

## AML Project 2 Group 1

### Github repo:

[https://github.com/Yifan-Zang/GR5074\\_Project2\\_MedicallImageClassification.git](https://github.com/Yifan-Zang/GR5074_Project2_MedicallImageClassification.git)

### group member:

1. Xingyu Shi xs2557
2. Yifan Zang yz4870
3. Chunlin An ca2965

## Introduction & Dataset Overview

Dataset: the dataset consists of a total of 15153 colored radiography images of patients across three conditions: COVID, normal, and pneumonia.

```
In [1]: import os
cwd = os.getcwd()
print(cwd)

C:\Users\1\AML_P2

In [3]: os.add_dll_directory(r"C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v11.2\bin")

Out[3]: <AddedDllDirectory('C:\\Program Files\\NVIDIA GPU Computing Toolkit\\CUDA\\v11.2\\bin')>

In [5]: # run on GPU
import tensorflow as tf
print("Built with CUDA:", tf.test.is_built_with_cuda())
try:
    from tensorflow.python.platform import build_info as tf_build_info
    print("TF build info:", tf_build_info.build_info.get("cuda_version"),
          tf_build_info.build_info.get("cudnn_version"))
except Exception as e:
    print("build_info not available:", e)

print("Visible GPUs:", tf.config.list_physical_devices("GPU"))

Built with CUDA: True
TF build info: 64_112 64_8
Visible GPUs: [PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]

In [7]: import tensorflow as tf
gpus = tf.config.list_physical_devices("GPU")
if gpus:
    for gpu in gpus:
        tf.config.experimental.set_memory_growth(gpu, True)

In [9]: import zipfile
import os

zip_path = r"C:\Users\1\AML_P2\COVID-19_Radiography_Dataset.zip"
extract_dir = r"C:\Users\1\AML_P2\MLP2_QMSS\dataset"

os.makedirs(extract_dir, exist_ok=True)

# unzip
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(extract_dir)

In [14]: import sys
import time
import cv2
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import tensorflow as tf
import zipfile

%matplotlib inline

from tensorflow.python.keras.utils import np_utils
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, Dropout, Flatten, Activation, BatchNormalization
from tensorflow.python.keras.layers.convolutional import Conv2D, MaxPooling2D
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import Adam, SGD, Adagrad, Adadelta, RMSprop
from tensorflow.keras.applications import VGG19, ResNet50, InceptionV3
```

## Exploratory Data Analysis (EDA)

```
In [19]: # Extracting all filenames iteratively
base_path = r"C:\Users\1\AML_P2\MLP2_QMSS\dataset\COVID-19_Radiography_Dataset"
categories = ['COVID/images', 'Normal/images', 'Viral Pneumonia/images']
```

```
# load file names to fnames list object
fnames = []
for category in categories:
    image_folder = os.path.join(base_path, category)
    file_names = os.listdir(image_folder)
    full_path = [os.path.join(image_folder, file_name) for file_name in file_names]
    fnames.append(full_path)

In [21]: # describe the dataset
# print('number of images for each category:', [len(f) for f in fnames])
print("sample file name: ", fnames[0][0]) #examples of file names

img_counts = pd.DataFrame()
img_counts['category'] = categories
img_counts['count'] = [len(f) for f in fnames]
display(img_counts)

sample file name: C:\Users\1\AML_P2\MLP2_QMSS\dataset\COVID-19_Radiography_Dataset\COVID/images\COVID-1.png
```

category	count
0 COVID/images	3616
1 Normal/images	10192
2 Viral Pneumonia/images	1345

Here we can see that the distribution of number of images for each category is uneven, with most images belonging to the 'normal' category, and the least belonging to the 'pneumonia' category'.

```
from mpl_toolkits.axes_grid1 import ImageGrid
import numpy as np
import random
import matplotlib.image as mpimg

# Load the image
cvdimg = mpimg.imread(fnames[0][0])
nrmimg = mpimg.imread(fnames[1][0])
pneimg = mpimg.imread(fnames[2][0])

# Display the three sample images

f, axarr = plt.subplots(1, 3, figsize=(10,4)) # 1 row, 3 columns

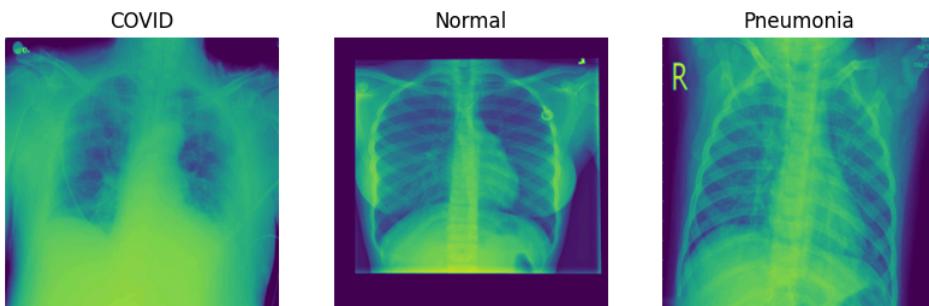
axarr[0].imshow(cvdimg)
axarr[0].set_title("COVID")

axarr[1].imshow(nrmimg)
axarr[1].set_title("Normal")

axarr[2].imshow(pneimg)
axarr[2].set_title("Pneumonia")

for ax in axarr:
    ax.axis('off')

plt.show()
```



```
# Write preprocessor that will match up with model's expected input shape.
from keras.preprocessing import image
import numpy as np
from PIL import Image

def preprocessor(img_path):
    img = Image.open(img_path).convert("RGB").resize((192,192)) # import image, make sure it's RGB and resize to height and width
    img = (np.float32(img)-1.)/(255-1.) # min max transformation
    img=img.reshape((192,192,3)) # Create final shape as array with correct dimensions for Keras
    return img

# Try on single file (imports file and preprocesses it to data with following shape)
preprocessor(r'C:\Users\1\AML_P2\MLP2_QMSS\dataset\COVID-19_Radiography_Dataset\COVID/images\COVID-1003.png').shape
```

Out[26]: (192, 192, 3)

```
In [28]: # sample images after preprocessing

im1 = preprocessor(fnames[0][0]) # COVID-positive image
im2 = preprocessor(fnames[1][0]) # normal image
im3 = preprocessor(fnames[2][0]) # viral pneumonia image

fig = plt.figure(figsize=(4., 4.))
```

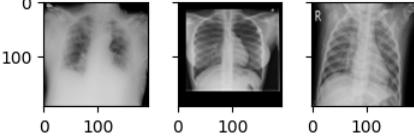
```

grid = ImageGrid(fig, 111, # similar to subplot(111)
                 nrows_ncols=(1, 3), # creates 2x2 grid of axes
                 axes_pad=0.25, # pad between axes in inch.
                 )

for ax, im in zip(grid, [im1, im2, im3]):
    # Iterating over the grid returns the Axes.
    ax.imshow(im)
plt.show()

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [-0.00393700
8..0.8425197].
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [-0.00393700
8..1.0].
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [-0.00393700
8..1.0].

```



As our data is heavily imbalanced, with the 'normal' class having almost 8 times more samples than the pneumonia class and about 3 times more than the COVID class, we would need to rebalance the dataset. We can conduct undersampling to have the sample number match the smallest class, but that way we would lose valuable data and our model would also have weaker generalizability. For similar reasons we would also want to avoid oversampling, which simply duplicates new samples from our smallest class and can result in the model overfitting. A better approach would be to apply data augmentation on the smallest class, while also calculating class weights by assigning higher loss weights to the minority classes during training, which is especially effective in training neural networks.

However, due to limitation of computing power, we will use the undersampling technique.

```
In [31]: #Reduce number of images to first 1345 for each category
fnames[0]=fnames[0][0:1344]
fnames[1]=fnames[1][0:1344]
fnames[2]=fnames[2][0:1344]
```

```
In [33]: #Import image files iteratively and preprocess them into array of correctly structured data

# Create list of file paths
image_filepaths=fnames[0]+fnames[1]+fnames[2]

# Iteratively import and preprocess data using map function

# map functions apply your preprocessor function one step at a time to each filepath
preprocessed_image_data=list(map(preprocessor,image_filepaths))

# Object needs to be an array rather than a list for Keras (map returns to list object)
X= np.array(preprocessed_image_data) # Assigning to X to highlight that this represents feature input data for our model
```

```
In [34]: print(len(X)) #same number of elements as filenames
print(X.shape) #dimensions now 192,192,3 for all images
print(X.min().round()) #min value of every image is zero
print(X.max()) #max value of every image is one
```

```
4032
(4032, 192, 192, 3)
-0.0
1.0
```

```
In [35]: # Create y data made up of correctly ordered labels from file folders
from itertools import repeat

# Recall that we have five folders with the following number of images in each folder
#...corresponding to each flower type

print('number of images for each category:', [len(f) for f in fnames])
covid=list(repeat("COVID", 1344))
normal=list(repeat("NORMAL", 1344))
pneumonia=list(repeat("PNEUMONIA", 1344))

#combine into single list of y labels
y_labels = covid+normal+pneumonia

#check length, same as X above
print(len(y_labels))

# Need to one hot encode for Keras. Let's use Pandas

import pandas as pd
y=pd.get_dummies(y_labels)

display(y)

number of images for each category: [1344, 1344, 1344]
4032
```

	COVID	NORMAL	PNEUMONIA
0	True	False	False
1	True	False	False
2	True	False	False
3	True	False	False
4	True	False	False
...	...	...	...
4027	False	False	True
4028	False	False	True
4029	False	False	True
4030	False	False	True
4031	False	False	True

4032 rows x 3 columns

```
In [39]: # Train test split resized images
import numpy as np
from sklearn.model_selection import train_test_split

y_idx = np.argmax(y.values, axis=1) if hasattr(y, "values") else np.argmax(y, axis=1)

# index
idx = np.arange(len(X))

#using index to split
train_idx, test_idx = train_test_split(
    idx, test_size=0.32, stratify=y_idx, random_state=1987
)

X_train = np.take(X, train_idx, axis=0)
X_test = np.take(X, test_idx, axis=0)
y_train = np.take(y.values if hasattr(y, "values") else y, train_idx, axis=0)
y_test = np.take(y.values if hasattr(y, "values") else y, test_idx, axis=0)

print(X_train.shape, X_test.shape)
print(y_train.shape, y_test.shape)

(2741, 192, 192, 3) (1291, 192, 192, 3)
(2741, 3) (1291, 3)
```

To explore which factors may be related to the classification of the three conditions, we tried comparing the average brightness images across each category.

```
In [44]: # plot distribution of brightness of images in each category

from PIL import ImageStat

# define image brightness function that converts images to greyscale

def brightness(im_file):
    im = Image.open(im_file).convert('L')
    stat = ImageStat.Stat(im)
    return stat.mean[0]

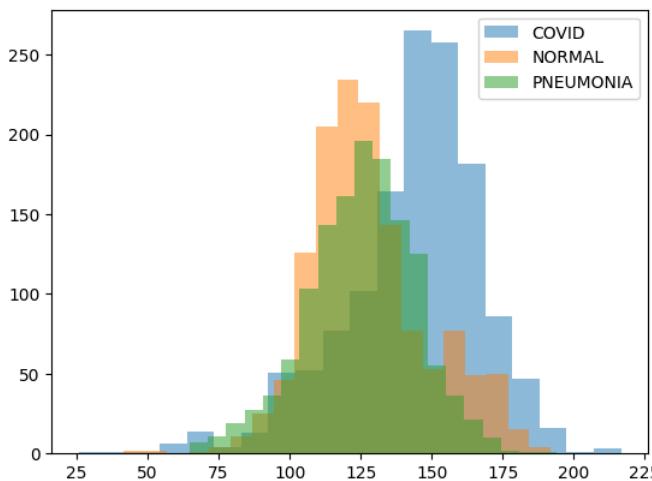
# iterate through data

covid_brightness=list(map(brightness, fnames[0]))
normal_brightness=list(map(brightness, fnames[1]))
pneumonia_brightness=list(map(brightness, fnames[2]))

# plot distribution of brightness

plt.hist(covid_brightness, bins=20, alpha=0.5, label='COVID')
plt.hist(normal_brightness, bins=20, alpha=0.5, label='NORMAL')
plt.hist(pneumonia_brightness, bins=20, alpha=0.5, label='PNEUMONIA')
plt.legend(loc='upper right')
```

Out[44]: <matplotlib.legend.Legend at 0x1d31bca97f0>



It can be seen from the histogram that while the average brightness for "normal"-labeled images is normally distributed around 125, the distribution of "covid"-labeled images is skewed left, and the distribution of "pneumonia"-labeled images is skewed right. To test this, we calculated the mean and sd for each category, and then conducted a one-way ANOVA to see if there is a significant difference across three groups.

```
In [45]: print("covid image average brightness: ", np.mean(covid_brightness), "standard deviation: ", np.std(covid_brightness))
print("normal image average brightness: ", np.mean(normal_brightness), "standard deviation: ", np.std(normal_brightness))
print("pneumonia image average brightness: ", np.mean(pneumonia_brightness), "standard deviation: ", np.std(pneumonia_brightness))

covid image average brightness: 143.66979247229312 standard deviation: 24.2521628644205
normal image average brightness: 127.91936884428159 standard deviation: 21.1949127758166
pneumonia image average brightness: 125.36907965268578 standard deviation: 18.98096347112496
```

```
In [46]: # conduct ANOVA for three averages

from scipy.stats import f_oneway

f_statistic, p_value = f_oneway(covid_brightness, normal_brightness, pneumonia_brightness)

print(f"F-statistic: {f_statistic}")
print(f"P-value: {p_value}")

F-statistic: 283.2191215491495
P-value: 8.171210395007046e-116
```

Based on the ANOVA, it can be seen that the average brightness is significantly different across the three types of radiography images.

Through modeling, we can more accurately classify radiography images to match their respective conditions. This is extremely helpful to support clinical decisions through a quicker identification of potential critical conditions that require more urgent attention. It can serve as a powerful screening tool for clinics where radiologists may be understaffed. Analyzing and identifying feature importance in these models can also improve understanding on potentially important biomarkers in these diseases.

## Baseline CNN Model

This baseline CNN consists of:

- 3 Convolutional blocks (Conv2D + MaxPooling + Dropout)
- Fully connected layers for classification
- Total of ~1.8M parameters

Architecture choices:

- ReLU activation for non-linearity
- MaxPooling for downsampling
- Dropout for regularization to prevent overfitting
- Softmax output for multi-class classification

```
In [59]: # load data
import pickle

class NpCompatUnpickler(pickle.Unpickler):
    def find_class(self, module, name):
        if module.startswith("numpy._core"):
            module = module.replace("numpy._core", "numpy.core")
        return super().find_class(module, name)

def load_pickle_compat(path):
    with open(path, 'rb') as f:
        return NpCompatUnpickler(f).load()

X_train = load_pickle_compat(r'C:\Users\1\AML_P2\X_train.pkl')
y_train = load_pickle_compat(r'C:\Users\1\AML_P2\y_train.pkl')
X_test = load_pickle_compat(r'C:\Users\1\AML_P2\X_test.pkl')
y_test = load_pickle_compat(r'C:\Users\1\AML_P2\y_test.pkl')

import numpy as np
import pandas as pd

np.savez_compressed(r'C:\Users\1\AML_P2\data_train.npz', X=X_train, y=y_train.values)
np.savez_compressed(r'C:\Users\1\AML_P2\data_test.npz', X=X_test, y=y_test.values)
```

```
dtr = np.load(r'C:\Users\1\AML_P2\data_train.npz')
dte = np.load(r'C:\Users\1\AML_P2\data_test.npz')
X_train, y_train = dtr['X'], dtr['y']
X_test, y_test = dte['X'], dte['y']
```

```
In [60]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
import matplotlib.pyplot as plt
```

#### Build Baseline CNN Architecture

```
In [62]: def create_baseline_cnn(input_shape=(192, 192, 3), num_classes=3):
    """
    Create a baseline CNN architecture for medical image classification.

    Parameters:
    - input_shape: tuple, shape of input images (height, width, channels)
    - num_classes: int, number of output classes

    Returns:
    - model: compiled Keras model
    """

    model = Sequential(name='Baseline_CNN')

    # First Convolutional Block
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
                    padding='same', input_shape=input_shape, name='conv1'))
    model.add(MaxPooling2D(pool_size=(2, 2), name='pool1'))
    model.add(Dropout(0.25, name='dropout1'))

    # Second Convolutional Block
    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu',
                    padding='same', name='conv2'))
    model.add(MaxPooling2D(pool_size=(2, 2), name='pool2'))
    model.add(Dropout(0.25, name='dropout2'))

    # Third Convolutional Block
    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu',
                    padding='same', name='conv3'))
    model.add(MaxPooling2D(pool_size=(2, 2), name='pool3'))
    model.add(Dropout(0.25, name='dropout3'))

    # Flatten and Fully Connected Layers
    model.add(Flatten(name='flatten'))
    model.add(Dense(256, activation='relu', name='fc1'))
    model.add(Dropout(0.5, name='dropout4'))
    model.add(Dense(num_classes, activation='softmax', name='output'))

    return model
```

```
In [63]: # Create the model
baseline_cnn = create_baseline_cnn(input_shape=(192, 192, 3), num_classes=3)

# Display model architecture
baseline_cnn.summary()
```

Model: "Baseline\_CNN"

Layer (type)	Output Shape	Param #
<hr/>		
conv1 (Conv2D)	(None, 192, 192, 32)	896
pool1 (MaxPooling2D)	(None, 96, 96, 32)	0
dropout1 (Dropout)	(None, 96, 96, 32)	0
conv2 (Conv2D)	(None, 96, 96, 64)	18496
pool2 (MaxPooling2D)	(None, 48, 48, 64)	0
dropout2 (Dropout)	(None, 48, 48, 64)	0
conv3 (Conv2D)	(None, 48, 48, 128)	73856
pool3 (MaxPooling2D)	(None, 24, 24, 128)	0
dropout3 (Dropout)	(None, 24, 24, 128)	0
flatten (Flatten)	(None, 73728)	0
fc1 (Dense)	(None, 256)	18874624
dropout4 (Dropout)	(None, 256)	0
output (Dense)	(None, 3)	771
<hr/>		

Total params: 18,968,643  
Trainable params: 18,968,643  
Non-trainable params: 0

#### Compile and Configure Training

Model Configuration:

- Loss Function: categorical\_crossentropy (for multi-class classification)
- Optimizer: Adam (learning rate of 0.001)
- Metrics: accuracy for performance evaluation

Callbacks:

- EarlyStopping: stops training if validation loss doesn't improve for 5 epochs
- ReduceLROnPlateau: reduces learning rate when validation loss plateaus

```
In [70]: # Compile the model
baseline_cnn.compile(
    optimizer=Adam(learning_rate=0.001),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

# Define callbacks for training
callbacks_baseline = [
    EarlyStopping(
        monitor='val_loss',
        patience=5,
        restore_best_weights=True,
        verbose=1
    ),
    ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=3,
        min_lr=1e-7,
        verbose=1
    )
]
```

### Train the Baseline CNN

Training Configuration:

- Epochs: 10 (with early stopping)
- Batch size: 32
- Validation split: 20% of training data

```
In [72]: history_baseline = baseline_cnn.fit(
    X_train, y_train,
    validation_split=0.2,
    epochs=10,
    batch_size=32,
    callbacks=callbacks_baseline,
    verbose=1
)

Epoch 1/10
69/69 [=====] - 10s 26ms/step - loss: 0.8819 - accuracy: 0.6250 - val_loss: 0.4580 - val_accuracy: 0.7960 -
lr: 0.0010
Epoch 2/10
69/69 [=====] - 1s 20ms/step - loss: 0.3909 - accuracy: 0.8449 - val_loss: 0.3142 - val_accuracy: 0.8743 - lr: 0.0010
Epoch 3/10
69/69 [=====] - 1s 20ms/step - loss: 0.2904 - accuracy: 0.8828 - val_loss: 0.3076 - val_accuracy: 0.9016 - lr: 0.0010
Epoch 4/10
69/69 [=====] - 1s 19ms/step - loss: 0.2419 - accuracy: 0.9033 - val_loss: 0.2566 - val_accuracy: 0.9089 - lr: 0.0010
Epoch 5/10
69/69 [=====] - 1s 20ms/step - loss: 0.1843 - accuracy: 0.9266 - val_loss: 0.2244 - val_accuracy: 0.9199 - lr: 0.0010
Epoch 6/10
69/69 [=====] - 1s 20ms/step - loss: 0.1546 - accuracy: 0.9389 - val_loss: 0.2286 - val_accuracy: 0.9326 - lr: 0.0010
Epoch 7/10
69/69 [=====] - 1s 19ms/step - loss: 0.1305 - accuracy: 0.9557 - val_loss: 0.2258 - val_accuracy: 0.9362 - lr: 0.0010
Epoch 8/10
69/69 [=====] - 1s 21ms/step - loss: 0.1025 - accuracy: 0.9644 - val_loss: 0.2104 - val_accuracy: 0.9490 - lr: 0.0010
Epoch 9/10
69/69 [=====] - 1s 20ms/step - loss: 0.0845 - accuracy: 0.9685 - val_loss: 0.2398 - val_accuracy: 0.9344 - lr: 0.0010
Epoch 10/10
69/69 [=====] - 1s 20ms/step - loss: 0.0762 - accuracy: 0.9763 - val_loss: 0.1959 - val_accuracy: 0.9454 - lr: 0.0010
```

### Evaluate Baseline CNN Performance

```
In [126]: # Evaluate on test set
test_loss_baseline, test_acc_baseline = baseline_cnn.evaluate(X_test, y_test, verbose=0)

print(f"Test Loss: {test_loss_baseline:.4f}")
print(f"Test Accuracy: {test_acc_baseline:.4f} ({test_acc_baseline*100:.2f}%)")

# Get training and validation accuracy and loss for final epoch
final_train_acc = history_baseline.history['accuracy'][-1]
final_train_loss = history_baseline.history['loss'][-1]
final_val_acc = history_baseline.history['val_accuracy'][-1]
final_val_loss = history_resnet.history['val_loss'][-1]

print(f"\nFinal Training Accuracy: {final_train_acc:.4f} ({final_train_acc*100:.2f}%)")
print(f"Final Validation Accuracy: {final_val_acc:.4f} ({final_val_acc*100:.2f}%)")
```

```
Test Loss: 0.1936
Test Accuracy: 0.9287 (92.87%)
Final Training Accuracy: 0.9763 (97.63%)
Final Validation Accuracy: 0.9454 (94.54%)
```

#### Visualize Training History

Plot training and validation loss & accuracy curves to assess model performance and check for overfitting or underfitting

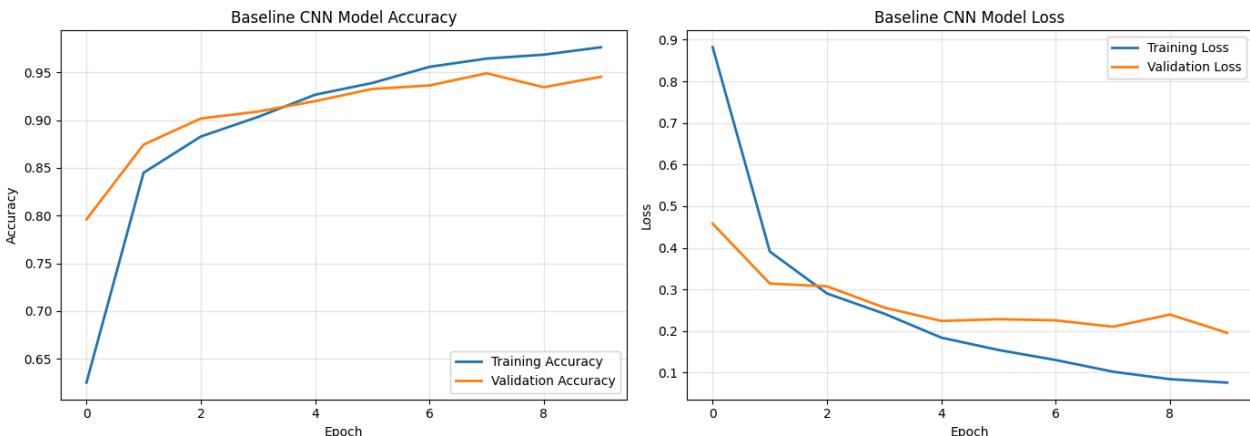
```
In [77]: fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Training & validation accuracy
axes[0].plot(history_baseline.history['accuracy'], label='Training Accuracy', linewidth=2)
axes[0].plot(history_baseline.history['val_accuracy'], label='Validation Accuracy', linewidth=2)
axes[0].set_title('Baseline CNN Model Accuracy')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Accuracy')
axes[0].legend(loc='lower right')
axes[0].grid(True, alpha=0.3)

# Training & validation loss
axes[1].plot(history_baseline.history['loss'], label='Training Loss', linewidth=2)
axes[1].plot(history_baseline.history['val_loss'], label='Validation Loss', linewidth=2)
axes[1].set_title('Baseline CNN Model Loss')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Loss')
axes[1].legend(loc='upper right')
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("\nTraining Summary:")
print(f"Total epochs trained: {len(history_baseline.history['loss'])}")
print(f"Best validation accuracy: {max(history_baseline.history['val_accuracy']):.4f}")
print(f"Best validation loss: {min(history_baseline.history['val_loss']):.4f}")
```



```
Training Summary:
Total epochs trained: 10
Best validation accuracy: 0.9490
Best validation loss: 0.1959
```

```
In [128]: # Save for comparison
perf_rows = []
perf_rows.append({
    'Model': 'BaselineCNN', # model name
    'Type': 'baseline', # model type
    'Train_Accuracy': float(final_train_acc), # final training accuracy
    'Val_Accuracy': float(final_val_acc), # final validation accuracy
    'Test_Accuracy': float(test_acc_baseline), # final test accuracy
    'Train_Loss': float(final_train_loss), # final training loss
    'Val_Loss': float(final_val_loss), # final validation loss
    'Test_Loss': float(test_loss_baseline) # final test loss
})
```

## Transfer Learning with ResNet

Transfer Learning:

1. Load ResNet50 pre-trained on ImageNet
2. Freeze the base convolutional layers (feature extractor)
3. Add custom classification layers
4. Fine-tune (maybe)

```
In [83]: from tensorflow.keras.applications import ResNet50
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, Dropout
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
```

```
In [85]: def create_resnet_transfer_model(input_shape=(192, 192, 3), num_classes=3, trainable_base=False):
    """
    Create ResNet50 model with transfer learning.
    """
```

```
Parameters:  
- input_shape: tuple, shape of input images  
- num_classes: int, number of output classes  
- trainable_base: bool, whether to fine-tune base layers  
  
Returns:  
- model: compiled Keras model  
"""  
  
# Load pre-trained ResNet50 without top classification layer  
base_model = ResNet50(  
    weights='imagenet',  
    include_top=False,  
    input_shape=input_shape  
)  
  
# Freeze base model layers  
base_model.trainable = trainable_base  
  
# Add custom classification head  
x = base_model.output  
x = GlobalAveragePooling2D(name='global_avg_pool')(x)  
x = Dense(256, activation='relu', name='fc1')(x)  
x = Dropout(0.5, name='dropout1')(x)  
x = Dense(128, activation='relu', name='fc2')(x)  
x = Dropout(0.3, name='dropout2')(x)  
outputs = Dense(num_classes, activation='softmax', name='output')(x)  
  
# Create final model  
model = Model(inputs=base_model.input, outputs=outputs, name='ResNet50_Transfer')  
  
return model, base_model
```

```
In [87]: # Create ResNet50 transfer learning model  
resnet_model, resnet_base = create_resnet_transfer_model(  
    input_shape=(192, 192, 3),  
    num_classes=3,  
    trainable_base=False  
)  
  
# Display model  
resnet_model.summary()
```

Downloading data from [https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50\\_weights\\_tf\\_dim\\_ordering\\_tf\\_kernels.h5](https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels.h5)  
94765736/94765736 [=====] - 1s 0us/step  
Model: "ResNet50\_Transfer"

Layer (type)	Output Shape	Param #	Connected to
<hr/>			
input_1 (InputLayer)	[(None, 192, 192, 3)]	0	[]
conv1_pad (ZeroPadding2D)	(None, 198, 198, 3)	0	['input_1[0][0]']
conv1_conv (Conv2D)	(None, 96, 96, 64)	9472	['conv1_pad[0][0]']
conv1_bn (BatchNormalization)	(None, 96, 96, 64)	256	['conv1_conv[0][0]']
conv1_relu (Activation)	(None, 96, 96, 64)	0	['conv1_bn[0][0]']
pool1_pad (ZeroPadding2D)	(None, 98, 98, 64)	0	['conv1_relu[0][0]']
pool1_pool (MaxPooling2D)	(None, 48, 48, 64)	0	['pool1_pad[0][0]']
conv2_block1_1_conv (Conv2D)	(None, 48, 48, 64)	4160	['pool1_pool[0][0]']
conv2_block1_1_bn (BatchNormal ization)	(None, 48, 48, 64)	256	['conv2_block1_1_conv[0][0]']
conv2_block1_1_relu (Activatio n)	(None, 48, 48, 64)	0	['conv2_block1_1_bn[0][0]']
conv2_block1_2_conv (Conv2D)	(None, 48, 48, 64)	36928	['conv2_block1_1_relu[0][0]']
conv2_block1_2_bn (BatchNormal ization)	(None, 48, 48, 64)	256	['conv2_block1_2_conv[0][0]']
conv2_block1_2_relu (Activatio n)	(None, 48, 48, 64)	0	['conv2_block1_2_bn[0][0]']
conv2_block1_0_conv (Conv2D)	(None, 48, 48, 256)	16640	['pool1_pool[0][0]']
conv2_block1_3_conv (Conv2D)	(None, 48, 48, 256)	16640	['conv2_block1_2_relu[0][0]']
conv2_block1_0_bn (BatchNormal ization)	(None, 48, 48, 256)	1024	['conv2_block1_0_conv[0][0]']
conv2_block1_3_bn (BatchNormal ization)	(None, 48, 48, 256)	1024	['conv2_block1_3_conv[0][0]']
conv2_block1_add (Add)	(None, 48, 48, 256)	0	['conv2_block1_0_bn[0][0]', 'conv2_block1_3_bn[0][0]']
conv2_block1_out (Activation)	(None, 48, 48, 256)	0	['conv2_block1_add[0][0]']
conv2_block2_1_conv (Conv2D)	(None, 48, 48, 64)	16448	['conv2_block1_out[0][0]']
conv2_block2_1_bn (BatchNormal ization)	(None, 48, 48, 64)	256	['conv2_block2_1_conv[0][0]']
conv2_block2_1_relu (Activatio n)	(None, 48, 48, 64)	0	['conv2_block2_1_bn[0][0]']
conv2_block2_2_conv (Conv2D)	(None, 48, 48, 64)	36928	['conv2_block2_1_relu[0][0]']
conv2_block2_2_bn (BatchNormal ization)	(None, 48, 48, 64)	256	['conv2_block2_2_conv[0][0]']
conv2_block2_2_relu (Activatio n)	(None, 48, 48, 64)	0	['conv2_block2_2_bn[0][0]']
conv2_block2_3_conv (Conv2D)	(None, 48, 48, 256)	16640	['conv2_block2_2_relu[0][0]']
conv2_block2_3_bn (BatchNormal ization)	(None, 48, 48, 256)	1024	['conv2_block2_3_conv[0][0]']
conv2_block2_add (Add)	(None, 48, 48, 256)	0	['conv2_block1_out[0][0]', 'conv2_block2_3_bn[0][0]']
conv2_block2_out (Activation)	(None, 48, 48, 256)	0	['conv2_block2_add[0][0]']
conv2_block3_1_conv (Conv2D)	(None, 48, 48, 64)	16448	['conv2_block2_out[0][0]']
conv2_block3_1_bn (BatchNormal ization)	(None, 48, 48, 64)	256	['conv2_block3_1_conv[0][0]']
conv2_block3_1_relu (Activatio n)	(None, 48, 48, 64)	0	['conv2_block3_1_bn[0][0]']
conv2_block3_2_conv (Conv2D)	(None, 48, 48, 64)	36928	['conv2_block3_1_relu[0][0]']
conv2_block3_2_bn (BatchNormal ization)	(None, 48, 48, 64)	256	['conv2_block3_2_conv[0][0]']
conv2_block3_2_relu (Activatio n)	(None, 48, 48, 64)	0	['conv2_block3_2_bn[0][0]']
conv2_block3_3_conv (Conv2D)	(None, 48, 48, 256)	16640	['conv2_block3_2_relu[0][0]']
conv2_block3_3_bn (BatchNormal ization)	(None, 48, 48, 256)	1024	['conv2_block3_3_conv[0][0]']

conv2_block3_add (Add)	(None, 48, 48, 256) 0	['conv2_block2_out[0][0]', 'conv2_block3_3_bn[0][0]']
conv2_block3_out (Activation)	(None, 48, 48, 256) 0	['conv2_block3_add[0][0]']
conv3_block1_1_conv (Conv2D)	(None, 24, 24, 128) 32896	['conv2_block3_out[0][0]']
conv3_block1_1_bn (BatchNormal ization)	(None, 24, 24, 128) 512	['conv3_block1_1_conv[0][0]']
conv3_block1_1_relu (Activatio n)	(None, 24, 24, 128) 0	['conv3_block1_1_bn[0][0]']
conv3_block1_2_conv (Conv2D)	(None, 24, 24, 128) 147584	['conv3_block1_1_relu[0][0]']
conv3_block1_2_bn (BatchNormal ization)	(None, 24, 24, 128) 512	['conv3_block1_2_conv[0][0]']
conv3_block1_2_relu (Activatio n)	(None, 24, 24, 128) 0	['conv3_block1_2_bn[0][0]']
conv3_block1_0_conv (Conv2D)	(None, 24, 24, 512) 131584	['conv2_block3_out[0][0]']
conv3_block1_3_conv (Conv2D)	(None, 24, 24, 512) 66048	['conv3_block1_2_relu[0][0]']
conv3_block1_0_bn (BatchNormal ization)	(None, 24, 24, 512) 2048	['conv3_block1_0_conv[0][0]']
conv3_block1_3_bn (BatchNormal ization)	(None, 24, 24, 512) 2048	['conv3_block1_3_conv[0][0]']
conv3_block1_add (Add)	(None, 24, 24, 512) 0	['conv3_block1_0_bn[0][0]', 'conv3_block1_3_bn[0][0]']
conv3_block1_out (Activation)	(None, 24, 24, 512) 0	['conv3_block1_add[0][0]']
conv3_block2_1_conv (Conv2D)	(None, 24, 24, 128) 65664	['conv3_block1_out[0][0]']
conv3_block2_1_bn (BatchNormal ization)	(None, 24, 24, 128) 512	['conv3_block2_1_conv[0][0]']
conv3_block2_1_relu (Activatio n)	(None, 24, 24, 128) 0	['conv3_block2_1_bn[0][0]']
conv3_block2_2_conv (Conv2D)	(None, 24, 24, 128) 147584	['conv3_block2_1_relu[0][0]']
conv3_block2_2_bn (BatchNormal ization)	(None, 24, 24, 128) 512	['conv3_block2_2_conv[0][0]']
conv3_block2_2_relu (Activatio n)	(None, 24, 24, 128) 0	['conv3_block2_2_bn[0][0]']
conv3_block2_3_conv (Conv2D)	(None, 24, 24, 512) 66048	['conv3_block2_2_relu[0][0]']
conv3_block2_3_bn (BatchNormal ization)	(None, 24, 24, 512) 2048	['conv3_block2_3_conv[0][0]']
conv3_block2_add (Add)	(None, 24, 24, 512) 0	['conv3_block1_out[0][0]', 'conv3_block2_3_bn[0][0]']
conv3_block2_out (Activation)	(None, 24, 24, 512) 0	['conv3_block2_add[0][0]']
conv3_block3_1_conv (Conv2D)	(None, 24, 24, 128) 65664	['conv3_block2_out[0][0]']
conv3_block3_1_bn (BatchNormal ization)	(None, 24, 24, 128) 512	['conv3_block3_1_conv[0][0]']
conv3_block3_1_relu (Activatio n)	(None, 24, 24, 128) 0	['conv3_block3_1_bn[0][0]']
conv3_block3_2_conv (Conv2D)	(None, 24, 24, 128) 147584	['conv3_block3_1_relu[0][0]']
conv3_block3_2_bn (BatchNormal ization)	(None, 24, 24, 128) 512	['conv3_block3_2_conv[0][0]']
conv3_block3_2_relu (Activatio n)	(None, 24, 24, 128) 0	['conv3_block3_2_bn[0][0]']
conv3_block3_3_conv (Conv2D)	(None, 24, 24, 512) 66048	['conv3_block3_2_relu[0][0]']
conv3_block3_3_bn (BatchNormal ization)	(None, 24, 24, 512) 2048	['conv3_block3_3_conv[0][0]']
conv3_block3_add (Add)	(None, 24, 24, 512) 0	['conv3_block2_out[0][0]', 'conv3_block3_3_bn[0][0]']
conv3_block3_out (Activation)	(None, 24, 24, 512) 0	['conv3_block3_add[0][0]']
conv3_block4_1_conv (Conv2D)	(None, 24, 24, 128) 65664	['conv3_block3_out[0][0]']
conv3_block4_1_bn (BatchNormal ization)	(None, 24, 24, 128) 512	['conv3_block4_1_conv[0][0]']
conv3_block4_1_relu (Activatio n)	(None, 24, 24, 128) 0	['conv3_block4_1_bn[0][0]']
conv3_block4_2_conv (Conv2D)	(None, 24, 24, 128) 147584	['conv3_block4_1_relu[0][0]']
conv3_block4_2_bn (BatchNormal ization)	(None, 24, 24, 128) 512	['conv3_block4_2_conv[0][0]']

conv3_block4_2_relu (Activation) (None, 24, 24, 128) 0 n)	['conv3_block4_2_bn[0][0]']
conv3_block4_3_conv (Conv2D) (None, 24, 24, 512) 66048	['conv3_block4_2_relu[0][0]']
conv3_block4_3_bn (BatchNormal (None, 24, 24, 512) 2048 ization)	['conv3_block4_3_conv[0][0]']
conv3_block4_add (Add) (None, 24, 24, 512) 0	['conv3_block3_out[0][0]', 'conv3_block4_3_bn[0][0]']
conv3_block4_out (Activation) (None, 24, 24, 512) 0	['conv3_block4_add[0][0]']
conv4_block1_1_conv (Conv2D) (None, 12, 12, 256) 131328	['conv3_block4_out[0][0]']
conv4_block1_1_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block1_1_conv[0][0]']
conv4_block1_1_relu (Activation) (None, 12, 12, 256) 0 n)	['conv4_block1_1_bn[0][0]']
conv4_block1_2_conv (Conv2D) (None, 12, 12, 256) 590080	['conv4_block1_1_relu[0][0]']
conv4_block1_2_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block1_2_conv[0][0]']
conv4_block1_2_relu (Activation) (None, 12, 12, 256) 0 n)	['conv4_block1_2_bn[0][0]']
conv4_block1_0_conv (Conv2D) (None, 12, 12, 1024 525312 )	['conv3_block4_out[0][0]']
conv4_block1_3_conv (Conv2D) (None, 12, 12, 1024 263168 )	['conv4_block1_2_relu[0][0]']
conv4_block1_0_bn (BatchNormal (None, 12, 12, 1024 4096 ization) )	['conv4_block1_0_conv[0][0]']
conv4_block1_3_bn (BatchNormal (None, 12, 12, 1024 4096 ization) )	['conv4_block1_3_conv[0][0]']
conv4_block1_add (Add) (None, 12, 12, 1024 0 )	['conv4_block1_0_bn[0][0]', 'conv4_block1_3_bn[0][0]']
conv4_block1_out (Activation) (None, 12, 12, 1024 0 )	['conv4_block1_add[0][0]']
conv4_block2_1_conv (Conv2D) (None, 12, 12, 256) 262400	['conv4_block1_out[0][0]']
conv4_block2_1_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block2_1_conv[0][0]']
conv4_block2_1_relu (Activation) (None, 12, 12, 256) 0 n)	['conv4_block2_1_bn[0][0]']
conv4_block2_2_conv (Conv2D) (None, 12, 12, 256) 590080	['conv4_block2_1_relu[0][0]']
conv4_block2_2_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block2_2_conv[0][0]']
conv4_block2_2_relu (Activation) (None, 12, 12, 256) 0 n)	['conv4_block2_2_bn[0][0]']
conv4_block2_3_conv (Conv2D) (None, 12, 12, 1024 263168 )	['conv4_block2_2_relu[0][0]']
conv4_block2_3_bn (BatchNormal (None, 12, 12, 1024 4096 ization) )	['conv4_block2_3_conv[0][0]']
conv4_block2_add (Add) (None, 12, 12, 1024 0 )	['conv4_block1_out[0][0]', 'conv4_block2_3_bn[0][0]']
conv4_block2_out (Activation) (None, 12, 12, 1024 0 )	['conv4_block2_add[0][0]']
conv4_block3_1_conv (Conv2D) (None, 12, 12, 256) 262400	['conv4_block2_out[0][0]']
conv4_block3_1_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block3_1_conv[0][0]']
conv4_block3_1_relu (Activation) (None, 12, 12, 256) 0 n)	['conv4_block3_1_bn[0][0]']
conv4_block3_2_conv (Conv2D) (None, 12, 12, 256) 590080	['conv4_block3_1_relu[0][0]']
conv4_block3_2_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block3_2_conv[0][0]']
conv4_block3_2_relu (Activation) (None, 12, 12, 256) 0 n)	['conv4_block3_2_bn[0][0]']
conv4_block3_3_conv (Conv2D) (None, 12, 12, 1024 263168 )	['conv4_block3_2_relu[0][0]']
conv4_block3_3_bn (BatchNormal (None, 12, 12, 1024 4096 ization) )	['conv4_block3_3_conv[0][0]']
conv4_block3_add (Add) (None, 12, 12, 1024 0 )	['conv4_block2_out[0][0]', 'conv4_block3_3_bn[0][0]']

conv4_block3_out (Activation) (None, 12, 12, 1024 0 )	['conv4_block3_add[0] [0]']
conv4_block4_1_conv (Conv2D) (None, 12, 12, 256) 262400	['conv4_block3_out[0] [0]']
conv4_block4_1_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block4_1_conv[0] [0]']
conv4_block4_1_relu (Activatio (None, 12, 12, 256) 0 n)	['conv4_block4_1_bn[0] [0]']
conv4_block4_2_conv (Conv2D) (None, 12, 12, 256) 590080	['conv4_block4_1_relu[0] [0]']
conv4_block4_2_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block4_2_conv[0] [0]']
conv4_block4_2_relu (Activatio (None, 12, 12, 256) 0 n)	['conv4_block4_2_bn[0] [0]']
conv4_block4_3_conv (Conv2D) (None, 12, 12, 1024 263168 )	['conv4_block4_2_relu[0] [0]']
conv4_block4_3_bn (BatchNormal (None, 12, 12, 1024 4096 ization)	['conv4_block4_3_conv[0] [0]']
conv4_block4_add (Add) (None, 12, 12, 1024 0 )	['conv4_block3_out[0] [0]', 'conv4_block4_3_bn[0] [0]']
conv4_block4_out (Activation) (None, 12, 12, 1024 0 )	['conv4_block4_add[0] [0]']
conv4_block5_1_conv (Conv2D) (None, 12, 12, 256) 262400	['conv4_block4_out[0] [0]']
conv4_block5_1_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block5_1_conv[0] [0]']
conv4_block5_1_relu (Activatio (None, 12, 12, 256) 0 n)	['conv4_block5_1_bn[0] [0]']
conv4_block5_2_conv (Conv2D) (None, 12, 12, 256) 590080	['conv4_block5_1_relu[0] [0]']
conv4_block5_2_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block5_2_conv[0] [0]']
conv4_block5_2_relu (Activatio (None, 12, 12, 256) 0 n)	['conv4_block5_2_bn[0] [0]']
conv4_block5_3_conv (Conv2D) (None, 12, 12, 1024 263168 )	['conv4_block5_2_relu[0] [0]']
conv4_block5_3_bn (BatchNormal (None, 12, 12, 1024 4096 ization)	['conv4_block5_3_conv[0] [0]']
conv4_block5_add (Add) (None, 12, 12, 1024 0 )	['conv4_block4_out[0] [0]', 'conv4_block5_3_bn[0] [0]']
conv4_block5_out (Activation) (None, 12, 12, 1024 0 )	['conv4_block5_add[0] [0]']
conv4_block6_1_conv (Conv2D) (None, 12, 12, 256) 262400	['conv4_block5_out[0] [0]']
conv4_block6_1_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block6_1_conv[0] [0]']
conv4_block6_1_relu (Activatio (None, 12, 12, 256) 0 n)	['conv4_block6_1_bn[0] [0]']
conv4_block6_2_conv (Conv2D) (None, 12, 12, 256) 590080	['conv4_block6_1_relu[0] [0]']
conv4_block6_2_bn (BatchNormal (None, 12, 12, 256) 1024 ization)	['conv4_block6_2_conv[0] [0]']
conv4_block6_2_relu (Activatio (None, 12, 12, 256) 0 n)	['conv4_block6_2_bn[0] [0]']
conv4_block6_3_conv (Conv2D) (None, 12, 12, 1024 263168 )	['conv4_block6_2_relu[0] [0]']
conv4_block6_3_bn (BatchNormal (None, 12, 12, 1024 4096 ization)	['conv4_block6_3_conv[0] [0]']
conv4_block6_add (Add) (None, 12, 12, 1024 0 )	['conv4_block5_out[0] [0]', 'conv4_block6_3_bn[0] [0]']
conv4_block6_out (Activation) (None, 12, 12, 1024 0 )	['conv4_block6_add[0] [0]']
conv5_block1_1_conv (Conv2D) (None, 6, 6, 512) 524800	['conv4_block6_out[0] [0]']
conv5_block1_1_bn (BatchNormal (None, 6, 6, 512) 2048 ization)	['conv5_block1_1_conv[0] [0]']
conv5_block1_1_relu (Activatio (None, 6, 6, 512) 0 n)	['conv5_block1_1_bn[0] [0]']
conv5_block1_2_conv (Conv2D) (None, 6, 6, 512) 2359808	['conv5_block1_1_relu[0] [0]']
conv5_block1_2_bn (BatchNormal (None, 6, 6, 512) 2048 ization)	['conv5_block1_2_conv[0] [0]']

conv5_block1_2_relu (Activation)	(None, 6, 6, 512)	0	['conv5_block1_2_bn[0][0]']
conv5_block1_0_conv (Conv2D)	(None, 6, 6, 2048)	2099200	['conv4_block6_out[0][0]']
conv5_block1_3_conv (Conv2D)	(None, 6, 6, 2048)	1050624	['conv5_block1_2_relu[0][0]']
conv5_block1_0_bn (BatchNormaliza-	(None, 6, 6, 2048)	8192	['conv5_block1_0_conv[0][0]']
tion)			
conv5_block1_3_bn (BatchNormaliza-	(None, 6, 6, 2048)	8192	['conv5_block1_3_conv[0][0]']
tion)			
conv5_block1_add (Add)	(None, 6, 6, 2048)	0	['conv5_block1_0_bn[0][0]', 'conv5_block1_3_bn[0][0]']
conv5_block1_out (Activation)	(None, 6, 6, 2048)	0	['conv5_block1_add[0][0]']
conv5_block2_1_conv (Conv2D)	(None, 6, 6, 512)	1049088	['conv5_block1_out[0][0]']
conv5_block2_1_bn (BatchNormaliza-	(None, 6, 6, 512)	2048	['conv5_block2_1_conv[0][0]']
tion)			
conv5_block2_1_relu (Activatio-	(None, 6, 6, 512)	0	['conv5_block2_1_bn[0][0]']
n)			
conv5_block2_2_conv (Conv2D)	(None, 6, 6, 512)	2359808	['conv5_block2_1_relu[0][0]']
conv5_block2_2_bn (BatchNormaliza-	(None, 6, 6, 512)	2048	['conv5_block2_2_conv[0][0]']
tion)			
conv5_block2_2_relu (Activatio-	(None, 6, 6, 512)	0	['conv5_block2_2_bn[0][0]']
n)			
conv5_block2_3_conv (Conv2D)	(None, 6, 6, 2048)	1050624	['conv5_block2_2_relu[0][0]']
conv5_block2_3_bn (BatchNormaliza-	(None, 6, 6, 2048)	8192	['conv5_block2_3_conv[0][0]']
tion)			
conv5_block2_add (Add)	(None, 6, 6, 2048)	0	['conv5_block1_out[0][0]', 'conv5_block2_3_bn[0][0]']
conv5_block2_out (Activation)	(None, 6, 6, 2048)	0	['conv5_block2_add[0][0]']
conv5_block3_1_conv (Conv2D)	(None, 6, 6, 512)	1049088	['conv5_block2_out[0][0]']
conv5_block3_1_bn (BatchNormaliza-	(None, 6, 6, 512)	2048	['conv5_block3_1_conv[0][0]']
tion)			
conv5_block3_1_relu (Activatio-	(None, 6, 6, 512)	0	['conv5_block3_1_bn[0][0]']
n)			
conv5_block3_2_conv (Conv2D)	(None, 6, 6, 512)	2359808	['conv5_block3_1_relu[0][0]']
conv5_block3_2_bn (BatchNormaliza-	(None, 6, 6, 512)	2048	['conv5_block3_2_conv[0][0]']
tion)			
conv5_block3_2_relu (Activatio-	(None, 6, 6, 512)	0	['conv5_block3_2_bn[0][0]']
n)			
conv5_block3_3_conv (Conv2D)	(None, 6, 6, 2048)	1050624	['conv5_block3_2_relu[0][0]']
conv5_block3_3_bn (BatchNormaliza-	(None, 6, 6, 2048)	8192	['conv5_block3_3_conv[0][0]']
tion)			
conv5_block3_add (Add)	(None, 6, 6, 2048)	0	['conv5_block2_out[0][0]', 'conv5_block3_3_bn[0][0]']
conv5_block3_out (Activation)	(None, 6, 6, 2048)	0	['conv5_block3_add[0][0]']
global_avg_pool (GlobalAverage	(None, 2048)	0	['conv5_block3_out[0][0]']
Pooling2D)			
fc1 (Dense)	(None, 256)	524544	['global_avg_pool[0][0]']
dropout1 (Dropout)	(None, 256)	0	['fc1[0][0]']
fc2 (Dense)	(None, 128)	32896	['dropout1[0][0]']
dropout2 (Dropout)	(None, 128)	0	['fc2[0][0]']
output (Dense)	(None, 3)	387	['dropout2[0][0]']

=====
Total params: 24,145,539  
Trainable params: 557,827  
Non-trainable params: 23,587,712

#### Preprocess Data for ResNet

ResNet50 requires specific preprocessing:

- Input images should be in range [0, 255]
- Apply ImageNet preprocessing (mean subtraction and scaling)

Our data is currently in [0, 1], so we need to scale it back.

```
In [89]: from tensorflow.keras.applications.resnet50 import preprocess_input as resnet_preprocess

# Prepare data for ResNet
X_train_resnet = resnet_preprocess((np.copy(X_train) * 255.0).astype('float32'))
X_test_resnet = resnet_preprocess((np.copy(X_test) * 255.0).astype('float32'))

print(f"Training data shape: {X_train_resnet.shape}")
print(f"Test data shape: {X_test_resnet.shape}")
print(f"Training data range: [{X_train_resnet.min():.2f}, {X_train_resnet.max():.2f}]")

Training data shape: (2741, 192, 192, 3)
Test data shape: (1291, 192, 192, 3)
Training data range: [-124.68, 151.06]
```

#### Compile and Train ResNet Model

Training Configuration for ResNet:

- Lower learning rate (0.0001)
- Same callbacks as baseline for fair comparison

```
In [91]: # Compile the model
resnet_model.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

# Define callbacks
callbacks_resnet = [
    EarlyStopping(
        monitor='val_loss',
        patience=5,
        restore_best_weights=True,
        verbose=1
    ),
    ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=3,
        min_lr=1e-8,
        verbose=1
    )
]
```

```
In [92]: # Train the model
history_resnet = resnet_model.fit(
    X_train_resnet, y_train,
    validation_split=0.2,
    epochs=10,
    batch_size=32,
    callbacks=callbacks_resnet,
    verbose=1
)
```

```
Epoch 1/10
69/69 [=====] - 4s 42ms/step - loss: 0.9498 - accuracy: 0.6008 - val_loss: 0.3948 - val_accuracy: 0.8361 - lr: 1.0000e-04
Epoch 2/10
69/69 [=====] - 2s 30ms/step - loss: 0.4976 - accuracy: 0.7824 - val_loss: 0.3238 - val_accuracy: 0.8579 - lr: 1.0000e-04
Epoch 3/10
69/69 [=====] - 2s 29ms/step - loss: 0.4085 - accuracy: 0.8317 - val_loss: 0.2956 - val_accuracy: 0.8616 - lr: 1.0000e-04
Epoch 4/10
69/69 [=====] - 2s 30ms/step - loss: 0.3407 - accuracy: 0.8577 - val_loss: 0.2812 - val_accuracy: 0.8707 - lr: 1.0000e-04
Epoch 5/10
69/69 [=====] - 2s 28ms/step - loss: 0.3060 - accuracy: 0.8714 - val_loss: 0.2570 - val_accuracy: 0.8889 - lr: 1.0000e-04
Epoch 6/10
69/69 [=====] - 2s 29ms/step - loss: 0.2815 - accuracy: 0.8846 - val_loss: 0.2417 - val_accuracy: 0.8907 - lr: 1.0000e-04
Epoch 7/10
69/69 [=====] - 2s 29ms/step - loss: 0.2588 - accuracy: 0.9019 - val_loss: 0.2348 - val_accuracy: 0.8962 - lr: 1.0000e-04
Epoch 8/10
69/69 [=====] - 2s 28ms/step - loss: 0.2347 - accuracy: 0.9056 - val_loss: 0.2226 - val_accuracy: 0.9053 - lr: 1.0000e-04
Epoch 9/10
69/69 [=====] - 2s 27ms/step - loss: 0.2147 - accuracy: 0.9211 - val_loss: 0.2227 - val_accuracy: 0.9107 - lr: 1.0000e-04
Epoch 10/10
69/69 [=====] - 2s 27ms/step - loss: 0.1959 - accuracy: 0.9270 - val_loss: 0.2306 - val_accuracy: 0.9016 - lr: 1.0000e-04
```

#### Evaluate ResNet Performance

```
In [130]: # Evaluate on the test set
test_loss_resnet, test_acc_resnet = resnet_model.evaluate(X_test_resnet, y_test, verbose=0)

print(f"Test Loss: {test_loss_resnet:.4f}")
print(f"Test Accuracy: {test_acc_resnet:.4f} ({test_acc_resnet*100:.2f}%)")

# Get training and validation accuracy and loss
final_train_acc_resnet = history_resnet.history['accuracy'][-1]
final_train_loss_resnet = history_resnet.history['loss'][-1]
final_val_acc_resnet = history_resnet.history['val_accuracy'][-1]
final_val_loss_resnet = history_resnet.history['val_loss'][-1]
```

```

print(f"\nFinal Training Accuracy: {final_train_acc_resnet:.4f} ({final_train_acc_resnet*100:.2f}%)")
print(f"Final Validation Accuracy: {final_val_acc_resnet:.4f} ({final_val_acc_resnet*100:.2f}%)")

Test Loss: 0.1598
Test Accuracy: 0.9342 (93.42%)

Final Training Accuracy: 0.9270 (92.70%)
Final Validation Accuracy: 0.9016 (90.16%)

```

```
In [132]: # Save for comparison
perf_rows.append({
    'Model': 'ResNet',
    'Type': 'transfer',
    'Train_Accuracy': float(final_train_acc_resnet),
    'Val_Accuracy': float(final_val_acc_resnet),
    'Test_Accuracy': float(test_acc_resnet),
    'Train_Loss': float(final_train_loss_resnet),
    'Val_Loss': float(final_val_loss_resnet),
    'Test_Loss': float(test_loss_resnet)
})
```

#### Visualize ResNet Training History

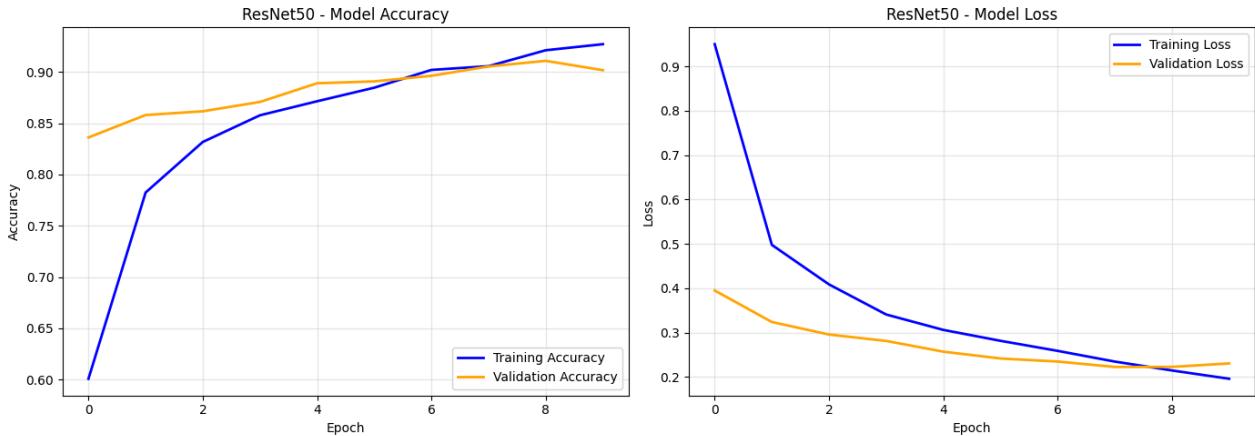
Plot training curves for ResNet50

```
In [102]: fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Training & validation accuracy
axes[0].plot(history_resnet.history['accuracy'], label='Training Accuracy', linewidth=2, color='blue')
axes[0].plot(history_resnet.history['val_accuracy'], label='Validation Accuracy', linewidth=2, color='orange')
axes[0].set_title('ResNet50 - Model Accuracy')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Accuracy')
axes[0].legend(loc='lower right')
axes[0].grid(True, alpha=0.3)

# Training & validation loss
axes[1].plot(history_resnet.history['loss'], label='Training Loss', linewidth=2, color='blue')
axes[1].plot(history_resnet.history['val_loss'], label='Validation Loss', linewidth=2, color='orange')
axes[1].set_title('ResNet50 - Model Loss')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Loss')
axes[1].legend(loc='upper right')
axes[1].grid(True, alpha=0.3)

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



## Additional 3 transfer model

### VGG16

This model applies transfer learning using the VGG16 architecture pre-trained on ImageNet as the convolutional feature extractor. All convolutional layers in the VGG16 base are frozen (trainable=False) to retain learned visual features while training a lightweight classification head on top. The input images are preprocessed with VGG's standard preprocess\_input (after rescaling to 0–255 and converting to float32) and resized to 192×192×3.

The model's top layers consist of a GlobalAveragePooling2D layer to reduce spatial dimensions, a Dense(128, relu) layer to learn higher-level representations, a Dropout(0.3) layer to prevent overfitting, and a Dense(3, softmax) output layer for 3-class prediction.

The network is compiled with Adam optimizer (default learning rate 1e-3), categorical cross-entropy loss, and accuracy as the evaluation metric. During training, two callbacks are employed:

EarlyStopping(patience=5, restore\_best\_weights=True) — stops training if validation loss stops improving for 5 epochs and restores the best weights.

ReduceLROnPlateau(patience=3, factor=0.5, verbose=1) — halves the learning rate if validation loss remains stagnant for 3 epochs, helping the optimizer make finer updates near convergence.

Training is executed for up to 25 epochs with a batch size of 32 and an 80/20 validation split, allowing the model to learn efficiently while monitoring overfitting.

In [173]

```
## VGG16
from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input as vgg_preprocess
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, Dropout
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

# VGG16 data prepossessing(make a copy prevent trouble)
Xtr_vgg = vgg_preprocess((np.copy(X_train) * 255.0).astype('float32'))
Xte_vgg = vgg_preprocess((np.copy(X_test) * 255.0).astype('float32'))

# model build
base_vgg = VGG16(weights='imagenet', include_top=False, input_shape=(192,192,3))
for l in base_vgg.layers:
    l.trainable = False #using the pre-training weight, fix it to nontrainable

x = GlobalAveragePooling2D()(base_vgg.output)
x = Dense(128, activation='relu')(x)
x = Dropout(0.3)(x) #add dropout to prevent overfitting
out = Dense(3, activation='softmax')(x)
model_vgg16 = Model(inputs=base_vgg.input, outputs=out)

model_vgg16.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
print(model_vgg16.summary())
```

Model: "model\_3"

Layer (type)	Output Shape	Param #
<hr/>		
input_5 (InputLayer)	[(None, 192, 192, 3)]	0
block1_conv1 (Conv2D)	(None, 192, 192, 64)	1792
block1_conv2 (Conv2D)	(None, 192, 192, 64)	36928
block1_pool (MaxPooling2D)	(None, 96, 96, 64)	0
block2_conv1 (Conv2D)	(None, 96, 96, 128)	73856
block2_conv2 (Conv2D)	(None, 96, 96, 128)	147584
block2_pool (MaxPooling2D)	(None, 48, 48, 128)	0
block3_conv1 (Conv2D)	(None, 48, 48, 256)	295168
block3_conv2 (Conv2D)	(None, 48, 48, 256)	590080
block3_conv3 (Conv2D)	(None, 48, 48, 256)	590080
block3_pool (MaxPooling2D)	(None, 24, 24, 256)	0
block4_conv1 (Conv2D)	(None, 24, 24, 512)	1180160
block4_conv2 (Conv2D)	(None, 24, 24, 512)	2359808
block4_conv3 (Conv2D)	(None, 24, 24, 512)	2359808
block4_pool (MaxPooling2D)	(None, 12, 12, 512)	0
block5_conv1 (Conv2D)	(None, 12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None, 12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None, 12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None, 6, 6, 512)	0
global_average_pooling2d_3 (GlobalAveragePooling2D)	(None, 512)	0
dense_4 (Dense)	(None, 128)	65664
dropout_3 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 3)	387
<hr/>		

Total params: 14,780,739

Trainable params: 66,051

Non-trainable params: 14,714,688

None

In [174]

```
# training and callbacks
cb = [
    EarlyStopping(patience=5, restore_best_weights=True),
    ReduceLROnPlateau(patience=3, factor=0.5, verbose=1)
] #define the callbacks: use earlystopping to reduce overfitting and learning rate adjustment to prevent divergence

history_vgg16 = model_vgg16.fit(
    Xtr_vgg, y_train,
    validation_split=0.2,
    epochs=25, batch_size=32,
    callbacks=cb, verbose=1
) #fit the model and print the process

# evaluate
```

```

best_epoch = np.argmax(history_vgg16.history['val_accuracy'])
#(the best epoch not necessarily the last one (because use the early stopping)
best_train_acc = history_vgg16.history['accuracy'][best_epoch]
best_val_acc = history_vgg16.history['val_accuracy'][best_epoch]
best_train_loss = history_vgg16.history['loss'][best_epoch]
best_val_loss = history_vgg16.history['val_loss'][best_epoch]

test_loss_vgg16, test_acc_vgg16 = model_vgg16.evaluate(Xte_vgg, y_test, verbose=0)

print(f"== VGG16 Early-Stopped Performance ==")
print(f"Best Epoch: {best_epoch + 1}")
print(f"Training Accuracy: {best_train_acc:.4f} | Loss: {best_train_loss:.4f}")
print(f"Validation Accuracy: {best_val_acc:.4f} | Loss: {best_val_loss:.4f}")
print(f"Test Accuracy: {test_acc_vgg16:.4f} | Loss: {test_loss_vgg16:.4f}")

perf_rows.append({
    'Model': 'VGG16',
    'Type': 'transfer',
    'Train_Accuracy': float(best_train_acc),
    'Val_Accuracy': float(best_val_acc),
    'Test_Accuracy': float(test_acc_vgg16),
    'Train_Loss': float(best_train_loss),
    'Val_Loss': float(best_val_loss),
    'Test_Loss': float(test_loss_vgg16)
})

```

Epoch 1/25  
69/69 [=====] - 4s 44ms/step - loss: 0.7077 - accuracy: 0.7979 - val\_loss: 0.2746 - val\_accuracy: 0.8852 - lr: 0.0010  
Epoch 2/25  
69/69 [=====] - 3s 39ms/step - loss: 0.2311 - accuracy: 0.9088 - val\_loss: 0.2433 - val\_accuracy: 0.9016 - lr: 0.0010  
Epoch 3/25  
69/69 [=====] - 3s 39ms/step - loss: 0.1890 - accuracy: 0.9170 - val\_loss: 0.1796 - val\_accuracy: 0.9381 - lr: 0.0010  
Epoch 4/25  
69/69 [=====] - 3s 41ms/step - loss: 0.1431 - accuracy: 0.9425 - val\_loss: 0.2020 - val\_accuracy: 0.9180 - lr: 0.0010  
Epoch 5/25  
69/69 [=====] - 3s 39ms/step - loss: 0.1094 - accuracy: 0.9580 - val\_loss: 0.1480 - val\_accuracy: 0.9381 - lr: 0.0010  
Epoch 6/25  
69/69 [=====] - 3s 39ms/step - loss: 0.0949 - accuracy: 0.9644 - val\_loss: 0.1581 - val\_accuracy: 0.9326 - lr: 0.0010  
Epoch 7/25  
69/69 [=====] - 3s 38ms/step - loss: 0.0836 - accuracy: 0.9667 - val\_loss: 0.1458 - val\_accuracy: 0.9490 - lr: 0.0010  
Epoch 8/25  
69/69 [=====] - 3s 38ms/step - loss: 0.0643 - accuracy: 0.9776 - val\_loss: 0.1386 - val\_accuracy: 0.9472 - lr: 0.0010  
Epoch 9/25  
69/69 [=====] - 3s 38ms/step - loss: 0.0526 - accuracy: 0.9813 - val\_loss: 0.1593 - val\_accuracy: 0.9344 - lr: 0.0010  
Epoch 10/25  
69/69 [=====] - 3s 39ms/step - loss: 0.0478 - accuracy: 0.9859 - val\_loss: 0.1741 - val\_accuracy: 0.9308 - lr: 0.0010  
Epoch 11/25  
69/69 [=====] - ETA: 0s - loss: 0.0571 - accuracy: 0.9767  
Epoch 11: ReduceLROnPlateau reducing learning rate to 0.000500000237487257.  
69/69 [=====] - 3s 41ms/step - loss: 0.0571 - accuracy: 0.9767 - val\_loss: 0.1530 - val\_accuracy: 0.9435 - lr: 0.0010  
Epoch 12/25  
69/69 [=====] - 3s 42ms/step - loss: 0.0330 - accuracy: 0.9891 - val\_loss: 0.1488 - val\_accuracy: 0.9435 - lr: 5.0000e-04  
Epoch 13/25  
69/69 [=====] - 3s 43ms/step - loss: 0.0300 - accuracy: 0.9891 - val\_loss: 0.1495 - val\_accuracy: 0.9454 - lr: 5.0000e-04  
== VGG16 Early-Stopped Performance ==
Best Epoch: 7
Training Accuracy: 0.9667 | Loss: 0.0836
Validation Accuracy: 0.9490 | Loss: 0.1458
Test Accuracy: 0.9589 | Loss: 0.1178

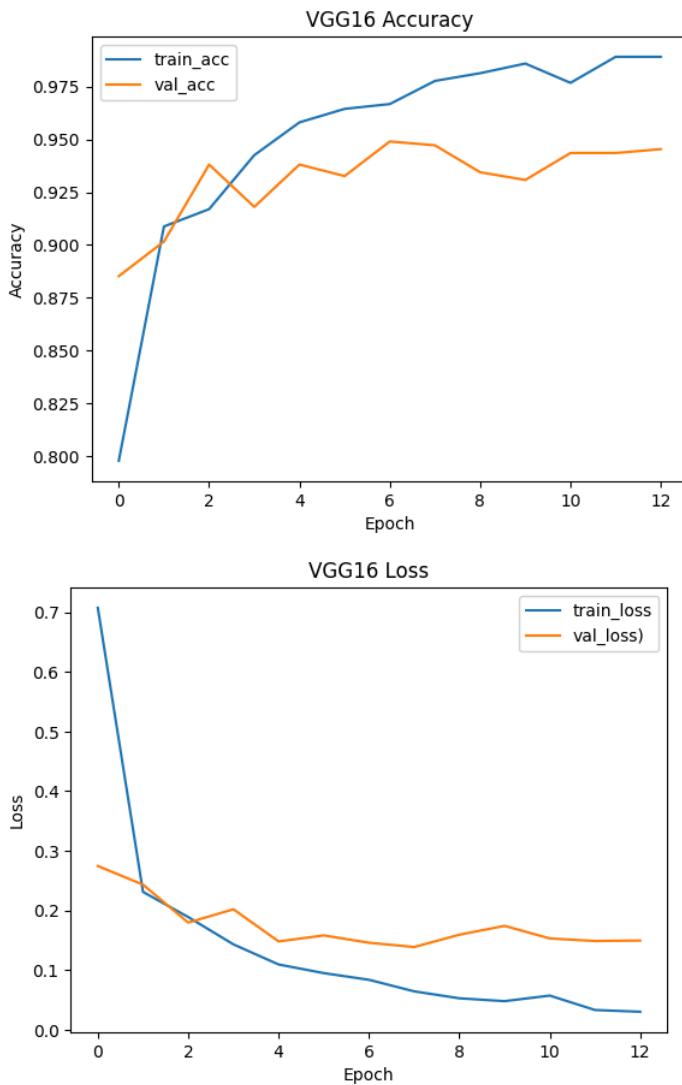
In [175]: #plot the accuracy and the loss curve

```

plt.figure()
plt.plot(history_vgg16.history['accuracy'], label='train_acc')
plt.plot(history_vgg16.history['val_accuracy'], label='val_acc')
plt.title('VGG16 Accuracy'); plt.xlabel('Epoch'); plt.ylabel('Accuracy'); plt.legend(); plt.show()

plt.figure()
plt.plot(history_vgg16.history['loss'], label='train_loss')
plt.plot(history_vgg16.history['val_loss'], label='val_loss')
plt.title('VGG16 Loss'); plt.xlabel('Epoch'); plt.ylabel('Loss'); plt.legend(); plt.show()

```



## Inception V3

This model employs InceptionV3, a high-performing convolutional neural network architecture pre-trained on ImageNet, as the backbone for transfer learning. InceptionV3 is chosen for its computational efficiency and multi-scale feature extraction capability — it processes information through parallel convolutional paths with different kernel sizes ( $1\times 1$ ,  $3\times 3$ ,  $5\times 5$ ), allowing the model to capture both fine-grained and global visual patterns. This makes it more flexible than simpler architectures like VGG16 and often more parameter-efficient than DenseNet121.

Input images are dynamically resized to  $299\times 299\times 3$  (the native InceptionV3 input size) and preprocessed with the architecture's own `preprocess_input` function to match the original ImageNet training distribution. The convolutional base is frozen (`trainable=False`) to preserve learned low-level features, while a new classification head is trained on top. The top layers include a `GlobalAveragePooling2D` layer for spatial aggregation, a `Dropout(0.3)` layer to reduce overfitting, and a `Dense(num_classes, softmax)` output layer for multi-class prediction.

The model is compiled with `Adam(learning_rate=1e-3)` optimizer, `categorical_crossentropy` loss, and accuracy as the evaluation metric. Training typically includes two adaptive callbacks:

1. `EarlyStopping(patience=5, restore_best_weights=True)` – stops training early if validation loss no longer improves.
2. `ReduceLROnPlateau(patience=3, factor=0.5, verbose=1)` – halves the learning rate when performance plateaus, refining convergence.

```
In [179]: ##InceptionV3
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras import layers, models, optimizers
from tensorflow.keras.applications.inception_v3 import InceptionV3, preprocess_input
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
#data preprocessing and resize
num_classes = y_train.shape[1]

inp = layers.Input(shape=(None, None, 3))
x = layers.Resizing(299, 299)(inp) #default size for InceptionV3
x = layers.Lambda(preprocess_input)(x)

# Backbone model create
base = InceptionV3(weights='imagenet', include_top=False, input_tensor=x)
base.trainable = False #use the imagenet pre trained weight, so need to fix the weight non trainable

h = layers.GlobalAveragePooling2D()(base.output)
h = layers.Dropout(0.3)(h) #add dropout to prevent overfitting
out = layers.Dense(num_classes, activation='softmax')(h)
model_iv3 = models.Model(inp, out)
```

```
# compile model
model_iv3.compile(optimizer=optimizers.Adam(1e-3),
                   loss='categorical_crossentropy',
                   metrics=['accuracy'])

print(model_iv3.summary())
```

Model: "model\_4"

Layer (type)	Output Shape	Param #	Connected to
input_6 (InputLayer)	[(None, None, None, 3)]	0	[]
resizing_2 (Resizing)	(None, 299, 299, 3)	0	['input_6[0][0]']
lambda_2 (Lambda)	(None, 299, 299, 3)	0	['resizing_2[0][0]']
conv2d_94 (Conv2D)	(None, 149, 149, 32)	864	['lambda_2[0][0]']
batch_normalization_94 (BatchN ormalization)	(None, 149, 149, 32)	96	['conv2d_94[0][0]']
activation_94 (Activation)	(None, 149, 149, 32)	0	['batch_normalization_94[0][0]']
conv2d_95 (Conv2D)	(None, 147, 147, 32)	9216	['activation_94[0][0]']
batch_normalization_95 (BatchN ormalization)	(None, 147, 147, 32)	96	['conv2d_95[0][0]']
activation_95 (Activation)	(None, 147, 147, 32)	0	['batch_normalization_95[0][0]']
conv2d_96 (Conv2D)	(None, 147, 147, 64)	18432	['activation_95[0][0]']
batch_normalization_96 (BatchN ormalization)	(None, 147, 147, 64)	192	['conv2d_96[0][0]']
activation_96 (Activation)	(None, 147, 147, 64)	0	['batch_normalization_96[0][0]']
max_pooling2d_4 (MaxPooling2D)	(None, 73, 73, 64)	0	['activation_96[0][0]']
conv2d_97 (Conv2D)	(None, 73, 73, 80)	5120	['max_pooling2d_4[0][0]']
batch_normalization_97 (BatchN ormalization)	(None, 73, 73, 80)	240	['conv2d_97[0][0]']
activation_97 (Activation)	(None, 73, 73, 80)	0	['batch_normalization_97[0][0]']
conv2d_98 (Conv2D)	(None, 71, 71, 192)	138240	['activation_97[0][0]']
batch_normalization_98 (BatchN ormalization)	(None, 71, 71, 192)	576	['conv2d_98[0][0]']
activation_98 (Activation)	(None, 71, 71, 192)	0	['batch_normalization_98[0][0]']
max_pooling2d_5 (MaxPooling2D)	(None, 35, 35, 192)	0	['activation_98[0][0]']
conv2d_102 (Conv2D)	(None, 35, 35, 64)	12288	['max_pooling2d_5[0][0]']
batch_normalization_102 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_102[0][0]']
activation_102 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_102[0][0]']
conv2d_100 (Conv2D)	(None, 35, 35, 48)	9216	['max_pooling2d_5[0][0]']
conv2d_103 (Conv2D)	(None, 35, 35, 96)	55296	['activation_102[0][0]']
batch_normalization_100 (Batch Normalization)	(None, 35, 35, 48)	144	['conv2d_100[0][0]']
batch_normalization_103 (Batch Normalization)	(None, 35, 35, 96)	288	['conv2d_103[0][0]']
activation_100 (Activation)	(None, 35, 35, 48)	0	['batch_normalization_100[0][0]']
activation_103 (Activation)	(None, 35, 35, 96)	0	['batch_normalization_103[0][0]']
average_pooling2d_9 (AveragePooling2D)	(None, 35, 35, 192)	0	['max_pooling2d_5[0][0]']
conv2d_99 (Conv2D)	(None, 35, 35, 64)	12288	['max_pooling2d_5[0][0]']
conv2d_101 (Conv2D)	(None, 35, 35, 64)	76800	['activation_100[0][0]']
conv2d_104 (Conv2D)	(None, 35, 35, 96)	82944	['activation_103[0][0]']
conv2d_105 (Conv2D)	(None, 35, 35, 32)	6144	['average_pooling2d_9[0][0]']
batch_normalization_99 (BatchN ormalization)	(None, 35, 35, 64)	192	['conv2d_99[0][0]']
batch_normalization_101 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_101[0][0]']
batch_normalization_104 (Batch Normalization)	(None, 35, 35, 96)	288	['conv2d_104[0][0]']
batch_normalization_105 (Batch Normalization)	(None, 35, 35, 32)	96	['conv2d_105[0][0]']

activation_99 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_99[0][0]']
activation_101 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_101[0][0]']
activation_104 (Activation)	(None, 35, 35, 96)	0	['batch_normalization_104[0][0]']
activation_105 (Activation)	(None, 35, 35, 32)	0	['batch_normalization_105[0][0]']
mixed0 (Concatenate)	(None, 35, 35, 256)	0	['activation_99[0][0]', 'activation_101[0][0]', 'activation_104[0][0]', 'activation_105[0][0]']
conv2d_109 (Conv2D)	(None, 35, 35, 64)	16384	['mixed0[0][0]']
batch_normalization_109 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_109[0][0]']
activation_109 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_109[0][0]']
conv2d_107 (Conv2D)	(None, 35, 35, 48)	12288	['mixed0[0][0]']
conv2d_110 (Conv2D)	(None, 35, 35, 96)	55296	['activation_109[0][0]']
batch_normalization_107 (Batch Normalization)	(None, 35, 35, 48)	144	['conv2d_107[0][0]']
batch_normalization_110 (Batch Normalization)	(None, 35, 35, 96)	288	['conv2d_110[0][0]']
activation_107 (Activation)	(None, 35, 35, 48)	0	['batch_normalization_107[0][0]']
activation_110 (Activation)	(None, 35, 35, 96)	0	['batch_normalization_110[0][0]']
average_pooling2d_10 (AveragePooling2D)	(None, 35, 35, 256)	0	['mixed0[0][0]']
conv2d_106 (Conv2D)	(None, 35, 35, 64)	16384	['mixed0[0][0]']
conv2d_108 (Conv2D)	(None, 35, 35, 64)	76800	['activation_107[0][0]']
conv2d_111 (Conv2D)	(None, 35, 35, 96)	82944	['activation_110[0][0]']
conv2d_112 (Conv2D)	(None, 35, 35, 64)	16384	['average_pooling2d_10[0][0]']
batch_normalization_106 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_106[0][0]']
batch_normalization_108 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_108[0][0]']
batch_normalization_111 (Batch Normalization)	(None, 35, 35, 96)	288	['conv2d_111[0][0]']
batch_normalization_112 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_112[0][0]']
activation_106 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_106[0][0]']
activation_108 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_108[0][0]']
activation_111 (Activation)	(None, 35, 35, 96)	0	['batch_normalization_111[0][0]']
activation_112 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_112[0][0]']
mixed1 (Concatenate)	(None, 35, 35, 288)	0	['activation_106[0][0]', 'activation_108[0][0]', 'activation_111[0][0]', 'activation_112[0][0]']
conv2d_116 (Conv2D)	(None, 35, 35, 64)	18432	['mixed1[0][0]']
batch_normalization_116 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_116[0][0]']
activation_116 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_116[0][0]']
conv2d_114 (Conv2D)	(None, 35, 35, 48)	13824	['mixed1[0][0]']
conv2d_117 (Conv2D)	(None, 35, 35, 96)	55296	['activation_116[0][0]']
batch_normalization_114 (Batch Normalization)	(None, 35, 35, 48)	144	['conv2d_114[0][0]']
batch_normalization_117 (Batch Normalization)	(None, 35, 35, 96)	288	['conv2d_117[0][0]']
activation_114 (Activation)	(None, 35, 35, 48)	0	['batch_normalization_114[0][0]']
activation_117 (Activation)	(None, 35, 35, 96)	0	['batch_normalization_117[0][0]']
average_pooling2d_11 (AveragePooling2D)	(None, 35, 35, 288)	0	['mixed1[0][0]']
conv2d_113 (Conv2D)	(None, 35, 35, 64)	18432	['mixed1[0][0]']
conv2d_115 (Conv2D)	(None, 35, 35, 64)	76800	['activation_114[0][0]']
conv2d_118 (Conv2D)	(None, 35, 35, 96)	82944	['activation_117[0][0]']

conv2d_119 (Conv2D)	(None, 35, 35, 64)	18432	['average_pooling2d_11[0][0]']
batch_normalization_113 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_113[0][0]']
batch_normalization_115 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_115[0][0]']
batch_normalization_118 (Batch Normalization)	(None, 35, 35, 96)	288	['conv2d_118[0][0]']
batch_normalization_119 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_119[0][0]']
activation_113 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_113[0][0]']
activation_115 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_115[0][0]']
activation_118 (Activation)	(None, 35, 35, 96)	0	['batch_normalization_118[0][0]']
activation_119 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_119[0][0]']
mixed2 (Concatenate)	(None, 35, 35, 288)	0	['activation_113[0][0]', 'activation_115[0][0]', 'activation_118[0][0]', 'activation_119[0][0]']
conv2d_121 (Conv2D)	(None, 35, 35, 64)	18432	['mixed2[0][0]']
batch_normalization_121 (Batch Normalization)	(None, 35, 35, 64)	192	['conv2d_121[0][0]']
activation_121 (Activation)	(None, 35, 35, 64)	0	['batch_normalization_121[0][0]']
conv2d_122 (Conv2D)	(None, 35, 35, 96)	55296	['activation_121[0][0]']
batch_normalization_122 (Batch Normalization)	(None, 35, 35, 96)	288	['conv2d_122[0][0]']
activation_122 (Activation)	(None, 35, 35, 96)	0	['batch_normalization_122[0][0]']
conv2d_120 (Conv2D)	(None, 17, 17, 384)	995328	['mixed2[0][0]']
conv2d_123 (Conv2D)	(None, 17, 17, 96)	82944	['activation_122[0][0]']
batch_normalization_120 (Batch Normalization)	(None, 17, 17, 384)	1152	['conv2d_120[0][0]']
batch_normalization_123 (Batch Normalization)	(None, 17, 17, 96)	288	['conv2d_123[0][0]']
activation_120 (Activation)	(None, 17, 17, 384)	0	['batch_normalization_120[0][0]']
activation_123 (Activation)	(None, 17, 17, 96)	0	['batch_normalization_123[0][0]']
max_pooling2d_6 (MaxPooling2D)	(None, 17, 17, 288)	0	['mixed2[0][0]']
mixed3 (Concatenate)	(None, 17, 17, 768)	0	['activation_120[0][0]', 'activation_123[0][0]', 'max_pooling2d_6[0][0]']
conv2d_128 (Conv2D)	(None, 17, 17, 128)	98304	['mixed3[0][0]']
batch_normalization_128 (Batch Normalization)	(None, 17, 17, 128)	384	['conv2d_128[0][0]']
activation_128 (Activation)	(None, 17, 17, 128)	0	['batch_normalization_128[0][0]']
conv2d_129 (Conv2D)	(None, 17, 17, 128)	114688	['activation_128[0][0]']
batch_normalization_129 (Batch Normalization)	(None, 17, 17, 128)	384	['conv2d_129[0][0]']
activation_129 (Activation)	(None, 17, 17, 128)	0	['batch_normalization_129[0][0]']
conv2d_125 (Conv2D)	(None, 17, 17, 128)	98304	['mixed3[0][0]']
conv2d_130 (Conv2D)	(None, 17, 17, 128)	114688	['activation_129[0][0]']
batch_normalization_125 (Batch Normalization)	(None, 17, 17, 128)	384	['conv2d_125[0][0]']
batch_normalization_130 (Batch Normalization)	(None, 17, 17, 128)	384	['conv2d_130[0][0]']
activation_125 (Activation)	(None, 17, 17, 128)	0	['batch_normalization_125[0][0]']
activation_130 (Activation)	(None, 17, 17, 128)	0	['batch_normalization_130[0][0]']
conv2d_126 (Conv2D)	(None, 17, 17, 128)	114688	['activation_125[0][0]']
conv2d_131 (Conv2D)	(None, 17, 17, 128)	114688	['activation_130[0][0]']
batch_normalization_126 (Batch Normalization)	(None, 17, 17, 128)	384	['conv2d_126[0][0]']
batch_normalization_131 (Batch Normalization)	(None, 17, 17, 128)	384	['conv2d_131[0][0]']
activation_126 (Activation)	(None, 17, 17, 128)	0	['batch_normalization_126[0][0]']

activation_131 (Activation)	(None, 17, 17, 128) 0	['batch_normalization_131[0][0]']
average_pooling2d_12 (AveragePooling2D)	(None, 17, 17, 768) 0	['mixed3[0][0]']
conv2d_124 (Conv2D)	(None, 17, 17, 192) 147456	['mixed3[0][0]']
conv2d_127 (Conv2D)	(None, 17, 17, 192) 172032	['activation_126[0][0]']
conv2d_132 (Conv2D)	(None, 17, 17, 192) 172032	['activation_131[0][0]']
conv2d_133 (Conv2D)	(None, 17, 17, 192) 147456	['average_pooling2d_12[0][0]']
batch_normalization_124 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_124[0][0]']
batch_normalization_127 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_127[0][0]']
batch_normalization_132 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_132[0][0]']
batch_normalization_133 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_133[0][0]']
activation_124 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_124[0][0]']
activation_127 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_127[0][0]']
activation_132 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_132[0][0]']
activation_133 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_133[0][0]']
mixed4 (Concatenate)	(None, 17, 17, 768) 0	['activation_124[0][0]', 'activation_127[0][0]', 'activation_132[0][0]', 'activation_133[0][0]']
conv2d_138 (Conv2D)	(None, 17, 17, 160) 122880	['mixed4[0][0]']
batch_normalization_138 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_138[0][0]']
activation_138 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_138[0][0]']
conv2d_139 (Conv2D)	(None, 17, 17, 160) 179200	['activation_138[0][0]']
batch_normalization_139 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_139[0][0]']
activation_139 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_139[0][0]']
conv2d_135 (Conv2D)	(None, 17, 17, 160) 122880	['mixed4[0][0]']
conv2d_140 (Conv2D)	(None, 17, 17, 160) 179200	['activation_139[0][0]']
batch_normalization_135 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_135[0][0]']
batch_normalization_140 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_140[0][0]']
activation_135 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_135[0][0]']
activation_140 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_140[0][0]']
conv2d_136 (Conv2D)	(None, 17, 17, 160) 179200	['activation_135[0][0]']
conv2d_141 (Conv2D)	(None, 17, 17, 160) 179200	['activation_140[0][0]']
batch_normalization_136 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_136[0][0]']
batch_normalization_141 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_141[0][0]']
activation_136 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_136[0][0]']
activation_141 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_141[0][0]']
average_pooling2d_13 (AveragePooling2D)	(None, 17, 17, 768) 0	['mixed4[0][0]']
conv2d_134 (Conv2D)	(None, 17, 17, 192) 147456	['mixed4[0][0]']
conv2d_137 (Conv2D)	(None, 17, 17, 192) 215040	['activation_136[0][0]']
conv2d_142 (Conv2D)	(None, 17, 17, 192) 215040	['activation_141[0][0]']
conv2d_143 (Conv2D)	(None, 17, 17, 192) 147456	['average_pooling2d_13[0][0]']
batch_normalization_134 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_134[0][0]']
batch_normalization_137 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_137[0][0]']
batch_normalization_142 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_142[0][0]']

batch_normalization_143 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_143[0][0]']
activation_134 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_134[0][0]']
activation_137 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_137[0][0]']
activation_142 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_142[0][0]']
activation_143 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_143[0][0]']
mixed5 (Concatenate)	(None, 17, 17, 768) 0	['activation_134[0][0]', 'activation_137[0][0]', 'activation_142[0][0]', 'activation_143[0][0]']
conv2d_148 (Conv2D)	(None, 17, 17, 160) 122880	['mixed5[0][0]']
batch_normalization_148 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_148[0][0]']
activation_148 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_148[0][0]']
conv2d_149 (Conv2D)	(None, 17, 17, 160) 179200	['activation_148[0][0]']
batch_normalization_149 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_149[0][0]']
activation_149 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_149[0][0]']
conv2d_145 (Conv2D)	(None, 17, 17, 160) 122880	['mixed5[0][0]']
conv2d_150 (Conv2D)	(None, 17, 17, 160) 179200	['activation_149[0][0]']
batch_normalization_145 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_145[0][0]']
batch_normalization_150 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_150[0][0]']
activation_145 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_145[0][0]']
activation_150 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_150[0][0]']
conv2d_146 (Conv2D)	(None, 17, 17, 160) 179200	['activation_145[0][0]']
conv2d_151 (Conv2D)	(None, 17, 17, 160) 179200	['activation_150[0][0]']
batch_normalization_146 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_146[0][0]']
batch_normalization_151 (Batch Normalization)	(None, 17, 17, 160) 480	['conv2d_151[0][0]']
activation_146 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_146[0][0]']
activation_151 (Activation)	(None, 17, 17, 160) 0	['batch_normalization_151[0][0]']
average_pooling2d_14 (AveragePooling2D)	(None, 17, 17, 768) 0	['mixed5[0][0]']
conv2d_144 (Conv2D)	(None, 17, 17, 192) 147456	['mixed5[0][0]']
conv2d_147 (Conv2D)	(None, 17, 17, 192) 215040	['activation_146[0][0]']
conv2d_152 (Conv2D)	(None, 17, 17, 192) 215040	['activation_151[0][0]']
conv2d_153 (Conv2D)	(None, 17, 17, 192) 147456	['average_pooling2d_14[0][0]']
batch_normalization_144 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_144[0][0]']
batch_normalization_147 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_147[0][0]']
batch_normalization_152 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_152[0][0]']
batch_normalization_153 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_153[0][0]']
activation_144 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_144[0][0]']
activation_147 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_147[0][0]']
activation_152 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_152[0][0]']
activation_153 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_153[0][0]']
mixed6 (Concatenate)	(None, 17, 17, 768) 0	['activation_144[0][0]', 'activation_147[0][0]', 'activation_152[0][0]', 'activation_153[0][0]']
conv2d_158 (Conv2D)	(None, 17, 17, 192) 147456	['mixed6[0][0]']
batch_normalization_158 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_158[0][0]']

activation_158 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_158[0][0]']
conv2d_159 (Conv2D)	(None, 17, 17, 192) 258048	['activation_158[0][0]']
batch_normalization_159 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_159[0][0]']
activation_159 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_159[0][0]']
conv2d_155 (Conv2D)	(None, 17, 17, 192) 147456	['mixed6[0][0]']
conv2d_160 (Conv2D)	(None, 17, 17, 192) 258048	['activation_159[0][0]']
batch_normalization_155 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_155[0][0]']
batch_normalization_160 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_160[0][0]']
activation_155 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_155[0][0]']
activation_160 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_160[0][0]']
conv2d_156 (Conv2D)	(None, 17, 17, 192) 258048	['activation_155[0][0]']
conv2d_161 (Conv2D)	(None, 17, 17, 192) 258048	['activation_160[0][0]']
batch_normalization_156 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_156[0][0]']
batch_normalization_161 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_161[0][0]']
activation_156 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_156[0][0]']
activation_161 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_161[0][0]']
average_pooling2d_15 (AveragePooling2D)	(None, 17, 17, 768) 0	['mixed6[0][0]']
conv2d_154 (Conv2D)	(None, 17, 17, 192) 147456	['mixed6[0][0]']
conv2d_157 (Conv2D)	(None, 17, 17, 192) 258048	['activation_156[0][0]']
conv2d_162 (Conv2D)	(None, 17, 17, 192) 258048	['activation_161[0][0]']
conv2d_163 (Conv2D)	(None, 17, 17, 192) 147456	['average_pooling2d_15[0][0]']
batch_normalization_154 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_154[0][0]']
batch_normalization_157 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_157[0][0]']
batch_normalization_162 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_162[0][0]']
batch_normalization_163 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_163[0][0]']
activation_154 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_154[0][0]']
activation_157 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_157[0][0]']
activation_162 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_162[0][0]']
activation_163 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_163[0][0]']
mixed7 (Concatenate)	(None, 17, 17, 768) 0	['activation_154[0][0]', 'activation_157[0][0]', 'activation_162[0][0]', 'activation_163[0][0]']
conv2d_166 (Conv2D)	(None, 17, 17, 192) 147456	['mixed7[0][0]']
batch_normalization_166 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_166[0][0]']
activation_166 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_166[0][0]']
conv2d_167 (Conv2D)	(None, 17, 17, 192) 258048	['activation_166[0][0]']
batch_normalization_167 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_167[0][0]']
activation_167 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_167[0][0]']
conv2d_164 (Conv2D)	(None, 17, 17, 192) 147456	['mixed7[0][0]']
conv2d_168 (Conv2D)	(None, 17, 17, 192) 258048	['activation_167[0][0]']
batch_normalization_164 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_164[0][0]']
batch_normalization_168 (Batch Normalization)	(None, 17, 17, 192) 576	['conv2d_168[0][0]']
activation_164 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_164[0][0]']
activation_168 (Activation)	(None, 17, 17, 192) 0	['batch_normalization_168[0][0]']

conv2d_165 (Conv2D)	(None, 8, 8, 320)	552960	['activation_164[0][0]']
conv2d_169 (Conv2D)	(None, 8, 8, 192)	331776	['activation_168[0][0]']
batch_normalization_165 (Batch Normalization)	(None, 8, 8, 320)	960	['conv2d_165[0][0]']
batch_normalization_169 (Batch Normalization)	(None, 8, 8, 192)	576	['conv2d_169[0][0]']
activation_165 (Activation)	(None, 8, 8, 320)	0	['batch_normalization_165[0][0]']
activation_169 (Activation)	(None, 8, 8, 192)	0	['batch_normalization_169[0][0]']
max_pooling2d_7 (MaxPooling2D)	(None, 8, 8, 768)	0	['mixed7[0][0]']
mixed8 (Concatenate)	(None, 8, 8, 1280)	0	['activation_165[0][0]', 'activation_169[0][0]', 'max_pooling2d_7[0][0]']
conv2d_174 (Conv2D)	(None, 8, 8, 448)	573440	['mixed8[0][0]']
batch_normalization_174 (Batch Normalization)	(None, 8, 8, 448)	1344	['conv2d_174[0][0]']
activation_174 (Activation)	(None, 8, 8, 448)	0	['batch_normalization_174[0][0]']
conv2d_171 (Conv2D)	(None, 8, 8, 384)	491520	['mixed8[0][0]']
conv2d_175 (Conv2D)	(None, 8, 8, 384)	1548288	['activation_174[0][0]']
batch_normalization_171 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_171[0][0]']
batch_normalization_175 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_175[0][0]']
activation_171 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_171[0][0]']
activation_175 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_175[0][0]']
conv2d_172 (Conv2D)	(None, 8, 8, 384)	442368	['activation_171[0][0]']
conv2d_173 (Conv2D)	(None, 8, 8, 384)	442368	['activation_171[0][0]']
conv2d_176 (Conv2D)	(None, 8, 8, 384)	442368	['activation_175[0][0]']
conv2d_177 (Conv2D)	(None, 8, 8, 384)	442368	['activation_175[0][0]']
average_pooling2d_16 (AveragePooling2D)	(None, 8, 8, 1280)	0	['mixed8[0][0]']
conv2d_170 (Conv2D)	(None, 8, 8, 320)	409600	['mixed8[0][0]']
batch_normalization_172 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_172[0][0]']
batch_normalization_173 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_173[0][0]']
batch_normalization_176 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_176[0][0]']
batch_normalization_177 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_177[0][0]']
conv2d_178 (Conv2D)	(None, 8, 8, 192)	245760	['average_pooling2d_16[0][0]']
batch_normalization_170 (Batch Normalization)	(None, 8, 8, 320)	960	['conv2d_170[0][0]']
activation_172 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_172[0][0]']
activation_173 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_173[0][0]']
activation_176 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_176[0][0]']
activation_177 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_177[0][0]']
batch_normalization_178 (Batch Normalization)	(None, 8, 8, 192)	576	['conv2d_178[0][0]']
activation_170 (Activation)	(None, 8, 8, 320)	0	['batch_normalization_170[0][0]']
mixed9_0 (Concatenate)	(None, 8, 8, 768)	0	['activation_172[0][0]', 'activation_173[0][0]']
concatenate_2 (Concatenate)	(None, 8, 8, 768)	0	['activation_176[0][0]', 'activation_177[0][0]']
activation_178 (Activation)	(None, 8, 8, 192)	0	['batch_normalization_178[0][0]']
mixed9 (Concatenate)	(None, 8, 8, 2048)	0	['activation_170[0][0]', 'mixed9_0[0][0]', 'concatenate_2[0][0]', 'activation_178[0][0]']
conv2d_183 (Conv2D)	(None, 8, 8, 448)	917504	['mixed9[0][0]']

batch_normalization_183 (Batch Normalization)	(None, 8, 8, 448)	1344	['conv2d_183[0][0]']
activation_183 (Activation)	(None, 8, 8, 448)	0	['batch_normalization_183[0][0]']
conv2d_180 (Conv2D)	(None, 8, 8, 384)	786432	['mixed9[0][0]']
conv2d_184 (Conv2D)	(None, 8, 8, 384)	1548288	['activation_183[0][0]']
batch_normalization_180 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_180[0][0]']
batch_normalization_184 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_184[0][0]']
activation_180 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_180[0][0]']
activation_184 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_184[0][0]']
conv2d_181 (Conv2D)	(None, 8, 8, 384)	442368	['activation_180[0][0]']
conv2d_182 (Conv2D)	(None, 8, 8, 384)	442368	['activation_180[0][0]']
conv2d_185 (Conv2D)	(None, 8, 8, 384)	442368	['activation_184[0][0]']
conv2d_186 (Conv2D)	(None, 8, 8, 384)	442368	['activation_184[0][0]']
average_pooling2d_17 (AveragePooling2D)	(None, 8, 8, 2048)	0	['mixed9[0][0]']
conv2d_179 (Conv2D)	(None, 8, 8, 320)	655360	['mixed9[0][0]']
batch_normalization_181 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_181[0][0]']
batch_normalization_182 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_182[0][0]']
batch_normalization_185 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_185[0][0]']
batch_normalization_186 (Batch Normalization)	(None, 8, 8, 384)	1152	['conv2d_186[0][0]']
conv2d_187 (Conv2D)	(None, 8, 8, 192)	393216	['average_pooling2d_17[0][0]']
batch_normalization_179 (Batch Normalization)	(None, 8, 8, 320)	960	['conv2d_179[0][0]']
activation_181 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_181[0][0]']
activation_182 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_182[0][0]']
activation_185 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_185[0][0]']
activation_186 (Activation)	(None, 8, 8, 384)	0	['batch_normalization_186[0][0]']
batch_normalization_187 (Batch Normalization)	(None, 8, 8, 192)	576	['conv2d_187[0][0]']
activation_179 (Activation)	(None, 8, 8, 320)	0	['batch_normalization_179[0][0]']
mixed9_1 (Concatenate)	(None, 8, 8, 768)	0	['activation_181[0][0]', 'activation_182[0][0]']
concatenate_3 (Concatenate)	(None, 8, 8, 768)	0	['activation_185[0][0]', 'activation_186[0][0]']
activation_187 (Activation)	(None, 8, 8, 192)	0	['batch_normalization_187[0][0]']
mixed10 (Concatenate)	(None, 8, 8, 2048)	0	['activation_179[0][0]', 'mixed9_1[0][0]', 'concatenate_3[0][0]', 'activation_187[0][0]']
global_average_pooling2d_4 (GlobalAveragePooling2D)	(None, 2048)	0	['mixed10[0][0]']
dropout_4 (Dropout)	(None, 2048)	0	['global_average_pooling2d_4[0][0]']
dense_6 (Dense)	(None, 3)	6147	['dropout_4[0][0]']

=====
Total params: 21,808,931  
Trainable params: 6,147  
Non-trainable params: 21,802,784

None

```
In [181]: # callback and fit
cb = [
    EarlyStopping(patience=5, restore_best_weights=True),
    ReduceLROnPlateau(patience=3, factor=0.5, verbose=1)
]# same call back function used (early stopping and learning rate adjustment)
history_iv3 = model_iv3.fit(
    X_train, y_train,
    validation_split=0.2,
    epochs=25, batch_size=32,
    callbacks=cb, verbose=1
```

```
)  
  
# evaluate  
test_loss_iv3, test_acc_iv3 = model_iv3.evaluate(X_test, y_test, verbose=0)  
  
best_epoch = np.argmax(history_iv3.history['val_accuracy'])  
# find the Best epoch (Because using the early stopping )  
best_train_acc = history_iv3.history['accuracy'][best_epoch]  
best_val_acc = history_iv3.history['val_accuracy'][best_epoch]  
best_train_loss = history_iv3.history['loss'][best_epoch]  
best_val_loss = history_iv3.history['val_loss'][best_epoch]  
  
print("== InceptionV3 Early-Stopped Performance ==")  
print(f"Best Epoch: {best_epoch + 1}")  
print(f"Training Accuracy: {best_train_acc:.4f} | Loss: {best_train_loss:.4f}")  
print(f"Validation Accuracy: {best_val_acc:.4f} | Loss: {best_val_loss:.4f}")  
print(f"Test Accuracy: {test_acc_iv3:.4f} | Loss: {test_loss_iv3:.4f}")  
  
#store the result  
perf_rows.append({  
    'Model': 'InceptionV3',  
    'Type': 'transfer',  
    'Train_Accuracy': float(best_train_acc),  
    'Val_Accuracy': float(best_val_acc),  
    'Test_Accuracy': float(test_acc_iv3),  
    'Train_Loss': float(best_train_loss),  
    'Val_Loss': float(best_val_loss),  
    'Test_Loss': float(test_loss_iv3)  
})
```

```

Epoch 1/25
69/69 [=====] - 8s 72ms/step - loss: 1.1263 - accuracy: 0.3490 - val_loss: 1.0786 - val_accuracy: 0.3279 - lr: 0.0010
Epoch 2/25
69/69 [=====] - 4s 53ms/step - loss: 1.0591 - accuracy: 0.4407 - val_loss: 1.0316 - val_accuracy: 0.3862 - lr: 0.0010
Epoch 3/25
69/69 [=====] - 4s 52ms/step - loss: 1.0304 - accuracy: 0.4909 - val_loss: 0.9855 - val_accuracy: 0.7268 - lr: 0.0010
Epoch 4/25
69/69 [=====] - 4s 51ms/step - loss: 0.9934 - accuracy: 0.5502 - val_loss: 0.9651 - val_accuracy: 0.5647 - lr: 0.0010
Epoch 5/25
69/69 [=====] - 4s 52ms/step - loss: 0.9701 - accuracy: 0.5908 - val_loss: 0.9240 - val_accuracy: 0.7268 - lr: 0.0010
Epoch 6/25
69/69 [=====] - 4s 51ms/step - loss: 0.9354 - accuracy: 0.6323 - val_loss: 0.9098 - val_accuracy: 0.6721 - lr: 0.0010
Epoch 7/25
69/69 [=====] - 3s 51ms/step - loss: 0.9131 - accuracy: 0.6323 - val_loss: 0.8893 - val_accuracy: 0.6248 - lr: 0.0010
Epoch 8/25
69/69 [=====] - 4s 54ms/step - loss: 0.8928 - accuracy: 0.6661 - val_loss: 0.8497 - val_accuracy: 0.7705 - lr: 0.0010
Epoch 9/25
69/69 [=====] - 4s 52ms/step - loss: 0.8831 - accuracy: 0.6478 - val_loss: 0.8298 - val_accuracy: 0.7814 - lr: 0.0010
Epoch 10/25
69/69 [=====] - 4s 51ms/step - loss: 0.8481 - accuracy: 0.6984 - val_loss: 0.8165 - val_accuracy: 0.7559 - lr: 0.0010
Epoch 11/25
69/69 [=====] - 4s 61ms/step - loss: 0.8328 - accuracy: 0.6902 - val_loss: 0.8007 - val_accuracy: 0.7432 - lr: 0.0010
Epoch 12/25
69/69 [=====] - 4s 52ms/step - loss: 0.8248 - accuracy: 0.6898 - val_loss: 0.7785 - val_accuracy: 0.7741 - lr: 0.0010
Epoch 13/25
69/69 [=====] - 3s 51ms/step - loss: 0.8121 - accuracy: 0.6966 - val_loss: 0.7609 - val_accuracy: 0.7905 - lr: 0.0010
Epoch 14/25
69/69 [=====] - 3s 50ms/step - loss: 0.7956 - accuracy: 0.7108 - val_loss: 0.7493 - val_accuracy: 0.7905 - lr: 0.0010
Epoch 15/25
69/69 [=====] - 3s 51ms/step - loss: 0.7822 - accuracy: 0.7003 - val_loss: 0.7344 - val_accuracy: 0.7887 - lr: 0.0010
Epoch 16/25
69/69 [=====] - 4s 52ms/step - loss: 0.7662 - accuracy: 0.7281 - val_loss: 0.7222 - val_accuracy: 0.7923 - lr: 0.0010
Epoch 17/25
69/69 [=====] - 4s 53ms/step - loss: 0.7641 - accuracy: 0.7263 - val_loss: 0.7153 - val_accuracy: 0.7778 - lr: 0.0010
Epoch 18/25
69/69 [=====] - 4s 51ms/step - loss: 0.7551 - accuracy: 0.7258 - val_loss: 0.7130 - val_accuracy: 0.7741 - lr: 0.0010
Epoch 19/25
69/69 [=====] - 4s 51ms/step - loss: 0.7441 - accuracy: 0.7153 - val_loss: 0.6969 - val_accuracy: 0.7942 - lr: 0.0010
Epoch 20/25
69/69 [=====] - 4s 56ms/step - loss: 0.7382 - accuracy: 0.7153 - val_loss: 0.6821 - val_accuracy: 0.7869 - lr: 0.0010
Epoch 21/25
69/69 [=====] - 5s 68ms/step - loss: 0.7236 - accuracy: 0.7345 - val_loss: 0.6772 - val_accuracy: 0.7832 - lr: 0.0010
Epoch 22/25
69/69 [=====] - 4s 65ms/step - loss: 0.7063 - accuracy: 0.7349 - val_loss: 0.6664 - val_accuracy: 0.7851 - lr: 0.0010
Epoch 23/25
69/69 [=====] - 4s 62ms/step - loss: 0.7063 - accuracy: 0.7359 - val_loss: 0.6673 - val_accuracy: 0.7851 - lr: 0.0010
Epoch 24/25
69/69 [=====] - 4s 53ms/step - loss: 0.6987 - accuracy: 0.7400 - val_loss: 0.6568 - val_accuracy: 0.7996 - lr: 0.0010
Epoch 25/25
69/69 [=====] - 4s 52ms/step - loss: 0.6962 - accuracy: 0.7295 - val_loss: 0.6419 - val_accuracy: 0.7996 - lr: 0.0010
== InceptionV3 Early-Stopped Performance ==
Best Epoch: 24
Training Accuracy: 0.7400 | Loss: 0.6987
Validation Accuracy: 0.7996 | Loss: 0.6568
Test Accuracy: 0.7947 | Loss: 0.6488

```

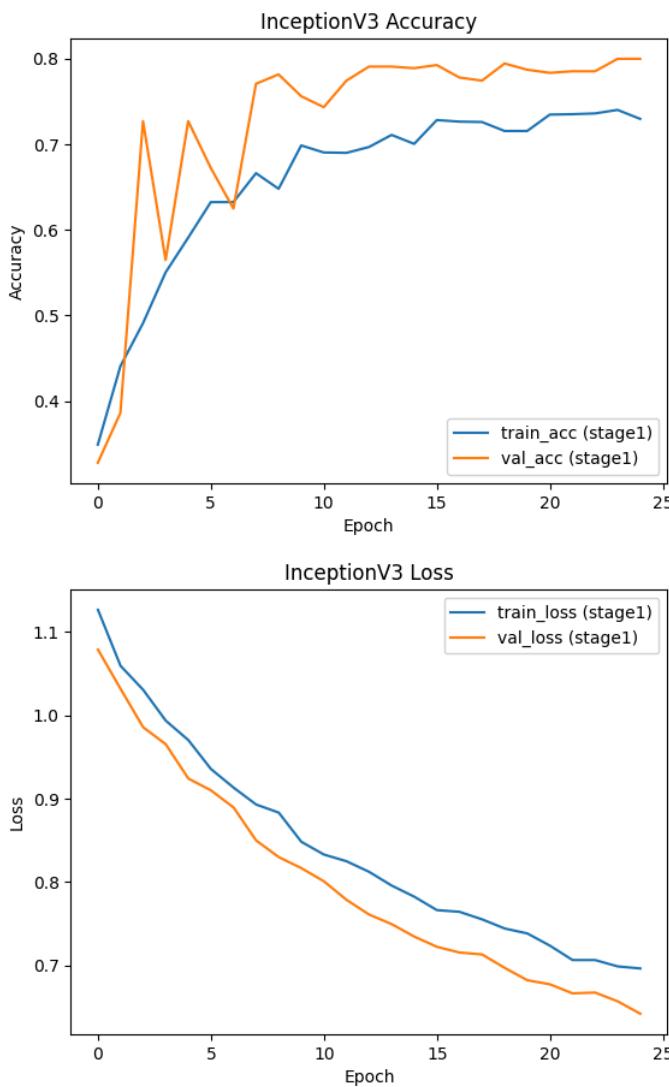
In [182...]

```

#visualization
epochs1 = range(len(history_iv3.history['accuracy']))
plt.figure()
plt.plot(epochs1, history_iv3.history['accuracy'], label='train_acc (stage1)')
plt.plot(epochs1, history_iv3.history['val_accuracy'], label='val_acc (stage1)')
plt.title('InceptionV3 Accuracy')
plt.xlabel('Epoch'); plt.ylabel('Accuracy'); plt.legend(); plt.show()

plt.figure()
plt.plot(epochs1, history_iv3.history['loss'], label='train_loss (stage1)')
plt.plot(epochs1, history_iv3.history['val_loss'], label='val_loss (stage1)')
plt.title('InceptionV3 Loss')
plt.xlabel('Epoch'); plt.ylabel('Loss'); plt.legend(); plt.show()

```



## DenseNet121

### Model Summary

This model implements a transfer-learning pipeline based on DenseNet121 pre-trained on ImageNet. The base network serves as a fixed feature extractor while a lightweight custom classification head is trained on top. Input images are resized to 224x224 and normalized through DenseNet's standard preprocess\_input function.

After the convolutional backbone, a GlobalAveragePooling2D layer condenses spatial features, followed by a Dropout(0.3) layer for regularization and a Dense(num\_classes, softmax) output layer for multi-class probability prediction. The model is compiled with Adam (learning rate = 1e-3), categorical cross-entropy loss, and accuracy as the evaluation metric.

### Training typically incorporates two key callbacks:

1. ReduceLROnPlateau – automatically halves the learning rate when validation loss stops improving for several epochs (e.g., patience=3, factor=0.5), enabling finer optimization near minima.
2. EarlyStopping – terminates training when no validation improvement occurs for a specified patience period (e.g., 5 epochs) and restores the best weights to prevent overfitting.

```
In [147]: ##DenseNet121
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras import layers, models, optimizers
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from tensorflow.keras.applications.densenet import DenseNet121, preprocess_input

num_classes = y_train.shape[1] if y_train.ndim == 2 else int(y_train.max()) + 1

inp = layers.Input(shape=(None, None, 3))
x = layers.Resizing(224, 224)(inp) # DenseNet121 default input size
x = layers.Lambda(preprocess_input)(x)

# Backbone model create
base = DenseNet121(weights='imagenet', include_top=False, input_tensor=x)
base.trainable = False #use the pre trained weight from imagenet

h = layers.GlobalAveragePooling2D()(base.output)
h = layers.Dropout(0.3)(h)
```

```
out = layers.Dense(num_classes, activation='softmax')(h)
model_dn = models.Model(inp, out)

# compile model
model_dn.compile(optimizer=optimizers.Adam(1e-3),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

print(model_dn.summary())
```

Downloading data from [https://storage.googleapis.com/tensorflow/keras-applications/densenet/densenet121\\_weights\\_tf\\_dim\\_ordering\\_tf\\_keras\\_notop.h5](https://storage.googleapis.com/tensorflow/keras-applications/densenet/densenet121_weights_tf_dim_ordering_tf_keras_notop.h5)  
29084464/29084464 [=====] - 0s 0us/step  
Model: "model\_2"

Layer (type)	Output Shape	Param #	Connected to
<hr/>			
input_4 (InputLayer)	(None, None, None, 3)	0	[]
resizing_1 (Resizing)	(None, 224, 224, 3)	0	['input_4[0][0]']
lambda_1 (Lambda)	(None, 224, 224, 3)	0	['resizing_1[0][0]']
zero_padding2d (ZeroPadding2D)	(None, 230, 230, 3)	0	['lambda_1[0][0]']
conv1/conv (Conv2D)	(None, 112, 112, 64)	9408	['zero_padding2d[0][0]']
conv1/bn (BatchNormalization)	(None, 112, 112, 64)	256	['conv1/conv[0][0]']
conv1/relu (Activation)	(None, 112, 112, 64)	0	['conv1/bn[0][0]']
zero_padding2d_1 (ZeroPadding2D)	(None, 114, 114, 64)	0	['conv1/relu[0][0]']
pool1 (MaxPooling2D)	(None, 56, 56, 64)	0	['zero_padding2d_1[0][0]']
conv2_block1_0_bn (BatchNormalization)	(None, 56, 56, 64)	256	['pool1[0][0]']
conv2_block1_0_relu (Activation)	(None, 56, 56, 64)	0	['conv2_block1_0_bn[0][0]']
conv2_block1_1_conv (Conv2D)	(None, 56, 56, 128)	8192	['conv2_block1_0_relu[0][0]']
conv2_block1_1_bn (BatchNormalization)	(None, 56, 56, 128)	512	['conv2_block1_1_conv[0][0]']
conv2_block1_1_relu (Activation)	(None, 56, 56, 128)	0	['conv2_block1_1_bn[0][0]']
conv2_block1_2_conv (Conv2D)	(None, 56, 56, 32)	36864	['conv2_block1_1_relu[0][0]']
conv2_block1_concat (Concatenate)	(None, 56, 56, 96)	0	['pool1[0][0]', 'conv2_block1_2_conv[0][0]']
conv2_block2_0_bn (BatchNormalization)	(None, 56, 56, 96)	384	['conv2_block1_concat[0][0]']
conv2_block2_0_relu (Activation)	(None, 56, 56, 96)	0	['conv2_block2_0_bn[0][0]']
conv2_block2_1_conv (Conv2D)	(None, 56, 56, 128)	12288	['conv2_block2_0_relu[0][0]']
conv2_block2_1_bn (BatchNormalization)	(None, 56, 56, 128)	512	['conv2_block2_1_conv[0][0]']
conv2_block2_1_relu (Activation)	(None, 56, 56, 128)	0	['conv2_block2_1_bn[0][0]']
conv2_block2_2_conv (Conv2D)	(None, 56, 56, 32)	36864	['conv2_block2_1_relu[0][0]']
conv2_block2_concat (Concatenate)	(None, 56, 56, 128)	0	['conv2_block1_concat[0][0]', 'conv2_block2_2_conv[0][0]']
conv2_block3_0_bn (BatchNormalization)	(None, 56, 56, 128)	512	['conv2_block2_concat[0][0]']
conv2_block3_0_relu (Activation)	(None, 56, 56, 128)	0	['conv2_block3_0_bn[0][0]']
conv2_block3_1_conv (Conv2D)	(None, 56, 56, 128)	16384	['conv2_block3_0_relu[0][0]']
conv2_block3_1_bn (BatchNormalization)	(None, 56, 56, 128)	512	['conv2_block3_1_conv[0][0]']
conv2_block3_1_relu (Activation)	(None, 56, 56, 128)	0	['conv2_block3_1_bn[0][0]']
conv2_block3_2_conv (Conv2D)	(None, 56, 56, 32)	36864	['conv2_block3_1_relu[0][0]']
conv2_block3_concat (Concatenate)	(None, 56, 56, 160)	0	['conv2_block2_concat[0][0]', 'conv2_block3_2_conv[0][0]']
conv2_block4_0_bn (BatchNormalization)	(None, 56, 56, 160)	640	['conv2_block3_concat[0][0]']
conv2_block4_0_relu (Activation)	(None, 56, 56, 160)	0	['conv2_block4_0_bn[0][0]']
conv2_block4_1_conv (Conv2D)	(None, 56, 56, 128)	20480	['conv2_block4_0_relu[0][0]']
conv2_block4_1_bn (BatchNormalization)	(None, 56, 56, 128)	512	['conv2_block4_1_conv[0][0]']
conv2_block4_1_relu (Activation)	(None, 56, 56, 128)	0	['conv2_block4_1_bn[0][0]']

conv2_block4_2_conv (Conv2D) (None, 56, 56, 32) 36864	['conv2_block4_1_relu[0][0]']
conv2_block4_concat (Concatenation) (None, 56, 56, 192) 0	['conv2_block3_concat[0][0]', 'conv2_block4_2_conv[0][0]']
conv2_block5_0_bn (BatchNormalizat (None, 56, 56, 192) 768	['conv2_block4_concat[0][0]']
conv2_block5_0_relu (Activation) (None, 56, 56, 192) 0	['conv2_block5_0_bn[0][0]']
conv2_block5_1_conv (Conv2D) (None, 56, 56, 128) 24576	['conv2_block5_0_relu[0][0]']
conv2_block5_1_bn (BatchNormalizat (None, 56, 56, 128) 512	['conv2_block5_1_conv[0][0]']
conv2_block5_1_relu (Activatio (None, 56, 56, 128) 0	['conv2_block5_1_bn[0][0]']
conv2_block5_2_conv (Conv2D) (None, 56, 56, 32) 36864	['conv2_block5_1_relu[0][0]']
conv2_block5_concat (Concatena (None, 56, 56, 224) 0	['conv2_block4_concat[0][0]', 'conv2_block5_2_conv[0][0]']
conv2_block6_0_bn (BatchNormalizat (None, 56, 56, 224) 896	['conv2_block5_concat[0][0]']
conv2_block6_0_relu (Activatio (None, 56, 56, 224) 0	['conv2_block6_0_bn[0][0]']
conv2_block6_1_conv (Conv2D) (None, 56, 56, 128) 28672	['conv2_block6_0_relu[0][0]']
conv2_block6_1_bn (BatchNormalizat (None, 56, 56, 128) 512	['conv2_block6_1_conv[0][0]']
conv2_block6_1_relu (Activatio (None, 56, 56, 128) 0	['conv2_block6_1_bn[0][0]']
conv2_block6_2_conv (Conv2D) (None, 56, 56, 32) 36864	['conv2_block6_1_relu[0][0]']
conv2_block6_concat (Concatena (None, 56, 56, 256) 0	['conv2_block5_concat[0][0]', 'conv2_block6_2_conv[0][0]']
pool2_bn (BatchNormalization) (None, 56, 56, 256) 1024	['conv2_block6_concat[0][0]']
pool2_relu (Activation) (None, 56, 56, 256) 0	['pool2_bn[0][0]']
pool2_conv (Conv2D) (None, 56, 56, 128) 32768	['pool2_relu[0][0]']
pool2_pool (AveragePooling2D) (None, 28, 28, 128) 0	['pool2_conv[0][0]']
conv3_block1_0_bn (BatchNormalizat (None, 28, 28, 128) 512	['pool2_pool[0][0]']
conv3_block1_0_relu (Activatio (None, 28, 28, 128) 0	['conv3_block1_0_bn[0][0]']
conv3_block1_1_conv (Conv2D) (None, 28, 28, 128) 16384	['conv3_block1_0_relu[0][0]']
conv3_block1_1_bn (BatchNormalizat (None, 28, 28, 128) 512	['conv3_block1_1_conv[0][0]']
conv3_block1_1_relu (Activatio (None, 28, 28, 128) 0	['conv3_block1_1_bn[0][0]']
conv3_block1_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block1_1_relu[0][0]']
conv3_block1_concat (Concatena (None, 28, 28, 160) 0	['pool2_pool[0][0]', 'conv3_block1_2_conv[0][0]']
conv3_block2_0_bn (BatchNormalizat (None, 28, 28, 160) 640	['conv3_block1_concat[0][0]']
conv3_block2_0_relu (Activatio (None, 28, 28, 160) 0	['conv3_block2_0_bn[0][0]']
conv3_block2_1_conv (Conv2D) (None, 28, 28, 128) 20480	['conv3_block2_0_relu[0][0]']
conv3_block2_1_bn (BatchNormalizat (None, 28, 28, 128) 512	['conv3_block2_1_conv[0][0]']
conv3_block2_1_relu (Activatio (None, 28, 28, 128) 0	['conv3_block2_1_bn[0][0]']
conv3_block2_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block2_1_relu[0][0]']
conv3_block2_concat (Concatena (None, 28, 28, 192) 0	['conv3_block1_concat[0][0]', 'conv3_block2_2_conv[0][0]']
conv3_block3_0_bn (BatchNormalizat (None, 28, 28, 192) 768	['conv3_block2_concat[0][0]']
conv3_block3_0_relu (Activatio (None, 28, 28, 192) 0	['conv3_block3_0_bn[0][0]']
conv3_block3_1_conv (Conv2D) (None, 28, 28, 128) 24576	['conv3_block3_0_relu[0][0]']
conv3_block3_1_bn (BatchNormalizat (None, 28, 28, 128) 512	['conv3_block3_1_conv[0][0]']

conv3_block3_1_relu (Activation) (None, 28, 28, 128) 0	['conv3_block3_1_bn[0][0]']
conv3_block3_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block3_1_relu[0][0]']
conv3_block3_concat (Concatenate) (None, 28, 28, 224) 0	['conv3_block2_concat[0][0]', 'conv3_block3_2_conv[0][0]']
conv3_block4_0_bn (BatchNormalizatization) (None, 28, 28, 224) 896	['conv3_block3_concat[0][0]']
conv3_block4_0_relu (Activation) (None, 28, 28, 224) 0	['conv3_block4_0_bn[0][0]']
conv3_block4_1_conv (Conv2D) (None, 28, 28, 128) 28672	['conv3_block4_0_relu[0][0]']
conv3_block4_1_bn (BatchNormalizatization) (None, 28, 28, 128) 512	['conv3_block4_1_conv[0][0]']
conv3_block4_1_relu (Activation) (None, 28, 28, 128) 0	['conv3_block4_1_bn[0][0]']
conv3_block4_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block4_1_relu[0][0]']
conv3_block4_concat (Concatenate) (None, 28, 28, 256) 0	['conv3_block3_concat[0][0]', 'conv3_block4_2_conv[0][0]']
conv3_block5_0_bn (BatchNormalizatization) (None, 28, 28, 256) 1024	['conv3_block4_concat[0][0]']
conv3_block5_0_relu (Activation) (None, 28, 28, 256) 0	['conv3_block5_0_bn[0][0]']
conv3_block5_1_conv (Conv2D) (None, 28, 28, 128) 32768	['conv3_block5_0_relu[0][0]']
conv3_block5_1_bn (BatchNormalizatization) (None, 28, 28, 128) 512	['conv3_block5_1_conv[0][0]']
conv3_block5_1_relu (Activation) (None, 28, 28, 128) 0	['conv3_block5_1_bn[0][0]']
conv3_block5_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block5_1_relu[0][0]']
conv3_block5_concat (Concatenate) (None, 28, 28, 288) 0	['conv3_block4_concat[0][0]', 'conv3_block5_2_conv[0][0]']
conv3_block6_0_bn (BatchNormalizatization) (None, 28, 28, 288) 1152	['conv3_block5_concat[0][0]']
conv3_block6_0_relu (Activation) (None, 28, 28, 288) 0	['conv3_block6_0_bn[0][0]']
conv3_block6_1_conv (Conv2D) (None, 28, 28, 128) 36864	['conv3_block6_0_relu[0][0]']
conv3_block6_1_bn (BatchNormalizatization) (None, 28, 28, 128) 512	['conv3_block6_1_conv[0][0]']
conv3_block6_1_relu (Activation) (None, 28, 28, 128) 0	['conv3_block6_1_bn[0][0]']
conv3_block6_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block6_1_relu[0][0]']
conv3_block6_concat (Concatenate) (None, 28, 28, 320) 0	['conv3_block5_concat[0][0]', 'conv3_block6_2_conv[0][0]']
conv3_block7_0_bn (BatchNormalizatization) (None, 28, 28, 320) 1280	['conv3_block6_concat[0][0]']
conv3_block7_0_relu (Activation) (None, 28, 28, 320) 0	['conv3_block7_0_bn[0][0]']
conv3_block7_1_conv (Conv2D) (None, 28, 28, 128) 40960	['conv3_block7_0_relu[0][0]']
conv3_block7_1_bn (BatchNormalizatization) (None, 28, 28, 128) 512	['conv3_block7_1_conv[0][0]']
conv3_block7_1_relu (Activation) (None, 28, 28, 128) 0	['conv3_block7_1_bn[0][0]']
conv3_block7_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block7_1_relu[0][0]']
conv3_block7_concat (Concatenate) (None, 28, 28, 352) 0	['conv3_block6_concat[0][0]', 'conv3_block7_2_conv[0][0]']
conv3_block8_0_bn (BatchNormalizatization) (None, 28, 28, 352) 1408	['conv3_block7_concat[0][0]']
conv3_block8_0_relu (Activation) (None, 28, 28, 352) 0	['conv3_block8_0_bn[0][0]']
conv3_block8_1_conv (Conv2D) (None, 28, 28, 128) 45056	['conv3_block8_0_relu[0][0]']
conv3_block8_1_bn (BatchNormalizatization) (None, 28, 28, 128) 512	['conv3_block8_1_conv[0][0]']
conv3_block8_1_relu (Activation) (None, 28, 28, 128) 0	['conv3_block8_1_bn[0][0]']
conv3_block8_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block8_1_relu[0][0]']

conv3_block8_concat (Concatenation) (None, 28, 28, 384) 0	['conv3_block7_concat[0][0]', 'conv3_block8_2_conv[0][0]']
conv3_block9_0_bn (BatchNormalizat (None, 28, 28, 384) 1536	['conv3_block8_concat[0][0]']
conv3_block9_0_relu (Activation) (None, 28, 28, 384) 0	['conv3_block9_0_bn[0][0]']
conv3_block9_1_conv (Conv2D) (None, 28, 28, 128) 49152	['conv3_block9_0_relu[0][0]']
conv3_block9_1_bn (BatchNormalizat (None, 28, 28, 128) 512	['conv3_block9_1_conv[0][0]']
conv3_block9_1_relu (Activatio (None, 28, 28, 128) 0	['conv3_block9_1_bn[0][0]']
conv3_block9_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block9_1_relu[0][0]']
conv3_block9_concat (Concatenat (None, 28, 28, 416) 0	['conv3_block8_concat[0][0]', 'conv3_block9_2_conv[0][0]']
conv3_block10_0_bn (BatchNormalizat (None, 28, 28, 416) 1664	['conv3_block9_concat[0][0]']
conv3_block10_0_relu (Activati (None, 28, 28, 416) 0	['conv3_block10_0_bn[0][0]']
conv3_block10_1_conv (Conv2D) (None, 28, 28, 128) 53248	['conv3_block10_0_relu[0][0]']
conv3_block10_1_bn (BatchNormalizat (None, 28, 28, 128) 512	['conv3_block10_1_conv[0][0]']
conv3_block10_1_relu (Activati (None, 28, 28, 128) 0	['conv3_block10_1_bn[0][0]']
conv3_block10_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block10_1_relu[0][0]']
conv3_block10_concat (Concatenat (None, 28, 28, 448) 0	['conv3_block9_concat[0][0]', 'conv3_block10_2_conv[0][0]']
conv3_block11_0_bn (BatchNormalizat (None, 28, 28, 448) 1792	['conv3_block10_concat[0][0]']
conv3_block11_0_relu (Activati (None, 28, 28, 448) 0	['conv3_block11_0_bn[0][0]']
conv3_block11_1_conv (Conv2D) (None, 28, 28, 128) 57344	['conv3_block11_0_relu[0][0]']
conv3_block11_1_bn (BatchNormalizat (None, 28, 28, 128) 512	['conv3_block11_1_conv[0][0]']
conv3_block11_1_relu (Activati (None, 28, 28, 128) 0	['conv3_block11_1_bn[0][0]']
conv3_block11_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block11_1_relu[0][0]']
conv3_block11_concat (Concatenat (None, 28, 28, 480) 0	['conv3_block10_concat[0][0]', 'conv3_block11_2_conv[0][0]']
conv3_block12_0_bn (BatchNormalizat (None, 28, 28, 480) 1920	['conv3_block11_concat[0][0]']
conv3_block12_0_relu (Activati (None, 28, 28, 480) 0	['conv3_block12_0_bn[0][0]']
conv3_block12_1_conv (Conv2D) (None, 28, 28, 128) 61440	['conv3_block12_0_relu[0][0]']
conv3_block12_1_bn (BatchNormalizat (None, 28, 28, 128) 512	['conv3_block12_1_conv[0][0]']
conv3_block12_1_relu (Activati (None, 28, 28, 128) 0	['conv3_block12_1_bn[0][0]']
conv3_block12_2_conv (Conv2D) (None, 28, 28, 32) 36864	['conv3_block12_1_relu[0][0]']
conv3_block12_concat (Concatenat (None, 28, 28, 512) 0	['conv3_block11_concat[0][0]', 'conv3_block12_2_conv[0][0]']
pool3_bn (BatchNormalization) (None, 28, 28, 512) 2048	['conv3_block12_concat[0][0]']
pool3_relu (Activation) (None, 28, 28, 512) 0	['pool3_bn[0][0]']
pool3_conv (Conv2D) (None, 28, 28, 256) 131072	['pool3_relu[0][0]']
pool3_pool (AveragePooling2D) (None, 14, 14, 256) 0	['pool3_conv[0][0]']
conv4_block1_0_bn (BatchNormalizat (None, 14, 14, 256) 1024	['pool3_pool[0][0]']
conv4_block1_0_relu (Activatio (None, 14, 14, 256) 0	['conv4_block1_0_bn[0][0]']
conv4_block1_1_conv (Conv2D) (None, 14, 14, 128) 32768	['conv4_block1_0_relu[0][0]']
conv4_block1_1_bn (BatchNormalizat (None, 14, 14, 128) 512	['conv4_block1_1_conv[0][0]']
conv4_block1_1_relu (Activatio (None, 14, 14, 128) 0	['conv4_block1_1_bn[0][0]']

```

n)

conv4_block1_2_conv (Conv2D)  (None, 14, 14, 32)  36864      ['conv4_block1_1_relu[0][0]']

conv4_block1_concat (Concatenation)  (None, 14, 14, 288)  0      ['pool3_pool[0][0]', 'conv4_block1_2_conv[0][0]']

conv4_block2_0_bn (BatchNormal)  (None, 14, 14, 288)  1152      ['conv4_block1_concat[0][0]']

conv4_block2_0_relu (Activation)  (None, 14, 14, 288)  0      ['conv4_block2_0_bn[0][0]']

conv4_block2_1_conv (Conv2D)  (None, 14, 14, 128)  36864      ['conv4_block2_0_relu[0][0]']

conv4_block2_1_bn (BatchNormal)  (None, 14, 14, 128)  512      ['conv4_block2_1_conv[0][0]']

conv4_block2_1_relu (Activation)  (None, 14, 14, 128)  0      ['conv4_block2_1_bn[0][0]']

conv4_block2_2_conv (Conv2D)  (None, 14, 14, 32)  36864      ['conv4_block2_1_relu[0][0]']

conv4_block2_concat (Concatenation)  (None, 14, 14, 320)  0      ['conv4_block1_concat[0][0]', 'conv4_block2_2_conv[0][0]']

conv4_block3_0_bn (BatchNormal)  (None, 14, 14, 320)  1280      ['conv4_block2_concat[0][0]']

conv4_block3_0_relu (Activation)  (None, 14, 14, 320)  0      ['conv4_block3_0_bn[0][0]']

conv4_block3_1_conv (Conv2D)  (None, 14, 14, 128)  40960      ['conv4_block3_0_relu[0][0]']

conv4_block3_1_bn (BatchNormal)  (None, 14, 14, 128)  512      ['conv4_block3_1_conv[0][0]']

conv4_block3_1_relu (Activation)  (None, 14, 14, 128)  0      ['conv4_block3_1_bn[0][0]']

conv4_block3_2_conv (Conv2D)  (None, 14, 14, 32)  36864      ['conv4_block3_1_relu[0][0]']

conv4_block3_concat (Concatenation)  (None, 14, 14, 352)  0      ['conv4_block2_concat[0][0]', 'conv4_block3_2_conv[0][0]']

conv4_block4_0_bn (BatchNormal)  (None, 14, 14, 352)  1408      ['conv4_block3_concat[0][0]']

conv4_block4_0_relu (Activation)  (None, 14, 14, 352)  0      ['conv4_block4_0_bn[0][0]']

conv4_block4_1_conv (Conv2D)  (None, 14, 14, 128)  45056      ['conv4_block4_0_relu[0][0]']

conv4_block4_1_bn (BatchNormal)  (None, 14, 14, 128)  512      ['conv4_block4_1_conv[0][0]']

conv4_block4_1_relu (Activation)  (None, 14, 14, 128)  0      ['conv4_block4_1_bn[0][0]']

conv4_block4_2_conv (Conv2D)  (None, 14, 14, 32)  36864      ['conv4_block4_1_relu[0][0]']

conv4_block4_concat (Concatenation)  (None, 14, 14, 384)  0      ['conv4_block3_concat[0][0]', 'conv4_block4_2_conv[0][0]']

conv4_block5_0_bn (BatchNormal)  (None, 14, 14, 384)  1536      ['conv4_block4_concat[0][0]']

conv4_block5_0_relu (Activation)  (None, 14, 14, 384)  0      ['conv4_block5_0_bn[0][0]']

conv4_block5_1_conv (Conv2D)  (None, 14, 14, 128)  49152      ['conv4_block5_0_relu[0][0]']

conv4_block5_1_bn (BatchNormal)  (None, 14, 14, 128)  512      ['conv4_block5_1_conv[0][0]']

conv4_block5_1_relu (Activation)  (None, 14, 14, 128)  0      ['conv4_block5_1_bn[0][0]']

conv4_block5_2_conv (Conv2D)  (None, 14, 14, 32)  36864      ['conv4_block5_1_relu[0][0]']

conv4_block5_concat (Concatenation)  (None, 14, 14, 416)  0      ['conv4_block4_concat[0][0]', 'conv4_block5_2_conv[0][0]']

conv4_block6_0_bn (BatchNormal)  (None, 14, 14, 416)  1664      ['conv4_block5_concat[0][0]']

conv4_block6_0_relu (Activation)  (None, 14, 14, 416)  0      ['conv4_block6_0_bn[0][0]']

conv4_block6_1_conv (Conv2D)  (None, 14, 14, 128)  53248      ['conv4_block6_0_relu[0][0]']

conv4_block6_1_bn (BatchNormal)  (None, 14, 14, 128)  512      ['conv4_block6_1_conv[0][0]']

conv4_block6_1_relu (Activation)  (None, 14, 14, 128)  0      ['conv4_block6_1_bn[0][0]']

conv4_block6_2_conv (Conv2D)  (None, 14, 14, 32)  36864      ['conv4_block6_1_relu[0][0]']

conv4_block6_concat (Concatenation)  (None, 14, 14, 448)  0      ['conv4_block5_concat[0][0]', 'conv4_block6_2_conv[0][0]']

```

```

    te)

conv4_block7_0_bn (BatchNormal (None, 14, 14, 448) 1792
    ization)

conv4_block7_0_relu (Activatio (None, 14, 14, 448) 0
    n)

conv4_block7_1_conv (Conv2D) (None, 14, 14, 128) 57344
conv4_block7_1_bn (BatchNormal (None, 14, 14, 128) 512
    ization)

conv4_block7_1_relu (Activatio (None, 14, 14, 128) 0
    n)

conv4_block7_2_conv (Conv2D) (None, 14, 14, 32) 36864
conv4_block7_concat (Concatena (None, 14, 14, 480) 0
    te)

conv4_block8_0_bn (BatchNormal (None, 14, 14, 480) 1920
    ization)

conv4_block8_0_relu (Activatio (None, 14, 14, 480) 0
    n)

conv4_block8_1_conv (Conv2D) (None, 14, 14, 128) 61440
conv4_block8_1_bn (BatchNormal (None, 14, 14, 128) 512
    ization)

conv4_block8_1_relu (Activatio (None, 14, 14, 128) 0
    n)

conv4_block8_2_conv (Conv2D) (None, 14, 14, 32) 36864
conv4_block8_concat (Concatena (None, 14, 14, 512) 0
    te)

conv4_block9_0_bn (BatchNormal (None, 14, 14, 512) 2048
    ization)

conv4_block9_0_relu (Activatio (None, 14, 14, 512) 0
    n)

conv4_block9_1_conv (Conv2D) (None, 14, 14, 128) 65536
conv4_block9_1_bn (BatchNormal (None, 14, 14, 128) 512
    ization)

conv4_block9_1_relu (Activatio (None, 14, 14, 128) 0
    n)

conv4_block9_2_conv (Conv2D) (None, 14, 14, 32) 36864
conv4_block9_concat (Concatena (None, 14, 14, 544) 0
    te)

conv4_block10_0_bn (BatchNorma (None, 14, 14, 544) 2176
    lization)

conv4_block10_0_relu (Activati (None, 14, 14, 544) 0
    on)

conv4_block10_1_conv (Conv2D) (None, 14, 14, 128) 69632
conv4_block10_1_bn (BatchNorma (None, 14, 14, 128) 512
    lization)

conv4_block10_1_relu (Activati (None, 14, 14, 128) 0
    on)

conv4_block10_2_conv (Conv2D) (None, 14, 14, 32) 36864
conv4_block10_concat (Concaten (None, 14, 14, 576) 0
    ate)

conv4_block11_0_bn (BatchNorma (None, 14, 14, 576) 2304
    lization)

conv4_block11_0_relu (Activati (None, 14, 14, 576) 0
    on)

conv4_block11_1_conv (Conv2D) (None, 14, 14, 128) 73728
conv4_block11_1_bn (BatchNorma (None, 14, 14, 128) 512
    lization)

conv4_block11_1_relu (Activati (None, 14, 14, 128) 0
    on)

conv4_block11_2_conv (Conv2D) (None, 14, 14, 32) 36864
conv4_block11_concat (Concaten (None, 14, 14, 608) 0
    ate)

conv4_block12_0_bn (BatchNorma (None, 14, 14, 608) 2432
    lization)

```

'conv4\_block6\_2\_conv[0][0]']  
['conv4\_block6\_concat[0][0]']  
['conv4\_block7\_0\_bn[0][0]']  
['conv4\_block7\_0\_relu[0][0]']  
['conv4\_block7\_1\_conv[0][0]']  
['conv4\_block7\_1\_bn[0][0]']  
['conv4\_block7\_1\_relu[0][0]']  
['conv4\_block7\_2\_conv[0][0]']  
['conv4\_block7\_concat[0][0]']  
['conv4\_block8\_0\_bn[0][0]']  
['conv4\_block8\_0\_relu[0][0]']  
['conv4\_block8\_1\_conv[0][0]']  
['conv4\_block8\_1\_bn[0][0]']  
['conv4\_block8\_1\_relu[0][0]']  
['conv4\_block8\_2\_conv[0][0]']  
['conv4\_block8\_concat[0][0]']  
['conv4\_block9\_0\_bn[0][0]']  
['conv4\_block9\_0\_relu[0][0]']  
['conv4\_block9\_1\_conv[0][0]']  
['conv4\_block9\_1\_bn[0][0]']  
['conv4\_block9\_1\_relu[0][0]']  
['conv4\_block8\_concat[0][0]']  
['conv4\_block9\_2\_conv[0][0]']  
['conv4\_block9\_concat[0][0]']  
['conv4\_block10\_0\_bn[0][0]']  
['conv4\_block10\_0\_relu[0][0]']  
['conv4\_block10\_1\_conv[0][0]']  
['conv4\_block10\_1\_bn[0][0]']  
['conv4\_block10\_1\_relu[0][0]']  
['conv4\_block10\_2\_conv[0][0]']  
['conv4\_block10\_concat[0][0]']  
['conv4\_block11\_0\_bn[0][0]']  
['conv4\_block11\_0\_relu[0][0]']  
['conv4\_block11\_1\_conv[0][0]']  
['conv4\_block11\_1\_bn[0][0]']  
['conv4\_block11\_1\_relu[0][0]']  
['conv4\_block10\_concat[0][0]']  
['conv4\_block11\_2\_conv[0][0]']  
['conv4\_block11\_concat[0][0]']

conv4_block12_0_relu (Activati (None, 14, 14, 608) 0 on)	['conv4_block12_0_bn[0][0]']
conv4_block12_1_conv (Conv2D) (None, 14, 14, 128) 77824	['conv4_block12_0_relu[0][0]']
conv4_block12_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block12_1_conv[0][0]']
conv4_block12_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block12_1_bn[0][0]']
conv4_block12_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block12_1_relu[0][0]']
conv4_block12_concat (Concaten (None, 14, 14, 640) 0 ate)	['conv4_block11_concat[0][0]', 'conv4_block12_2_conv[0][0]']
conv4_block13_0_bn (BatchNorma (None, 14, 14, 640) 2560 lization)	['conv4_block12_concat[0][0]']
conv4_block13_0_relu (Activati (None, 14, 14, 640) 0 on)	['conv4_block13_0_bn[0][0]']
conv4_block13_1_conv (Conv2D) (None, 14, 14, 128) 81920	['conv4_block13_0_relu[0][0]']
conv4_block13_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block13_1_conv[0][0]']
conv4_block13_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block13_1_bn[0][0]']
conv4_block13_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block13_1_relu[0][0]']
conv4_block13_concat (Concaten (None, 14, 14, 672) 0 ate)	['conv4_block12_concat[0][0]', 'conv4_block13_2_conv[0][0]']
conv4_block14_0_bn (BatchNorma (None, 14, 14, 672) 2688 lization)	['conv4_block13_concat[0][0]']
conv4_block14_0_relu (Activati (None, 14, 14, 672) 0 on)	['conv4_block14_0_bn[0][0]']
conv4_block14_1_conv (Conv2D) (None, 14, 14, 128) 86016	['conv4_block14_0_relu[0][0]']
conv4_block14_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block14_1_conv[0][0]']
conv4_block14_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block14_1_bn[0][0]']
conv4_block14_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block14_1_relu[0][0]']
conv4_block14_concat (Concaten (None, 14, 14, 704) 0 ate)	['conv4_block13_concat[0][0]', 'conv4_block14_2_conv[0][0]']
conv4_block15_0_bn (BatchNorma (None, 14, 14, 704) 2816 lization)	['conv4_block14_concat[0][0]']
conv4_block15_0_relu (Activati (None, 14, 14, 704) 0 on)	['conv4_block15_0_bn[0][0]']
conv4_block15_1_conv (Conv2D) (None, 14, 14, 128) 90112	['conv4_block15_0_relu[0][0]']
conv4_block15_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block15_1_conv[0][0]']
conv4_block15_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block15_1_bn[0][0]']
conv4_block15_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block15_1_relu[0][0]']
conv4_block15_concat (Concaten (None, 14, 14, 736) 0 ate)	['conv4_block14_concat[0][0]', 'conv4_block15_2_conv[0][0]']
conv4_block16_0_bn (BatchNorma (None, 14, 14, 736) 2944 lization)	['conv4_block15_concat[0][0]']
conv4_block16_0_relu (Activati (None, 14, 14, 736) 0 on)	['conv4_block16_0_bn[0][0]']
conv4_block16_1_conv (Conv2D) (None, 14, 14, 128) 94208	['conv4_block16_0_relu[0][0]']
conv4_block16_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block16_1_conv[0][0]']
conv4_block16_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block16_1_bn[0][0]']
conv4_block16_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block16_1_relu[0][0]']
conv4_block16_concat (Concaten (None, 14, 14, 768) 0 ate)	['conv4_block15_concat[0][0]', 'conv4_block16_2_conv[0][0]']
conv4_block17_0_bn (BatchNorma (None, 14, 14, 768) 3072 lization)	['conv4_block16_concat[0][0]']
conv4_block17_0_relu (Activati (None, 14, 14, 768) 0 on)	['conv4_block17_0_bn[0][0]']
conv4_block17_1_conv (Conv2D) (None, 14, 14, 128) 98304	['conv4_block17_0_relu[0][0]']

conv4_block17_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block17_1_conv[0][0]']
conv4_block17_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block17_1_bn[0][0]']
conv4_block17_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block17_1_relu[0][0]']
conv4_block17_concat (Concaten (None, 14, 14, 800) 0 ate)	['conv4_block16_concat[0][0]', 'conv4_block17_2_conv[0][0]']
conv4_block18_0_bn (BatchNorma (None, 14, 14, 800) 3200 lization)	['conv4_block17_concat[0][0]']
conv4_block18_0_relu (Activati (None, 14, 14, 800) 0 on)	['conv4_block18_0_bn[0][0]']
conv4_block18_1_conv (Conv2D) (None, 14, 14, 128) 102400	['conv4_block18_0_relu[0][0]']
conv4_block18_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block18_1_conv[0][0]']
conv4_block18_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block18_1_bn[0][0]']
conv4_block18_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block18_1_relu[0][0]']
conv4_block18_concat (Concaten (None, 14, 14, 832) 0 ate)	['conv4_block17_concat[0][0]', 'conv4_block18_2_conv[0][0]']
conv4_block19_0_bn (BatchNorma (None, 14, 14, 832) 3328 lization)	['conv4_block18_concat[0][0]']
conv4_block19_0_relu (Activati (None, 14, 14, 832) 0 on)	['conv4_block19_0_bn[0][0]']
conv4_block19_1_conv (Conv2D) (None, 14, 14, 128) 106496	['conv4_block19_0_relu[0][0]']
conv4_block19_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block19_1_conv[0][0]']
conv4_block19_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block19_1_bn[0][0]']
conv4_block19_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block19_1_relu[0][0]']
conv4_block19_concat (Concaten (None, 14, 14, 864) 0 ate)	['conv4_block18_concat[0][0]', 'conv4_block19_2_conv[0][0]']
conv4_block20_0_bn (BatchNorma (None, 14, 14, 864) 3456 lization)	['conv4_block19_concat[0][0]']
conv4_block20_0_relu (Activati (None, 14, 14, 864) 0 on)	['conv4_block20_0_bn[0][0]']
conv4_block20_1_conv (Conv2D) (None, 14, 14, 128) 110592	['conv4_block20_0_relu[0][0]']
conv4_block20_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block20_1_conv[0][0]']
conv4_block20_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block20_1_bn[0][0]']
conv4_block20_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block20_1_relu[0][0]']
conv4_block20_concat (Concaten (None, 14, 14, 896) 0 ate)	['conv4_block19_concat[0][0]', 'conv4_block20_2_conv[0][0]']
conv4_block21_0_bn (BatchNorma (None, 14, 14, 896) 3584 lization)	['conv4_block20_concat[0][0]']
conv4_block21_0_relu (Activati (None, 14, 14, 896) 0 on)	['conv4_block21_0_bn[0][0]']
conv4_block21_1_conv (Conv2D) (None, 14, 14, 128) 114688	['conv4_block21_0_relu[0][0]']
conv4_block21_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block21_1_conv[0][0]']
conv4_block21_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block21_1_bn[0][0]']
conv4_block21_2_conv (Conv2D) (None, 14, 14, 32) 36864	['conv4_block21_1_relu[0][0]']
conv4_block21_concat (Concaten (None, 14, 14, 928) 0 ate)	['conv4_block20_concat[0][0]', 'conv4_block21_2_conv[0][0]']
conv4_block22_0_bn (BatchNorma (None, 14, 14, 928) 3712 lization)	['conv4_block21_concat[0][0]']
conv4_block22_0_relu (Activati (None, 14, 14, 928) 0 on)	['conv4_block22_0_bn[0][0]']
conv4_block22_1_conv (Conv2D) (None, 14, 14, 128) 118784	['conv4_block22_0_relu[0][0]']
conv4_block22_1_bn (BatchNorma (None, 14, 14, 128) 512 lization)	['conv4_block22_1_conv[0][0]']
conv4_block22_1_relu (Activati (None, 14, 14, 128) 0 on)	['conv4_block22_1_bn[0][0]']

conv4_block22_2_conv (Conv2D) (None, 14, 14, 32)	36864	['conv4_block22_1_relu[0][0]']
conv4_block22_concat (Concaten ate)	0	['conv4_block21_concat[0][0]', 'conv4_block22_2_conv[0][0]']
conv4_block23_0_bn (BatchNorma lization)	3840	['conv4_block22_concat[0][0]']
conv4_block23_0_relu (Activati on)	0	['conv4_block23_0_bn[0][0]']
conv4_block23_1_conv (Conv2D) (None, 14, 14, 128)	122880	['conv4_block23_0_relu[0][0]']
conv4_block23_1_bn (BatchNorma lization)	512	['conv4_block23_1_conv[0][0]']
conv4_block23_1_relu (Activati on)	0	['conv4_block23_1_bn[0][0]']
conv4_block23_2_conv (Conv2D) (None, 14, 14, 32)	36864	['conv4_block23_1_relu[0][0]']
conv4_block23_concat (Concaten ate)	0	['conv4_block22_concat[0][0]', 'conv4_block23_2_conv[0][0]']
conv4_block24_0_bn (BatchNorma lization)	3968	['conv4_block23_concat[0][0]']
conv4_block24_0_relu (Activati on)	0	['conv4_block24_0_bn[0][0]']
conv4_block24_1_conv (Conv2D) (None, 14, 14, 128)	126976	['conv4_block24_0_relu[0][0]']
conv4_block24_1_bn (BatchNorma lization)	512	['conv4_block24_1_conv[0][0]']
conv4_block24_1_relu (Activati on)	0	['conv4_block24_1_bn[0][0]']
conv4_block24_2_conv (Conv2D) (None, 14, 14, 32)	36864	['conv4_block24_1_relu[0][0]']
conv4_block24_concat (Concaten ate)	0	['conv4_block23_concat[0][0]', 'conv4_block24_2_conv[0][0]']
pool4_bn (BatchNormalization)	4096	['conv4_block24_concat[0][0]']
pool4_relu (Activation)	0	['pool4_bn[0][0]']
pool4_conv (Conv2D)	524288	['pool4_relu[0][0]']
pool4_pool (AveragePooling2D)	0	['pool4_conv[0][0]']
conv5_block1_0_bn (BatchNormal ization)	2048	['pool4_pool[0][0]']
conv5_block1_0_relu (Activatio n)	0	['conv5_block1_0_bn[0][0]']
conv5_block1_1_conv (Conv2D) (None, 7, 7, 128)	65536	['conv5_block1_0_relu[0][0]']
conv5_block1_1_bn (BatchNormal ization)	512	['conv5_block1_1_conv[0][0]']
conv5_block1_1_relu (Activatio n)	0	['conv5_block1_1_bn[0][0]']
conv5_block1_2_conv (Conv2D) (None, 7, 7, 32)	36864	['conv5_block1_1_relu[0][0]']
conv5_block1_concat (Concatena te)	0	['pool4_pool[0][0]', 'conv5_block1_2_conv[0][0]']
conv5_block2_0_bn (BatchNormal ization)	2176	['conv5_block1_concat[0][0]']
conv5_block2_0_relu (Activatio n)	0	['conv5_block2_0_bn[0][0]']
conv5_block2_1_conv (Conv2D) (None, 7, 7, 128)	69632	['conv5_block2_0_relu[0][0]']
conv5_block2_1_bn (BatchNormal ization)	512	['conv5_block2_1_conv[0][0]']
conv5_block2_1_relu (Activatio n)	0	['conv5_block2_1_bn[0][0]']
conv5_block2_2_conv (Conv2D) (None, 7, 7, 32)	36864	['conv5_block2_1_relu[0][0]']
conv5_block2_concat (Concatena te)	0	['conv5_block1_concat[0][0]', 'conv5_block2_2_conv[0][0]']
conv5_block3_0_bn (BatchNormal ization)	2304	['conv5_block2_concat[0][0]']
conv5_block3_0_relu (Activatio n)	0	['conv5_block3_0_bn[0][0]']
conv5_block3_1_conv (Conv2D) (None, 7, 7, 128)	73728	['conv5_block3_0_relu[0][0]']

conv5_block3_1_bn (BatchNormal ization)	(None, 7, 7, 128)	512	['conv5_block3_1_conv[0][0]']
conv5_block3_1_relu (Activatio n)	(None, 7, 7, 128)	0	['conv5_block3_1_bn[0][0]']
conv5_block3_2_conv (Conv2D)	(None, 7, 7, 32)	36864	['conv5_block3_1_relu[0][0]']
conv5_block3_concat (Concatena te)	(None, 7, 7, 608)	0	['conv5_block2_concat[0][0]', 'conv5_block3_2_conv[0][0]']
conv5_block4_0_bn (BatchNormal ization)	(None, 7, 7, 608)	2432	['conv5_block3_concat[0][0]']
conv5_block4_0_relu (Activatio n)	(None, 7, 7, 608)	0	['conv5_block4_0_bn[0][0]']
conv5_block4_1_conv (Conv2D)	(None, 7, 7, 128)	77824	['conv5_block4_0_relu[0][0]']
conv5_block4_1_bn (BatchNormal ization)	(None, 7, 7, 128)	512	['conv5_block4_1_conv[0][0]']
conv5_block4_1_relu (Activatio n)	(None, 7, 7, 128)	0	['conv5_block4_1_bn[0][0]']
conv5_block4_2_conv (Conv2D)	(None, 7, 7, 32)	36864	['conv5_block4_1_relu[0][0]']
conv5_block4_concat (Concatena te)	(None, 7, 7, 640)	0	['conv5_block3_concat[0][0]', 'conv5_block4_2_conv[0][0]']
conv5_block5_0_bn (BatchNormal ization)	(None, 7, 7, 640)	2560	['conv5_block4_concat[0][0]']
conv5_block5_0_relu (Activatio n)	(None, 7, 7, 640)	0	['conv5_block5_0_bn[0][0]']
conv5_block5_1_conv (Conv2D)	(None, 7, 7, 128)	81920	['conv5_block5_0_relu[0][0]']
conv5_block5_1_bn (BatchNormal ization)	(None, 7, 7, 128)	512	['conv5_block5_1_conv[0][0]']
conv5_block5_1_relu (Activatio n)	(None, 7, 7, 128)	0	['conv5_block5_1_bn[0][0]']
conv5_block5_2_conv (Conv2D)	(None, 7, 7, 32)	36864	['conv5_block5_1_relu[0][0]']
conv5_block5_concat (Concatena te)	(None, 7, 7, 672)	0	['conv5_block4_concat[0][0]', 'conv5_block5_2_conv[0][0]']
conv5_block6_0_bn (BatchNormal ization)	(None, 7, 7, 672)	2688	['conv5_block5_concat[0][0]']
conv5_block6_0_relu (Activatio n)	(None, 7, 7, 672)	0	['conv5_block6_0_bn[0][0]']
conv5_block6_1_conv (Conv2D)	(None, 7, 7, 128)	86016	['conv5_block6_0_relu[0][0]']
conv5_block6_1_bn (BatchNormal ization)	(None, 7, 7, 128)	512	['conv5_block6_1_conv[0][0]']
conv5_block6_1_relu (Activatio n)	(None, 7, 7, 128)	0	['conv5_block6_1_bn[0][0]']
conv5_block6_2_conv (Conv2D)	(None, 7, 7, 32)	36864	['conv5_block6_1_relu[0][0]']
conv5_block6_concat (Concatena te)	(None, 7, 7, 704)	0	['conv5_block5_concat[0][0]', 'conv5_block6_2_conv[0][0]']
conv5_block7_0_bn (BatchNormal ization)	(None, 7, 7, 704)	2816	['conv5_block6_concat[0][0]']
conv5_block7_0_relu (Activatio n)	(None, 7, 7, 704)	0	['conv5_block7_0_bn[0][0]']
conv5_block7_1_conv (Conv2D)	(None, 7, 7, 128)	90112	['conv5_block7_0_relu[0][0]']
conv5_block7_1_bn (BatchNormal ization)	(None, 7, 7, 128)	512	['conv5_block7_1_conv[0][0]']
conv5_block7_1_relu (Activatio n)	(None, 7, 7, 128)	0	['conv5_block7_1_bn[0][0]']
conv5_block7_2_conv (Conv2D)	(None, 7, 7, 32)	36864	['conv5_block7_1_relu[0][0]']
conv5_block7_concat (Concatena te)	(None, 7, 7, 736)	0	['conv5_block6_concat[0][0]', 'conv5_block7_2_conv[0][0]']
conv5_block8_0_bn (BatchNormal ization)	(None, 7, 7, 736)	2944	['conv5_block7_concat[0][0]']
conv5_block8_0_relu (Activatio n)	(None, 7, 7, 736)	0	['conv5_block8_0_bn[0][0]']
conv5_block8_1_conv (Conv2D)	(None, 7, 7, 128)	94208	['conv5_block8_0_relu[0][0]']
conv5_block8_1_bn (BatchNormal ization)	(None, 7, 7, 128)	512	['conv5_block8_1_conv[0][0]']
conv5_block8_1_relu (Activatio n)	(None, 7, 7, 128)	0	['conv5_block8_1_bn[0][0]']

conv5_block8_2_conv (Conv2D) (None, 7, 7, 32)	36864	['conv5_block8_1_relu[0][0]']
conv5_block8_concat (Concatenation) (None, 7, 7, 768)	0	['conv5_block7_concat[0][0]', 'conv5_block8_2_conv[0][0]']
conv5_block9_0_bn (BatchNormalization) (None, 7, 7, 768)	3072	['conv5_block8_concat[0][0]']
conv5_block9_0_relu (Activation) (None, 7, 7, 768)	0	['conv5_block9_0_bn[0][0]']
conv5_block9_1_conv (Conv2D) (None, 7, 7, 128)	98304	['conv5_block9_0_relu[0][0]']
conv5_block9_1_bn (BatchNormalization) (None, 7, 7, 128)	512	['conv5_block9_1_conv[0][0]']
conv5_block9_1_relu (Activation) (None, 7, 7, 128)	0	['conv5_block9_1_bn[0][0]']
conv5_block9_2_conv (Conv2D) (None, 7, 7, 32)	36864	['conv5_block9_1_relu[0][0]']
conv5_block9_concat (Concatenation) (None, 7, 7, 800)	0	['conv5_block8_concat[0][0]', 'conv5_block9_2_conv[0][0]']
conv5_block10_0_bn (BatchNormalization) (None, 7, 7, 800)	3200	['conv5_block9_concat[0][0]']
conv5_block10_0_relu (Activation) (None, 7, 7, 800)	0	['conv5_block10_0_bn[0][0]']
conv5_block10_1_conv (Conv2D) (None, 7, 7, 128)	102400	['conv5_block10_0_relu[0][0]']
conv5_block10_1_bn (BatchNormalization) (None, 7, 7, 128)	512	['conv5_block10_1_conv[0][0]']
conv5_block10_1_relu (Activation) (None, 7, 7, 128)	0	['conv5_block10_1_bn[0][0]']
conv5_block10_2_conv (Conv2D) (None, 7, 7, 32)	36864	['conv5_block10_1_relu[0][0]']
conv5_block10_concat (Concatenation) (None, 7, 7, 832)	0	['conv5_block9_concat[0][0]', 'conv5_block10_2_conv[0][0]']
conv5_block11_0_bn (BatchNormalization) (None, 7, 7, 832)	3328	['conv5_block10_concat[0][0]']
conv5_block11_0_relu (Activation) (None, 7, 7, 832)	0	['conv5_block11_0_bn[0][0]']
conv5_block11_1_conv (Conv2D) (None, 7, 7, 128)	106496	['conv5_block11_0_relu[0][0]']
conv5_block11_1_bn (BatchNormalization) (None, 7, 7, 128)	512	['conv5_block11_1_conv[0][0]']
conv5_block11_1_relu (Activation) (None, 7, 7, 128)	0	['conv5_block11_1_bn[0][0]']
conv5_block11_2_conv (Conv2D) (None, 7, 7, 32)	36864	['conv5_block11_1_relu[0][0]']
conv5_block11_concat (Concatenation) (None, 7, 7, 864)	0	['conv5_block10_concat[0][0]', 'conv5_block11_2_conv[0][0]']
conv5_block12_0_bn (BatchNormalization) (None, 7, 7, 864)	3456	['conv5_block11_concat[0][0]']
conv5_block12_0_relu (Activation) (None, 7, 7, 864)	0	['conv5_block12_0_bn[0][0]']
conv5_block12_1_conv (Conv2D) (None, 7, 7, 128)	110592	['conv5_block12_0_relu[0][0]']
conv5_block12_1_bn (BatchNormalization) (None, 7, 7, 128)	512	['conv5_block12_1_conv[0][0]']
conv5_block12_1_relu (Activation) (None, 7, 7, 128)	0	['conv5_block12_1_bn[0][0]']
conv5_block12_2_conv (Conv2D) (None, 7, 7, 32)	36864	['conv5_block12_1_relu[0][0]']
conv5_block12_concat (Concatenation) (None, 7, 7, 896)	0	['conv5_block11_concat[0][0]', 'conv5_block12_2_conv[0][0]']
conv5_block13_0_bn (BatchNormalization) (None, 7, 7, 896)	3584	['conv5_block12_concat[0][0]']
conv5_block13_0_relu (Activation) (None, 7, 7, 896)	0	['conv5_block13_0_bn[0][0]']
conv5_block13_1_conv (Conv2D) (None, 7, 7, 128)	114688	['conv5_block13_0_relu[0][0]']
conv5_block13_1_bn (BatchNormalization) (None, 7, 7, 128)	512	['conv5_block13_1_conv[0][0]']
conv5_block13_1_relu (Activation) (None, 7, 7, 128)	0	['conv5_block13_1_bn[0][0]']
conv5_block13_2_conv (Conv2D) (None, 7, 7, 32)	36864	['conv5_block13_1_relu[0][0]']
conv5_block13_concat (Concatenation) (None, 7, 7, 928)	0	['conv5_block12_concat[0][0]', 'conv5_block13_2_conv[0][0]']

conv5_block14_0_bn (BatchNormalizati	(None, 7, 7, 928)	3712	['conv5_block13_concat[0][0]']
on)			
conv5_block14_0_relu (Activati	(None, 7, 7, 928)	0	['conv5_block14_0_bn[0][0]']
on)			
conv5_block14_1_conv (Conv2D)	(None, 7, 7, 128)	118784	['conv5_block14_0_relu[0][0]']
conv5_block14_1_bn (BatchNormalizati	(None, 7, 7, 128)	512	['conv5_block14_1_conv[0][0]']
onization)			
conv5_block14_1_relu (Activati	(None, 7, 7, 128)	0	['conv5_block14_1_bn[0][0]']
on)			
conv5_block14_2_conv (Conv2D)	(None, 7, 7, 32)	36864	['conv5_block14_1_relu[0][0]']
conv5_block14_concat (Concatenat	(None, 7, 7, 960)	0	['conv5_block13_concat[0][0]',
e)			'conv5_block14_2_conv[0][0]']
conv5_block15_0_bn (BatchNormalizati	(None, 7, 7, 960)	3840	['conv5_block14_concat[0][0]']
onization)			
conv5_block15_0_relu (Activati	(None, 7, 7, 960)	0	['conv5_block15_0_bn[0][0]']
on)			
conv5_block15_1_conv (Conv2D)	(None, 7, 7, 128)	122880	['conv5_block15_0_relu[0][0]']
conv5_block15_1_bn (BatchNormalizati	(None, 7, 7, 128)	512	['conv5_block15_1_conv[0][0]']
onization)			
conv5_block15_1_relu (Activati	(None, 7, 7, 128)	0	['conv5_block15_1_bn[0][0]']
on)			
conv5_block15_2_conv (Conv2D)	(None, 7, 7, 32)	36864	['conv5_block15_1_relu[0][0]']
conv5_block15_concat (Concatenat	(None, 7, 7, 992)	0	['conv5_block14_concat[0][0]',
e)			'conv5_block15_2_conv[0][0]']
conv5_block16_0_bn (BatchNormalizati	(None, 7, 7, 992)	3968	['conv5_block15_concat[0][0]']
onization)			
conv5_block16_0_relu (Activati	(None, 7, 7, 992)	0	['conv5_block16_0_bn[0][0]']
on)			
conv5_block16_1_conv (Conv2D)	(None, 7, 7, 128)	126976	['conv5_block16_0_relu[0][0]']
conv5_block16_1_bn (BatchNormalizati	(None, 7, 7, 128)	512	['conv5_block16_1_conv[0][0]']
onization)			
conv5_block16_1_relu (Activati	(None, 7, 7, 128)	0	['conv5_block16_1_bn[0][0]']
on)			
conv5_block16_2_conv (Conv2D)	(None, 7, 7, 32)	36864	['conv5_block16_1_relu[0][0]']
conv5_block16_concat (Concatenat	(None, 7, 7, 1024)	0	['conv5_block15_concat[0][0]',
e)			'conv5_block16_2_conv[0][0]']
bn (BatchNormalization)	(None, 7, 7, 1024)	4096	['conv5_block16_concat[0][0]']
relu (Activation)	(None, 7, 7, 1024)	0	['bn[0][0]']
global_average_pooling2d_2 (Globa	(None, 1024)	0	['relu[0][0]']
lAveragePooling2D)			
dropout_2 (Dropout)	(None, 1024)	0	['global_average_pooling2d_2[0][0]']
dense_3 (Dense)	(None, 3)	3075	['dropout_2[0][0]']

---

Total params: 7,040,579  
Trainable params: 3,075  
Non-trainable params: 7,037,504

---

None

```
In [148]: # callback and fit
cb = [
    EarlyStopping(patience=5, restore_best_weights=True),
    ReduceLROnPlateau(patience=3, factor=0.5, verbose=1)
] # same callback used here to prevent overfitting and divergence
history_dn = model_dn.fit(
    X_train, y_train,
    validation_split=0.2,
    epochs=25, batch_size=32,
    callbacks=cb, verbose=1
)

# evaluate
test_loss_dn, test_acc_dn = model_dn.evaluate(X_test, y_test, verbose=0)
print(f"[DenseNet121] Test Accuracy: {test_acc_dn:.4f}")

# report
best_epoch = np.argmax(history_dn.history['val_accuracy'])
# find the best epoch (because earlystopping is used)
best_train_acc = history_dn.history['accuracy'][best_epoch]
best_val_acc = history_dn.history['val_accuracy'][best_epoch]
best_train_loss = history_dn.history['loss'][best_epoch]
best_val_loss = history_dn.history['val_loss'][best_epoch]
```

```

print("==> DenseNet121 Early-Stopped Performance ==>")
print(f"Best Epoch: {best_epoch + 1}")
print(f"Training Accuracy: {best_train_acc:.4f} | Loss: {best_train_loss:.4f}")
print(f"Validation Accuracy: {best_val_acc:.4f} | Loss: {best_val_loss:.4f}")
print(f"Test Accuracy: {test_acc_dn:.4f} | Loss: {test_loss_dn:.4f}")

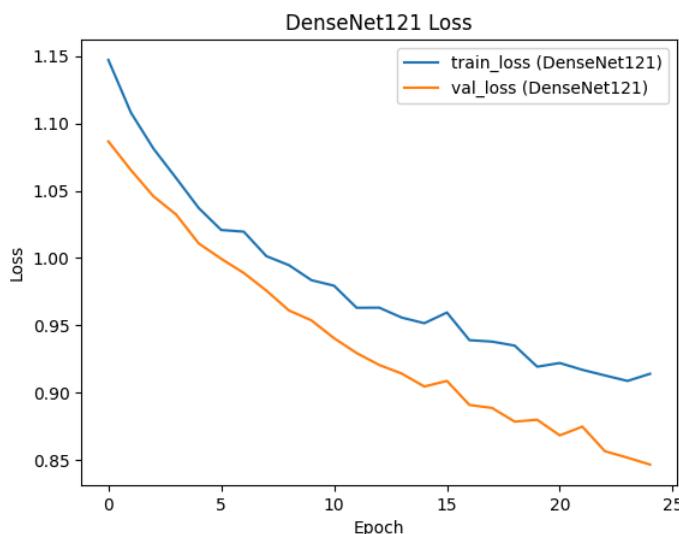
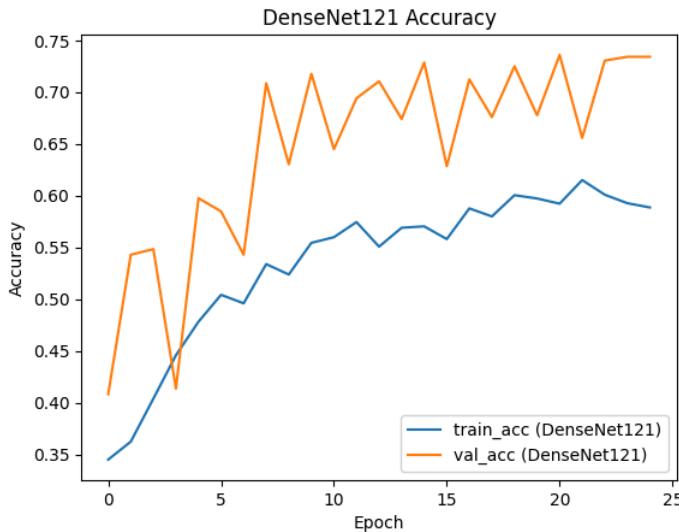
#store the model result
perf_rows.append({
    'Model': 'DenseNet121',
    'Type': 'transfer',
    'Train_Accuracy': float(best_train_acc),
    'Val_Accuracy': float(best_val_acc),
    'Test_Accuracy': float(test_acc_dn),
    'Train_Loss': float(best_train_loss),
    'Val_Loss': float(best_val_loss),
    'Test_Loss': float(test_loss_dn)
})

Epoch 1/25
69/69 [=====] - 7s 73ms/step - loss: 1.1472 - accuracy: 0.3449 - val_loss: 1.0866 - val_accuracy: 0.4080 - lr: 0.0010
Epoch 2/25
69/69 [=====] - 4s 54ms/step - loss: 1.1080 - accuracy: 0.3622 - val_loss: 1.0653 - val_accuracy: 0.5428 - lr: 0.0010
Epoch 3/25
69/69 [=====] - 4s 53ms/step - loss: 1.0812 - accuracy: 0.4037 - val_loss: 1.0458 - val_accuracy: 0.5483 - lr: 0.0010
Epoch 4/25
69/69 [=====] - 4s 54ms/step - loss: 1.0594 - accuracy: 0.4457 - val_loss: 1.0323 - val_accuracy: 0.4135 - lr: 0.0010
Epoch 5/25
69/69 [=====] - 4s 53ms/step - loss: 1.0372 - accuracy: 0.4781 - val_loss: 1.0109 - val_accuracy: 0.5974 - lr: 0.0010
Epoch 6/25
69/69 [=====] - 4s 53ms/step - loss: 1.0208 - accuracy: 0.5041 - val_loss: 0.9994 - val_accuracy: 0.5847 - lr: 0.0010
Epoch 7/25
69/69 [=====] - 4s 53ms/step - loss: 1.0196 - accuracy: 0.4959 - val_loss: 0.9889 - val_accuracy: 0.5428 - lr: 0.0010
Epoch 8/25
69/69 [=====] - 4s 53ms/step - loss: 1.0014 - accuracy: 0.5338 - val_loss: 0.9758 - val_accuracy: 0.7086 - lr: 0.0010
Epoch 9/25
69/69 [=====] - 4s 52ms/step - loss: 0.9947 - accuracy: 0.5237 - val_loss: 0.9611 - val_accuracy: 0.6302 - lr: 0.0010
Epoch 10/25
69/69 [=====] - 4s 53ms/step - loss: 0.9835 - accuracy: 0.5543 - val_loss: 0.9537 - val_accuracy: 0.7177 - lr: 0.0010
Epoch 11/25
69/69 [=====] - 4s 53ms/step - loss: 0.9794 - accuracy: 0.5598 - val_loss: 0.9404 - val_accuracy: 0.6448 - lr: 0.0010
Epoch 12/25
69/69 [=====] - 4s 53ms/step - loss: 0.9630 - accuracy: 0.5744 - val_loss: 0.9294 - val_accuracy: 0.6940 - lr: 0.0010
Epoch 13/25
69/69 [=====] - 4s 52ms/step - loss: 0.9631 - accuracy: 0.5506 - val_loss: 0.9206 - val_accuracy: 0.7104 - lr: 0.0010
Epoch 14/25
69/69 [=====] - 4s 54ms/step - loss: 0.9557 - accuracy: 0.5689 - val_loss: 0.9141 - val_accuracy: 0.6740 - lr: 0.0010
Epoch 15/25
69/69 [=====] - 4s 53ms/step - loss: 0.9516 - accuracy: 0.5703 - val_loss: 0.9045 - val_accuracy: 0.7286 - lr: 0.0010
Epoch 16/25
69/69 [=====] - 4s 52ms/step - loss: 0.9595 - accuracy: 0.5579 - val_loss: 0.9087 - val_accuracy: 0.6284 - lr: 0.0010
Epoch 17/25
69/69 [=====] - 4s 54ms/step - loss: 0.9390 - accuracy: 0.5876 - val_loss: 0.8908 - val_accuracy: 0.7122 - lr: 0.0010
Epoch 18/25
69/69 [=====] - 4s 53ms/step - loss: 0.9379 - accuracy: 0.5798 - val_loss: 0.8886 - val_accuracy: 0.6758 - lr: 0.0010
Epoch 19/25
69/69 [=====] - 4s 53ms/step - loss: 0.9349 - accuracy: 0.6004 - val_loss: 0.8785 - val_accuracy: 0.7250 - lr: 0.0010
Epoch 20/25
69/69 [=====] - 4s 52ms/step - loss: 0.9193 - accuracy: 0.5972 - val_loss: 0.8798 - val_accuracy: 0.6776 - lr: 0.0010
Epoch 21/25
69/69 [=====] - 4s 54ms/step - loss: 0.9220 - accuracy: 0.5922 - val_loss: 0.8683 - val_accuracy: 0.7359 - lr: 0.0010
Epoch 22/25
69/69 [=====] - 4s 56ms/step - loss: 0.9170 - accuracy: 0.6150 - val_loss: 0.8748 - val_accuracy: 0.6557 - lr: 0.0010
Epoch 23/25
69/69 [=====] - 4s 54ms/step - loss: 0.9128 - accuracy: 0.6008 - val_loss: 0.8565 - val_accuracy: 0.7304 - lr: 0.0010
Epoch 24/25
69/69 [=====] - 4s 54ms/step - loss: 0.9087 - accuracy: 0.5926 - val_loss: 0.8517 - val_accuracy: 0.7341 - lr: 0.0010
Epoch 25/25
69/69 [=====] - 4s 53ms/step - loss: 0.9140 - accuracy: 0.5885 - val_loss: 0.8465 - val_accuracy: 0.7341 - lr: 0.0010
[DenseNet121] Test Accuracy: 0.6840
==> DenseNet121 Early-Stopped Performance ==
Best Epoch: 21
Training Accuracy: 0.5922 | Loss: 0.9220
Validation Accuracy: 0.7359 | Loss: 0.8683
Test Accuracy: 0.6840 | Loss: 0.8739

```

```
In [150]: # visualization
epochs1 = range(len(history_dn.history['accuracy']))
plt.figure()
plt.plot(epochs1, history_dn.history['accuracy'], label='train_acc (DenseNet121)')
plt.plot(epochs1, history_dn.history['val_accuracy'], label='val_acc (DenseNet121)')
plt.title('DenseNet121 Accuracy'); plt.xlabel('Epoch'); plt.ylabel('Accuracy'); plt.legend(); plt.show()

plt.figure()
plt.plot(epochs1, history_dn.history['loss'], label='train_loss (DenseNet121)')
plt.plot(epochs1, history_dn.history['val_loss'], label='val_loss (DenseNet121)')
plt.title('DenseNet121 Loss'); plt.xlabel('Epoch'); plt.ylabel('Loss'); plt.legend(); plt.show()
```



## Model comparison

pervious testing are all using the same test data set

```
In [167]: import pandas as pd
import matplotlib.pyplot as plt

# performance df
perf_df = pd.DataFrame(perf_rows)
display(perf_df)

# sort by test acc
cols = ['Model', 'Train_Accuracy', 'Val_Accuracy', 'Test_Accuracy',
        'Train_Loss', 'Val_Loss', 'Test_Loss']
perf_summary = perf_df[cols].sort_values('Test_Accuracy', ascending=False).reset_index(drop=True)

# Hyper parameter
hparams = pd.DataFrame([
    ['BaselineCNN', 'Adam', 1e-3, 32],
    ['ResNet50', 'Adam', 1e-4, 32],
    ['VGG16', 'Adam', 3e-4, 32],
    ['InceptionV3', 'Adam', 3e-4, 32],
    ['DenseNet121', 'Adam', 3e-4, 32],
], columns=['Model','Optimizer','LR','Batch']) #check every model's hyperparameter and make them into a dataframe
perf_final = perf_summary.merge(hparams, on='Model', how='left') #merge two dfs
display(perf_final)

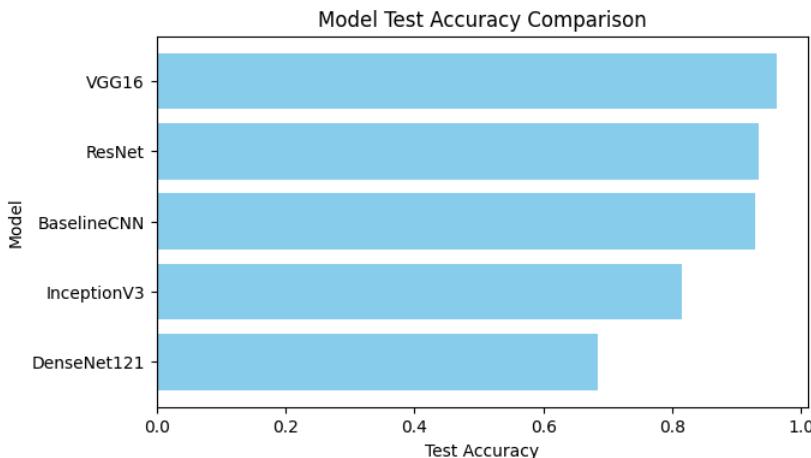
# find best model (use the test accuracy)
best = perf_summary.iloc[0]
print(f" Best model: {best['Model']} (Test Accuracy = {best['Test_Accuracy']:.4f})")
```

```
# plot the comparison of test accuracy
plt.figure(figsize=(7,4))
plt.barh(perf_summary['Model'], perf_summary['Test_Accuracy'], color='skyblue')
plt.xlabel('Test Accuracy'); plt.ylabel('Model')
plt.title('Model Test Accuracy Comparison')
plt.gca().invert_yaxis()
plt.show()
```

	Model	Type	Train_Accuracy	Val_Accuracy	Test_Accuracy	Train_Loss	Val_Loss	Test_Loss
0	BaselineCNN	baseline	0.976277	0.945355	0.928737	0.076183	0.230559	0.193557
1	ResNet	transfer	0.927007	0.901639	0.934160	0.195937	0.230559	0.159828
2	VGG16	transfer	1.000000	0.952641	0.962820	0.008862	0.139908	0.104191
3	InceptionV3	transfer	0.774635	0.826958	0.814872	0.602524	0.547989	0.534623
4	DenseNet121	transfer	0.592153	0.735883	0.683966	0.921994	0.868250	0.873892

	Model	Train_Accuracy	Val_Accuracy	Test_Accuracy	Train_Loss	Val_Loss	Test_Loss	Optimizer	LR	Batch
0	VGG16	1.000000	0.952641	0.962820	0.008862	0.139908	0.104191	Adam	0.0003	32.0
1	ResNet	0.927007	0.901639	0.934160	0.195937	0.230559	0.159828	NaN	NaN	NaN
2	BaselineCNN	0.976277	0.945355	0.928737	0.076183	0.230559	0.193557	Adam	0.0010	32.0
3	InceptionV3	0.774635	0.826958	0.814872	0.602524	0.547989	0.534623	Adam	0.0003	32.0
4	DenseNet121	0.592153	0.735883	0.683966	0.921994	0.868250	0.873892	Adam	0.0003	32.0

Best model: VGG16 (Test Accuracy = 0.9628)



The best model is VGG16 with 0.96280 test accuracy

As summarized in above table, the five models showed clear performance differences on the same test set. VGG16 achieved the highest test accuracy (0.9628) and lowest test loss (0.104), indicating the most reliable generalization. ResNet50 and Baseline CNN followed with accuracies around 0.93, while InceptionV3 (0.81) and DenseNet121 (0.68) performed worse.

Models with moderate depth and balanced fine-tuning, such as VGG16 and ResNet50, converged more stably and generalized better than deeper ones like InceptionV3 or DenseNet121, which required longer training and showed signs of underfitting. The Baseline CNN performed decently but lacked the representational power of pretrained models.

Overall, transfer-learning architectures with well-controlled complexity proved most effective under our limited training schedule, while deeper networks were less efficient and slower to converge.

**About epoch comparation:** We did not directly compare the number of epochs among models, because each architecture was defined and trained under different configurations and convergence speeds. Some models (e.g., InceptionV3, DenseNet121) have deeper structures and require more iterations to converge, while others reach optimal validation accuracy earlier. Therefore, **the number of epochs itself is not a fair indicator of performance or efficiency in this context**. Our early-stopping strategy ensured that each model was evaluated at its best validation performance rather than its final epoch.

But the best epoch of our training for each model are listed in the graphs below. (the vertical line)

### Accuracy and Loss Plot

```
In [190]: # plot in one
model_names = list(histories.keys())
n_models = len(model_names)

#big plot for all models
fig, axes = plt.subplots(2, n_models, figsize=(4*n_models, 7))
fig.suptitle("Training & Validation Curves for All Models", fontsize=16, y=1.02)

for i, (name, hist) in enumerate(histories.items()):
    H = getattr(hist, "history", {})
    acc, val_acc = H.get("accuracy", []), H.get("val_accuracy", [])
    loss, val_loss = H.get("loss", []), H.get("val_loss", [])
    epochs = range(1, max(len(acc), len(val_acc), len(loss), len(val_loss)) + 1)

    # --- Accuracy subplot ---
    ax = axes[0, i] if n_models > 1 else axes[0]
    if acc: ax.plot(epochs, acc, label="Train Acc")
    if val_acc: ax.plot(epochs, val_acc, label="Val Acc")
```

```

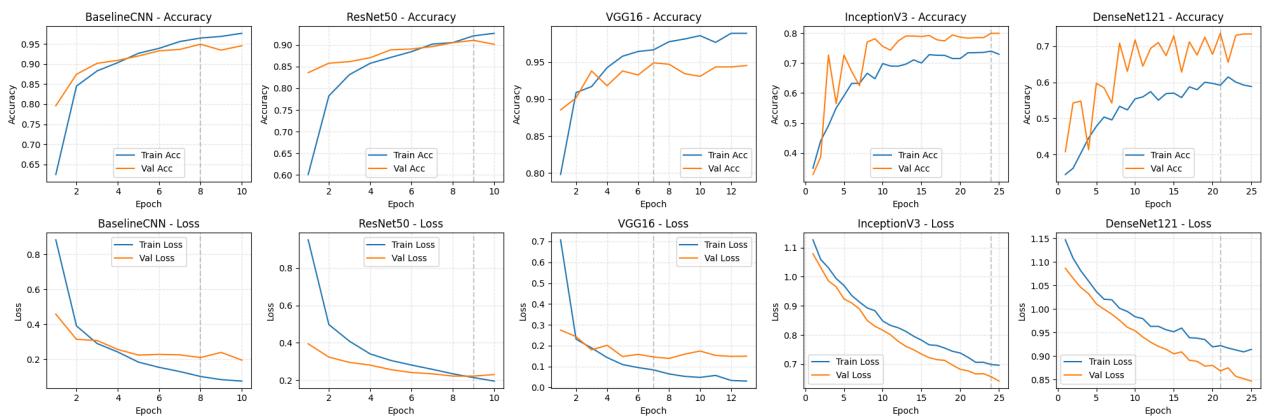
if val_acc:
    best_ep = np.argmax(val_acc) + 1
    ax.axvline(best_ep, ls="--", alpha=0.4, color='gray')
ax.set_title(f"{name} - Accuracy")
ax.set_xlabel("Epoch"); ax.set_ylabel("Accuracy")
ax.grid(ls="--", alpha=0.3)
ax.legend()

# --- Loss subplot ---
ax = axes[1, i] if n_models > 1 else axes[1]
if loss:
    ax.plot(epochs, loss, label="Train Loss")
if val_loss:
    ax.plot(epochs, val_loss, label="Val Loss")
if val_acc:
    ax.axvline(best_ep, ls="--", alpha=0.4, color='gray')
ax.set_title(f"{name} - Loss")
ax.set_xlabel("Epoch"); ax.set_ylabel("Loss")
ax.grid(ls="--", alpha=0.3)
ax.legend()

plt.tight_layout()
plt.show()

```

Training &amp; Validation Curves for All Models



## Data Augmentation

For medical images (chest X-rays), we use CONSERVATIVE augmentation:

- $\pm 5$  degrees small rotations to account for patient positioning
- $\pm 5\%$  small shifts for horizontal and vertical translations
- 95%–105% small zoom to simulate distance variations
- NO horizontal/vertical flips
- NO heavy distortions

This increases dataset size and improves model generalization without compromising the clinical validity of the images.

```
In [152]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
# Define augmentation parameters for medical images
medical_augmentation = ImageDataGenerator(
    rotation_range=5,           # Small rotation (+5 degrees)
    width_shift_range=0.05,      # Horizontal shift (+-5%)
    height_shift_range=0.05,     # Vertical shift (+-5%)
    zoom_range=0.05,            # Zoom in&out (95%-105%)
    horizontal_flip=False,       # NO flip
    vertical_flip=False,         # NO vertical flip
    fill_mode='nearest',          # Fill empty pixels with nearest values
    validation_split=0.2          # 20% for validation
)

# No augmentation for test set
test_datagen = ImageDataGenerator()
```

### Visualize Augmented Samples

```
In [154]: # Create augmentation generator for visualization
vis_augmentation = ImageDataGenerator(
    rotation_range=5,
    width_shift_range=0.05,
    height_shift_range=0.05,
    zoom_range=0.05,
    horizontal_flip=False,
    vertical_flip=False,
    fill_mode='nearest'
)

# Take a look at a sample image from training set
sample_image = X_train[0:1]

# Generate augmented versions
plt.figure(figsize=(15, 3))

# Original image
plt.subplot(1, 6, 1)
```

```

plt.imshow(sample_image[0])
plt.title('Original', fontweight='bold')
plt.axis('off')

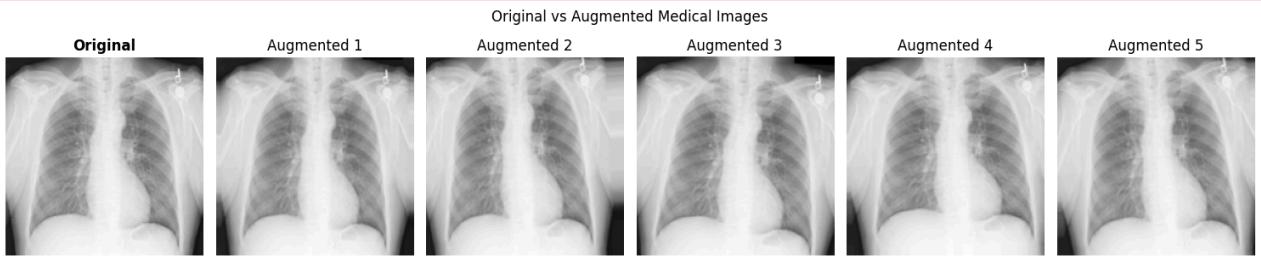
# Generate 5 augmented versions
for i in range(5):
    aug_iter = vis_augmentation.flow(sample_image, batch_size=1)
    aug_image = next(aug_iter)[0]

    plt.subplot(1, 6, i+2)
    plt.imshow(aug_image)
    plt.title(f'Augmented {i+1}')
    plt.axis('off')

plt.suptitle('Original vs Augmented Medical Images', y=1.02)
plt.tight_layout()
plt.show()

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [-0.00393700
8..0.992126].
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [-0.00393700
8..0.988189].
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [-0.00393700
8..0.9860631].

```



#### Create CNN Model with Augmentation

We'll use the same architecture as the baseline CNN, but train it with augmented data.

```

In [198]: # Create the same baseline CNN model
def create_baseline_cnn_augmented(input_shape=(192, 192, 3), num_classes=3):
    """
    Same CNN architecture to baseline model.
    """

    model = Sequential(name='Baseline_CNN_Augmented')

    # First Convolutional Block
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
                    padding='same', input_shape=input_shape, name='conv1'))
    model.add(MaxPooling2D(pool_size=(2, 2), name='pool1'))
    model.add(Dropout(0.25, name='dropout1'))

    # Second Convolutional Block
    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu',
                    padding='same', name='conv2'))
    model.add(MaxPooling2D(pool_size=(2, 2), name='pool2'))
    model.add(Dropout(0.25, name='dropout2'))

    # Third Convolutional Block
    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu',
                    padding='same', name='conv3'))
    model.add(MaxPooling2D(pool_size=(2, 2), name='pool3'))
    model.add(Dropout(0.25, name='dropout3'))

    # Flatten and fully connected layers
    model.add(Flatten(name='flatten'))
    model.add(Dense(256, activation='relu', name='fc1'))
    model.add(Dropout(0.5, name='dropout4'))
    model.add(Dense(num_classes, activation='softmax', name='output'))

    return model

```

```

In [200]: # Create the augmented CNN
cnn_augmented = create_baseline_cnn_augmented(input_shape=(192, 192, 3), num_classes=3)

```

```

In [201]: # Compile
cnn_augmented.compile(
    optimizer=Adam(learning_rate=0.001),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

# Display
cnn_augmented.summary()

```

Model: "Baseline\_CNN\_Augmented"

Layer (type)	Output Shape	Param #
conv1 (Conv2D)	(None, 192, 192, 32)	896
pool1 (MaxPooling2D)	(None, 96, 96, 32)	0
dropout1 (Dropout)	(None, 96, 96, 32)	0
conv2 (Conv2D)	(None, 96, 96, 64)	18496
pool2 (MaxPooling2D)	(None, 48, 48, 64)	0
dropout2 (Dropout)	(None, 48, 48, 64)	0
conv3 (Conv2D)	(None, 48, 48, 128)	73856
pool3 (MaxPooling2D)	(None, 24, 24, 128)	0
dropout3 (Dropout)	(None, 24, 24, 128)	0
flatten (Flatten)	(None, 73728)	0
fc1 (Dense)	(None, 256)	18874624
dropout4 (Dropout)	(None, 256)	0
output (Dense)	(None, 3)	771

Total params: 18,968,643

Trainable params: 18,968,643

Non-trainable params: 0

#### Train CNN with Augmented Data

```
In [203]: # Callbacks
callbacks_augmented = [
    EarlyStopping(
        monitor='val_loss',
        patience=5,
        restore_best_weights=True,
        verbose=1
    ),
    ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=3,
        min_lr=1e-7,
        verbose=1
    )
]

# Train with augmented data using flow()
history_cnn_augmented = cnn_augmented.fit(
    medical_augmentation.flow(X_train, y_train, batch_size=32, subset='training'),
    validation_data=medical_augmentation.flow(X_train, y_train, batch_size=32, subset='validation'),
    epochs=10,
    callbacks=callbacks_augmented,
    verbose=1
)

Epoch 1/10
69/69 [=====] - 15s 215ms/step - loss: 1.2392 - accuracy: 0.5732 - val_loss: 0.6065 - val_accuracy: 0.6405 -
lr: 0.0010
Epoch 2/10
69/69 [=====] - 14s 203ms/step - loss: 0.5319 - accuracy: 0.7246 - val_loss: 0.5164 - val_accuracy: 0.7336 -
lr: 0.0010
Epoch 3/10
69/69 [=====] - 14s 202ms/step - loss: 0.4611 - accuracy: 0.7715 - val_loss: 0.5186 - val_accuracy: 0.7536 -
lr: 0.0010
Epoch 4/10
69/69 [=====] - 14s 203ms/step - loss: 0.4302 - accuracy: 0.7953 - val_loss: 0.4266 - val_accuracy: 0.8230 -
lr: 0.0010
Epoch 5/10
69/69 [=====] - 16s 236ms/step - loss: 0.3940 - accuracy: 0.8313 - val_loss: 0.3967 - val_accuracy: 0.8577 -
lr: 0.0010
Epoch 6/10
69/69 [=====] - 14s 203ms/step - loss: 0.3501 - accuracy: 0.8627 - val_loss: 0.4115 - val_accuracy: 0.8376 -
lr: 0.0010
Epoch 7/10
69/69 [=====] - 14s 202ms/step - loss: 0.3223 - accuracy: 0.8586 - val_loss: 0.3835 - val_accuracy: 0.8613 -
lr: 0.0010
Epoch 8/10
69/69 [=====] - 16s 237ms/step - loss: 0.2940 - accuracy: 0.8801 - val_loss: 0.3410 - val_accuracy: 0.8796 -
lr: 0.0010
Epoch 9/10
69/69 [=====] - 17s 238ms/step - loss: 0.2624 - accuracy: 0.8883 - val_loss: 0.3092 - val_accuracy: 0.8905 -
lr: 0.0010
Epoch 10/10
69/69 [=====] - 14s 203ms/step - loss: 0.2522 - accuracy: 0.8919 - val_loss: 0.3677 - val_accuracy: 0.8832 -
lr: 0.0010
```

#### Evaluate CNN with Augmentation

```
In [205]: # Evaluate test set
test_loss_augmented, test_acc_augmented = cnn_augmented.evaluate(X_test, y_test, verbose=0)
```

```

print(f"Test Loss: {test_loss_augmented:.4f}")
print(f"Test Accuracy: {test_acc_augmented:.4f} ({test_acc_augmented*100:.2f}%)")

# Final training and validation accuracy and loss
final_train_acc_aug = history_cnn_augmented.history['accuracy'][-1]
final_train_loss_aug = history_cnn_augmented.history['loss'][-1]
final_val_acc_aug = history_cnn_augmented.history['val_accuracy'][-1]
final_val_loss_aug = history_cnn_augmented.history['val_loss'][-1]

print(f"\nFinal Training Accuracy: {final_train_acc_aug:.4f} ({final_train_acc_aug*100:.2f}%)")
print(f"Final Validation Accuracy: {final_val_acc_aug:.4f} ({final_val_acc_aug*100:.2f}%)")

```

Test Loss: 0.2785  
 Test Accuracy: 0.9032 (90.32%)  
 Final Training Accuracy: 0.8919 (89.19%)  
 Final Validation Accuracy: 0.8832 (88.32%)

#### Visualize Augmented CNN Training History

Training curves for CNN with augmentation

```

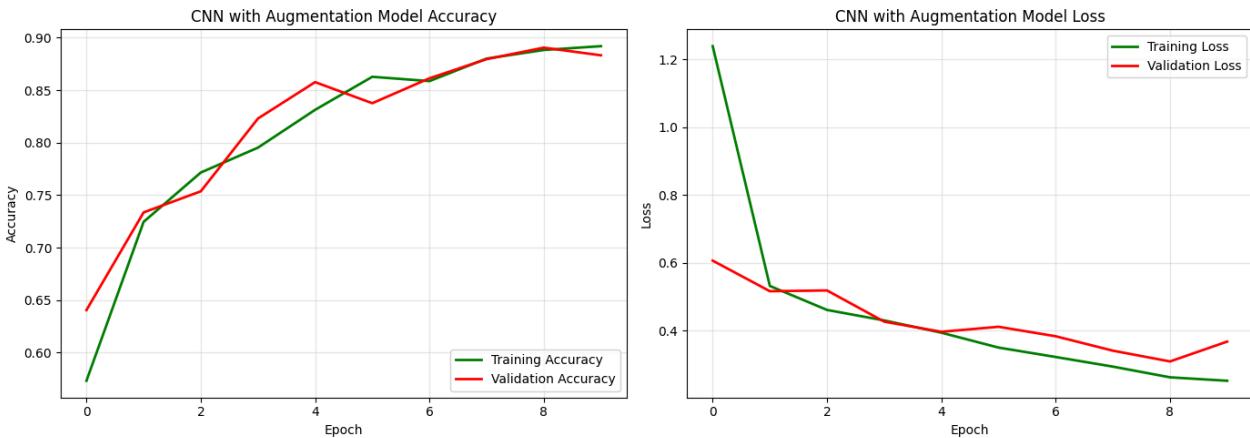
In [207]: fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Training & validation accuracy
axes[0].plot(history_cnn_augmented.history['accuracy'], label='Training Accuracy', linewidth=2, color='green')
axes[0].plot(history_cnn_augmented.history['val_accuracy'], label='Validation Accuracy', linewidth=2, color='red')
axes[0].set_title('CNN with Augmentation Model Accuracy')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Accuracy')
axes[0].legend(loc='lower right')
axes[0].grid(True, alpha=0.3)

# Training & validation loss
axes[1].plot(history_cnn_augmented.history['loss'], label='Training Loss', linewidth=2, color='green')
axes[1].plot(history_cnn_augmented.history['val_loss'], label='Validation Loss', linewidth=2, color='red')
axes[1].set_title('CNN with Augmentation Model Loss')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Loss')
axes[1].legend(loc='upper right')
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

```



## Interpretability & Insights

### Best model: VGG16.

By both accuracy and loss, VGG16 is the clear winner (Test Acc = 0.9628, Loss = 0.104). ResNet50 and Baseline CNN follow (~0.93 acc; losses 0.160 and 0.194), while InceptionV3 (0.815; 0.535) and DenseNet121 (0.684; 0.874) lag behind.

### Why VGG16 wins (with evidence):

- Stable generalization: Train vs. val gap is small (Train Acc 1.00 vs. Val Acc 0.953), and the learning curves rise smoothly without late-epoch divergence—consistent with good regularization and early stopping.
- Right complexity for our data/epochs: VGG16's simple 3x3 conv blocks transfer well with partial fine-tuning. Deeper nets (InceptionV3/DenseNet121) likely needed more compute/epochs to reach their potential; their curves plateau early (underfitting) and keep higher validation loss.
- Efficiency–performance trade-off: Compared with DenseNet121/InceptionV3, VGG16 reached higher accuracy with less training instability and lower test loss, making it the most reliable choice under our constraints.

### Practical utility of the best model (VGG16)

#### Who benefits

Practitioners who need high accuracy with predictable training: teaching labs, small research groups, and product teams with limited GPU time.

Domain analysts/clinicians (if this is medical imaging): teams needing a strong pretrained backbone that is easy to validate and monitor.

## Real-world scenarios

Screening & triage: high-recall pre-filtering to flag likely positives before expert review.

Quality control pipelines: stable feature extractor for consistent batch inference.

Dataset labeling/active learning: reliable pseudo-labels to prioritize uncertain samples.

Edge/near-real-time inference (light servers): VGG16 is heavier than MobileNet but simpler/more predictable than very deep nets; with pruning/INT8 it can meet latency targets.

## Conclusion

Given the metrics (highest test accuracy, lowest test loss) and the smooth, well-behaved training curves, VGG16 offers the best balance of accuracy, stability, and practicality for our current data size and compute budget.

In [ ]: