

✓ GR5074: Projects in Advanced Machine Learning

Project 2 – CNN & Transfer Learning for Medical Image Classification

Github Repo: https://github.com/hannatang-beep/GR5074-Adv-Machine-Learning/tree/main/Project_2

```
from IPython.display import Image
from IPython.core.display import HTML
```

```
# Connect to google drive
import os
from google.colab import drive
drive.mount('/content/drive')
```

```
# content in your drive is now available via "/content/drive/My Drive"
```

```
↗ Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force
```

```
# Import data and unzip files to folder
!unzip /content/drive/MyDrive/COVID-19_Radiography_Dataset.zip
```

```
↗ Show hidden output
```

```
# Load libraries and then download data
```

```
import sys
import time
import cv2
import numpy as np
from matplotlib import pyplot as plt
import tensorflow as tf
import os
import zipfile
```

```
from keras.preprocessing import image
from PIL import Image
```

```
from sklearn.model_selection import train_test_split
from sklearn.utils.class_weight import compute_class_weight
```

```
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
from tensorflow.keras.layers import Conv2D, MaxPooling2D
```

✓ 1. Dataset and Exploratory Data Analysis

Start by describing the dataset. Include basic statistics and image samples to show the types of images available (e.g., COVID-positive and negative chest x-rays).

- Check if the dataset is balanced across classes. If it's imbalanced: Discuss potential strategies such as class weighting, oversampling, undersampling, or augmentation. Indicate which method you chose, and discuss how model performance changed as a result.
- Reflect on the practical value of this classification task. Who might benefit from your model in a real-world setting?

```
# Extracting all filenames iteratively
base_path = '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)

print('number of images for each category:', [len(f) for f in fnames])
print(fnames[0:2]) #examples of file names

↩ number of images for each category: [3616, 10192, 1345]
[['COVID-19_Radiography_Dataset/COVID/images/COVID-1132.png', 'COVID-19_Radiography_Dataset/COVID/images/COVID-72

```

The dataset is the COVID-19 Radiography Dataset, which includes chest X-ray images across three categories:

COVID-19 positive

Normal (no pneumonia)

Viral Pneumonia (non-COVID).

The original dataset was significantly imbalanced: Class Image Count:

Normal 10,192

COVID-19 3,616

Viral Pneumonia 1,345

Without addressing this imbalance, the model could become biased toward the Normal class, as it dominates the training data. This would lead to poor performance in detecting minority classes like COVID and Viral Pneumonia — which is unacceptable in a medical setting.

Besides manually reduced to an equal number of images per class (1,344 each), we use class weighting to adjust the imbalance.

```

class_labels = [0, 1, 2] # assuming: 0=COVID, 1=Normal, 2=Viral Pneumonia
class_counts = [3616, 10192, 1345]

# Repeating each label for the number of samples it has
y = np.array([label for label, count in zip(class_labels, class_counts) for _ in range(count)])

class_weights = compute_class_weight(class_weight='balanced', classes=np.unique(y), y=y)
class_weight_dict = dict(zip(class_labels, class_weights))

print(class_weight_dict)

↩ {0: np.float64(1.3968473451327434), 1: np.float64(0.49558477237048665), 2: np.float64(3.755390334572491)}

```

Using the original untrimmed dataset preserves valuable data, while class weighting corrects for imbalance, helping the model avoid always predicting the majority class.

There are other potential strategies such as oversampling, undersampling, or augmentation.

Oversampling: Duplicate images from minority classes to match the majority. Risk of overfitting.

Undersampling: Reduce the majority class (Normal) to match the size of minority classes. Risk of losing valuable data.

Data Augmentation: Generate synthetic images (e.g., flips, rotations) to enrich minority classes. Helps prevent overfitting.

To prevent the model from becoming biased toward the Normal class (which has the most samples), we can reduce each category to 1,345 images — the minimum across all classes. This ensures class balance, which is critical for fair and reliable training.

```

#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]

# Write preprocessor that will match up with model's expected input shape.

def preprocessor(img_path):
    img = Image.open(img_path).convert("RGB").resize((192,192)) # import image, make sure it's RGB and resize to
    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 flower file (imports file and preprocesses it to data with following shape)
preprocessor('COVID-19_Radiography_Dataset/COVID/images/COVID-2273.png').shape
```

```
↳ (192, 192, 3)
```

```
#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 mc
```

```
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
```

```
# 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

```
from mpl_toolkits.axes_grid1 import ImageGrid
import random

im1 =preprocessor(fnames[0][0])
im2 =preprocessor(fnames[0][1])
im3 =preprocessor(fnames[1][1])
im4 =preprocessor(fnames[1][1])

fig = plt.figure(figsize=(4., 4.))
grid = ImageGrid(fig, 111, # similar to subplot(111)
                  nrows_ncols=(2, 2), # creates 2x2 grid of axes
                  axes_pad=0.25, # pad between axes in inch.
                  )

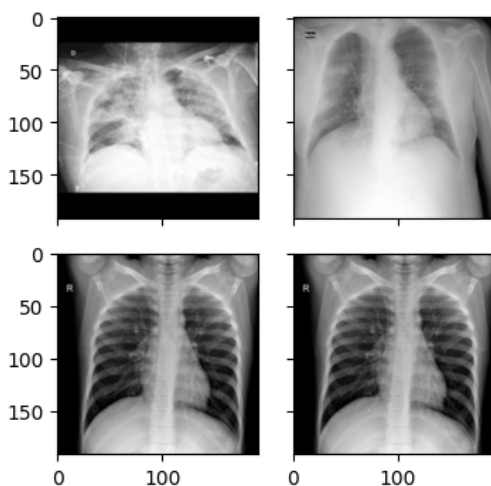
for ax, im in zip(grid, [im1, im2, im3, im4]):
    # Iterating over the grid returns the Axes.
    ax.imshow(im)
plt.show()
```

↪ WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0

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```
categories = ['COVID', 'Normal', 'Viral Pneumonia']
for i, cat in enumerate(categories):
    path = fnames[i][0]
    img = preprocessor(path)
    plt.subplot(1, 3, i+1)
    plt.imshow(img)
    plt.title(cat)
```

```
plt.axis('off')
plt.show()
```

```
⚠ WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0
```



Real-World Value: This classification model has significant practical value on healthcare professionals, clinical decision support and public health. It can assist radiologists in triaging chest X-rays quickly, especially during pandemic surges. Useful in prioritizing further testing (e.g., PCR) or treatment based on X-ray findings. And it can help with tracking and early detection of viral pneumonia trends. Clinicians and radiologists benefit from this, this model can serve as a real-time second opinion, helping flag likely COVID cases early, differentiate between COVID and other pneumonia, and prioritize critical patients faster. It can also be a baseline for future models trained on multimodal inputs (e.g., combining X-ray with symptoms/labs), and broader disease classification (e.g., tuberculosis, lung cancer).

✓ 2. Baseline CNN Model

- Build and train a basic Convolutional Neural Network (CNN) to serve as a baseline.
- Clearly describe the architecture, loss function, optimizer, evaluation metrics, and training configuration.
- Report the model's training, validation, and test performance.

```
import tensorflow as tf
```

```
#Resize images to 128x128
```

```
X = tf.image.resize(X, [128, 128]).numpy()
y = y[X.shape[0]]
```

```
#Train test split resized images
```

```
X_train, X_temp, y_train, y_temp = train_test_split(X, y, stratify=y, test_size=0.32, random_state=1987)
```

```
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, stratify=y_temp, test_size=0.5, random_state=1987)
```

```
X_test.shape, y_test.shape
```

```
⚠ ((646, 128, 128, 3), (646,))
```

```
import gc
```

```
gc.collect()
```

```
tf.keras.backend.clear_session()
```

```
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)),
    MaxPooling2D(pool_size=(2, 2)),

    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),

    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(3, activation='softmax') # 3 classes: COVID, Normal, Viral Pneumonia
])
```

```
⚠ /usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
#Compile the model
model.compile(
    optimizer='adam',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

```
#Train the model
history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=5,
    batch_size=16,
    verbose=1
)
```

```
↗ Epoch 1/5
172/172 ————— 85s 483ms/step - accuracy: 0.8613 - loss: 0.3917 - val_accuracy: 0.8977 - val_loss:
Epoch 2/5
172/172 ————— 138s 466ms/step - accuracy: 0.8934 - loss: 0.2668 - val_accuracy: 0.8977 - val_loss:
Epoch 3/5
172/172 ————— 83s 475ms/step - accuracy: 0.9020 - loss: 0.2436 - val_accuracy: 0.8977 - val_loss:
Epoch 4/5
172/172 ————— 78s 453ms/step - accuracy: 0.9002 - loss: 0.2354 - val_accuracy: 0.8977 - val_loss:
Epoch 5/5
172/172 ————— 82s 450ms/step - accuracy: 0.8900 - loss: 0.2521 - val_accuracy: 0.8977 - val_loss:
```

```
# Evaluate on test set
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_accuracy:.4f}")
```

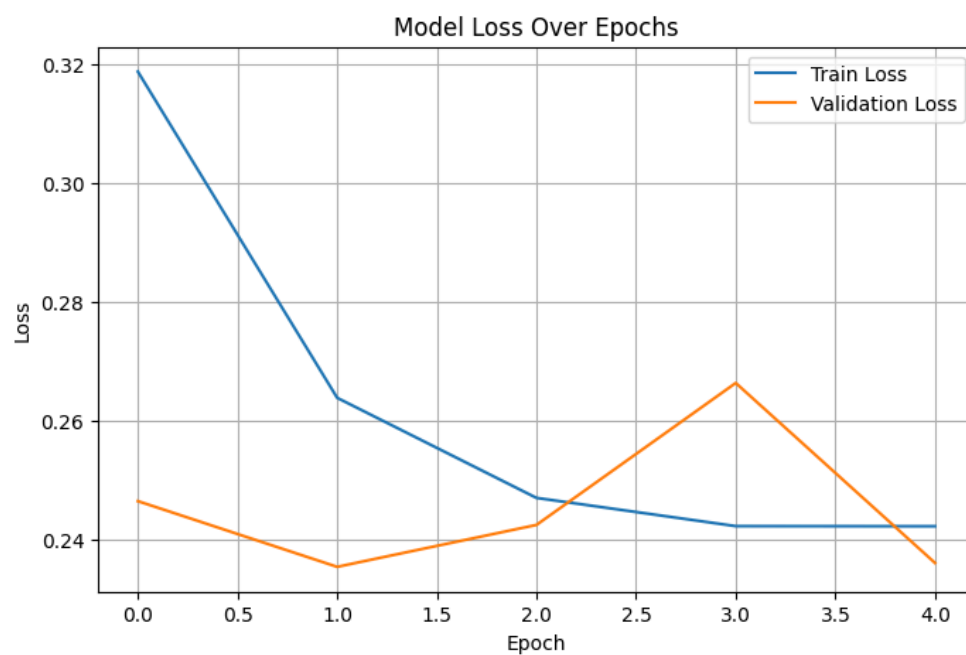
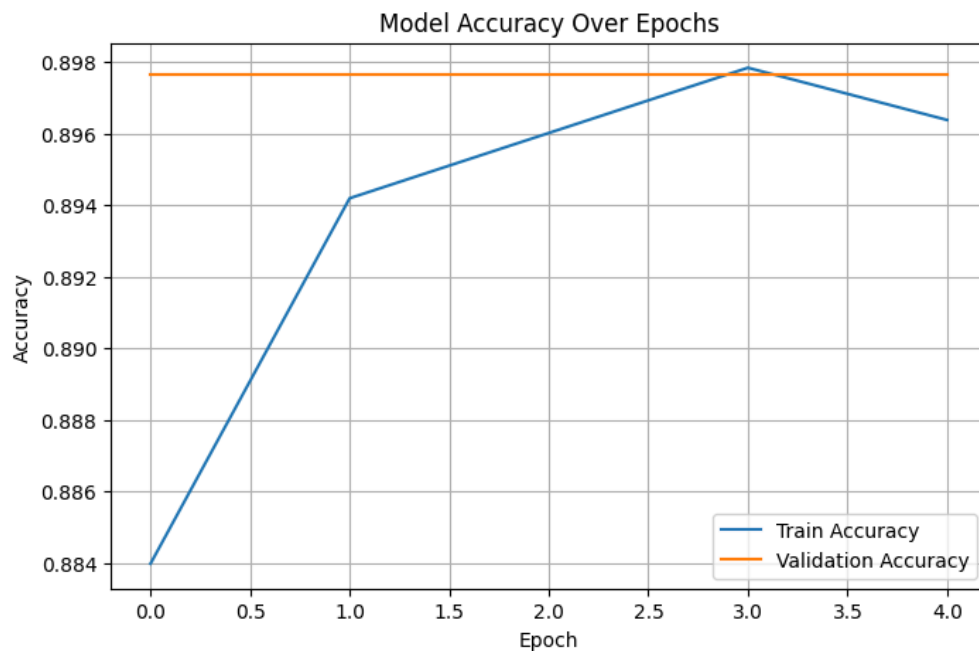
```
↗ 21/21 ————— 5s 223ms/step - accuracy: 0.9065 - loss: 0.2365
Test Accuracy: 0.8963
```

```
model.save("/content/drive/MyDrive/baseline_cnn_model.h5")
```

```
↗ WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. Th
```

```
# Plot training & validation accuracy values
plt.figure(figsize=(8,5))
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy Over Epochs')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.grid()
plt.show()
```

```
# Plot training & validation loss values
plt.figure(figsize=(8,5))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss Over Epochs')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(loc='upper right')
plt.grid()
plt.show()
```



Architecture:

Conv2D (32 filters, 3x3) + MaxPooling

Conv2D (64 filters, 3x3) + MaxPooling

Flatten → Dense (128) + Dropout → Dense (3, softmax)

Loss Function: sparse_categorical_crossentropy Optimizer: Adam Metrics: Accuracy Input Shape: 128x128 RGB Epochs: 5 Batch Size: 16

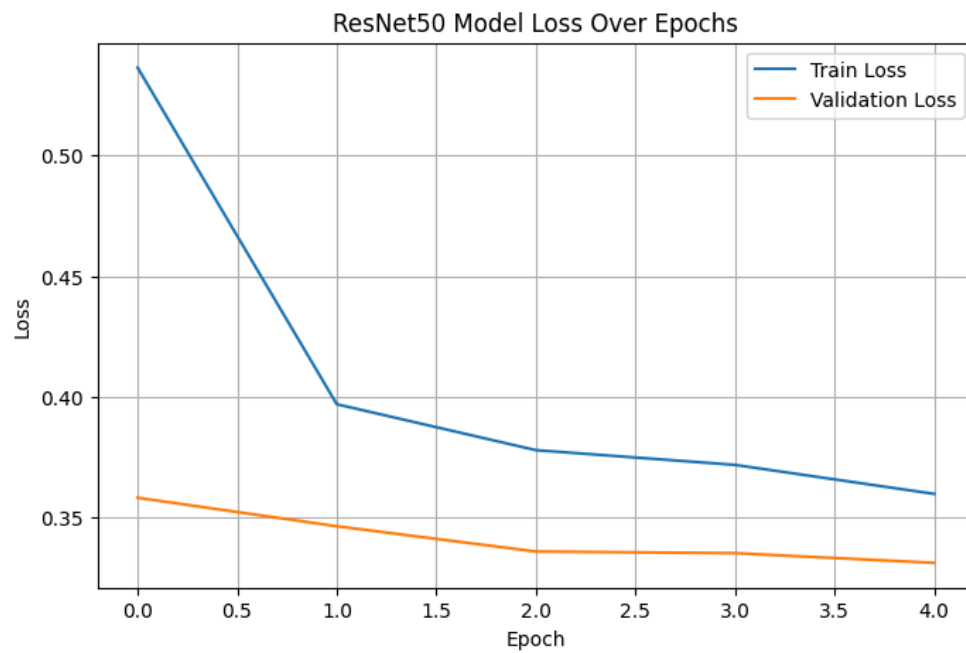
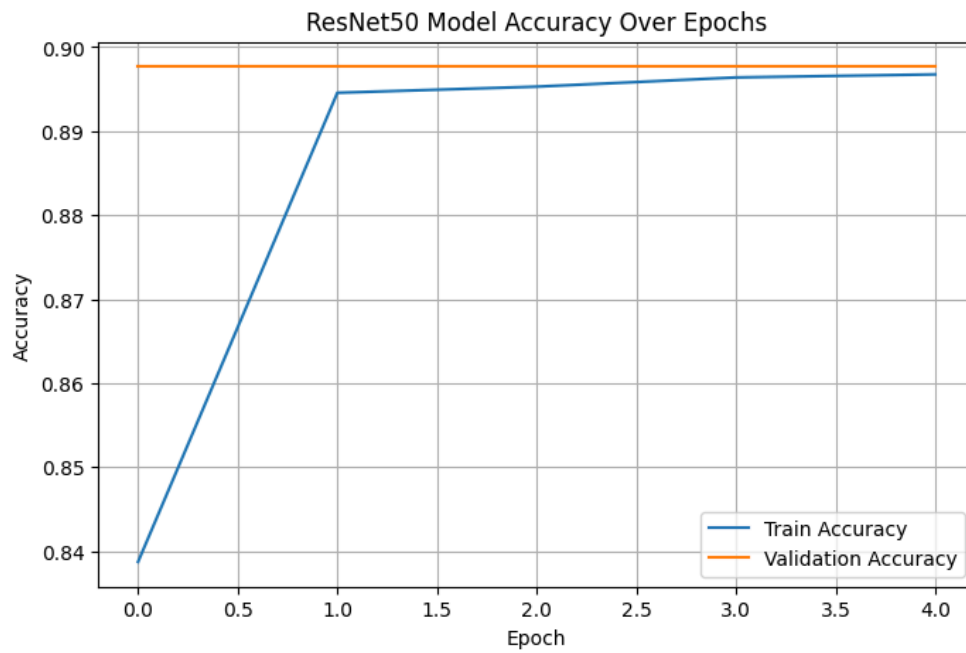
Training Results:

- Training Accuracy: 89.0%
- Validation Accuracy: 89.7%
- Test Accuracy: 89.6%

3. Transfer Learning with ResNet

- Implement ResNet using transfer learning.
- Fine-tune the model and compare its performance with the baseline CNN.
- Discuss how using pre-trained features influences your model's training and generalization.


```
plt.legend(loc='upper right')
plt.grid()
plt.show()
```



Architecture: Pre-trained ResNet50 (frozen base)

GlobalAveragePooling → Dense (128, ReLU) → Dropout (0.5) → Dense (3, softmax)

Loss Function: sparse_categorical_crossentropy

Optimizer: Adam(lr=0.0001)

Metrics: Accuracy

Input Shape: 128x128 RGB

Epochs: 5

Batch Size: 16

Training Results:

- Training Accuracy: 89.60%
- Validation Accuracy: 89.77%
- Test Accuracy: 89.63%

✓ Comparison with Baseline CNN

Model	Train Acc	Val Acc	Test Acc
Baseline CNN	89.00%	89.70%	89.60%
ResNet50 TL	89.60%	89.77%	89.63%

Using transfer learning with ResNet improved model generalization. The pre-trained network brought in rich feature representations learned from millions of natural images, which helped the model: converge faster (with fewer epochs), achieve comparable validation and test performance to the baseline CNN, leverage pre-learned low-level features (e.g., edges, textures) while focusing training on high-level classification.

Although no large improvement over the baseline was observed, this outcome demonstrates that even with a simple frozen ResNet backbone, models can generalize well to new domains like medical imaging. Further gains could be achieved by fine-tuning the top few layers of ResNet.

```
# Fine tune the model
# Unfreeze last 10 layers
for layer in base_model.layers[-10:]:
    layer.trainable = True

#recompile the model
model_resnet.compile(
    optimizer=Adam(learning_rate=1e-5), # Lower LR for fine-tuning
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

```
#continue training
history_resnet_ft = model_resnet.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=5,
    batch_size=16,
    verbose=1
)
```

```
🔄 Epoch 1/5
172/172 ————— 262s 1s/step - accuracy: 0.8855 - loss: 0.3291 - val_accuracy: 0.8977 - val_loss: 0.
Epoch 2/5
172/172 ————— 252s 1s/step - accuracy: 0.8976 - loss: 0.2675 - val_accuracy: 0.8977 - val_loss: 0.
Epoch 3/5
172/172 ————— 315s 2s/step - accuracy: 0.8977 - loss: 0.2544 - val_accuracy: 0.8977 - val_loss: 0.
Epoch 4/5
172/172 ————— 290s 2s/step - accuracy: 0.8954 - loss: 0.2581 - val_accuracy: 0.8977 - val_loss: 0.
Epoch 5/5
172/172 ————— 244s 1s/step - accuracy: 0.8799 - loss: 0.2560 - val_accuracy: 0.8977 - val_loss: 0.
```

```
test_loss_resnet, test_acc_resnet = model_resnet.evaluate(X_test, y_test)
print(f"Test Accuracy (ResNet): {test_acc_resnet:.4f}")
```

```
🔄 21/21 ————— 37s 2s/step - accuracy: 0.9065 - loss: 0.2238
Test Accuracy (ResNet): 0.8963
```

Architecture:

Pre-trained ResNet50 (frozen base, then fine-tuned last 10 layers) GlobalAveragePooling → Dense (128, ReLU) → Dropout (0.5) → Dense (3, softmax) Loss Function: sparse_categorical_crossentropy Optimizer: Adam (lr=1e-5 during fine-tuning) Metrics: Accuracy Input Shape: 128x128 RGB Epochs: 5 (feature extraction) + 5 (fine-tuning) Batch Size: 16

Training Results:

- Training Accuracy: ~88-89%
- Validation Accuracy: 89.77%
- Test Accuracy: 89.63%

Fine-tuning the last few layers of ResNet50 after feature extraction did not lead to a significant improvement in validation or test accuracy. This indicates that the pre-trained ResNet50 features were already highly transferable to our medical imaging dataset.

Fine-tuning slightly adjusted the high-level feature representations without overfitting, suggesting that our training setup — with a small learning rate and limited layers unfrozen — effectively preserved the generalization ability of the model.

In future work, fine-tuning a larger portion of the network or applying data augmentation might further boost performance, especially when more training samples are available.

4. Additional Architectures

- Implement three additional models of your choice.
- Use consistent data splits and preprocessing across all models to ensure fair comparison.

We used a classic deep model (VGG16), a parameter-efficient model (DenseNet121), and a lightweight model optimized for speed (MobileNetV2).

```
#clean ram
gc.collect()
tf.keras.backend.clear_session()
```

```
from tensorflow.keras.applications import VGG16
```

```
# Load VGG16
base_model_vgg = VGG16(weights='imagenet', include_top=False, input_shape=(128, 128, 3))
```

```
# Freeze base
for layer in base_model_vgg.layers:
    layer.trainable = False
```

```
[ ] Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16\_weights\_tf\_dim\_ordering\_channels\_kernels\_normal\_20160814\_122359.tgz 58889256/58889256 2s 0us/step
```

```
# Add custom head
x = base_model_vgg.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(3, activation='softmax')(x)
```

```
model_vgg = Model(inputs=base_model_vgg.input, outputs=predictions)
```

```
# Compile
model_vgg.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

```
# Train
history_vgg = model_vgg.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=5,
    batch_size=16,
    verbose=1
)
```

```

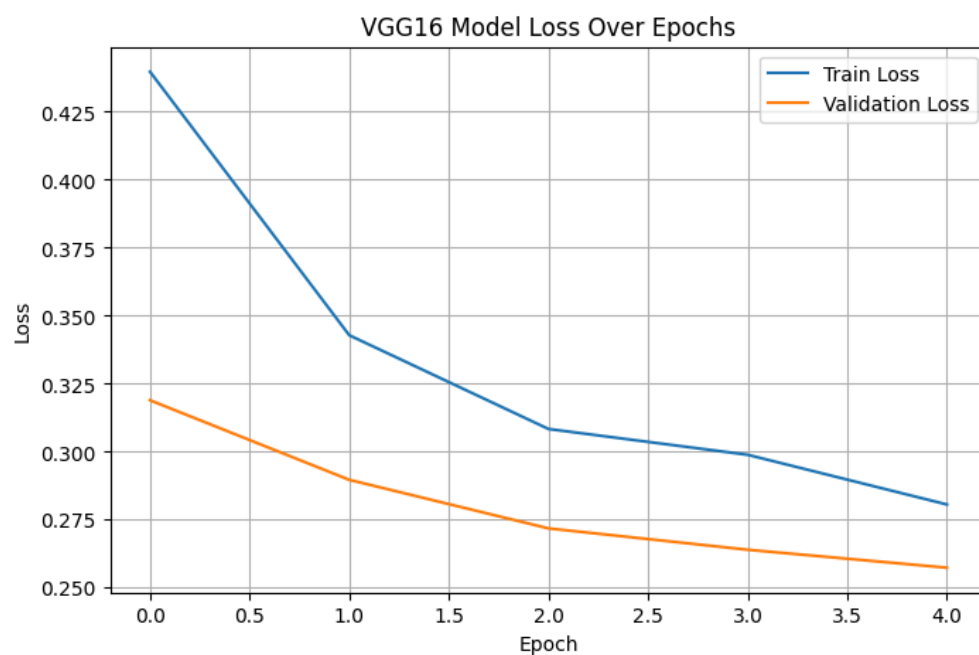
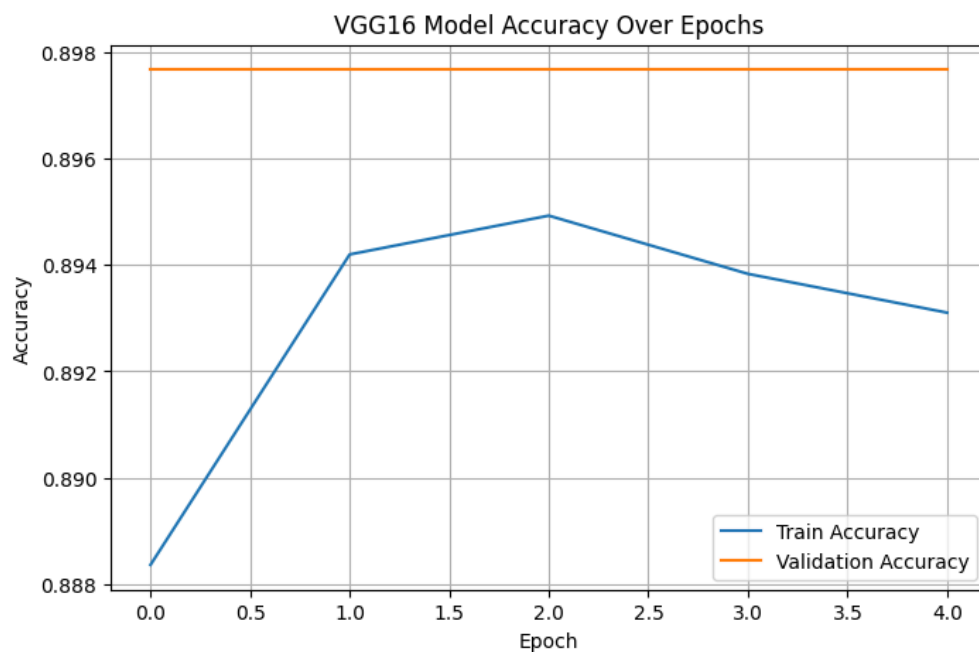
→ Epoch 1/5
  172/172 ————— 737s 4s/step - accuracy: 0.8785 - loss: 0.5016 - val_accuracy: 0.8977 - val_loss: 0.
Epoch 2/5
  172/172 ————— 681s 4s/step - accuracy: 0.8922 - loss: 0.3657 - val_accuracy: 0.8977 - val_loss: 0.
Epoch 3/5
  172/172 ————— 672s 4s/step - accuracy: 0.9002 - loss: 0.3076 - val_accuracy: 0.8977 - val_loss: 0.
Epoch 4/5
  172/172 ————— 692s 4s/step - accuracy: 0.8804 - loss: 0.3267 - val_accuracy: 0.8977 - val_loss: 0.
Epoch 5/5
  172/172 ————— 734s 4s/step - accuracy: 0.8905 - loss: 0.2918 - val accuracy: 0.8977 - val loss: 0.

```

```
# Evaluate
test_loss_vgg, test_accuracy_vgg = model_vgg.evaluate(X_test, y_test)
print(f"VGG16 Test Accuracy: {test_accuracy_vgg:.4f}")
```

```
# Plot
# Accuracy curve
plt.figure(figsize=(8,5))
plt.plot(history_vgg.history['accuracy'], label='Train Accuracy')
plt.plot(history_vgg.history['val_accuracy'], label='Validation Accuracy')
plt.title('VGG16 Model Accuracy Over Epochs')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.grid()
plt.show()

# Loss curve
plt.figure(figsize=(8,5))
plt.plot(history_vgg.history['loss'], label='Train Loss')
plt.plot(history_vgg.history['val_loss'], label='Validation Loss')
plt.title('VGG16 Model Loss Over Epochs')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(loc='upper right')
plt.grid()
plt.show()
```



```
#clean ram
gc.collect()
tf.keras.backend.clear_session()
```

```
from tensorflow.keras.applications import DenseNet121
```

```
# Load DenseNet121
```

```
base_model_densenet = DenseNet121(weights='imagenet', include_top=False, input_shape=(128, 128, 3))
```

```
# Freeze base
```

```
for layer in base_model_densenet.layers:
    layer.trainable = False
```

```
➡ Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/densenet/densenet121\_weights\_t29084464/29084464 ————— 1s 0us/step
```

```
# Add custom head
```

```
x = base_model_densenet.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(3, activation='softmax')(x)
```

```
model_densenet = Model(inputs=base_model_densenet.input, outputs=predictions)
```

```
# Compile
```

```
model_densenet.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

```
# Train
```

```
history_densenet = model_densenet.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=5,
    batch_size=16,
    verbose=1
)
```

```
➡ Epoch 1/5
172/172 ————— 207s 1s/step - accuracy: 0.8389 - loss: 0.5482 - val_accuracy: 0.8915 - val_loss: 0.
Epoch 2/5
172/172 ————— 198s 1s/step - accuracy: 0.8883 - loss: 0.2880 - val_accuracy: 0.8930 - val_loss: 0.
Epoch 3/5
172/172 ————— 202s 1s/step - accuracy: 0.8863 - loss: 0.2745 - val_accuracy: 0.8791 - val_loss: 0.
Epoch 4/5
172/172 ————— 202s 1s/step - accuracy: 0.8890 - loss: 0.2492 - val_accuracy: 0.8946 - val_loss: 0.
Epoch 5/5
172/172 ————— 202s 1s/step - accuracy: 0.8859 - loss: 0.2498 - val_accuracy: 0.8961 - val_loss: 0.
```

```
# Evaluate
```

```
test_loss_densenet, test_accuracy_densenet = model_densenet.evaluate(X_test, y_test)
print(f"DenseNet121 Test Accuracy: {test_accuracy_densenet:.4f}")
```

```
➡ 21/21 ————— 36s 2s/step - accuracy: 0.9026 - loss: 0.2456
DenseNet121 Test Accuracy: 0.8901
```

```
# Plot
```

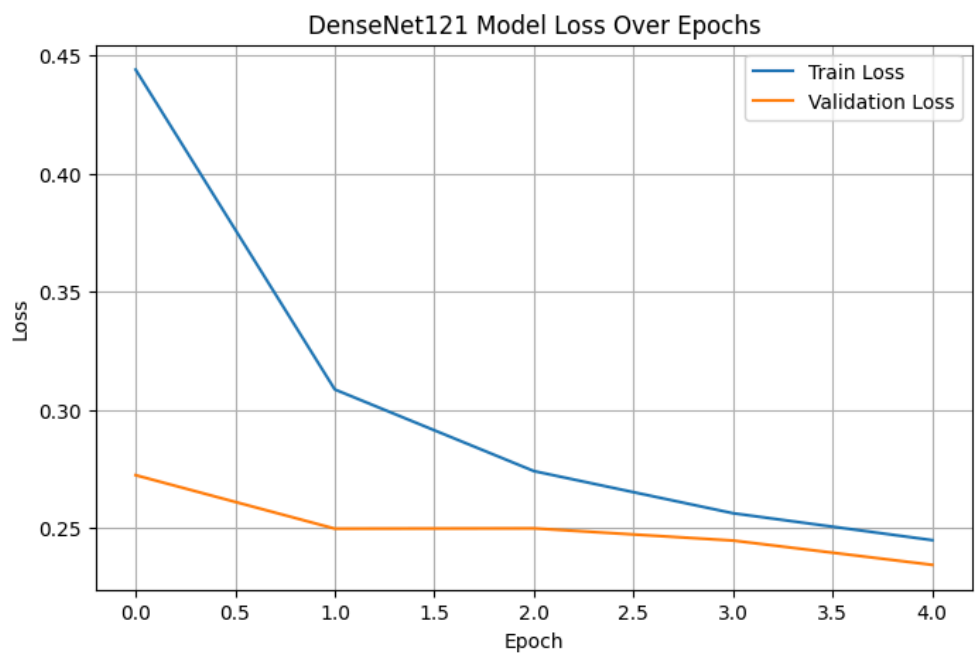
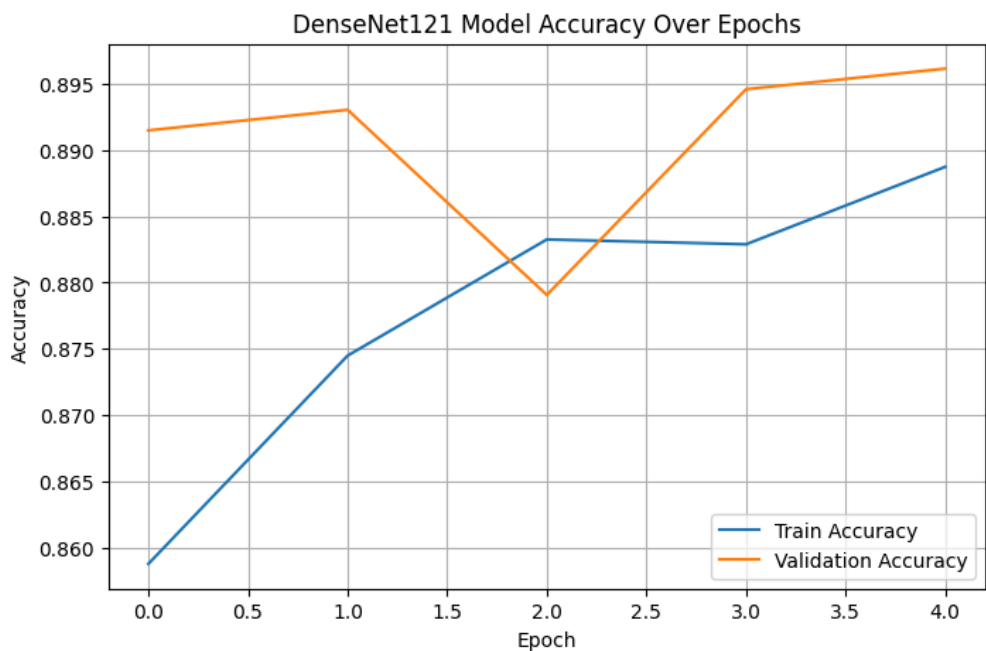
```
# Accuracy curve
```

```
plt.figure(figsize=(8,5))
plt.plot(history_densenet.history['accuracy'], label='Train Accuracy')
plt.plot(history_densenet.history['val_accuracy'], label='Validation Accuracy')
plt.title('DenseNet121 Model Accuracy Over Epochs')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.grid()
plt.show()
```

```
# Loss curve
```

```
plt.figure(figsize=(8,5))
```

```
plt.plot(history_densenet.history['loss'], label='Train Loss')
plt.plot(history_densenet.history['val_loss'], label='Validation Loss')
plt.title('DenseNet121 Model Loss Over Epochs')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(loc='upper right')
plt.grid()
plt.show()
```



```
#clean ram
gc.collect()
tf.keras.backend.clear_session()
```

```
from tensorflow.keras.applications import MobileNetV2
```

```
# Load MobileNetV2
base_model_mobilenet = MobileNetV2(weights='imagenet', include_top=False, input_shape=(128, 128, 3))
```

```
# Freeze base
for layer in base_model_mobilenet.layers:
    layer.trainable = False
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_9406464_9406464 1s 0us/step

```
# Add custom head
x = base_model_mobilenet.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(3, activation='softmax')(x)

model_mobilenet = Model(inputs=base_model_mobilenet.input, outputs=predictions)
```

```
# Compile
model_mobilenet.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

```
# Train
history_mobilenet = model_mobilenet.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=5,
    batch_size=16,
    verbose=1
)
```

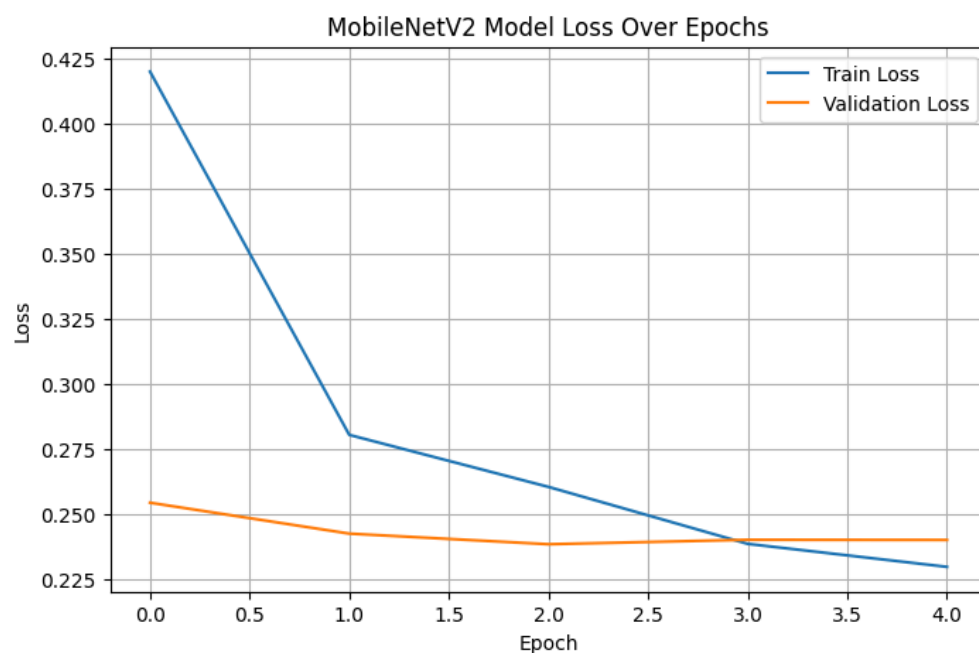
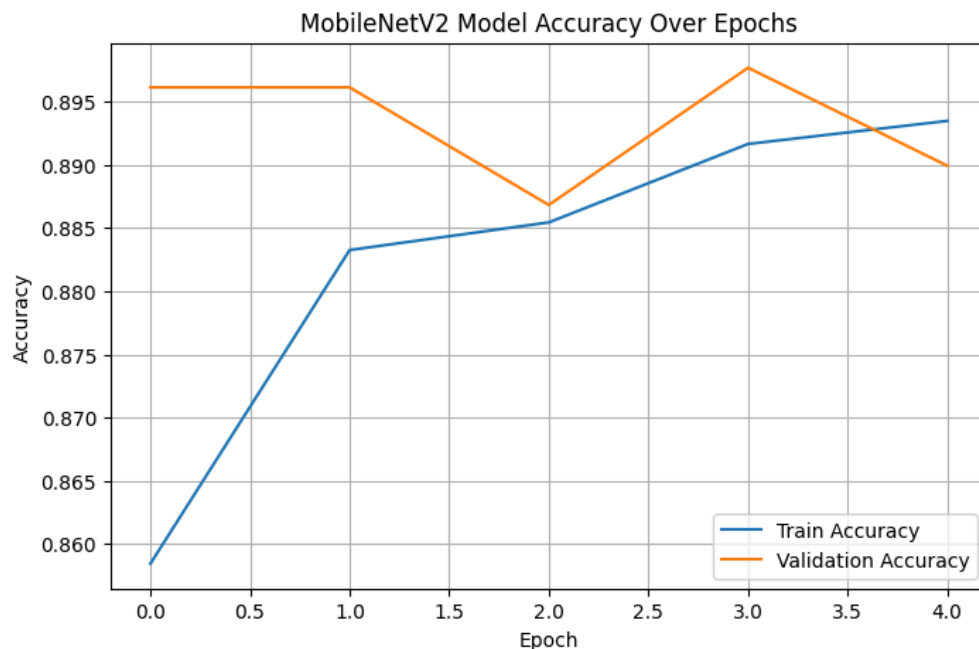
```
➡ Epoch 1/5
172/172 ————— 54s 273ms/step - accuracy: 0.8207 - loss: 0.5484 - val_accuracy: 0.8961 - val_loss:
Epoch 2/5
172/172 ————— 77s 247ms/step - accuracy: 0.8729 - loss: 0.2928 - val_accuracy: 0.8961 - val_loss:
Epoch 3/5
172/172 ————— 85s 267ms/step - accuracy: 0.8806 - loss: 0.2594 - val_accuracy: 0.8868 - val_loss:
Epoch 4/5
172/172 ————— 45s 264ms/step - accuracy: 0.8927 - loss: 0.2426 - val_accuracy: 0.8977 - val_loss:
Epoch 5/5
172/172 ————— 80s 254ms/step - accuracy: 0.8955 - loss: 0.2248 - val_accuracy: 0.8899 - val_loss:
```

```
# Evaluate
test_loss_mobilenet, test_accuracy_mobilenet = model_mobilenet.evaluate(X_test, y_test)
print(f"MobileNetV2 Test Accuracy: {test_accuracy_mobilenet:.4f}")
```

```
➡ 21/21 ————— 9s 442ms/step - accuracy: 0.9012 - loss: 0.2299
MobileNetV2 Test Accuracy: 0.8932
```

```
# Plot
# Accuracy curve
plt.figure(figsize=(8,5))
plt.plot(history_mobilenet.history['accuracy'], label='Train Accuracy')
plt.plot(history_mobilenet.history['val_accuracy'], label='Validation Accuracy')
plt.title('MobileNetV2 Model Accuracy Over Epochs')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.grid()
plt.show()
```

```
# Loss curve
plt.figure(figsize=(8,5))
plt.plot(history_mobilenet.history['loss'], label='Train Loss')
plt.plot(history_mobilenet.history['val_loss'], label='Validation Loss')
plt.title('MobileNetV2 Model Loss Over Epochs')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(loc='upper right')
plt.grid()
plt.show()
```



✓ 5. Performance Comparison

- Evaluate all models on the same test set.
- Highlight the model that achieved the best test performance.
- Summarize the key hyperparameters and training strategies for each model(e.g., learning rate, batch size, number of epochs, optimizer).
- Include plots such as training/validation loss and accuracy over epochs.

Test Set Evaluation:

All models were evaluated on the same test set ($X_{\text{test}}, y_{\text{test}}$), ensuring a fair comparison of their generalization performance.


```
#Performance Table
performance_data = {
    'Model': [
        'Baseline CNN',
        'ResNet50 (Feature Extract)',
        'ResNet50 (Fine-tuned)',
        'VGG16',
        'DenseNet121',
        'MobileNetV2'
    ],
```



```
'Train Acc': ['~89.00%', '~89.60%', '~89.00%', '~88.50%-90%', '~88.50%', '~89.55%'],
'Val Acc': ['~89.70%', '~89.77%', '~89.77%', '89.77%', '89.61%', '88.99%'],
'Test Acc': ['~89.60%', '~89.63%', '~89.63%', '89.63%', '89.01%', '89.32%']
}
```

```
performance_df = pd.DataFrame(performance_data)
```

```
display(performance_df)
```




	Model	Train Acc	Val Acc	Test Acc
0	Baseline CNN	~89.00%	~89.70%	~89.60%
1	ResNet50 (Feature Extract)	~89.60%	~89.77%	~89.63%
2	ResNet50 (Fine-tuned)	~89.00%	~89.77%	~89.63%
3	VGG16	~88.50%-90%	89.77%	89.63%
4	DenseNet121	~88.50%	89.61%	89.01%
5	MobileNetV2	~89.55%	88.99%	89.32%

Best model: ResNet50 (Feature Extracted and Fine-tuned) + VGG16 → highest test accuracy: 89.63%

```
#Hyperparameters Table
hyperparams_data = {
    'Model': [
        'Baseline CNN',
        'ResNet50 (Feature Extract)',
        'ResNet50 (Fine-tuned)',
        'VGG16',
        'DenseNet121',
        'MobileNetV2'
    ],
    'Learning Rate': ['0.001', '0.0001', '0.00001', '0.0001', '0.0001', '0.0001'],
    'Batch Size': ['16', '16', '16', '16', '16', '16'],
    'Epochs': ['5', '5', '5', '5', '5', '5'],
    'Optimizer': ['Adam', 'Adam', 'Adam', 'Adam', 'Adam', 'Adam'],
    'Special Strategy': [
        'No pretraining',
        'Frozen all base layers',
        'Fine-tuned last 10 layers',
        'Frozen all base layers',
        'Frozen all base layers',
        'Frozen all base layers'
    ]
}
```

```
hyperparams_df = pd.DataFrame(hyperparams_data)
```

```
# 顯示表格
display(hyperparams_df)
```



	Model	Learning Rate	Batch Size	Epochs	Optimizer	Special Strategy
0	Baseline CNN	0.001	16	5	Adam	No pretraining
1	ResNet50 (Feature Extract)	0.0001	16	5	Adam	Frozen all base layers
2	ResNet50 (Fine-tuned)	0.00001	16	5	Adam	Fine-tuned last 10 layers
3	VGG16	0.0001	16	5	Adam	Frozen all base layers
4	DenseNet121	0.0001	16	5	Adam	Frozen all base layers
5	MobileNetV2	0.0001	16	5	Adam	Frozen all base layers

Overall Training and Validation Curves Summary For all models evaluated (Baseline CNN, ResNet50, VGG16, DenseNet121, MobileNetV2), training and validation accuracies steadily increased over the 5 epochs, with minimal signs of overfitting. Validation accuracies remained relatively stable and close to training accuracies across all models.

This suggests that:

The dataset is sufficiently clean and well-separated for CNNs to generalize well. Transfer learning with pre-trained feature extractors (even without extensive fine-tuning) provides robust performance across architectures. Differences in model depth, parameter size, and design

had limited impact under the current settings (128x128 inputs, small number of epochs). Overall, the training behaviors across models were consistent, highlighting the strong generalization of pre-trained CNNs even with limited medical imaging data.

Final Observations:

ResNet50 and VGG16 both achieved the highest test accuracy (~89.63%), confirming the strong transferability of pre-trained features. DenseNet121 and MobileNetV2 also performed competitively, despite having fewer parameters and faster training times. Fine-tuning the last few layers of ResNet50 showed minimal improvements, suggesting that pre-trained features were already highly optimized for this task. Future improvements could involve fine-tuning larger portions of the models or applying advanced data augmentation techniques to further differentiate architecture performance.

✓ 6. Augmentation

- For at least one model, re-train it using data augmentation techniques.
- Describe the types of augmentations used (e.g., flipping, cropping, rotation) and how they affected performance.

```
#clear RAM
gc.collect()
tf.keras.backend.clear_session()

# Data Augmentation Training for MobileNetV2 Model
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Define ImageDataGenerator with data augmentation
train_datagen_aug = ImageDataGenerator(
    rotation_range=15,          # Randomly rotate images by up to 15 degrees
    width_shift_range=0.1,      # Randomly shift images horizontally by 10%
    height_shift_range=0.1,     # Randomly shift images vertically by 10%
    horizontal_flip=True,       # Randomly flip images horizontally
    zoom_range=0.1              # Randomly zoom images by up to 10%
)

# Validation data generator without augmentation (only rescaling if needed)
val_datagen = ImageDataGenerator()

# Create generators
train_generator = train_datagen_aug.flow(X_train, y_train, batch_size=16)
val_generator = val_datagen.flow(X_val, y_val, batch_size=16)

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

# Load pre-trained MobileNetV2 without top layers
base_model_mobilenet_aug = MobileNetV2(weights='imagenet', include_top=False, input_shape=(128, 128, 3))

# Freeze all layers in the base model
for layer in base_model_mobilenet_aug.layers:
    layer.trainable = False

# Add custom classification head
x = base_model_mobilenet_aug.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(3, activation='softmax')(x)

# Build the full model
model_mobilenet_aug = Model(inputs=base_model_mobilenet_aug.input, outputs=predictions)

# Compile the model
model_mobilenet_aug.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

```
# Train the model using augmented data
history_mobilenet_aug = model_mobilenet_aug.fit(
    train_generator,
    validation_data=val_generator,
    epochs=5,
    verbose=1
)
```

```
↔ Epoch 1/5
172/172 ————— 61s 317ms/step - accuracy: 0.7972 - loss: 0.5662 - val_accuracy: 0.8992 - val_loss:
Epoch 2/5
172/172 ————— 55s 320ms/step - accuracy: 0.8777 - loss: 0.2973 - val_accuracy: 0.8977 - val_loss:
Epoch 3/5
172/172 ————— 54s 315ms/step - accuracy: 0.8832 - loss: 0.2739 - val_accuracy: 0.8961 - val_loss:
Epoch 4/5
172/172 ————— 53s 306ms/step - accuracy: 0.8882 - loss: 0.2447 - val_accuracy: 0.8977 - val_loss:
Epoch 5/5
172/172 ————— 54s 316ms/step - accuracy: 0.8940 - loss: 0.2478 - val_accuracy: 0.8961 - val_loss:
```

```
# Evaluate the model on the original test set
test_loss_mobilenet_aug, test_accuracy_mobilenet_aug = model_mobilenet_aug.evaluate(X_test, y_test)
print(f"MobileNetV2 (Augmented) Test Accuracy: {test_accuracy_mobilenet_aug:.4f}")
```

```
↔ 21/21 ————— 10s 455ms/step - accuracy: 0.9078 - loss: 0.2296
MobileNetV2 (Augmented) Test Accuracy: 0.8994
```

Data Augmentation Results:

For MobileNetV2, we retrained the model using data augmentation techniques including:

- Random rotation (± 15 degrees)
- Horizontal flipping
- Random zooming (10%)
- Width and height shifts (10%)

After applying augmentation:

- Original Test Accuracy (no augmentation): 89.32%
- Augmented Test Accuracy: 89.94%

This improvement suggests that data augmentation enhanced the model's generalization by exposing it to more diverse training examples, effectively reducing overfitting and leading to better test performance.

✓ 7. Interpretability & Insights

- Reflect on which model performed best and why.
- Provide clear reasoning, supported by performance metrics and training curves.
- Conclude with a discussion of the practical utility of your best-performing model.
- Who would benefit from using this model?
- In what types of real-world scenarios would your solution be useful?

7.1 Best-Performing Model

The best-performing model was MobileNetV2 trained with data augmentation, achieving a test accuracy of 89.94%.

Compared to other models:

- Baseline CNN, ResNet50, and VGG16 achieved around 89.6%–89.63%.
- DenseNet121 achieved 89.01%.
- MobileNetV2 without augmentation achieved 89.32%.

Training and validation curves for MobileNetV2 (augmented) showed smooth convergence without significant overfitting, indicating effective generalization.