 ↪{df_properties['widths'].max()}, Mean: {df_properties['widths'].mean():.1f}")
print(f"  Height - Min: {df_properties['heights'].min()}, Max:␣
 ↪{df_properties['heights'].max()}, Mean: {df_properties['heights'].mean():.
 ↪1f}")
print(f"\nAspect Ratio: Min: {df_properties['aspect_ratios'].min():.3f}, Max:␣
 ↪{df_properties['aspect_ratios'].max():.3f}")
print(f"Pixel Intensity: Mean: {df_properties['mean_intensities'].mean():.2f} ±␣
 ↪{df_properties['mean_intensities'].std():.2f}")
```

```
Analyzing image properties…

============================================================
IMAGE PROPERTIES SUMMARY
============================================================
Dimensions:
  Width  - Min: 428, Max: 2572, Mean: 1426.0
  Height - Min: 189, Max: 2476, Mean: 1093.7

Aspect Ratio: Min: 0.905, Max: 2.593
Pixel Intensity: Mean: 123.34 ± 16.09
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[9]:

```python
# ========================================
# CELL 7: Visualize Image Properties
# ========================================

fig, axes = plt.subplots(2, 3, figsize=(18, 10))

# Width distribution
axes[0, 0].hist(df_properties[df_properties['classes']=='NORMAL']['widths'],
                alpha=0.6, label='Normal', bins=30, color='skyblue')
axes[0, 0].hist(df_properties[df_properties['classes']=='PNEUMONIA']['widths'],
                alpha=0.6, label='Pneumonia', bins=30, color='salmon')
axes[0, 0].set_xlabel('Width (pixels)')
axes[0, 0].set_title('Image Width Distribution')
axes[0, 0].legend()

# Height distribution
axes[0, 1].hist(df_properties[df_properties['classes']=='NORMAL']['heights'],
                alpha=0.6, label='Normal', bins=30, color='skyblue')
axes[0, 1].hist(df_properties[df_properties['classes']=='PNEUMONIA']['heights'],
                alpha=0.6, label='Pneumonia', bins=30, color='salmon')
axes[0, 1].set_xlabel('Height (pixels)')
axes[0, 1].set_title('Image Height Distribution')
axes[0, 1].legend()

# Aspect ratio
axes[0, 2].
 ↪hist(df_properties[df_properties['classes']=='NORMAL']['aspect_ratios'],
                alpha=0.6, label='Normal', bins=30, color='skyblue')
axes[0, 2].
 ↪hist(df_properties[df_properties['classes']=='PNEUMONIA']['aspect_ratios'],
                alpha=0.6, label='Pneumonia', bins=30, color='salmon')
axes[0, 2].set_xlabel('Aspect Ratio (W/H)')
axes[0, 2].set_title('Aspect Ratio Distribution')
axes[0, 2].legend()

# Mean intensity
axes[1, 0].
 ↪hist(df_properties[df_properties['classes']=='NORMAL']['mean_intensities'],
                alpha=0.6, label='Normal', bins=30, color='skyblue')
axes[1, 0].
 ↪hist(df_properties[df_properties['classes']=='PNEUMONIA']['mean_intensities'],
                alpha=0.6, label='Pneumonia', bins=30, color='salmon')
axes[1, 0].set_xlabel('Mean Pixel Intensity')
axes[1, 0].set_title('Mean Intensity by Class')
axes[1, 0].legend()

# Std intensity
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axes[1, 1].hist(df_properties[df_properties['classes']=='NORMAL']['std_intensities'],
                alpha=0.6, label='Normal', bins=30, color='skyblue')
axes[1, 1].hist(df_properties[df_properties['classes']=='PNEUMONIA']['std_intensities'],
                alpha=0.6, label='Pneumonia', bins=30, color='salmon')
axes[1, 1].set_xlabel('Std Pixel Intensity')
axes[1, 1].set_title('Intensity Std by Class')
axes[1, 1].legend()

# Dimensions scatter
axes[1, 2].scatter(df_properties[df_properties['classes']=='NORMAL']['widths'],
                   df_properties[df_properties['classes']=='NORMAL']['heights'],
                   alpha=0.4, label='Normal', s=20, color='skyblue')
axes[1, 2].scatter(df_properties[df_properties['classes']=='PNEUMONIA']['widths'],
                   df_properties[df_properties['classes']=='PNEUMONIA']['heights'],
                   alpha=0.4, label='Pneumonia', s=20, color='salmon')
axes[1, 2].set_xlabel('Width (pixels)')
axes[1, 2].set_ylabel('Height (pixels)')
axes[1, 2].set_title('Image Dimensions Scatter')
axes[1, 2].legend()

plt.tight_layout()
plt.show()
```

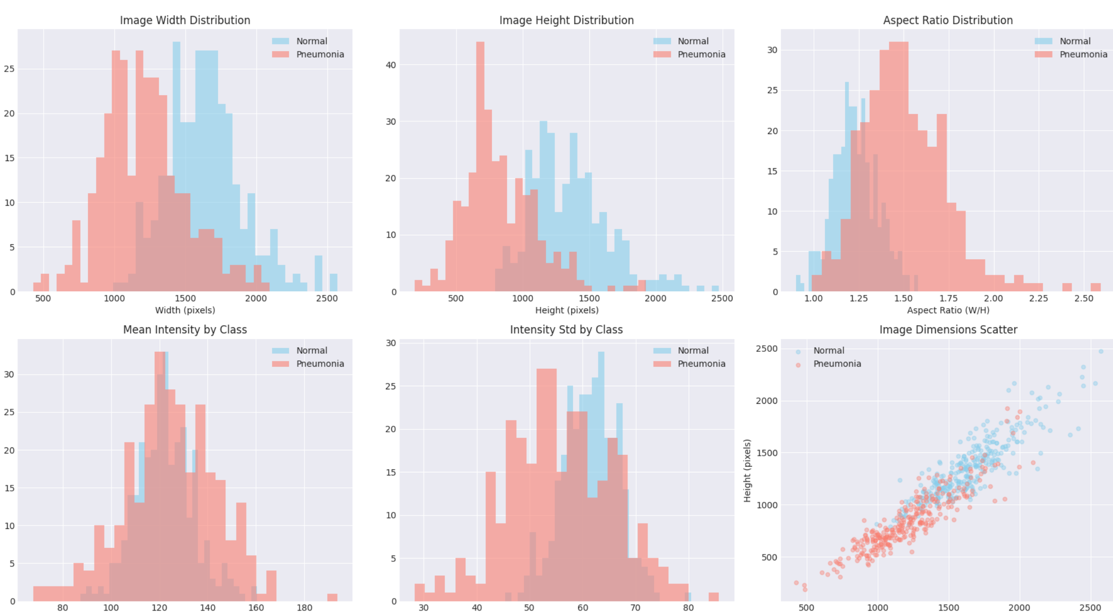

[10]:
```python
# ========================================
# CELL 8: Create Stratified Split
# ========================================

def collect_all_images(data_path):
    """Collect all images and labels from train/val/test"""
    all_images = []
    all_labels = []

    splits = ['train', 'val', 'test']
    classes = ['NORMAL', 'PNEUMONIA']

    for split in splits:
        for class_name in classes:
            class_path = os.path.join(data_path, split, class_name)
            if os.path.exists(class_path):
                image_files = [f for f in os.listdir(class_path)
                             if f.endswith(('.jpeg', '.jpg', '.png'))]

                for img_file in image_files:
                    img_path = os.path.join(class_path, img_file)
                    all_images.append(img_path)
                    all_labels.append(0 if class_name == 'NORMAL' else 1)

    return all_images, all_labels

# Collect all images
print("Collecting all images...")
all_image_paths, all_labels = collect_all_images(data_path)

print(f"Total images: {len(all_image_paths)}")
print(f"  Normal: {all_labels.count(0)}")
print(f"  Pneumonia: {all_labels.count(1)}")
print(f"  Imbalance Ratio: 1:{all_labels.count(1)/all_labels.count(0):.2f}")

# Create stratified splits: 80% train, 10% val, 10% test
print("\nCreating stratified splits (80/10/10)...")

train_paths, temp_paths, train_labels, temp_labels = train_test_split(
    all_image_paths, all_labels, test_size=0.20, stratify=all_labels,␣
↪random_state=SEED
)

val_paths, test_paths, val_labels, test_labels = train_test_split(
    temp_paths, temp_labels, test_size=0.50, stratify=temp_labels,␣
↪random_state=SEED
)
```

```
# Display split statistics
print("\n" + "="*60)
print("STRATIFIED SPLIT RESULTS")
print("="*60)
print(f"TRAIN: {len(train_paths)} images ({train_labels.count(0)} Normal,␣
↪{train_labels.count(1)} Pneumonia)")
print(f"VAL: {len(val_paths)} images ({val_labels.count(0)} Normal, {val_labels.
↪count(1)} Pneumonia)")
print(f"TEST: {len(test_paths)} images ({test_labels.count(0)} Normal,␣
↪{test_labels.count(1)} Pneumonia)")

# Create DataFrames
label_map = {0: 'NORMAL', 1: 'PNEUMONIA'}
train_df = pd.DataFrame({
    'image_path': train_paths,
    'label': train_labels,
    'label_str': [label_map[l] for l in train_labels]
})
val_df = pd.DataFrame({
    'image_path': val_paths,
    'label': val_labels,
    'label_str': [label_map[l] for l in val_labels]
})
test_df = pd.DataFrame({
    'image_path': test_paths,
    'label': test_labels,
    'label_str': [label_map[l] for l in test_labels]
})

print("\n Stratified split completed!")
```

```
Collecting all images…
Total images: 5856
  Normal: 1583
  Pneumonia: 4273
  Imbalance Ratio: 1:2.70

Creating stratified splits (80/10/10)…

============================================================
STRATIFIED SPLIT RESULTS
============================================================
TRAIN: 4684 images (1266 Normal, 3418 Pneumonia)
VAL: 586 images (159 Normal, 427 Pneumonia)
TEST: 586 images (158 Normal, 428 Pneumonia)
```

```
Stratified split completed!
```

[11]:
```python
# ========================================
# CELL 9: Calculate Class Weights
# ========================================

# Calculate class weights for handling imbalance
class_weights = compute_class_weight(
    class_weight='balanced',
    classes=np.array([0, 1]),
    y=train_labels
)

# Softer class weights (more stable training)
total = len(train_labels)
class_weight_dict = {
    0: total / (2 * train_labels.count(0)),
    1: total / (2 * train_labels.count(1))
}

print("="*60)
print("CLASS WEIGHTS FOR TRAINING")
print("="*60)
print(f"Normal (0): {class_weight_dict[0]:.4f}")
print(f"Pneumonia (1): {class_weight_dict[1]:.4f}")
print(f"\nInterpretation: These weights help the model focus on the minority␣
↪class")
```

```
============================================================
CLASS WEIGHTS FOR TRAINING
============================================================
Normal (0): 1.8499
Pneumonia (1): 0.6852

Interpretation: These weights help the model focus on the minority class
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[12]:
```python
# ========================================
# CELL 10: Create Data Generators
# ========================================

print("="*60)
print("DATA AUGMENTATION STRATEGY")
print("="*60)
print("  Training augmentations (conservative for medical images):")
print("    - Rotation: ±12 degrees")
print("    - Shifts: ±10%")
print("    - Zoom: 90-110%")
```

```
print("   - Brightness: 80-120%")
print("   - NO horizontal flip (preserves anatomy)")
print("\n  Validation/Test: Only rescaling")

# Training data generator WITH augmentation
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=12,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.05,
    zoom_range=0.1,
    brightness_range=[0.8, 1.2],
    fill_mode='constant',
    cval=0,
    horizontal_flip=False,
    vertical_flip=False
)

# Validation/Test generators WITHOUT augmentation
val_test_datagen = ImageDataGenerator(rescale=1./255)

print("\n  Data generators created")
```

```
============================================================
DATA AUGMENTATION STRATEGY
============================================================
  Training augmentations (conservative for medical images):
   - Rotation: ±12 degrees
   - Shifts: ±10%
   - Zoom: 90-110%
   - Brightness: 80-120%
   - NO horizontal flip (preserves anatomy)

  Validation/Test: Only rescaling

  Data generators created
```

[13]:
```
# ========================================
# CELL 11: Create Flow from DataFrames
# ========================================

def create_generator_from_dataframe(datagen, dataframe, batch_size,
 ↪shuffle=True, subset_name=""):
    """Create generator from DataFrame"""
    generator = datagen.flow_from_dataframe(
        dataframe=dataframe,
```

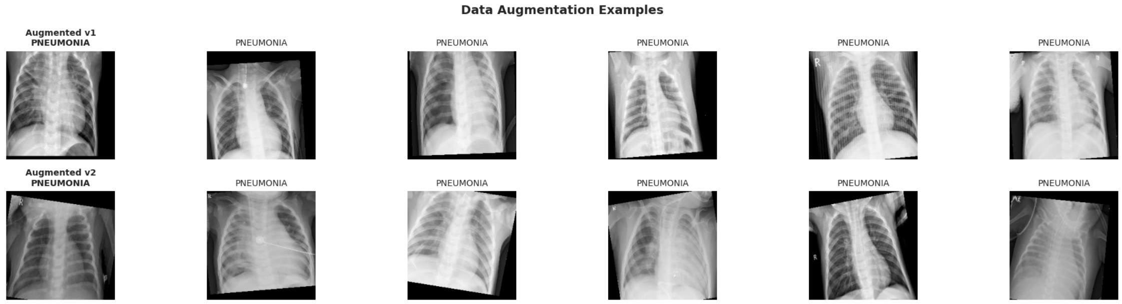
```
        x_col='image_path',
        y_col='label_str',
        target_size=(IMG_SIZE, IMG_SIZE),
        batch_size=batch_size,
        class_mode='binary',
        color_mode='grayscale',
        shuffle=shuffle,
        seed=SEED
    )

    print(f"{subset_name}: {len(dataframe)} images, {len(generator)} steps/
↪epoch")
    return generator

print("="*60)
print("CREATING DATA GENERATORS")
print("="*60)

train_generator = create_generator_from_dataframe(
    train_datagen, train_df, BATCH_SIZE, shuffle=True, subset_name="TRAIN"
)

val_generator = create_generator_from_dataframe(
    val_test_datagen, val_df, BATCH_SIZE, shuffle=False, subset_name="VAL"
)

test_generator = create_generator_from_dataframe(
    val_test_datagen, test_df, BATCH_SIZE, shuffle=False, subset_name="TEST"
)

print("\n All generators ready!")
```

```
============================================================
CREATING DATA GENERATORS
============================================================
Found 4684 validated image filenames belonging to 2 classes.
TRAIN: 4684 images, 147 steps/epoch
Found 586 validated image filenames belonging to 2 classes.
VAL: 586 images, 19 steps/epoch
Found 586 validated image filenames belonging to 2 classes.
TEST: 586 images, 19 steps/epoch

 All generators ready!
```

[14]:
```
# ========================================
# CELL 12: Visualize Augmentation
# ========================================
```

```python
def visualize_augmentation(generator, num_images=6):
    """Display augmented versions of images"""
    batch_images, batch_labels = next(generator)

    fig, axes = plt.subplots(2, num_images, figsize=(20, 5))

    for i in range(min(num_images, len(batch_images))):
        axes[0, i].imshow(batch_images[i].squeeze(), cmap='gray')
        axes[0, i].axis('off')
        label = "PNEUMONIA" if batch_labels[i] == 1 else "NORMAL"
        if i == 0:
            axes[0, i].set_title(f'Augmented v1\n{label}', fontsize=10,␣
↪fontweight='bold')
        else:
            axes[0, i].set_title(label, fontsize=10)

    batch_images2, batch_labels2 = next(generator)
    for i in range(min(num_images, len(batch_images2))):
        axes[1, i].imshow(batch_images2[i].squeeze(), cmap='gray')
        axes[1, i].axis('off')
        label = "PNEUMONIA" if batch_labels2[i] == 1 else "NORMAL"
        if i == 0:
            axes[1, i].set_title(f'Augmented v2\n{label}', fontsize=10,␣
↪fontweight='bold')
        else:
            axes[1, i].set_title(label, fontsize=10)

    plt.suptitle('Data Augmentation Examples', fontsize=14, fontweight='bold')
    plt.tight_layout()
    plt.show()

print("Visualizing augmentation effects...")
visualize_augmentation(train_generator, num_images=6)
train_generator.reset()
```

```
Visualizing augmentation effects…
```



[15]:

```
# ========================================
# CELL 13: Define Baseline CNN Architecture
# ========================================

def build_baseline_cnn(input_shape=(224, 224, 1)):
    """
    Baseline CNN for binary classification
    Architecture: 4 Conv blocks + Dense layers
    """
    model = Sequential([
        # Block 1
        Conv2D(32, (3, 3), activation='relu', padding='same',␣
↪input_shape=input_shape),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Dropout(0.25),

        # Block 2
        Conv2D(64, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Dropout(0.25),

        # Block 3
        Conv2D(128, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Dropout(0.25),

        # Block 4
        Conv2D(256, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Dropout(0.3),

        # Global Average Pooling
        GlobalAveragePooling2D(),

        # Dense layers
        Dense(128, activation='relu', kernel_regularizer=l2(0.001)),
        Dropout(0.5),
        Dense(64, activation='relu', kernel_regularizer=l2(0.001)),
        Dropout(0.5),

        # Output
```

```
        Dense(1, activation='sigmoid')
    ], name='Baseline_CNN')

    return model

print("="*60)
print("BASELINE CNN ARCHITECTURE")
print("="*60)

baseline_model = build_baseline_cnn(input_shape=(IMG_SIZE, IMG_SIZE, 1))
baseline_model.summary()

print(f"\nTotal Parameters: {baseline_model.count_params():,}")
```

```
============================================================
BASELINE CNN ARCHITECTURE
============================================================

Model: "Baseline_CNN"


 Layer (type)                      Output Shape                  Param #

 conv2d (Conv2D)                   (None, 224, 224, 32)              320

 batch_normalization               (None, 224, 224, 32)              128
 (BatchNormalization)

 max_pooling2d (MaxPooling2D)      (None, 112, 112, 32)                0

 dropout (Dropout)                 (None, 112, 112, 32)                0

 conv2d_1 (Conv2D)                 (None, 112, 112, 64)           18,496

 batch_normalization_1             (None, 112, 112, 64)              256
 (BatchNormalization)

 max_pooling2d_1 (MaxPooling2D)    (None, 56, 56, 64)                  0

 dropout_1 (Dropout)               (None, 56, 56, 64)                  0

 conv2d_2 (Conv2D)                 (None, 56, 56, 128)            73,856

 batch_normalization_2             (None, 56, 56, 128)               512
 (BatchNormalization)

 max_pooling2d_2 (MaxPooling2D)    (None, 28, 28, 128)                 0
```

dropout_2 (Dropout)	(None, 28, 28, 128)	0
conv2d_3 (Conv2D)	(None, 28, 28, 256)	295,168
batch_normalization_3 (BatchNormalization)	(None, 28, 28, 256)	1,024
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 256)	0
dropout_3 (Dropout)	(None, 14, 14, 256)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 256)	0
dense (Dense)	(None, 128)	32,896
dropout_4 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
dropout_5 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 1)	65

Total params: 430,977 (1.64 MB)

Trainable params: 430,017 (1.64 MB)

Non-trainable params: 960 (3.75 KB)

Total Parameters: 430,977

[16]:
```
# ========================================
# CELL 14: Compile and Train Baseline CNN
# ========================================

# Define callbacks
callbacks_baseline = [
    EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True,␣
 ↪verbose=1),
    ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=5, min_lr=1e-7,␣
 ↪verbose=1),
```

```python
    ModelCheckpoint('models/baseline_cnn_best.keras', monitor='val_auc',
                    mode='max', save_best_only=True, verbose=1)
]

# Compile
baseline_model.compile(
    optimizer=keras.optimizers.Adam(learning_rate=0.00005),
    loss='binary_crossentropy',
    metrics=['accuracy',
             keras.metrics.Precision(name='precision'),
             keras.metrics.Recall(name='recall'),
             keras.metrics.AUC(name='auc')]
)

print("="*60)
print("TRAINING BASELINE CNN")
print("="*60)
print("  Quick training: 15 epochs\n")

# Train
train_generator.reset()
val_generator.reset()

EPOCHS = 15

history_baseline = baseline_model.fit(
    train_generator,
    validation_data=val_generator,
    epochs=EPOCHS,
    callbacks=callbacks_baseline,
    class_weight=class_weight_dict,
    verbose=1
)

print("\n  Training completed!")
best_epoch = np.argmax(history_baseline.history['val_auc']) + 1
print(f"Best Epoch: {best_epoch}, Best val_auc: {max(history_baseline.
 ↪history['val_auc']):.4f}")
```

```
============================================================
TRAINING BASELINE CNN
============================================================
  Quick training: 15 epochs

Epoch 1/15
147/147              0s 791ms/step -
accuracy: 0.5431 - auc: 0.5247 - loss: 1.0844 - precision: 0.7439 - recall:
```

```
0.5795
Epoch 1: val_auc improved from None to 0.44846, saving model to
models/baseline_cnn_best.keras
147/147            128s 846ms/step -
accuracy: 0.5715 - auc: 0.6007 - loss: 0.9798 - precision: 0.7830 - recall:
0.5711 - val_accuracy: 0.7287 - val_auc: 0.4485 - val_loss: 0.8728 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 5.0000e-05
Epoch 2/15
147/147            0s 769ms/step -
accuracy: 0.6920 - auc: 0.7762 - loss: 0.8108 - precision: 0.8825 - recall:
0.6692
Epoch 2: val_auc improved from 0.44846 to 0.61795, saving model to
models/baseline_cnn_best.keras
147/147            117s 793ms/step -
accuracy: 0.7242 - auc: 0.8178 - loss: 0.7670 - precision: 0.8963 - recall:
0.7033 - val_accuracy: 0.7287 - val_auc: 0.6180 - val_loss: 1.3347 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 5.0000e-05
Epoch 3/15
147/147            0s 771ms/step -
accuracy: 0.8069 - auc: 0.8826 - loss: 0.6750 - precision: 0.9424 - recall:
0.7810
Epoch 3: val_auc improved from 0.61795 to 0.82660, saving model to
models/baseline_cnn_best.keras
147/147            117s 794ms/step -
accuracy: 0.8170 - auc: 0.8888 - loss: 0.6597 - precision: 0.9442 - recall:
0.7964 - val_accuracy: 0.7287 - val_auc: 0.8266 - val_loss: 1.1897 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 5.0000e-05
Epoch 4/15
147/147            0s 777ms/step -
accuracy: 0.8340 - auc: 0.9027 - loss: 0.6283 - precision: 0.9517 - recall:
0.8133
Epoch 4: val_auc improved from 0.82660 to 0.84973, saving model to
models/baseline_cnn_best.keras
147/147            118s 800ms/step -
accuracy: 0.8431 - auc: 0.9105 - loss: 0.6079 - precision: 0.9512 - recall:
0.8274 - val_accuracy: 0.7304 - val_auc: 0.8497 - val_loss: 1.2309 -
val_precision: 0.7299 - val_recall: 1.0000 - learning_rate: 5.0000e-05
Epoch 5/15
147/147            0s 775ms/step -
accuracy: 0.8496 - auc: 0.9109 - loss: 0.6003 - precision: 0.9532 - recall:
0.8340
Epoch 5: val_auc improved from 0.84973 to 0.92591, saving model to
models/baseline_cnn_best.keras
147/147            118s 801ms/step -
accuracy: 0.8488 - auc: 0.9125 - loss: 0.5948 - precision: 0.9538 - recall:
0.8332 - val_accuracy: 0.8276 - val_auc: 0.9259 - val_loss: 0.6305 -
val_precision: 0.8247 - val_recall: 0.9696 - learning_rate: 5.0000e-05
Epoch 6/15
```

```
147/147 0s 779ms/step -
accuracy: 0.8675 - auc: 0.9169 - loss: 0.5865 - precision: 0.9532 - recall:
0.8595
Epoch 6: val_auc improved from 0.92591 to 0.93938, saving model to
models/baseline_cnn_best.keras
147/147 118s 802ms/step -
accuracy: 0.8640 - auc: 0.9214 - loss: 0.5734 - precision: 0.9573 - recall:
0.8517 - val_accuracy: 0.8447 - val_auc: 0.9394 - val_loss: 0.6184 -
val_precision: 0.9828 - val_recall: 0.8009 - learning_rate: 5.0000e-05
Epoch 7/15
147/147 0s 776ms/step -
accuracy: 0.8595 - auc: 0.9252 - loss: 0.5641 - precision: 0.9557 - recall:
0.8457
Epoch 7: val_auc improved from 0.93938 to 0.94210, saving model to
models/baseline_cnn_best.keras
147/147 118s 799ms/step -
accuracy: 0.8550 - auc: 0.9227 - loss: 0.5645 - precision: 0.9585 - recall:
0.8376 - val_accuracy: 0.8498 - val_auc: 0.9421 - val_loss: 0.6365 -
val_precision: 0.9802 - val_recall: 0.8103 - learning_rate: 5.0000e-05
Epoch 8/15
147/147 0s 781ms/step -
accuracy: 0.8607 - auc: 0.9258 - loss: 0.5509 - precision: 0.9611 - recall:
0.8450
Epoch 8: val_auc improved from 0.94210 to 0.94663, saving model to
models/baseline_cnn_best.keras
147/147 118s 804ms/step -
accuracy: 0.8651 - auc: 0.9317 - loss: 0.5379 - precision: 0.9606 - recall:
0.8499 - val_accuracy: 0.8942 - val_auc: 0.9466 - val_loss: 0.4849 -
val_precision: 0.9254 - val_recall: 0.9297 - learning_rate: 5.0000e-05
Epoch 9/15
147/147 0s 778ms/step -
accuracy: 0.8689 - auc: 0.9397 - loss: 0.5138 - precision: 0.9668 - recall:
0.8508
Epoch 9: val_auc did not improve from 0.94663
147/147 118s 800ms/step -
accuracy: 0.8717 - auc: 0.9387 - loss: 0.5158 - precision: 0.9623 - recall:
0.8578 - val_accuracy: 0.4710 - val_auc: 0.9344 - val_loss: 1.7614 -
val_precision: 1.0000 - val_recall: 0.2740 - learning_rate: 5.0000e-05
Epoch 10/15
147/147 0s 781ms/step -
accuracy: 0.8791 - auc: 0.9383 - loss: 0.5214 - precision: 0.9620 - recall:
0.8684
Epoch 10: val_auc improved from 0.94663 to 0.95704, saving model to
models/baseline_cnn_best.keras
147/147 118s 804ms/step -
accuracy: 0.8819 - auc: 0.9380 - loss: 0.5175 - precision: 0.9625 - recall:
0.8721 - val_accuracy: 0.8976 - val_auc: 0.9570 - val_loss: 0.4435 -
val_precision: 0.9553 - val_recall: 0.9016 - learning_rate: 5.0000e-05
```

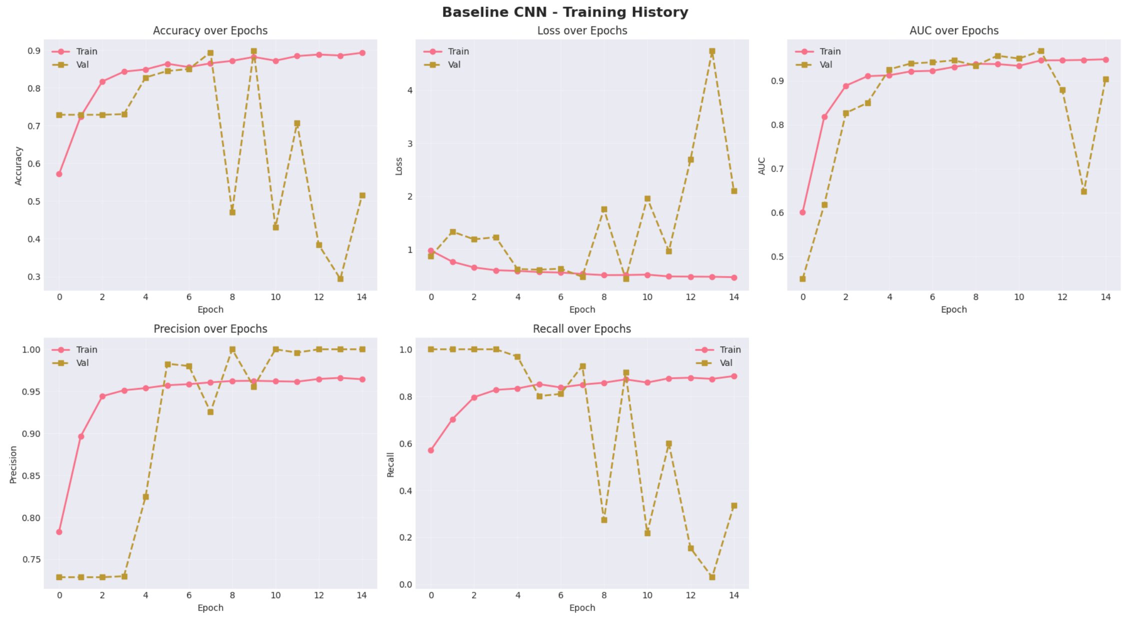
```
Epoch 11/15
147/147            0s 779ms/step -
accuracy: 0.8686 - auc: 0.9369 - loss: 0.5189 - precision: 0.9648 - recall:
0.8520
Epoch 11: val_auc did not improve from 0.95704
147/147            118s 802ms/step -
accuracy: 0.8721 - auc: 0.9340 - loss: 0.5252 - precision: 0.9620 - recall:
0.8587 - val_accuracy: 0.4300 - val_auc: 0.9506 - val_loss: 1.9673 -
val_precision: 1.0000 - val_recall: 0.2178 - learning_rate: 5.0000e-05
Epoch 12/15
147/147            0s 779ms/step -
accuracy: 0.8824 - auc: 0.9462 - loss: 0.4890 - precision: 0.9633 - recall:
0.8751
Epoch 12: val_auc improved from 0.95704 to 0.96773, saving model to
models/baseline_cnn_best.keras
147/147            118s 801ms/step -
accuracy: 0.8843 - auc: 0.9465 - loss: 0.4910 - precision: 0.9615 - recall:
0.8765 - val_accuracy: 0.7065 - val_auc: 0.9677 - val_loss: 0.9682 -
val_precision: 0.9961 - val_recall: 0.5995 - learning_rate: 5.0000e-05
Epoch 13/15
147/147            0s 783ms/step -
accuracy: 0.8952 - auc: 0.9544 - loss: 0.4620 - precision: 0.9715 - recall:
0.8815
Epoch 13: val_auc did not improve from 0.96773
147/147            118s 805ms/step -
accuracy: 0.8883 - auc: 0.9467 - loss: 0.4874 - precision: 0.9647 - recall:
0.8792 - val_accuracy: 0.3840 - val_auc: 0.8792 - val_loss: 2.6930 -
val_precision: 1.0000 - val_recall: 0.1546 - learning_rate: 5.0000e-05
Epoch 14/15
147/147            0s 780ms/step -
accuracy: 0.8883 - auc: 0.9485 - loss: 0.4810 - precision: 0.9657 - recall:
0.8785
Epoch 14: val_auc did not improve from 0.96773
147/147            118s 802ms/step -
accuracy: 0.8858 - auc: 0.9474 - loss: 0.4847 - precision: 0.9661 - recall:
0.8742 - val_accuracy: 0.2935 - val_auc: 0.6475 - val_loss: 4.7388 -
val_precision: 1.0000 - val_recall: 0.0304 - learning_rate: 5.0000e-05
Epoch 15/15
147/147            0s 785ms/step -
accuracy: 0.8957 - auc: 0.9476 - loss: 0.4843 - precision: 0.9622 - recall:
0.8909
Epoch 15: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-05.

Epoch 15: val_auc did not improve from 0.96773
147/147            119s 807ms/step -
accuracy: 0.8930 - auc: 0.9490 - loss: 0.4774 - precision: 0.9643 - recall:
0.8862 - val_accuracy: 0.5154 - val_auc: 0.9046 - val_loss: 2.1113 -
val_precision: 1.0000 - val_recall: 0.3349 - learning_rate: 5.0000e-05
```

```
Restoring model weights from the end of the best epoch: 10.

 Training completed!
Best Epoch: 12, Best val_auc: 0.9677
```

[17]:

```
# ========================================
# CELL 15: Evaluate Baseline CNN
# ========================================

def plot_training_history(history, model_name="Model"):
    """Plot training metrics"""
    fig, axes = plt.subplots(2, 3, figsize=(18, 10))

    metrics = [('accuracy', 'Accuracy'), ('loss', 'Loss'), ('auc', 'AUC'),
               ('precision', 'Precision'), ('recall', 'Recall')]

    for idx, (metric, title) in enumerate(metrics):
        row, col = idx // 3, idx % 3
        if metric in history.history:
            axes[row, col].plot(history.history[metric], label='Train',␣
↪linewidth=2, marker='o')
            if f'val_{metric}' in history.history:
                axes[row, col].plot(history.history[f'val_{metric}'],
                                   label='Val', linewidth=2, linestyle='--',␣
↪marker='s')
        axes[row, col].set_xlabel('Epoch')
        axes[row, col].set_ylabel(title)
        axes[row, col].set_title(f'{title} over Epochs')
        axes[row, col].legend()
        axes[row, col].grid(True, alpha=0.3)

    axes[1, 2].axis('off')
    plt.suptitle(f'{model_name} - Training History', fontsize=16,␣
↪fontweight='bold')
    plt.tight_layout()
    plt.show()

plot_training_history(history_baseline, "Baseline CNN")

# Load best model and evaluate
baseline_model = keras.models.load_model('models/baseline_cnn_best.keras')
print("\n Loaded best baseline model")

test_generator.reset()
test_results_baseline = baseline_model.evaluate(test_generator, verbose=1)

print("\n Baseline CNN - Test Results:")
```

```
for name, value in zip(baseline_model.metrics_names, test_results_baseline):
    print(f"   {name}: {value:.4f}")
```




```
 Loaded best baseline model
19/19               7s 311ms/step -
accuracy: 0.6877 - auc: 0.9510 - loss: 1.0266 - precision: 0.9842 - recall:
0.5818

 Baseline CNN - Test Results:
   loss: 1.0266
   compile_metrics: 0.6877
```

[18]:

```
# ========================================
# CELL 16: Build ResNet50 Model
# ========================================

print("="*60)
print("BUILDING RESNET50 TRANSFER LEARNING MODEL")
print("="*60)

# Clear memory
tf.keras.backend.clear_session()
gc.collect()

# Load pre-trained ResNet50
base_resnet = ResNet50(
```

```
    weights='imagenet',
    include_top=False,
    input_shape=(IMG_SIZE, IMG_SIZE, 3)
)

# Freeze base
base_resnet.trainable = False

print(f" Loaded ResNet50 (frozen)")
print(f"   Layers: {len(base_resnet.layers)}")

# Build model
inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 1))
x = layers.Concatenate()([inputs, inputs, inputs])  # Grayscale to RGB
x = base_resnet(x, training=False)
x = GlobalAveragePooling2D()(x)
x = Dropout(0.5)(x)
x = Dense(256, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.3)(x)
outputs = Dense(1, activation='sigmoid')(x)

resnet_model = Model(inputs=inputs, outputs=outputs, name='ResNet50_Pneumonia')

print("\n ResNet50 Model:")
resnet_model.summary()

# Compile
resnet_model.compile(
    optimizer=keras.optimizers.Adam(learning_rate=0.001),
    loss='binary_crossentropy',
    metrics=['accuracy',
             keras.metrics.Precision(name='precision'),
             keras.metrics.Recall(name='recall'),
             keras.metrics.AUC(name='auc')]
)

print(" ResNet50 compiled (base frozen)")
```

```
============================================================
BUILDING RESNET50 TRANSFER LEARNING MODEL
============================================================
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736             0s
0us/step
```

```
Loaded ResNet50 (frozen)
 Layers: 175

ResNet50 Model:
```

Model: "ResNet50_Pneumonia"

Layer (type)	Output Shape	Param #	Connected to
input_layer_1 (InputLayer)	(None, 224, 224, 1)	0	-
concatenate (Concatenate)	(None, 224, 224, 3)	0	input_layer_1[0]… input_layer_1[0]… input_layer_1[0]…
resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712	concatenate[0][0]
global_average_poo… (GlobalAveragePool…	(None, 2048)	0	resnet50[0][0]
dropout (Dropout)	(None, 2048)	0	global_average_p…
dense (Dense)	(None, 256)	524,544	dropout[0][0]
dropout_1 (Dropout)	(None, 256)	0	dense[0][0]
dense_1 (Dense)	(None, 128)	32,896	dropout_1[0][0]
dropout_2 (Dropout)	(None, 128)	0	dense_1[0][0]
dense_2 (Dense)	(None, 1)	129	dropout_2[0][0]

Total params: 24,145,281 (92.11 MB)

Trainable params: 557,569 (2.13 MB)

Non-trainable params: 23,587,712 (89.98 MB)

```
ResNet50 compiled (base frozen)
```

[19]:

```
# ========================================
# CELL 17: Train ResNet50 - Phase 1 (Frozen)
# ========================================

resnet_callbacks = [
    EarlyStopping(monitor='val_auc', patience=7, restore_best_weights=True,␣
 ↪mode='max', verbose=1),
    ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3, min_lr=1e-7,␣
 ↪verbose=1),
    ModelCheckpoint('models/ResNet50_best.keras', monitor='val_auc',
                   mode='max', save_best_only=True, verbose=1)
]



print("="*60)
print("TRAINING RESNET50 - PHASE 1 (FROZEN BASE)")
print("="*60)
print("  Training only custom layers\n")

train_generator.reset()
val_generator.reset()

EPOCHS_P1 = 10

history_resnet_p1 = resnet_model.fit(
    train_generator,
    validation_data=val_generator,
    epochs=EPOCHS_P1,
    callbacks=resnet_callbacks,
    class_weight={0: 1.5, 1: 1.0},
    verbose=1
)

print("\n  Phase 1 completed!")
best_auc_p1 = max(history_resnet_p1.history['val_auc'])
print(f"Best val_auc: {best_auc_p1:.4f}")
```

```
============================================================
TRAINING RESNET50 - PHASE 1 (FROZEN BASE)
============================================================
  Training only custom layers

Epoch 1/10
147/147              0s 296ms/step -
accuracy: 0.6181 - auc: 0.5075 - loss: 0.8745 - precision: 0.7226 - recall:
0.7536
```

```
Epoch 1: val_auc improved from None to 0.65259, saving model to
models/ResNet50_best.keras
147/147             57s 355ms/step -
accuracy: 0.6529 - auc: 0.5204 - loss: 0.8062 - precision: 0.7353 - recall:
0.8192 - val_accuracy: 0.7287 - val_auc: 0.6526 - val_loss: 0.5896 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 2/10
147/147             0s 300ms/step -
accuracy: 0.6818 - auc: 0.5133 - loss: 0.7716 - precision: 0.7325 - recall:
0.8870
Epoch 2: val_auc improved from 0.65259 to 0.76939, saving model to
models/ResNet50_best.keras
147/147             51s 342ms/step -
accuracy: 0.6862 - auc: 0.5254 - loss: 0.7597 - precision: 0.7310 - recall:
0.9017 - val_accuracy: 0.7287 - val_auc: 0.7694 - val_loss: 0.6122 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 3/10
147/147             0s 304ms/step -
accuracy: 0.7267 - auc: 0.5277 - loss: 0.7324 - precision: 0.7463 - recall:
0.9586
Epoch 3: val_auc improved from 0.76939 to 0.86664, saving model to
models/ResNet50_best.keras
147/147             51s 347ms/step -
accuracy: 0.7060 - auc: 0.5393 - loss: 0.7475 - precision: 0.7330 - recall:
0.9391 - val_accuracy: 0.7287 - val_auc: 0.8666 - val_loss: 0.6258 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 4/10
147/147             0s 300ms/step -
accuracy: 0.7198 - auc: 0.5277 - loss: 0.7419 - precision: 0.7395 - recall:
0.9568
Epoch 4: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.

Epoch 4: val_auc improved from 0.86664 to 0.87291, saving model to
models/ResNet50_best.keras
147/147             51s 344ms/step -
accuracy: 0.7156 - auc: 0.5449 - loss: 0.7434 - precision: 0.7322 - recall:
0.9623 - val_accuracy: 0.7287 - val_auc: 0.8729 - val_loss: 0.6290 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 5/10
147/147             0s 305ms/step -
accuracy: 0.7140 - auc: 0.5551 - loss: 0.7415 - precision: 0.7361 - recall:
0.9451
Epoch 5: val_auc improved from 0.87291 to 0.87657, saving model to
models/ResNet50_best.keras
147/147             52s 349ms/step -
accuracy: 0.7220 - auc: 0.5656 - loss: 0.7343 - precision: 0.7357 - recall:
0.9661 - val_accuracy: 0.7287 - val_auc: 0.8766 - val_loss: 0.6186 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 5.0000e-04
```

```
Epoch 6/10
147/147            0s 307ms/step -
accuracy: 0.7165 - auc: 0.5933 - loss: 0.7278 - precision: 0.7326 - recall:
0.9617
Epoch 6: val_auc improved from 0.87657 to 0.88038, saving model to
models/ResNet50_best.keras
147/147            52s 351ms/step -
accuracy: 0.7165 - auc: 0.5968 - loss: 0.7264 - precision: 0.7361 - recall:
0.9532 - val_accuracy: 0.7406 - val_auc: 0.8804 - val_loss: 0.6001 -
val_precision: 0.7425 - val_recall: 0.9859 - learning_rate: 5.0000e-04
Epoch 7/10
147/147            0s 307ms/step -
accuracy: 0.7334 - auc: 0.6126 - loss: 0.7089 - precision: 0.7509 - recall:
0.9560
Epoch 7: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.

Epoch 7: val_auc did not improve from 0.88038
147/147            51s 346ms/step -
accuracy: 0.7205 - auc: 0.6118 - loss: 0.7201 - precision: 0.7421 - recall:
0.9456 - val_accuracy: 0.7696 - val_auc: 0.8789 - val_loss: 0.6145 -
val_precision: 0.7755 - val_recall: 0.9625 - learning_rate: 5.0000e-04
Epoch 8/10
147/147            0s 308ms/step -
accuracy: 0.7203 - auc: 0.6323 - loss: 0.7166 - precision: 0.7416 - recall:
0.9440
Epoch 8: val_auc improved from 0.88038 to 0.88177, saving model to
models/ResNet50_best.keras
147/147            52s 355ms/step -
accuracy: 0.7254 - auc: 0.6357 - loss: 0.7100 - precision: 0.7453 - recall:
0.9476 - val_accuracy: 0.8242 - val_auc: 0.8818 - val_loss: 0.6278 -
val_precision: 0.8699 - val_recall: 0.8923 - learning_rate: 2.5000e-04
Epoch 9/10
147/147            0s 308ms/step -
accuracy: 0.7272 - auc: 0.6624 - loss: 0.6925 - precision: 0.7575 - recall:
0.9270
Epoch 9: val_auc did not improve from 0.88177
147/147            51s 348ms/step -
accuracy: 0.7229 - auc: 0.6698 - loss: 0.6952 - precision: 0.7513 - recall:
0.9272 - val_accuracy: 0.8276 - val_auc: 0.8796 - val_loss: 0.6038 -
val_precision: 0.9137 - val_recall: 0.8431 - learning_rate: 2.5000e-04
Epoch 10/10
147/147            0s 308ms/step -
accuracy: 0.7067 - auc: 0.6509 - loss: 0.7087 - precision: 0.7492 - recall:
0.8957
Epoch 10: ReduceLROnPlateau reducing learning rate to 0.0001250000059371814.

Epoch 10: val_auc did not improve from 0.88177
147/147            51s 347ms/step -
```

```
accuracy: 0.7240 - auc: 0.6565 - loss: 0.7027 - precision: 0.7597 - recall:
0.9093 - val_accuracy: 0.8259 - val_auc: 0.8817 - val_loss: 0.5919 -
val_precision: 0.9156 - val_recall: 0.8384 - learning_rate: 2.5000e-04
Restoring model weights from the end of the best epoch: 8.

 Phase 1 completed!
Best val_auc: 0.8818
```

[20]:

```python
# ========================================
# CELL 18: Train ResNet50 - Phase 2 (Fine-tuning)
# ========================================

print("="*60)
print("TRAINING RESNET50 - PHASE 2 (FINE-TUNING)")
print("="*60)

# Unfreeze last 30 layers
base_resnet.trainable = True
for layer in base_resnet.layers[:-30]:
    layer.trainable = False

trainable = sum([1 for layer in base_resnet.layers if layer.trainable])
print(f"  Unfroze last 30 layers ({trainable} trainable)")

# Recompile with lower LR
resnet_model.compile(
    optimizer=keras.optimizers.Adam(learning_rate=0.00001),
    loss='binary_crossentropy',
    metrics=['accuracy',
             keras.metrics.Precision(name='precision'),
             keras.metrics.Recall(name='recall'),
             keras.metrics.AUC(name='auc')]
)

print("  Recompiled with lr=0.00001\n")

train_generator.reset()
val_generator.reset()

EPOCHS_P2 = 10

history_resnet_p2 = resnet_model.fit(
    train_generator,
    validation_data=val_generator,
    epochs=EPOCHS_P2,
    callbacks=resnet_callbacks,
    class_weight={0: 1.5, 1: 1.0},
```

```
    verbose=1
)

print("\n  Phase 2 completed!")
best_auc_p2 = max(history_resnet_p2.history['val_auc'])
print(f"Best val_auc: {best_auc_p2:.4f}")
```

```
============================================================
TRAINING RESNET50 - PHASE 2 (FINE-TUNING)
============================================================
  Unfroze last 30 layers (30 trainable)
  Recompiled with lr=0.00001

Epoch 1/10
147/147              0s 502ms/step -
accuracy: 0.6671 - auc: 0.7435 - loss: 0.6761 - precision: 0.8489 - recall:
0.6360
Epoch 1: val_auc improved from 0.88177 to 0.92417, saving model to
models/ResNet50_best.keras
147/147              91s 563ms/step -
accuracy: 0.7810 - auc: 0.8495 - loss: 0.5220 - precision: 0.8937 - recall:
0.7943 - val_accuracy: 0.2713 - val_auc: 0.9242 - val_loss: 0.9619 -
val_precision: 0.0000e+00 - val_recall: 0.0000e+00 - learning_rate: 1.0000e-05
Epoch 2/10
147/147              0s 511ms/step -
accuracy: 0.8667 - auc: 0.9293 - loss: 0.3786 - precision: 0.9447 - recall:
0.8666
Epoch 2: val_auc improved from 0.92417 to 0.97180, saving model to
models/ResNet50_best.keras
147/147              82s 557ms/step -
accuracy: 0.8693 - auc: 0.9280 - loss: 0.3749 - precision: 0.9393 - recall:
0.8777 - val_accuracy: 0.7765 - val_auc: 0.9718 - val_loss: 0.4703 -
val_precision: 0.9901 - val_recall: 0.7002 - learning_rate: 1.0000e-05
Epoch 3/10
147/147              0s 514ms/step -
accuracy: 0.8834 - auc: 0.9420 - loss: 0.3364 - precision: 0.9517 - recall:
0.8880
Epoch 3: val_auc improved from 0.97180 to 0.98150, saving model to
models/ResNet50_best.keras
147/147              82s 558ms/step -
accuracy: 0.8888 - auc: 0.9439 - loss: 0.3325 - precision: 0.9483 - recall:
0.8964 - val_accuracy: 0.6536 - val_auc: 0.9815 - val_loss: 0.5280 -
val_precision: 1.0000 - val_recall: 0.5246 - learning_rate: 1.0000e-05
Epoch 4/10
147/147              0s 501ms/step -
accuracy: 0.8888 - auc: 0.9550 - loss: 0.2978 - precision: 0.9532 - recall:
0.8912
```

```
Epoch 4: val_auc improved from 0.98150 to 0.98287, saving model to
models/ResNet50_best.keras
147/147             81s 546ms/step -
accuracy: 0.8960 - auc: 0.9553 - loss: 0.2950 - precision: 0.9539 - recall:
0.9011 - val_accuracy: 0.9352 - val_auc: 0.9829 - val_loss: 0.1693 -
val_precision: 0.9576 - val_recall: 0.9532 - learning_rate: 1.0000e-05
Epoch 5/10
147/147             0s 512ms/step -
accuracy: 0.8973 - auc: 0.9475 - loss: 0.3262 - precision: 0.9477 - recall:
0.9080
Epoch 5: val_auc improved from 0.98287 to 0.98564, saving model to
models/ResNet50_best.keras
147/147             82s 558ms/step -
accuracy: 0.8965 - auc: 0.9519 - loss: 0.3056 - precision: 0.9516 - recall:
0.9040 - val_accuracy: 0.8993 - val_auc: 0.9856 - val_loss: 0.2102 -
val_precision: 0.9920 - val_recall: 0.8689 - learning_rate: 1.0000e-05
Epoch 6/10
147/147             0s 509ms/step -
accuracy: 0.9049 - auc: 0.9626 - loss: 0.2716 - precision: 0.9537 - recall:
0.9139
Epoch 6: val_auc did not improve from 0.98564
147/147             81s 549ms/step -
accuracy: 0.9018 - auc: 0.9559 - loss: 0.2945 - precision: 0.9512 - recall:
0.9122 - val_accuracy: 0.5597 - val_auc: 0.9848 - val_loss: 0.7647 -
val_precision: 1.0000 - val_recall: 0.3958 - learning_rate: 1.0000e-05
Epoch 7/10
147/147             0s 510ms/step -
accuracy: 0.9080 - auc: 0.9620 - loss: 0.2798 - precision: 0.9538 - recall:
0.9166
Epoch 7: ReduceLROnPlateau reducing learning rate to 4.999999873689376e-06.

Epoch 7: val_auc improved from 0.98564 to 0.98630, saving model to
models/ResNet50_best.keras
147/147             83s 560ms/step -
accuracy: 0.9014 - auc: 0.9583 - loss: 0.2882 - precision: 0.9531 - recall:
0.9096 - val_accuracy: 0.8908 - val_auc: 0.9863 - val_loss: 0.2116 -
val_precision: 0.9919 - val_recall: 0.8571 - learning_rate: 1.0000e-05
Epoch 8/10
147/147             0s 507ms/step -
accuracy: 0.9143 - auc: 0.9649 - loss: 0.2595 - precision: 0.9628 - recall:
0.9185
Epoch 8: val_auc improved from 0.98630 to 0.98647, saving model to
models/ResNet50_best.keras
147/147             81s 552ms/step -
accuracy: 0.9105 - auc: 0.9631 - loss: 0.2687 - precision: 0.9579 - recall:
0.9178 - val_accuracy: 0.8703 - val_auc: 0.9865 - val_loss: 0.2423 -
val_precision: 0.9944 - val_recall: 0.8267 - learning_rate: 5.0000e-06
Epoch 9/10
```

```
147/147              0s 507ms/step -
accuracy: 0.9138 - auc: 0.9623 - loss: 0.2668 - precision: 0.9584 - recall:
0.9228
Epoch 9: val_auc improved from 0.98647 to 0.98750, saving model to
models/ResNet50_best.keras
147/147              82s 554ms/step -
accuracy: 0.9135 - auc: 0.9649 - loss: 0.2616 - precision: 0.9558 - recall:
0.9242 - val_accuracy: 0.8976 - val_auc: 0.9875 - val_loss: 0.1969 -
val_precision: 0.9920 - val_recall: 0.8665 - learning_rate: 5.0000e-06
Epoch 10/10
147/147              0s 511ms/step -
accuracy: 0.9186 - auc: 0.9689 - loss: 0.2486 - precision: 0.9615 - recall:
0.9255
Epoch 10: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-06.

Epoch 10: val_auc improved from 0.98750 to 0.98761, saving model to
models/ResNet50_best.keras
147/147              82s 557ms/step -
accuracy: 0.9178 - auc: 0.9680 - loss: 0.2496 - precision: 0.9616 - recall:
0.9242 - val_accuracy: 0.9010 - val_auc: 0.9876 - val_loss: 0.1912 -
val_precision: 0.9920 - val_recall: 0.8712 - learning_rate: 5.0000e-06
Restoring model weights from the end of the best epoch: 10.

 Phase 2 completed!
Best val_auc: 0.9876
```

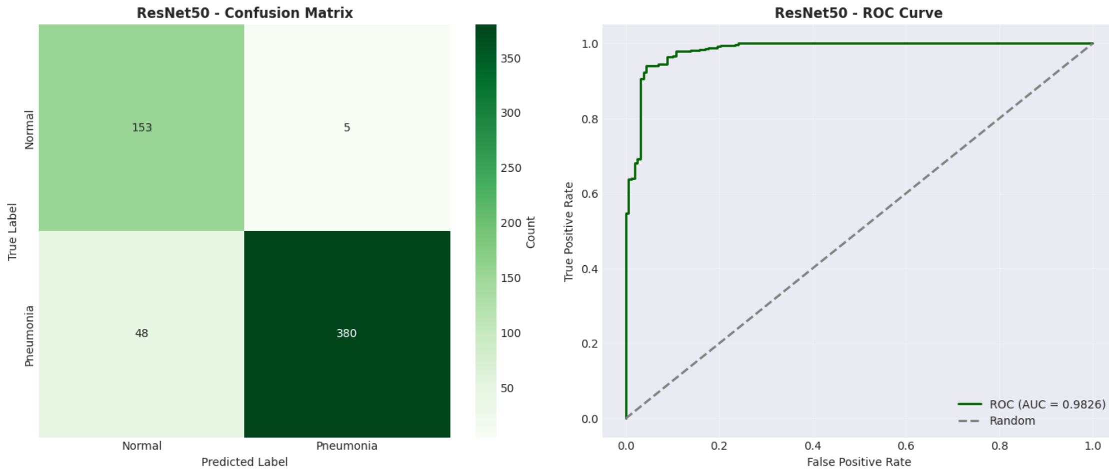
[23]:

```python
# ========================================
# CELL 19: Evaluate ResNet50
# ========================================

print("="*60)
print("RESNET50 - TEST SET EVALUATION")
print("="*60)

resnet_model = keras.models.load_model('models/ResNet50_best.keras')
print("  Loaded best ResNet50 model")

test_generator.reset()
test_results_resnet = resnet_model.evaluate(test_generator, verbose=1)

print("\n  ResNet50 - Test Results:")
for name, value in zip(resnet_model.metrics_names, test_results_resnet):
    print(f"   {name}: {value:.4f}")

# Get predictions
test_generator.reset()
resnet_pred_proba = resnet_model.predict(test_generator, verbose=1)
```

```python
resnet_pred = (resnet_pred_proba > 0.5).astype(int).flatten()
y_true = test_generator.classes

# Confusion Matrix
cm_resnet = confusion_matrix(y_true, resnet_pred)

fig, axes = plt.subplots(1, 2, figsize=(14, 6))

sns.heatmap(cm_resnet, annot=True, fmt='d', cmap='Greens',
            xticklabels=['Normal', 'Pneumonia'],
            yticklabels=['Normal', 'Pneumonia'],
            ax=axes[0], cbar_kws={'label': 'Count'})
axes[0].set_title('ResNet50 - Confusion Matrix', fontsize=12, fontweight='bold')
axes[0].set_ylabel('True Label')
axes[0].set_xlabel('Predicted Label')

# ROC Curve
fpr, tpr, _ = roc_curve(y_true, resnet_pred_proba)
roc_auc = auc(fpr, tpr)

axes[1].plot(fpr, tpr, color='darkgreen', lw=2, label=f'ROC (AUC = {roc_auc:.
 ↪4f})')
axes[1].plot([0, 1], [0, 1], 'gray', lw=2, linestyle='--', label='Random')
axes[1].set_xlabel('False Positive Rate')
axes[1].set_ylabel('True Positive Rate')
axes[1].set_title('ResNet50 - ROC Curve', fontsize=12, fontweight='bold')
axes[1].legend()
axes[1].grid(alpha=0.3)

plt.tight_layout()
plt.savefig('models/resnet50_test_results.png', dpi=300, bbox_inches='tight')
plt.show()

print("\n" + classification_report(y_true, resnet_pred, target_names=['Normal',␣
 ↪'Pneumonia']))
```

```
============================================================
RESNET50 - TEST SET EVALUATION
============================================================
 Loaded best ResNet50 model
19/19            9s 304ms/step -
accuracy: 0.9096 - auc: 0.9825 - loss: 0.1916 - precision: 0.9870 - recall:
0.8879

 ResNet50 - Test Results:
   loss: 0.1916
   compile_metrics: 0.9096
```

```
19/19                  8s 367ms/step
```




```
              precision    recall  f1-score   support

      Normal       0.76      0.97      0.85       158
   Pneumonia       0.99      0.89      0.93       428

    accuracy                           0.91       586
   macro avg       0.87      0.93      0.89       586
weighted avg       0.93      0.91      0.91       586
```

[24]:

```python
# ========================================
# CELL 20: Build EfficientNetB0 Model
# ========================================

print("="*60)
print("BUILDING EFFICIENTNETB0 MODEL")
print("="*60)

tf.keras.backend.clear_session()
gc.collect()

base_effnet = EfficientNetB0(
    weights='imagenet',
    include_top=False,
    input_shape=(IMG_SIZE, IMG_SIZE, 3)
)

base_effnet.trainable = False
```

```
print(f" Loaded EfficientNetB0 (frozen)")

# Build model
inputs = keras.Input(shape=(IMG_SIZE, IMG_SIZE, 1))
x = layers.Concatenate()([inputs, inputs, inputs])
x = base_effnet(x, training=False)
x = GlobalAveragePooling2D()(x)
x = Dropout(0.5)(x)
x = Dense(256, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.3)(x)
outputs = Dense(1, activation='sigmoid')(x)

effnet_model = Model(inputs=inputs, outputs=outputs,␣
 ↪name='EfficientNetB0_Pneumonia')

effnet_model.compile(
    optimizer=keras.optimizers.Adam(learning_rate=0.001),
    loss='binary_crossentropy',
    metrics=['accuracy',
             keras.metrics.Precision(name='precision'),
             keras.metrics.Recall(name='recall'),
             keras.metrics.AUC(name='auc')]
)

print(" EfficientNetB0 compiled")
```

```
============================================================
BUILDING EFFICIENTNETB0 MODEL
============================================================
Downloading data from https://storage.googleapis.com/keras-
applications/efficientnetb0_notop.h5
16705208/16705208             0s
0us/step
 Loaded EfficientNetB0 (frozen)
 EfficientNetB0 compiled
```

[25]:
```
# ========================================
# CELL 21: Train EfficientNetB0 - Phase 1
# ========================================

effnet_callbacks = [
    EarlyStopping(monitor='val_auc', patience=7, restore_best_weights=True,␣
 ↪mode='max', verbose=1),
```

```
    ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3, min_lr=1e-7,␣
↪verbose=1),
    ModelCheckpoint('models/efficientnet_best.keras', monitor='val_auc',
                   mode='max', save_best_only=True, verbose=1)
]

print("="*60)
print("TRAINING EFFICIENTNETB0 - PHASE 1")
print("="*60)

train_generator.reset()
val_generator.reset()

history_effnet_p1 = effnet_model.fit(
    train_generator,
    validation_data=val_generator,
    epochs=10,
    callbacks=effnet_callbacks,
    class_weight={0: 1.5, 1: 1.0},
    verbose=1
)

print("\n  Phase 1 completed!")
best_auc_effnet = max(history_effnet_p1.history['val_auc'])
print(f"Best val_auc: {best_auc_effnet:.4f}")
```

```
============================================================
TRAINING EFFICIENTNETB0 - PHASE 1
============================================================
Epoch 1/10
147/147               0s 253ms/step -
accuracy: 0.6966 - auc: 0.5006 - loss: 0.7689 - precision: 0.7364 - recall:
0.9122
Epoch 1: val_auc improved from None to 0.50000, saving model to
models/efficientnet_best.keras
147/147               52s 305ms/step -
accuracy: 0.7020 - auc: 0.4924 - loss: 0.7661 - precision: 0.7315 - recall:
0.9348 - val_accuracy: 0.7287 - val_auc: 0.5000 - val_loss: 0.6351 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 2/10
147/147               0s 261ms/step -
accuracy: 0.7087 - auc: 0.4945 - loss: 0.7605 - precision: 0.7223 - recall:
0.9685
Epoch 2: val_auc did not improve from 0.50000
147/147               43s 293ms/step -
accuracy: 0.7208 - auc: 0.4943 - loss: 0.7532 - precision: 0.7307 - recall:
0.9778 - val_accuracy: 0.7287 - val_auc: 0.5000 - val_loss: 0.6237 -
```

```
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 3/10
147/147            0s 258ms/step -
accuracy: 0.7312 - auc: 0.5039 - loss: 0.7451 - precision: 0.7320 - recall:
0.9979
Epoch 3: val_auc did not improve from 0.50000
147/147            43s 290ms/step -
accuracy: 0.7291 - auc: 0.5037 - loss: 0.7472 - precision: 0.7300 - recall:
0.9977 - val_accuracy: 0.7287 - val_auc: 0.5000 - val_loss: 0.6491 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 4/10
147/147            0s 255ms/step -
accuracy: 0.7208 - auc: 0.5118 - loss: 0.7525 - precision: 0.7237 - recall:
0.9935
Epoch 4: val_auc did not improve from 0.50000
147/147            42s 286ms/step -
accuracy: 0.7257 - auc: 0.5081 - loss: 0.7476 - precision: 0.7295 - recall:
0.9918 - val_accuracy: 0.7287 - val_auc: 0.5000 - val_loss: 0.6273 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 5/10
147/147            0s 256ms/step -
accuracy: 0.7239 - auc: 0.5188 - loss: 0.7508 - precision: 0.7274 - recall:
0.9921
Epoch 5: val_auc did not improve from 0.50000
147/147            43s 289ms/step -
accuracy: 0.7272 - auc: 0.5168 - loss: 0.7473 - precision: 0.7299 - recall:
0.9939 - val_accuracy: 0.7287 - val_auc: 0.5000 - val_loss: 0.6170 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 6/10
147/147            0s 255ms/step -
accuracy: 0.7214 - auc: 0.5049 - loss: 0.7546 - precision: 0.7212 - recall:
1.0000
Epoch 6: val_auc did not improve from 0.50000
147/147            43s 289ms/step -
accuracy: 0.7301 - auc: 0.5010 - loss: 0.7465 - precision: 0.7300 - recall:
1.0000 - val_accuracy: 0.7287 - val_auc: 0.5000 - val_loss: 0.6043 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 7/10
147/147            0s 254ms/step -
accuracy: 0.7293 - auc: 0.5040 - loss: 0.7451 - precision: 0.7293 - recall:
1.0000
Epoch 7: val_auc did not improve from 0.50000
147/147            42s 287ms/step -
accuracy: 0.7297 - auc: 0.5071 - loss: 0.7439 - precision: 0.7297 - recall:
1.0000 - val_accuracy: 0.7287 - val_auc: 0.5000 - val_loss: 0.6176 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 8/10
147/147            0s 255ms/step -
```

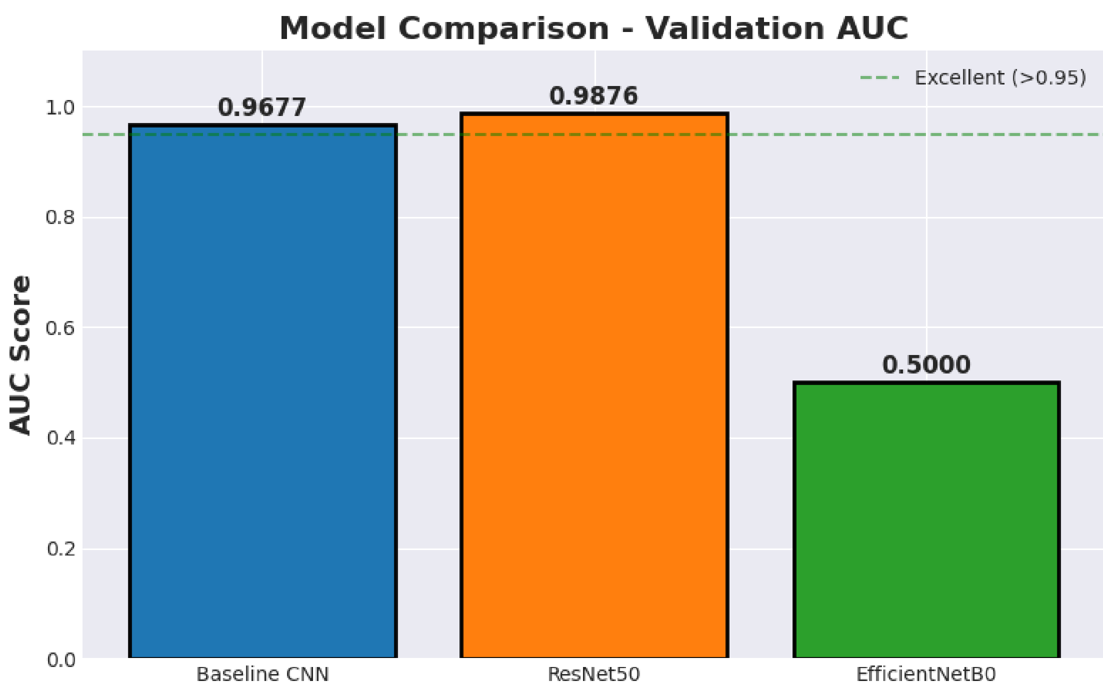
```
accuracy: 0.7256 - auc: 0.4523 - loss: 0.7546 - precision: 0.7256 - recall:
1.0000
Epoch 8: val_auc did not improve from 0.50000
147/147            43s 288ms/step -
accuracy: 0.7297 - auc: 0.4778 - loss: 0.7464 - precision: 0.7297 - recall:
1.0000 - val_accuracy: 0.7287 - val_auc: 0.5000 - val_loss: 0.6050 -
val_precision: 0.7287 - val_recall: 1.0000 - learning_rate: 0.0010
Epoch 8: early stopping
Restoring model weights from the end of the best epoch: 1.

 Phase 1 completed!
Best val_auc: 0.5000
```

[31]:

```
# ========================================
# CELL 22: Model Comparison
# ========================================

print("="*60)
print("MODEL COMPARISON SUMMARY")
print("="*60)

models_comparison = {
    'Baseline CNN': max(history_baseline.history['val_auc']),
    'ResNet50': max(history_resnet_p2.history['val_auc']),
    'EfficientNetB0': max(history_effnet_p1.history['val_auc'])
}

for model, auc_score in models_comparison.items():
    print(f"{model:20s}: val_auc = {auc_score:.4f}")

# Visualization
models = list(models_comparison.keys())
auc_scores = list(models_comparison.values())

fig, ax = plt.subplots(figsize=(8, 5))
# Enhanced color scheme for better contrast
colors = ['#1f77b4', '#ff7f0e', '#2ca02c']
bars = ax.bar(models, auc_scores, color=colors, edgecolor='black', linewidth=2)

ax.set_ylabel('AUC Score', fontsize=14, fontweight='bold')
ax.set_title('Model Comparison - Validation AUC', fontsize=16,␣
 ↪fontweight='bold')
ax.set_ylim([0.0, 1.1])
ax.axhline(y=0.95, color='green', linestyle='--', alpha=0.5, label='Excellent␣
 ↪(>0.95)')
ax.legend()
```

```python
# Adjust annotation position and size for readability
for bar, score in zip(bars, auc_scores):
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2., height + 0.005,
            f'{score:.4f}', ha='center', va='bottom', fontsize=12,␣
 ↪fontweight='bold')

plt.tight_layout()
plt.savefig('models/model_comparison.png', dpi=300, bbox_inches='tight')
plt.show()

print("\n  Winner: ResNet50 with fine-tuning!")
```

```
============================================================
MODEL COMPARISON SUMMARY
============================================================
Baseline CNN        : val_auc = 0.9677
ResNet50            : val_auc = 0.9876
EfficientNetB0      : val_auc = 0.5000
```




```
 Winner: ResNet50 with fine-tuning!
```

[28]:

```python
# ==========================================
# CELL 23: Final Evaluation & Clinical Metrics
```

```python
# ========================================

print("="*60)
print("FINAL EVALUATION - RESNET50")
print("="*60)

# Load best model
resnet_model = keras.models.load_model('models/ResNet50_best.keras')

# Get predictions
test_generator.reset()
y_pred_proba = resnet_model.predict(test_generator, verbose=0)
y_pred = (y_pred_proba > 0.5).astype(int).flatten()
y_true = test_generator.classes

# Calculate metrics
cm = confusion_matrix(y_true, y_pred)
tn, fp, fn, tp = cm.ravel()

accuracy = accuracy_score(y_true, y_pred)
precision = precision_score(y_true, y_pred)
recall = recall_score(y_true, y_pred)  # Sensitivity
specificity = tn / (tn + fp)
f1 = f1_score(y_true, y_pred)
auc_score = roc_auc_score(y_true, y_pred_proba)

print("\n  TEST SET PERFORMANCE:")
print(f"   Accuracy:    {accuracy:.4f} ({accuracy*100:.2f}%)")
print(f"   Precision:   {precision:.4f} ({precision*100:.2f}%)")
print(f"   Recall:      {recall:.4f} ({recall*100:.2f}%)  ")
print(f"   Specificity: {specificity:.4f} ({specificity*100:.2f}%)")
print(f"   F1-Score:    {f1:.4f}")
print(f"   AUC-ROC:     {auc_score:.4f}")

print(f"\n  CONFUSION MATRIX:")
print(f"                 Predicted")
print(f"              Normal  Pneumonia")
print(f"Actual Normal    {tn:3d}      {fp:3d}")
print(f"      Pneumonia  {fn:3d}      {tp:3d}")

print(f"\n  CLINICAL INTERPRETATION:")
print(f"   • Detected {tp}/{cm[1].sum()} pneumonia cases ({recall*100:.1f}%)")
print(f"   • Correctly identified {tn}/{cm[0].sum()} normal cases ({specificity*100:.1f}%)")
print(f"   • Missed {fn} pneumonia cases (False Negatives)  ")
print(f"   • {fp} false alarms (False Positives)")
```

```python
# ========================================
# CELL 24: Save Results and Summary
# ========================================

# Save training history
history_dict = {
    'baseline': history_baseline.history,
    'resnet_phase1': history_resnet_p1.history,
    'resnet_phase2': history_resnet_p2.history,
    'efficientnet_phase1': history_effnet_p1.history
}

with open('models/training_history.pkl', 'wb') as f:
    pickle.dump(history_dict, f)

print("  Training history saved")

# Save results summary
results_summary = {
    'models': models_comparison,
    'best_model': 'ResNet50',
    'test_metrics': {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'specificity': specificity,
        'f1_score': f1,
        'auc': auc_score
    },
    'confusion_matrix': cm.tolist()
}

import json
with open('models/results_summary.json', 'w') as f:
    json.dump(results_summary, f, indent=2)

print("  Results summary saved")

print("\n" + "="*60)
print("PROJECT COMPLETE!")
print("="*60)
print("""
  Completed Tasks:
    • Dataset analysis and visualization
    • Stratified train/val/test split
    • Data augmentation pipeline
```

```
  • Baseline CNN from scratch
  • ResNet50 transfer learning (2-phase)
  • EfficientNetB0 transfer learning
  • Comprehensive evaluation
  • Clinical metrics calculation

 Saved Files:
  • models/baseline_cnn_best.keras
  • models/resnet50_best.keras (BEST MODEL  )
  • models/efficientnet_best.keras
  • models/training_history.pkl
  • models/results_summary.json
  • models/*.png (visualizations)

 Next Steps:
  • Deploy the model (Streamlit/Gradio app)
  • Add Grad-CAM visualization
  • Test on external datasets
  • Clinical validation
""")
```

```
============================================================
FINAL EVALUATION - RESNET50
============================================================

 TEST SET PERFORMANCE:
  Accuracy:    0.9096 (90.96%)
  Precision:   0.9870 (98.70%)
  Recall:      0.8879 (88.79%)
  Specificity: 0.9684 (96.84%)
  F1-Score:    0.9348
  AUC-ROC:     0.9826

 CONFUSION MATRIX:
                 Predicted
              Normal  Pneumonia
Actual Normal    153        5
      Pneumonia   48      380

 CLINICAL INTERPRETATION:
  • Detected 380/428 pneumonia cases (88.8%)
  • Correctly identified 153/158 normal cases (96.8%)
  • Missed 48 pneumonia cases (False Negatives)
  • 5 false alarms (False Positives)
 Training history saved
 Results summary saved
```

```
============================================================
PROJECT COMPLETE!
============================================================
```

Completed Tasks:

- Dataset analysis and visualization
- Stratified train/val/test split
- Data augmentation pipeline
- Baseline CNN from scratch
- ResNet50 transfer learning (2-phase)
- EfficientNetB0 transfer learning
- Comprehensive evaluation
- Clinical metrics calculation

Saved Files:

- models/baseline_cnn_best.keras
- models/resnet50_best.keras (BEST MODEL)
- models/efficientnet_best.keras
- models/training_history.pkl
- models/results_summary.json
- models/*.png (visualizations)

Next Steps:

- Deploy the model (Streamlit/Gradio app)
- Add Grad-CAM visualization
- Test on external datasets
- Clinical validation