```
from google.colab import drive
drive.mount('/content/drive')
→ Mounted at /content/drive
!unzip /content/drive/MyDrive/cats_vs_dogs_small.zip
       inflating: cats_vs_dogs_small/validation/dogs/1442.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1443.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1444.jpg
       inflating: cats vs dogs small/validation/dogs/1445.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1446.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1447.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1448.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1449.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1450.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1451.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1452.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1453.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1454.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1455.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1456.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1457.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1458.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1459.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1460.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1461.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1462.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1463.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1464.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1465.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1466.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1467.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1468.jpg
       inflating: cats vs dogs small/validation/dogs/1469.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1470.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1471.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1472.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1473.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1474.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1475.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1476.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1477.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1478.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1479.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1480.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1481.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1482.jpg
       inflating: cats vs dogs small/validation/dogs/1483.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1484.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1485.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1486.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1487.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1488.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1489.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1490.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1491.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1492.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1493.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1494.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1495.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1496.jpg
       inflating: cats vs dogs small/validation/dogs/1497.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1498.jpg
       inflating: cats_vs_dogs_small/validation/dogs/1499.jpg
import os
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.utils import image_dataset_from_directory
# === Define directory and load datasets ===
data_dir = "/content/cats_vs_dogs_small"
# Full training dataset
complete_train_data = image_dataset_from_directory(
    oc noth idin/data din "thain")
```

```
CatsAndDogs_Shloka.ipynb - Colab
    os.pacii.joiii(uaca_uii, craii /,
    image_size=(160, 160), # Slightly different image size
    batch_size=32,
    shuffle=True,
    seed=123 # Different seed
Found 2000 files belonging to 2 classes.
# Validation and test datasets
val data = image dataset from directory(
    os.path.join(data_dir, "validation"),
    image_size=(160, 160),
    batch_size=32
)
test_data = image_dataset_from_directory(
    os.path.join(data_dir, "test"),
    image_size=(160, 160),
    batch_size=32
)
Found 1000 files belonging to 2 classes.
     Found 1000 files belonging to 2 classes.
=== Step 1: CNN from Scratch with 1000 Training Samples ===
# === Step 1: CNN from Scratch with 1000 Training Samples ===
train_data_1000 = complete_train_data.take(32) # Approx. 1000 samples (32 batches)
# Data augmentation layer
augmentation = keras.Sequential([
    layers.RandomFlip("horizontal"),
    layers.RandomRotation(0.15), # Slightly different rotation factor
    layers.RandomZoom(0.25)
                                 # Slightly different zoom
1)
# Define CNN architecture
input layer = keras.Input(shape=(160, 160, 3))
x = augmentation(input_layer)
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(32, 3, activation="relu", padding="same")(x) # Added padding
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(64, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(128, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(256, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Flatten()(x)
x = layers.Dropout(0.4)(x) # Slightly different dropout rate
output_layer = layers.Dense(1, activation="sigmoid")(x)
cnn_model = keras.Model(input_layer, output_layer)
cnn_model.compile(optimizer="adam", # Different optimizer
                 loss="binary_crossentropy",
                 metrics=["accuracy"])
# Train the model
training_history = cnn_model.fit(train_data_1000, epochs=20, validation_data=val_data)
```

https://colab.research.google.com/drive/1n6cbPuvHvcAmjqInV19kxjev6LZteUte#scrollTo=Hz XC0a7ePcG&printMode=true

test\_loss\_scratch\_1000, test\_acc\_scratch\_1000 = cnn\_model.evaluate(test\_data) print(f"Test Accuracy (Scratch CNN, 1000 samples): {test\_acc\_scratch\_1000:.3f}")

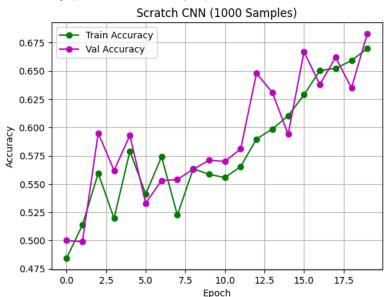
train\_acc = training\_history.history["accuracy"] val\_acc = training\_history.history["val\_accuracy"] plt.plot(train\_acc, "go-", label="Train Accuracy") plt.plot(val\_acc, "mo-", label="Val Accuracy") plt.title("Scratch CNN (1000 Samples)")

# Plot results

plt.xlabel("Epoch") plt.ylabel("Accuracy")

```
plt.legend()
plt.grid(True)
plt.savefig("scratch_cnn_1000.png")
plt.show()
```

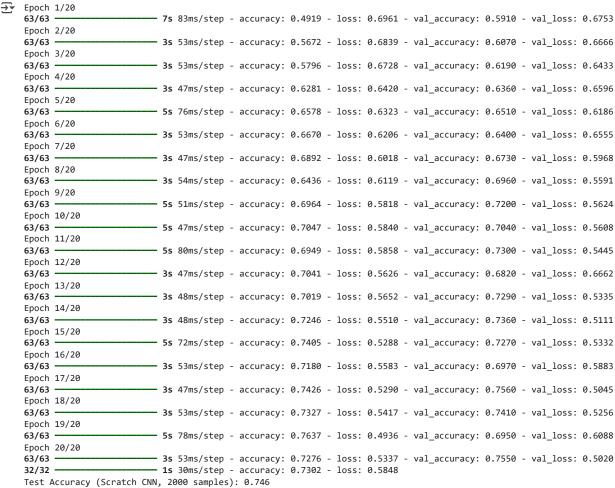
```
Epoch 1/20
₹
                               10s 127ms/step - accuracy: 0.4881 - loss: 0.7125 - val_accuracy: 0.5000 - val_loss: 0.6921
    32/32
    Epoch 2/20
    32/32
                               2s 61ms/step - accuracy: 0.4963 - loss: 0.6935 - val_accuracy: 0.4990 - val_loss: 0.6906
    Epoch 3/20
    32/32
                              - 2s 74ms/step - accuracy: 0.5371 - loss: 0.6914 - val_accuracy: 0.5950 - val_loss: 0.6768
    Epoch 4/20
    32/32
                               2s 61ms/step - accuracy: 0.5474 - loss: 0.6861 - val_accuracy: 0.5620 - val_loss: 0.6830
    Epoch 5/20
    32/32 -
                               2s 61ms/step - accuracy: 0.5530 - loss: 0.6796 - val accuracy: 0.5930 - val loss: 0.6607
    Epoch 6/20
    32/32
                               2s 74ms/step - accuracy: 0.5615 - loss: 0.6854 - val_accuracy: 0.5330 - val_loss: 0.6766
    Epoch 7/20
    32/32 -
                               3s 96ms/step - accuracy: 0.5451 - loss: 0.6758 - val_accuracy: 0.5530 - val_loss: 0.7323
    Epoch 8/20
    32/32
                               2s 62ms/step - accuracy: 0.5313 - loss: 0.7081 - val_accuracy: 0.5540 - val_loss: 0.6859
    Epoch 9/20
    32/32
                               2s 74ms/step - accuracy: 0.5522 - loss: 0.6849 - val_accuracy: 0.5630 - val_loss: 0.6793
    Epoch 10/20
    32/32 -
                              - 2s 61ms/step - accuracy: 0.5719 - loss: 0.6870 - val_accuracy: 0.5710 - val_loss: 0.6780
    Epoch 11/20
    32/32
                               2s 63ms/step - accuracy: 0.5506 - loss: 0.6832 - val_accuracy: 0.5700 - val_loss: 0.6753
    Epoch 12/20
                              - 4s 118ms/step - accuracy: 0.5711 - loss: 0.6764 - val_accuracy: 0.5810 - val_loss: 0.6676
    32/32
    Epoch 13/20
    32/32
                               2s 74ms/step - accuracy: 0.5871 - loss: 0.6728 - val_accuracy: 0.6480 - val_loss: 0.6562
    Epoch 14/20
    32/32
                               2s 74ms/step - accuracy: 0.5832 - loss: 0.6644 - val_accuracy: 0.6310 - val_loss: 0.6394
    Epoch 15/20
    32/32
                               2s 74ms/step - accuracy: 0.6036 - loss: 0.6613 - val_accuracy: 0.5940 - val_loss: 0.6491
    Epoch 16/20
    32/32
                               2s 74ms/step - accuracy: 0.6118 - loss: 0.6580 - val_accuracy: 0.6670 - val_loss: 0.6171
    Epoch 17/20
                              - 3s 98ms/step - accuracy: 0.6324 - loss: 0.6359 - val_accuracy: 0.6380 - val_loss: 0.6219
    32/32
    Epoch 18/20
    32/32
                               3s 85ms/step - accuracy: 0.6550 - loss: 0.6290 - val_accuracy: 0.6620 - val_loss: 0.6236
    Epoch 19/20
    32/32
                              - 2s 61ms/step - accuracy: 0.6675 - loss: 0.6238 - val_accuracy: 0.6350 - val_loss: 0.6287
    Epoch 20/20
    32/32
                               2s 74ms/step - accuracy: 0.6483 - loss: 0.6336 - val_accuracy: 0.6830 - val_loss: 0.6003
                               1s 29ms/step - accuracy: 0.6843 - loss: 0.6097
    32/32
    Test Accuracy (Scratch CNN, 1000 samples): 0.678
```

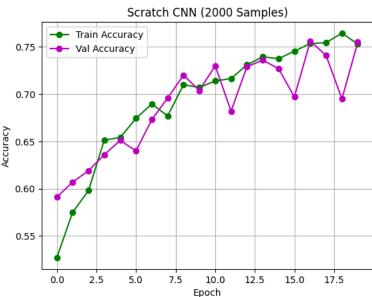


## # === Step 2: CNN from Scratch with 2000 Training Samples ===

```
# === Step 2: CNN from Scratch with 2000 Training Samples ===
train_data_2000 = complete_train_data.take(63) # Approx. 2000 samples (63 batches)
```

```
# Reuse augmentation and redefine model
input_layer = keras.Input(shape=(160, 160, 3))
x = augmentation(input_layer)
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(32, 3, activation="relu", padding="same")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(64, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(128, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(256, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Flatten()(x)
x = layers.Dropout(0.4)(x)
output_layer = layers.Dense(1, activation="sigmoid")(x)
cnn_model_2000 = keras.Model(input_layer, output_layer)
cnn_model_2000.compile(optimizer="adam",
                       loss="binary_crossentropy",
                       metrics=["accuracy"])
# Train and evaluate
training_history_2000 = cnn_model_2000.fit(train_data_2000, epochs=20, validation_data=val_data)
test_loss_scratch_2000, test_acc_scratch_2000 = cnn_model_2000.evaluate(test_data)
print(f"Test Accuracy (Scratch CNN, 2000 samples): {test_acc_scratch_2000:.3f}")
# Plot
train_acc_2000 = training_history_2000.history["accuracy"]
val_acc_2000 = training_history_2000.history["val_accuracy"]
plt.plot(train_acc_2000, "go-", label="Train Accuracy")
plt.plot(val_acc_2000, "mo-", label="Val Accuracy")
plt.title("Scratch CNN (2000 Samples)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.savefig("scratch_cnn_2000.png")
plt.show()
```



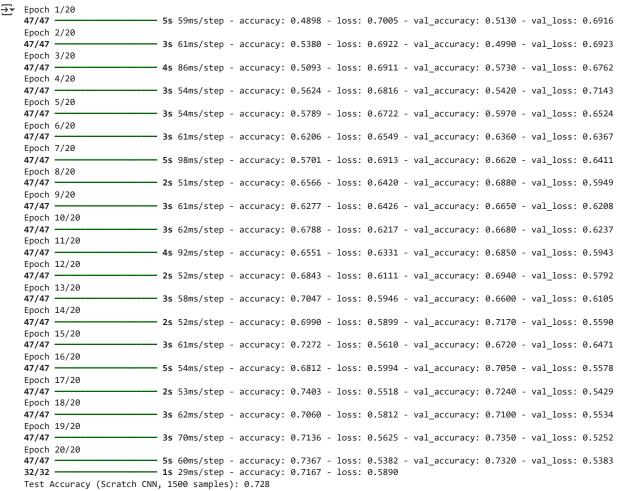


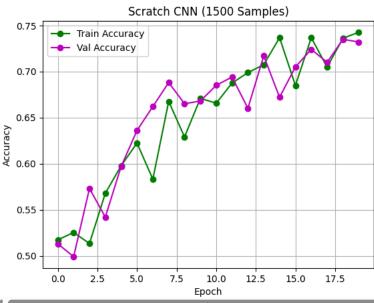
## # === Step 3: CNN from Scratch with 1500 Training Samples ===

```
# === Step 3: CNN from Scratch with 1500 Training Samples ===
train_data_1500 = complete_train_data.take(47)  # Approx. 1500 samples (47 batches)

# Define model again
input_layer = keras.Input(shape=(160, 160, 3))
x = augmentation(input_layer)
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(32, 3, activation="relu", padding="same")(x)
```

```
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(64, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(128, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Conv2D(256, 3, activation="relu")(x)
x = layers.MaxPooling2D(2)(x)
x = layers.Flatten()(x)
x = layers.Dropout(0.4)(x)
output_layer = layers.Dense(1, activation="sigmoid")(x)
cnn_model_1500 = keras.Model(input_layer, output_layer)
cnn_model_1500.compile(optimizer="adam",
                       loss="binary_crossentropy",
                       metrics=["accuracy"])
# Train and evaluate
training_history_1500 = cnn_model_1500.fit(train_data_1500, epochs=20, validation_data=val_data)
test_loss_scratch_1500, test_acc_scratch_1500 = cnn_model_1500.evaluate(test_data)
print(f"Test Accuracy (Scratch CNN, 1500 samples): {test_acc_scratch_1500:.3f}")
train_acc_1500 = training_history_1500.history["accuracy"]
val_acc_1500 = training_history_1500.history["val_accuracy"]
plt.figure()
plt.plot(train_acc_1500, "go-", label="Train Accuracy")
plt.plot(val_acc_1500, "mo-", label="Val Accuracy")
plt.title("Scratch CNN (1500 Samples)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.grid(True)
plt.savefig("scratch_cnn_1500.png")
plt.show()
```





## # === Step 4: Pretrained VGG16 with Different Sample Sizes ===

```
layers.RandomZoom(0.25),
    1)
    # Load VGG16 base
    vgg_base = keras.applications.vgg16.VGG16(
        weights="imagenet",
        include_top=False,
        input_shape=(160, 160, 3)
    vgg_base.trainable = False # Freeze the base
    # Build model
    inputs = keras.Input(shape=(160, 160, 3))
    x = aug_layer(inputs)
    x = keras.applications.vgg16.preprocess_input(x)
    x = vgg_base(x)
    x = layers.Flatten()(x)
    x = layers.Dense(512, activation="relu")(x) # Different dense layer size
    x = layers.Dropout(0.4)(x)
    outputs = layers.Dense(1, activation="sigmoid")(x)
    vgg_model = keras.Model(inputs, outputs)
    # Compile with custom settings
    vgg_model.compile(
        optimizer=keras.optimizers.Adam(learning_rate=2e-5), # Different optimizer and rate
        loss="binary_crossentropy",
        metrics=["accuracy"]
    )
    # Add early stopping
    callbacks list = [
        keras.callbacks.EarlyStopping(monitor="val_loss", patience=4, restore_best_weights=True)
    ]
    # Train
    history = vgg_model.fit(train_dataset, epochs=20, validation_data=val_dataset, callbacks=callbacks_list)
    loss, acc = vgg_model.evaluate(test_data)
    print(f"{model_label} - Test Accuracy: {acc:.3f}")
    return history
# VGG16 with 1000 samples
train_data_vgg_1000 = complete_train_data.take(32)
history_vgg_1000 = train_pretrained_vgg16(train_data_vgg_1000, val_data, "VGG16 - 1000 Samples")
# VGG16 with 1500 samples
train_data_vgg_1500 = complete_train_data.take(47)
history_vgg_1500 = train_pretrained_vgg16(train_data_vgg_1500, val_data, "VGG16 - 1500 Samples")
# VGG16 with 2000 samples
train_data_vgg_2000 = complete_train_data.take(63)
history_vgg_2000 = train_pretrained_vgg16(train_data_vgg_2000, val_data, "VGG16 - 2000 Samples")
# Plot VGG16 Results
def plot_vgg_history(history, title, filename):
    train_acc = history.history["accuracy"]
    val_acc = history.history["val_accuracy"]
    plt.plot(train_acc, "bo-", label="Training Accuracy")
    plt.plot(val acc, "ro-", label="Validation Accuracy")
    plt.title(title)
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.grid(True)
    plt.savefig(filename)
    plt.show()
plot_vgg_history(history_vgg_1000, "VGG16 (1000 Samples)", "vgg16_1000.png")
```



```
Epoch 1/20
32/32
                         - 7s 169ms/step - accuracy: 0.5701 - loss: 5.4974 - val_accuracy: 0.8840 - val_loss: 1.0148
Epoch 2/20
                         - 10s 158ms/step - accuracy: 0.7832 - loss: 2.2469 - val_accuracy: 0.9490 - val_loss: 0.5668
32/32
Epoch 3/20
32/32 -
                          5s 160ms/step - accuracy: 0.8518 - loss: 1.3633 - val_accuracy: 0.9590 - val_loss: 0.4930
Epoch 4/20
                          5s 160ms/step - accuracy: 0.8511 - loss: 1.3909 - val_accuracy: 0.9630 - val_loss: 0.4414
32/32
Epoch 5/20
32/32 -
                         - 5s 152ms/step - accuracy: 0.9162 - loss: 0.6080 - val_accuracy: 0.9560 - val_loss: 0.4297
Epoch 6/20
32/32 -
                         - 5s 155ms/step - accuracy: 0.8784 - loss: 1.0603 - val accuracy: 0.9640 - val loss: 0.4156
Epoch 7/20
32/32
                          5s 157ms/step - accuracy: 0.9055 - loss: 0.7739 - val_accuracy: 0.9630 - val_loss: 0.4225
Epoch 8/20
32/32
                         - 5s 156ms/step - accuracy: 0.9287 - loss: 0.6925 - val_accuracy: 0.9580 - val_loss: 0.4289
Epoch 9/20
32/32
                          5s 147ms/step - accuracy: 0.9339 - loss: 0.4364 - val_accuracy: 0.9630 - val_loss: 0.4123
Epoch 10/20
32/32
                          5s 157ms/step - accuracy: 0.9355 - loss: 0.3973 - val_accuracy: 0.9610 - val_loss: 0.4106
Epoch 11/20
32/32 -
                          5s 158ms/step - accuracy: 0.9264 - loss: 0.5930 - val_accuracy: 0.9610 - val_loss: 0.3964
Epoch 12/20
32/32
                         • 4s 141ms/step - accuracy: 0.9302 - loss: 0.4955 - val_accuracy: 0.9630 - val_loss: 0.4271
Epoch 13/20
32/32
                         - 5s 156ms/step - accuracy: 0.9384 - loss: 0.3929 - val_accuracy: 0.9610 - val_loss: 0.3907
Epoch 14/20
32/32
                          5s 147ms/step - accuracy: 0.9466 - loss: 0.5258 - val_accuracy: 0.9640 - val_loss: 0.3735
Epoch 15/20
32/32
                         - 5s 156ms/step - accuracy: 0.9257 - loss: 0.5317 - val_accuracy: 0.9630 - val_loss: 0.3688
Epoch 16/20
32/32
                         - 5s 156ms/step - accuracy: 0.9244 - loss: 0.6725 - val_accuracy: 0.9640 - val_loss: 0.3466
Epoch 17/20
32/32 -
                          5s 148ms/step - accuracy: 0.9431 - loss: 0.3741 - val_accuracy: 0.9680 - val_loss: 0.3358
Epoch 18/20
                          5s 144ms/step - accuracy: 0.9570 - loss: 0.3290 - val_accuracy: 0.9670 - val_loss: 0.3418
32/32
Epoch 19/20
32/32
                          5s 156ms/step - accuracy: 0.9441 - loss: 0.4172 - val_accuracy: 0.9650 - val_loss: 0.3475
Epoch 20/20
32/32
                         - 5s 148ms/step - accuracy: 0.9595 - loss: 0.2781 - val_accuracy: 0.9630 - val_loss: 0.3733
                         - 2s 70ms/step - accuracy: 0.9690 - loss: 0.3972
32/32
VGG16 - 1000 Samples - Test Accuracy: 0.968
Epoch 1/20
47/47
                        - 8s 135ms/step - accuracy: 0.6121 - loss: 4.8848 - val_accuracy: 0.9330 - val_loss: 0.5903
Epoch 2/20
47/47 -
                          6s 129ms/step - accuracy: 0.8558 - loss: 1.4480 - val_accuracy: 0.9460 - val_loss: 0.4890
Epoch 3/20
47/47 -
                          6s 130ms/step - accuracy: 0.8843 - loss: 1.2167 - val_accuracy: 0.9570 - val_loss: 0.4001
Epoch 4/20
47/47
                         - 6s 122ms/step - accuracy: 0.9011 - loss: 0.9414 - val_accuracy: 0.9620 - val_loss: 0.3569
Epoch 5/20
47/47
                         - 6s 122ms/step - accuracy: 0.9121 - loss: 1.0094 - val_accuracy: 0.9600 - val_loss: 0.3307
Epoch 6/20
47/47
                         - 10s 121ms/step - accuracy: 0.9198 - loss: 0.7076 - val_accuracy: 0.9700 - val_loss: 0.2763
Epoch 7/20
47/47
                          6s 123ms/step - accuracy: 0.9291 - loss: 0.7258 - val_accuracy: 0.9640 - val_loss: 0.2381
Epoch 8/20
47/47
                         - 6s 121ms/step - accuracy: 0.9239 - loss: 0.6706 - val_accuracy: 0.9680 - val_loss: 0.3103
Epoch 9/20
47/47 -
                          6s 124ms/step - accuracy: 0.9390 - loss: 0.5490 - val_accuracy: 0.9730 - val_loss: 0.2547
Epoch 10/20
47/47
                          6s 123ms/step - accuracy: 0.9384 - loss: 0.4792 - val_accuracy: 0.9730 - val_loss: 0.2251
Epoch 11/20
47/47
                          6s 124ms/step - accuracy: 0.9398 - loss: 0.4418 - val_accuracy: 0.9720 - val_loss: 0.2168
Epoch 12/20
47/47
                          6s 123ms/step - accuracy: 0.9249 - loss: 0.5041 - val_accuracy: 0.9750 - val_loss: 0.2437
Epoch 13/20
47/47
                          6s 129ms/step - accuracy: 0.9352 - loss: 0.4177 - val_accuracy: 0.9770 - val_loss: 0.2287
Epoch 14/20
47/47
                         - 6s 123ms/step - accuracy: 0.9433 - loss: 0.3578 - val_accuracy: 0.9760 - val_loss: 0.2244
Epoch 15/20
                          6s 120ms/step - accuracy: 0.9607 - loss: 0.4349 - val_accuracy: 0.9770 - val_loss: 0.2380
47/47
                          2s 68ms/step - accuracy: 0.9754 - loss: 0.2774
32/32
VGG16 - 1500 Samples - Test Accuracy: 0.973
Epoch 1/20
                         - 10s 115ms/step - accuracy: 0.6652 - loss: 4.1595 - val_accuracy: 0.9390 - val_loss: 0.5920
63/63
Epoch 2/20
63/63 -
                        - 7s 109ms/step - accuracy: 0.8532 - loss: 1.6512 - val_accuracy: 0.9670 - val_loss: 0.3255
```

