```
from google.colab import drive
drive.mount('/content/drive')
Mounted at /content/drive
import os
# Defining the path to the provided ZIP file in my Google Drive
zip path = '/content/drive/My Drive/Colab Notebooks/cats vs dogs smal
# Defining extracted files path into My Google Drive Folder
extract path = "/content/drive/My Drive/Colab Notebooks/"
# Unzipping the files quietely
!unzip -q "{zip path}" -d "{extract path}"
print("Files unzipped successfully")
Files unzipped successfully
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import shutil
import pathlib
import matplotlib.pyplot as plt
# Defining Original Base Directory
original base dir = pathlib.Path("/content/drive/My Drive/Colab Notebo
# Defining Original Base Subdirectories
original_train_dir = original_base_dir / "train"
original validation dir = original base dir / "validation"
original test dir = original base dir / "test"
# Dictionary to store all the results
results = {}
# Defining Subsets
def make_subset(subset_name, train_size, validation_size, test_size):
    new_base_dir = pathlib.Path(f"/content/{subset_name}")
    if new_base_dir.exists():
        shutil.rmtree(new base dir)
    print(f"Creating new dataset subset: {new base dir}")
    # Helper function to copy files
    def copy files(src dir, dst dir, num files):
```

```
os.makeairs(ast_air, exist_ok=irue)
                      # List all files in the source directory
                      all_files = sorted([f for f in os.listdir(src_dir) if os.path
                      # Copy the first 'num_files' from the list
                      files_to_copy = all_files[:num_files]
                      for fname in files_to_copy:
                                             src file = src dir / fname
                                             shutil.copyfile(src_file, dst_dir / fname)
                      print(f"Copied {len(files_to_copy)} files from {src_dir} to {
# --- Creating Training Set ---
copy_files(original_train_dir / "cats", new_base_dir / "train" /
copy_files(original_train_dir / "dogs", new_base_dir / "train" /
# --- Creating Validation Set ---
copy_files(original_validation_dir / "cats", new_base_dir / "validation_dir / "cats", new_base_dir / "
copy_files(original_validation_dir / "dogs", new_base_dir / "validation_dir / "dogs", new_base_dir / "
# --- Creating Test Set ---
copy_files(original_test_dir / "cats", new_base_dir / "test" / "cats")
copy_files(original_test_dir / "dogs", new_base_dir / "test" / "degs")
 return new_base_dir
```

```
# Loading Datasets
def get_datasets(base_dir, image_size=(180, 180), batch_size=32):
    train_dataset = keras.utils.image_dataset_from_directory(
        base_dir / "train",
        image_size=image_size,
        batch_size=batch_size
    validation dataset = keras.utils.image dataset from directory(
        base_dir / "validation",
        image_size=image_size,
        batch_size=batch_size
    test_dataset = keras.utils.image_dataset_from_directory(
        base_dir / "test",
        image_size=image_size,
        batch_size=batch_size
    return train_dataset, validation_dataset, test_dataset
def plot history(history, title):
    acc = history.history["accuracy"]
    val acc = history.history["val accuracy"]
    loss = history.history["loss"]
    val_loss = history.history["val_loss"]
```

```
epochs = range(1, len(acc) + 1)

plt.figure(figsize=(12, 4))
plt.suptitle(title, y=1.02)

plt.subplot(1, 2, 1)
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()

plt.show()
```

```
# 01,2,3
# Creating Subsets
# Step 1 subset: Train=1000, Val=500, Test=500
subset 1 dir = make subset("subset 1000 500 500",
                           train size=1000,
                           validation_size=500,
                           test size=500)
# Step 2 subset: Train=2000, Val=500, Test=500
subset 2 dir = make subset("subset 2000 500 500",
                           train size=2000,
                           validation size=500,
                           test size=500)
# Step 3 subset: "Ideal" size (using full original dataset)
subset_3_dir = make_subset("subset_2000_1000_1000",
                           train size=2000,
                           validation_size=1000,
                           test size=1000)
# Loading new subsetted datasets
print("\nLoading datasets...")
train_ds_1, val_ds_1, test_ds_1 = get_datasets(subset_1_dir)
train ds 2, val ds 2, test ds 2 = get datasets(subset 2 dir)
train_ds_3, val_ds_3, test_ds_3 = get_datasets(subset_3_dir)
Creating new dataset subset: /content/subset_1000_500_500
Copied 500 files from /content/drive/My Drive/Colab Notebooks/cats vs
Copied 500 files from /content/drive/My Drive/Colab Notebooks/cats vs (
Copied 250 files from /content/drive/My Drive/Colab Notebooks/cats_vs_
Conied 250 files from /content/drive/My Drive/Colah Notehooks/cats vs
```

```
COPTER 70 ITES TOWN / CONTENTS AND TAKES OF AN INCLESSORS / COLORS AND COLORS / COLO
Copied 250 files from /content/drive/My Drive/Colab Notebooks/cats_vs_
Copied 250 files from /content/drive/My Drive/Colab Notebooks/cats vs
Creating new dataset subset: /content/subset 2000 500 500
Copied 1000 files from /content/drive/My Drive/Colab Notebooks/cats_vs
Copied 1000 files from /content/drive/My Drive/Colab Notebooks/cats vs
Copied 250 files from /content/drive/My Drive/Colab Notebooks/cats vs
Copied 250 files from /content/drive/My Drive/Colab Notebooks/cats_vs_
Copied 250 files from /content/drive/My Drive/Colab Notebooks/cats vs
Copied 250 files from /content/drive/My Drive/Colab Notebooks/cats vs (
Creating new dataset subset: /content/subset 2000 1000 1000
Copied 1000 files from /content/drive/My Drive/Colab Notebooks/cats vs
Copied 1000 files from /content/drive/My Drive/Colab Notebooks/cats vs
Copied 500 files from /content/drive/My Drive/Colab Notebooks/cats vs
Copied 500 files from /content/drive/My Drive/Colab Notebooks/cats vs (
Copied 500 files from /content/drive/My Drive/Colab Notebooks/cats_vs_
Copied 500 files from /content/drive/My Drive/Colab Notebooks/cats vs (
Loading datasets...
Found 1000 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
Found 2000 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
Found 2000 files belonging to 2 classes.
Found 1000 files belonging to 2 classes.
Found 1000 files belonging to 2 classes.
```

```
# Building Scratch Model
def build model from scratch():
    # Data Augmentation layers
    data augmentation = keras.Sequential(
        [
            layers.RandomFlip("horizontal"),
            layers.RandomRotation(0.1),
            layers.RandomZoom(0.2),
        ]
    )
    # Model Architecture
    inputs = keras.Input(shape=(180, 180, 3))
    x = data augmentation(inputs)
    x = layers.Rescaling(1./255)(x)
    x = layers.Conv2D(filters=32, kernel size=3, activation="relu")(x
    x = layers.MaxPooling2D(pool size=2)(x)
    x = layers.Conv2D(filters=64, kernel size=3, activation="relu")(x
    x = layers.MaxPooling2D(pool size=2)(x)
    x = layers.Conv2D(filters=128, kernel size=3, activation="relu")();
    x = layers.MaxPooling2D(pool size=2)(x)
    x = lavers.Conv2D(filters=256, kernel size=3, activation="relu")()
```

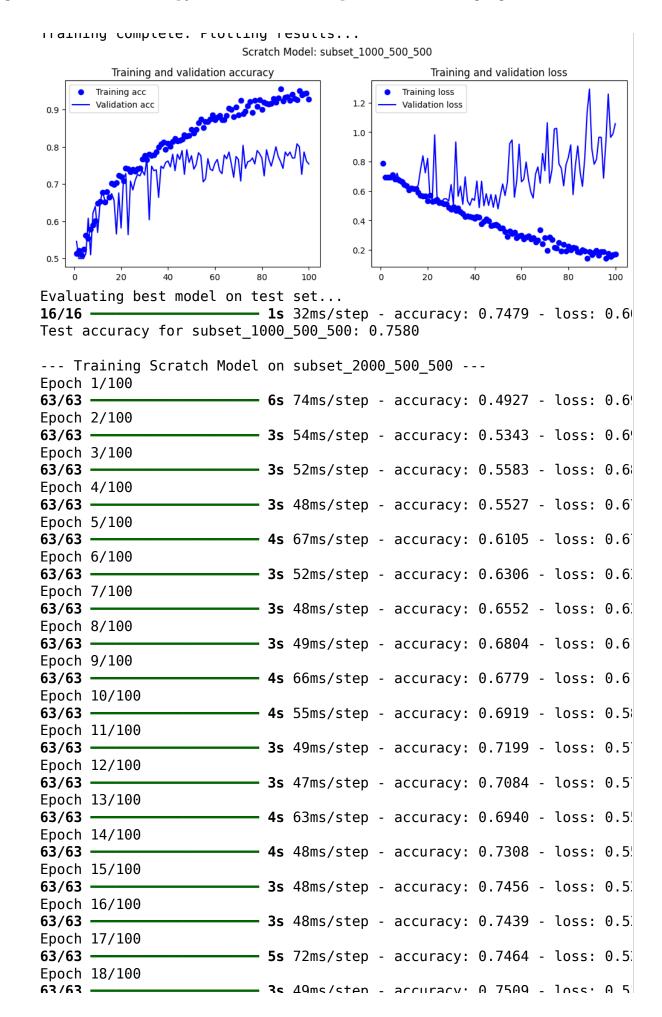
```
def train and evaluate scratch(subset name, train ds, val ds, test ds
    print(f"\n--- Training Scratch Model on {subset name} ---")
    keras.backend.clear session() # Resets model
    model = build model from scratch()
    checkpoint filepath = f"{subset name} scratch.keras"
    callbacks = [
        keras.callbacks.ModelCheckpoint(
            filepath=checkpoint filepath,
            save best only=True,
            monitor="val loss")
    ]
    # Training for 100 epochs, as provided in the sample notebook
    history = model.fit(
        train ds,
        epochs=100,
        validation data=val ds,
        callbacks=callbacks,
        verbose=1)
    print("Training complete. Plotting results...")
    plot history(history, f"Scratch Model: {subset name}")
   # Loading the best performing model (saved by ModelCheckpoint)
    print("Evaluating best model on test set...")
    test model = keras.models.load model(checkpoint filepath)
    test loss, test acc = test model.evaluate(test ds)
    print(f"Test accuracy for {subset name}: {test acc:.4f}")
    return test acc
```

```
# Step 1: Train=1000, Val=500, Test=500
results["scratch_1000"] = train_and_evaluate_scratch(
    "subset 1000 500 500", train ds 1, val ds 1, test ds 1)
# Step 2: Train=2000, Val=500, Test=500
results["scratch 2000"] = train_and_evaluate_scratch(
    "subset_2000_500_500", train_ds_2, val_ds_2, test_ds_2)
# Step 3: Train=2000, Val=1000, Test=1000 (The "ideal" from sample)
results["scratch ideal"] = train and evaluate scratch(
    "subset 2000 1000 1000", train ds 3, val ds 3, test ds 3)
print("\nScratch Model Results So Far:")
print(results)
--- Training Scratch Model on subset 1000 500 500 ---
Epoch 1/100
32/32 -
                       ---- 8s 79ms/step - accuracy: 0.5115 - loss: 0.8
Epoch 2/100
                          - 2s 57ms/step - accuracy: 0.4980 - loss: 0.6
32/32 -
Epoch 3/100
                          - 2s 68ms/step - accuracy: 0.5215 - loss: 0.6
32/32 -
Epoch 4/100
32/32 -
                          - 3s 93ms/step - accuracy: 0.5213 - loss: 0.6
Epoch 5/100
32/32 -
                          - 4s 62ms/step - accuracy: 0.5507 - loss: 0.7
Epoch 6/100
32/32 -
                          - 2s 62ms/step - accuracy: 0.5371 - loss: 0.6
Epoch 7/100
32/32 -
                          - 2s 54ms/step - accuracy: 0.5861 - loss: 0.6
Epoch 8/100
                          - 2s 57ms/step - accuracy: 0.5711 - loss: 0.6
32/32 -
Epoch 9/100
32/32 -
                          - 4s 90ms/step - accuracy: 0.6121 - loss: 0.6
Epoch 10/100
32/32 -
                          - 2s 55ms/step - accuracy: 0.6585 - loss: 0.6
Epoch 11/100
32/32 -
                          - 2s 57ms/step - accuracy: 0.6350 - loss: 0.6
Epoch 12/100
32/32 -
                          - 2s 60ms/step - accuracy: 0.6802 - loss: 0.6
Epoch 13/100
32/32 -
                          - 2s 56ms/step - accuracy: 0.6504 - loss: 0.6
Epoch 14/100
32/32 -
                          - 2s 59ms/step - accuracy: 0.6909 - loss: 0.6
Epoch 15/100
                           4s 107ms/step - accuracy: 0.6587 - loss: 0.
32/32 -
Epoch 16/100
                          - 3s 55ms/step - accuracy: 0.6885 - loss: 0.5
32/32 -
Epoch 17/100
32/32 -
                          - 2s 57ms/step - accuracy: 0.7091 - loss: 0.5
Fnoch 18/100
```

	10, 100								
32/32		2s	54ms/step	-	accuracy:	0.7073	-	loss:	0.5
•	19/100								
32/32 Enoch	20/100	35	55ms/step	-	accuracy:	0.0833	-	LOSS:	0.6
		3s	99ms/step	-	accuracy:	0.7387	-	loss:	0.5
	21/100	2 -	C 4 / - +			0.6044		1	0 5
	22/100	25	64ms/step	-	accuracy:	0.6944	-	LOSS:	0.5
32/32		2s	57ms/step	-	accuracy:	0.7519	-	loss:	0.5
	23/100	26	60mc/c+on		2661152674	0 7465		10001	0 5
	24/100	25	odiiis/step	-	accuracy.	0.7403	-	1055.	0.5
32/32		2s	54ms/step	-	accuracy:	0.7094	-	loss:	0.5
•	25/100	3¢	61ms/stan	_	accuracy:	0 7335	_	1000	0.5
	26/100	33	01m3/3ccp		accuracy.	0.7555		(033.	0.5.
-	27/100	3s	88ms/step	-	accuracy:	0.7369	-	loss:	0.5
	27/100	4s	61ms/step	_	accuracv:	0.7364	_	loss:	0.5
Epoch	28/100		•		-				
	29/100	2s	59ms/step	-	accuracy:	0.7356	-	loss:	0.5
32/32		2s	56ms/step	-	accuracy:	0.7709	-	loss:	0.4
•	30/100								
-	31/100	25	50ms/step	-	accuracy:	0.7633	-	LOSS:	0.4
32/32		4s	100ms/step)	- accuracy	: 0.7666) ·	- loss	: 0.
	32/100	25	66ms/sten	_	accuracy:	0 8022	_	1055.	0.4
Epoch	33/100		•		-				
	24/100	2s	55ms/step	-	accuracy:	0.7641	-	loss:	0.5
32/32	34/100	2s	56ms/step	-	accuracy:	0.7787	-	loss:	0.4
Epoch	35/100								
-	36/100	25	55ms/step	-	accuracy:	0.7934	-	LOSS:	0.4.
32/32		2s	57ms/step	-	accuracy:	0.8063	-	loss:	0.4
	37/100	25	72ms/stan	_	accuracy:	0 7018	_	1000	0.4
	38/100	23	7211373 CCP		accuracy.	0.7910		(033.	0.4.
-	20 /100	3s	81ms/step	-	accuracy:	0.8168	-	loss:	0.4
32/32	39/100	2s	57ms/step	_	accuracy:	0.7630	_	loss:	0.4
•	40/100	_			-				
	41/100	2s	55ms/step	-	accuracy:	0.8027	-	loss:	0.4
32/32		2s	55ms/step	-	accuracy:	0.7805	-	loss:	0.4
•	42/100	26	63mc/cton		accuracy:	0 8331		10001	0.30
Epoch	43/100		•		-				
	44/100	2s	56ms/step	-	accuracy:	0.8279	-	loss:	0.3
	44/100	3s	87ms/step	_	accuracv:	0.8262	_	loss:	0.3
Epoch	45/100		·		_				
32/32		2s	71ms/step	-	accuracy:	0.8041	-	loss:	0.4

	46 (100								1
32/32	46/100	2s	54ms/step	-	accuracy:	0.8144	-	loss:	0.4
	47/100	2s	56ms/step	_	accuracy:	0.8359	_	loss:	0.3
Epoch	48/100								
Epoch	49/100								
	50/100	2s	56ms/step	-	accuracy:	0.8320	-	loss:	0.3
	51/100	2s	59ms/step	-	accuracy:	0.8581	-	loss:	0.3
32/32		3s	93ms/step	-	accuracy:	0.8345	-	loss:	0.3
	52/100	2s	63ms/step	-	accuracy:	0.8364	-	loss:	0.3
	53/100	2s	54ms/step	_	accuracy:	0.8709	_	loss:	0.3
Epoch	54/100								
Epoch	55/100								
-	56/100	2s	54ms/step	-	accuracy:	0.8481	-	loss:	0.3
	57/100	2s	55ms/step	-	accuracy:	0.8648	-	loss:	0.3
32/32	58/100	3s	80ms/step	-	accuracy:	0.8669	-	loss:	0.3
32/32		2s	76ms/step	-	accuracy:	0.8843	-	loss:	0.2
Epoch 32/32	59/100	2s	55ms/step	-	accuracy:	0.8679	-	loss:	0.3
	60/100	2s	56ms/step	_	accuracv:	0.8625	_	loss:	0.3
Epoch	61/100		_		_				
Epoch	62/100		-		_				
Epoch	63/100		_		_				
	64/100	2s	58ms/step	-	accuracy:	0.8602	-	loss:	0.3
32/32		3s	91ms/step	-	accuracy:	0.8534	-	loss:	0.3
32/32		4s	65ms/step	-	accuracy:	0.8804	-	loss:	0.2
32/32		2s	56ms/step	-	accuracy:	0.8928	-	loss:	0.2
•	67/100	2s	55ms/step	_	accuracv:	0.9115	_	loss:	0.2
Epoch	68/100		•		_				
Epoch	69/100								
Epoch	70/100		•		-				
-	71/100	2s	73ms/step	-	accuracy:	0.8703	-	loss:	0.3
32/32		2s	60ms/step	-	accuracy:	0.9186	-	loss:	0.2
32/32		2s	59ms/step	-	accuracy:	0.8660	-	loss:	0.3
⊏pocn	73/100	_						-	

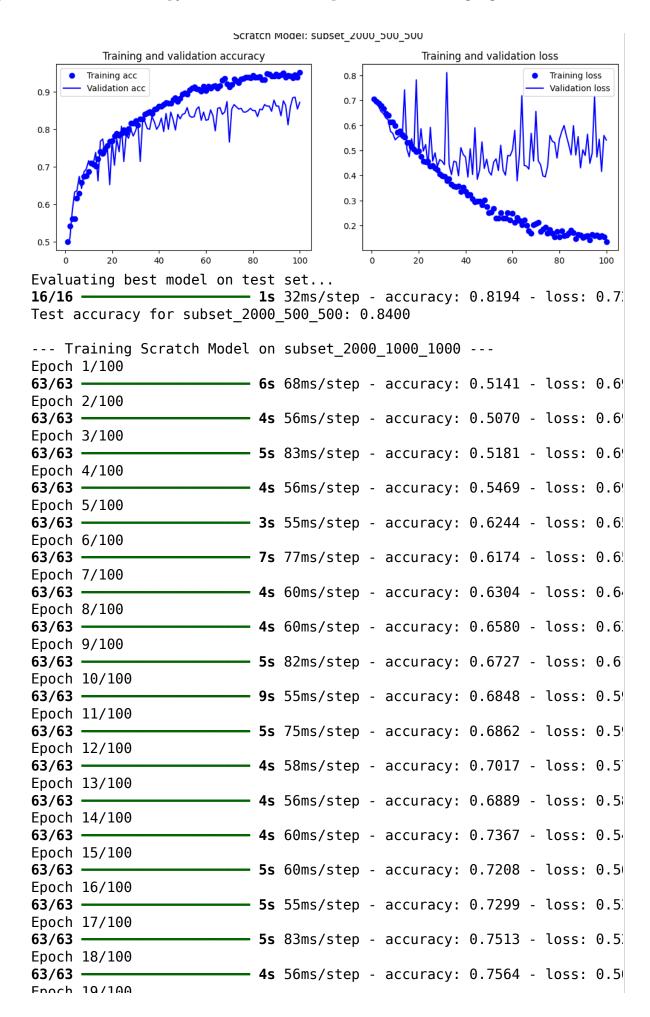
37/37		76	5/mc/cton	_	accuracy	0 8062	_	locc:	n 21
Epoch	74/100		·		_				
	75/100	3s	59ms/step	-	accuracy:	0.8948	-	loss:	0.2
32/32		3s	82ms/step	-	accuracy:	0.9116	-	loss:	0.2
	76/100	3s	81ms/sten	_	accuracy:	0.8707	_	loss:	0.2
Epoch	77/100		•		-				
32/32 Epoch	78/100	2s	60ms/step	-	accuracy:	0.9133	-	loss:	0.2
32/32		2s	55ms/step	-	accuracy:	0.9092	-	loss:	0.2
-	79/100	2s	56ms/step	_	accuracy:	0.9112	_	loss:	0.2
•	80/100		•		-				
Epoch	81/100		·		_				
	82/100	2s	60ms/step	-	accuracy:	0.9209	-	loss:	0.2
32/32		3s	90ms/step	-	accuracy:	0.9122	-	loss:	0.2
•	83/100	4 c	60ms/sten	_	accuracy:	n 9368	_	1055.	0 1
Epoch	84/100		·		_				
-	85/100	2s	65ms/step	-	accuracy:	0.9166	-	loss:	0.1
32/32		2s	57ms/step	-	accuracy:	0.9242	-	loss:	0.2
	86/100	2s	59ms/step	_	accuracy:	0.9306	_	loss:	0.1
Epoch	87/100	26	97ms /s+on		2661182671	0 0200		10001	0 1
	88/100								
-	89/100	2s	76ms/step	-	accuracy:	0.9704	-	loss:	0.1
32/32		2s	60ms/step	-	accuracy:	0.9268	-	loss:	0.1
Epoch 32/32	90/100	2s	56ms/step	_	accuracy:	0.9357	_	loss:	0.1
Epoch	91/100		•		-				
-	92/100	35	ooms/step	-	accuracy:	0.9322	-	toss:	0.10
32/32 Enoch	93/100	3s	59ms/step	-	accuracy:	0.9298	-	loss:	0.1
32/32		4s	92ms/step	-	accuracy:	0.9310	-	loss:	0.1
-	94/100	4s	60ms/step	_	accuracy:	0.9360	_	loss:	0.1
Epoch	95/100		•		-				
Epoch	96/100	25	50ms/step	-	accuracy:	0.9329	-	loss:	0.1
	97/100	2s	66ms/step	-	accuracy:	0.9446	-	loss:	0.1
32/32		2s	59ms/step	-	accuracy:	0.9493	-	loss:	0.1
•	98/100	49	114ms/ste	n	- accuracy	: 0.9298	3.	- loss	: 0
Epoch	99/100				-				
	100/100	35	60ms/step	-	accuracy:	0.9393	-	LOSS:	0.1
32/32	ing complete Plettin	2s	58ms/step	-	accuracy:	0.9123	-	loss:	0.2
		-							



55, 55 Fnoch	19/100	.	75m5/500p		accuracy.	0.,505			0.5
63/63		3s	48ms/step	-	accuracy:	0.7679	-	loss:	0.4
	20/100	3s	48ms/step	-	accuracy:	0.7541	_	loss:	0.5
	21/100								
Epoch	22/100		•		-				
	23/100	3s	51ms/step	-	accuracy:	0.7895	-	loss:	0.4
63/63		3s	47ms/step	-	accuracy:	0.7843	-	loss:	0.4
	24/100	6s	67ms/step	_	accuracy:	0.7860	_	loss:	0.4
•	25/100	26	EEms/stop		accuracy:	0 0005		10001	0.4
Epoch	26/100		·		_				
	27/100	5s	48ms/step	-	accuracy:	0.7720	-	loss:	0.4
63/63		6s	70ms/step	-	accuracy:	0.7999	-	loss:	0.4
63/63	28/100	3s	49ms/step	_	accuracy:	0.8190	_	loss:	0.4
Epoch	29/100								
Epoch	30/100		•		-				
	31/100	6s	63ms/step	-	accuracy:	0.8271	-	loss:	0.4
63/63		4s	49ms/step	-	accuracy:	0.8255	-	loss:	0.3
63/63	32/100	3s	48ms/step	-	accuracy:	0.8339	-	loss:	0.3
	33/100	6s	60ms/step	_	accuracy:	0.8272	_	loss:	0.3
Epoch	34/100								
-	35/100								
	36/100	5s	51ms/step	-	accuracy:	0.8390	-	loss:	0.3
63/63		4s	64ms/step	-	accuracy:	0.8398	-	loss:	0.3
	37/100	4s	56ms/step	_	accuracy:	0.8486	_	loss:	0.3
Epoch 63/63	38/100	5c	50mc/cton		accuracy:	0 8656		1000	0 3.
Epoch	39/100		·		_				
-	40/100	3s	51ms/step	-	accuracy:	0.8593	-	loss:	0.3
-	41/100	4s	70ms/step	-	accuracy:	0.8615	-	loss:	0.3
63/63		3s	49ms/step	-	accuracy:	0.8621	-	loss:	0.3
•	42/100	5s	50ms/step	_	accuracy:	0.8555	_	loss:	0.3
Epoch	43/100		•		-				
Epoch	44/100								
	45/100	3s	48ms/step	-	accuracy:	0.8659	-	loss:	0.3
63/63		5s	48ms/step	-	accuracy:	0.8662	-	loss:	0.2
Epoch	46/100								

Epoch	47/100								
	48/100								
63/63 Epoch	49/100	4s	48ms/step	-	accuracy:	0.8763	-	loss:	0.2
-	50/100	3s	48ms/step	-	accuracy:	0.8767	-	loss:	0.2
	51/100	4s	70ms/step	-	accuracy:	0.8931	-	loss:	0.2
Epoch	52/100				-				
Epoch	53/100								
	54/100								
63/63 Epoch	55/100		_		_				
-	56/100		_		_				
Epoch	57/100		•		-				
Epoch	58/100								
Epoch	59/100								
Epoch	60/100		47ms/step		-				
Epoch	61/100		_		_				
Epoch	62/100		50ms/step		-				
Epoch	63/100		48ms/step		-				
Epoch	64/100		_		_				
Epoch	65/100		52ms/step		-				
Epoch	66/100		•		-				
Epoch	67/100		-		_				
Epoch	68/100								
Epoch	69/100								
Epoch	70/100		•		-				
Epoch	71/100		_		_				
Epoch	72/100		•		-				
Epoch	73/100				_				
03/03		72	TIII2\2 reh	-	accuracy:	0.9001	-	1033.	0.1

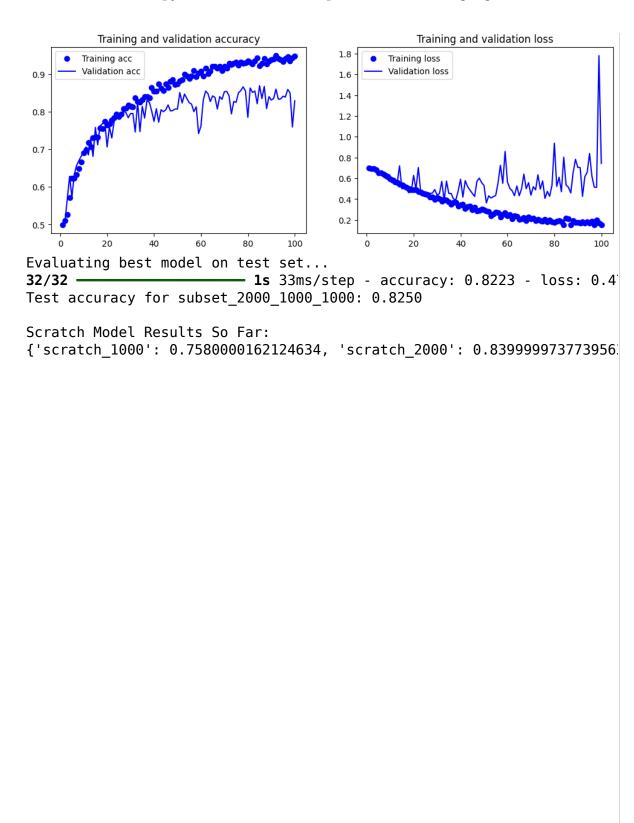
Fnoch	74/100								
•		3s	47ms/step	_	accuracy:	0.9269	_	loss:	0.1
	75/100								
		3s	49ms/step	-	accuracy:	0.9328	-	loss:	0.1
	76/100		67 / 1			0 0404			0 1
	77/100	45	6/ms/step	-	accuracy:	0.9404	-	loss:	0.1
•	77/100	4 s	48ms/sten	_	accuracy:	0 9405	_	1055.	0 1
-	78/100		.05, 5 cop		acca. acy.	010.00			0.1
63/63		3s	47ms/step	-	accuracy:	0.9433	-	loss:	0.1
•	79/100	_						_	
-	00 /100	6s	63ms/step	-	accuracy:	0.9369	-	loss:	0.1
•	80/100	4 s	47ms/sten	_	accuracy:	ი 9465	_	1055.	0 1
-	81/100		1711137 3 2 2 5		accar acy i	013103			0.1
63/63		3s	47ms/step	-	accuracy:	0.9366	-	loss:	0.1
Epoch	82/100	_						_	
	83/100	3s	49ms/step	-	accuracy:	0.9483	-	loss:	0.1
63/63		55	72ms/sten	_	accuracy:	0.9382	_	1055:	0.1
-	84/100	-	, 2.113, 3 ccp		accaracy	013302			0.1
		3s	48ms/step	-	accuracy:	0.9307	-	loss:	0.1
•	85/100	_	47 ()			0 0010			0 1
	86/100	35	4/ms/step	-	accuracy:	0.9319	-	loss:	0.1
		3s	47ms/step	_	accuracy:	0.9554	_	loss:	0.1
Epoch	87/100								
		4s	67ms/step	-	accuracy:	0.9460	-	loss:	0.1
•	88/100	2-	FOme /ston			0 0421		1	0 1
-	89/100	25	50IIIS/Step	-	accuracy:	0.9421	-	toss:	0.1
•		5s	50ms/step	-	accuracy:	0.9472	-	loss:	0.1
	90/100								
		3s	53ms/step	-	accuracy:	0.9482	-	loss:	0.1
•	91/100	55	50ms/sten	_	accuracy:	0 9510	_	1055.	o 1
-	92/100	,	3011137 3 CCP		accaracy.	0.3310			0.1.
63/63		3s	49ms/step	-	accuracy:	0.9528	-	loss:	0.1
	93/100	_	60 / 1			0 0510		-	
	94/100	65	62ms/step	-	accuracy:	0.9518	-	loss:	0.1.
		45	59ms/step	_	accuracy:	0.9398	_	loss:	0.1
-	95/100		333, 3 tap		acca. acy.	0.0000			0.1
		3s	50ms/step	-	accuracy:	0.9422	-	loss:	0.1
	96/100	٦-	47			0 0533		1	0 1
	97/100	35	4/ms/step	-	accuracy:	0.9533	-	toss:	0.1.
		4s	66ms/step	_	accuracy:	0.9402	_	loss:	0.1
-	98/100		, ,		,				
-		4s	55ms/step	-	accuracy:	0.9496	-	loss:	0.1
•	99/100	2-	10mc/c+on		accuracy:	0.0410		locci	0 1
	100/100	25	48ms/step	-	accuracy:	0.9410	-	(055;	0.1
		3s	50ms/step	-	accuracy:	0.9541	-	loss:	0.1
	ing complete. Plottin				-				
	_			^ ^					1



63/63	13/ 100	4s	59ms/step	-	accuracy:	0.7811	-	loss:	0.4
	20/100								
-	21/100	65	77ms/step	-	accuracy:	0.7604	-	loss:	0.5
		4s	56ms/step	-	accuracy:	0.7563	-	loss:	0.4
•	22/100		•		•				
	22 /100	5s	56ms/step	-	accuracy:	0.7760	-	loss:	0.4
	23/100	5s	72ms/step	_	accuracv:	0.7721	_	loss:	0.4
Epoch	24/100		·		_				
	25 /100	4s	61ms/step	-	accuracy:	0.7860	-	loss:	0.4
•	25/100	5s	60ms/step	_	accuracv:	0.7779	_	loss:	0.4
-	26/100								
-		6s	80ms/step	-	accuracy:	0.7973	-	loss:	0.4
•	27/100	45	56ms/sten	_	accuracy:	0.7997	_	loss:	0.4
Epoch	28/100		•		-				
	20./100	5s	61ms/step	-	accuracy:	0.8057	-	loss:	0.4
63/63	29/100	5s	79ms/step	_	accuracy:	0.8155	_	loss:	0.3
Epoch	30/100								
-	21/100	4s	55ms/step	-	accuracy:	0.8128	-	loss:	0.3
•	31/100	5s	56ms/step	_	accuracv:	0.8147	_	loss:	0.4
Epoch	32/100		·		_				
	33/100	6s	99ms/step	-	accuracy:	0.8298	-	loss:	0.3
•		4s	56ms/step	_	accuracy:	0.8314	_	loss:	0.3
Epoch	34/100		•		-				
	35/100	4s	56ms/step	-	accuracy:	0.8295	-	loss:	0.3
63/63		6s	92ms/step	-	accuracy:	0.8294	-	loss:	0.3
•	36/100	4 -	CO (-+			0.0422		1	0 0
-	37/100	45	60ms/step	-	accuracy:	0.8432	-	loss:	0.3
63/63		5s	55ms/step	-	accuracy:	0.8474	-	loss:	0.3
	38/100	Ec	01mc/c+on		2661182671	0 0560		10001	0.2
-	39/100	25	oriiis/sreh	-	accuracy.	0.6500	-	1055.	0.3.
63/63		3s	55ms/step	-	accuracy:	0.8678	-	loss:	0.3
Epoch 63/63	40/100	1 c	55mc/ctan	_	accuracy	0 8540	_	1000	0.3
-	41/100	73	J311137 3 CCP		accuracy.	0.0540		(033.	0.5
		5s	80ms/step	-	accuracy:	0.8515	-	loss:	0.3
•	42/100	45	64ms/sten	_	accuracy:	0.8759	_	loss:	0.3
Epoch	43/100		•		-				
	44/100	4s	55ms/step	-	accuracy:	0.8577	-	loss:	0.3
	44/100	6s	72ms/sten	_	accuracv:	0.8636	_	loss:	0.3
Epoch	45/100								
63/63 Enoch	46/100	4s	55ms/step	-	accuracy:	0.8777	-	loss:	0.2
63/63		5s	55ms/step	-	accuracy:	0.8748	-	loss:	0.3
			•		-				

					-				
	47/100	7s	81ms/step	-	accuracy:	0.8761	-	loss:	0.2
	48/100	3¢	55ms/sten	_	accuracy:	A 8867	_	1055.	0.20
Epoch	49/100								
Epoch	50/100								
	51/100	5s	81ms/step	-	accuracy:	0.8724	-	loss:	0.3
	52/100	4s	57ms/step	-	accuracy:	0.8817	-	loss:	0.2
63/63		4s	61ms/step	-	accuracy:	0.8852	-	loss:	0.2
63/63	53/100	6s	90ms/step	-	accuracy:	0.9140	-	loss:	0.2
Epoch 63/63	54/100	4s	56ms/step	_	accuracv:	0.8982	_	loss:	0.2
Epoch	55/100								
Epoch	56/100								
Epoch	57/100				_				
	58/100	3s	55ms/step	-	accuracy:	0.9081	-	loss:	0.2
63/63	59/100	5s	60ms/step	-	accuracy:	0.8903	-	loss:	0.2
63/63		5s	75ms/step	-	accuracy:	0.8942	-	loss:	0.2
63/63	60/100	3s	55ms/step	-	accuracy:	0.9119	-	loss:	0.2
	61/100	5s	56ms/step	_	accuracy:	0.8940	_	loss:	0.2
	62/100								
Epoch	63/100		•		-				
Epoch	64/100		60ms/step						
63/63 Epoch	65/100	5s	55ms/step	-	accuracy:	0.9089	-	loss:	0.2
63/63 Epoch	66/100	5s	80ms/step	-	accuracy:	0.9241	-	loss:	0.1
63/63		3s	55ms/step	-	accuracy:	0.9246	-	loss:	0.1
63/63		4s	55ms/step	-	accuracy:	0.9222	-	loss:	0.2
63/63	68/100	7s	79ms/step	-	accuracy:	0.9126	-	loss:	0.2
•	69/100	4s	60ms/step	_	accuracy:	0.9022	_	loss:	0.2
-	70/100		60ms/step		-				
Epoch	71/100		•		-				
Epoch	72/100		81ms/step		-				
-	73/100	3s	55ms/step	-	accuracy:	0.9338	-	loss:	0.1
-	74/100	5s	56ms/step	-	accuracy:	0.9259	-	loss:	0.1
= 12 0 0	, =								

								_	
	75/100	5s	76ms/step	-	accuracy:	0.9284	-	loss:	0.1
63/63		4s	59ms/step	-	accuracy:	0.9273	-	loss:	0.1
Epoch	76/100								
	77/100	45	6⊍ms/step	-	accuracy:	0.9327	-	loss:	0.1
		4s	59ms/step	-	accuracy:	0.9338	-	loss:	0.1
•	78/100	_	01 / 1			0 0045		,	0.1
-	79/100	55	81ms/step	-	accuracy:	0.9345	-	LOSS:	0.1
		3s	55ms/step	-	accuracy:	0.9320	-	loss:	0.1
	80/100	4 -	C1 / - +			0 0001		1	0 1
	81/100	45	oıms/step	-	accuracy:	0.9331	-	loss:	0.1
		6s	92ms/step	-	accuracy:	0.9344	-	loss:	0.1
	82/100	4-	FC /-+			0 0262		1	0 1
English and the	83/100								
63/63	83/100	4s	60ms/step	-	accuracy:	0.9361	-	loss:	0.1
•	84/100	F-	OFma /atan			0.0520		1	0 1
-	<u>85/100</u>	55	85IIIS/S Lep	-	accuracy:	0.9529	-	1055:	0.1.
		4s	61ms/step	-	accuracy:	0.9123	-	loss:	0.2
Epoch	86/100	1-	FFmc/cton			0 0241		1	0 1
	87/100	45	55ms/step	-	accuracy:	0.9341	-	loss:	0.1
		5s	82ms/step	-	accuracy:	0.9368	-	loss:	0.1
Epoch	88/100	4-	FC /-+			0 0202		1	0 1
	89/100	45	Sollis/Step	-	accuracy:	0.9282	-	1055:	0.1
63/63		3s	55ms/step	-	accuracy:	0.9340	-	loss:	0.1
	90/100	46	60mc/c+on		2661182674	0 0202		10001	0.2
	91/100	45	odiiis/step	-	accuracy:	0.9203	-	1055;	0.2
63/63		5s	60ms/step	-	accuracy:	0.9459	-	loss:	0.1
	92/100	5.0	56mc/cton		accuracy	0.502		10001	0 1
	93/100	23	Julia/ a cep	_	accuracy.	0.9302	_	(033.	0.1
-		4s	70ms/step	-	accuracy:	0.9393	-	loss:	0.1
•	94/100	4 c	57ms/step	_	accuracy:	0 9376	_	1000	ი 1
	95/100	73	3711137 3 CCP		accuracy.	0.3370			0.1
		4s	60ms/step	-	accuracy:	0.9276	-	loss:	0.1
	96/100	45	64ms/sten	_	accuracy:	0.9439	_	loss:	0.1
Epoch	97/100	5	04m3/3ccp		accaracy	013433			0.1
	00/100	5s	77ms/step	-	accuracy:	0.9470	-	loss:	0.1
	98/100	45	55ms/step	_	accuracy:	0.9372	_	loss:	0.1
	99/100		33m3, 3 ccp		accaracy	013372		(0551	0.1
-		6s	64ms/step	-	accuracy:	0.9450	-	loss:	0.1
	100/100	55	77ms/sten	_	accuracy:	0.9413	_	loss:	0.1
	ing complete. Plottin		•		2000.00,1	2.3.13		-555.	
	Scrat	ch Mo	odel: subset_200	0_1	000_1000				



From Step 1 to 2, Increasing training data from 1,000 \rightarrow 2,000 improved test accuracy substantially (0.758 \rightarrow 0.840). In Step 3, The 'ideal' run used the same training amount as Step 2 (2,000) but larger validation/test splits; test accuracy for that run was slightly lower (0.825), likely because the larger test set is a stricter estimate and/or because of variance in which images were selected.

J

```
def build_and_train_pretrained(subset_name, train_ds, val_ds, test_ds
    print(f"\n--- Training Pretrained Model on {subset name} ---")
    keras.backend.clear session()
    # 1. Loading VGG16 base, frozen
    conv base = keras.applications.vgg16.VGG16(
        weights="imagenet",
        include top=False,
        input_shape=(180, 180, 3))
    conv base.trainable = False
    # 2. Adding augmentation, classifier head
    data augmentation = keras.Sequential(
        [layers.RandomFlip("horizontal"),
         layers.RandomRotation(0.1),
         layers.RandomZoom(0.2)]
    )
    inputs = keras.Input(shape=(180, 180, 3))
    x = data augmentation(inputs)
    x = keras.applications.vgg16.preprocess_input(x)
    x = conv_base(x)
    x = layers.Flatten()(x)
    x = layers.Dense(256)(x)
    x = layers.Dropout(0.5)(x)
    outputs = layers.Dense(1, activation="sigmoid")(x)
    model = keras.Model(inputs, outputs)
    # 3. --- PHASE 1: FEATURE EXTRACTION ---
    print("... Phase 1: Training classifier head ...")
    checkpoint_filepath_phase1 = f"{subset_name}_pretrained_phase1.ke
    callbacks phase1 = [
        keras.callbacks.ModelCheckpoint(
            filepath=checkpoint_filepath_phase1,
            save best only=True,
            monitor="val_loss")
    ]
    model.compile(loss="binary_crossentropy",
                  optimizer="rmsprop",
                  metrics=["accuracy"])
    history_phase1 = model.fit(
        train ds,
        epochs=50, # Training classifier for 50 epochs
        validation data=val ds,
        callhacks-callhacks nhase1
```

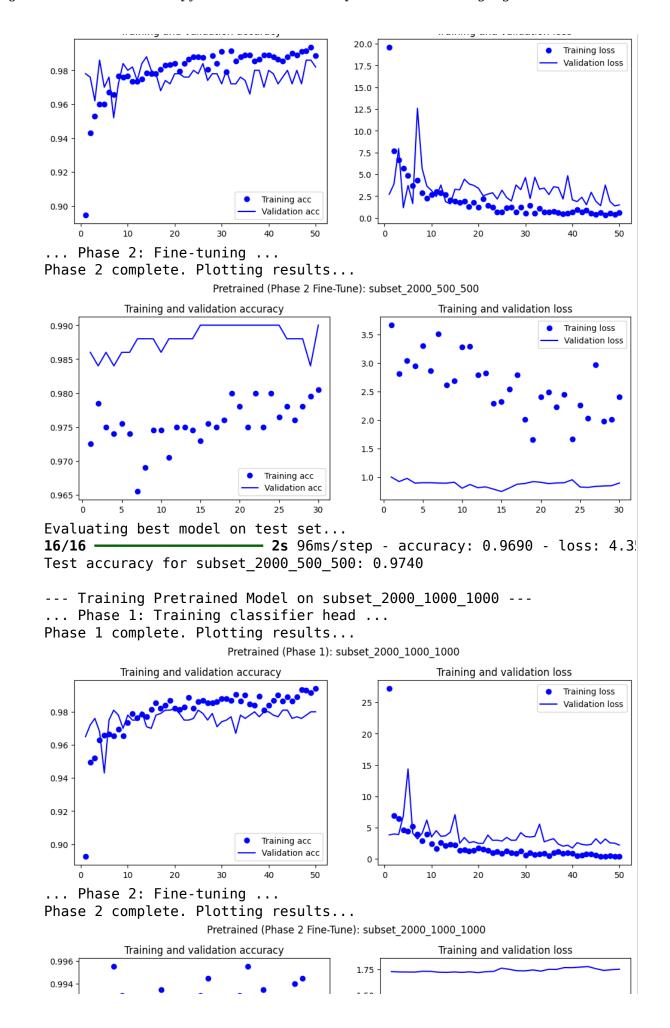
caιιραςκο-ςαιιραςκο_pπαοςτ,

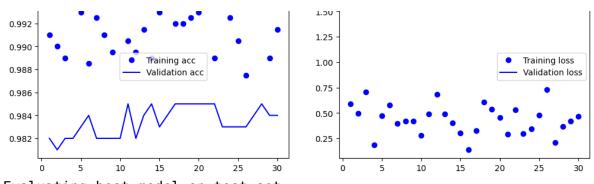
```
verbose=0)
    print("Phase 1 complete. Plotting results...")
    plot_history(history_phase1, f"Pretrained (Phase 1): {subset_name}
    # 4. --- PHASE 2: FINE-TUNING ---
    print("... Phase 2: Fine-tuning ...")
    model = keras.models.load model(checkpoint filepath phasel) # Load
    # Unfreeze the top layers of VGG16
    conv_base.trainable = True
    for layer in conv_base.layers[:-4]:
        layer.trainable = False
    checkpoint_filepath_phase2 = f"{subset_name}_pretrained_phase2.ke
    callbacks_phase2 = [
        keras.callbacks.ModelCheckpoint(
            filepath=checkpoint_filepath_phase2,
            save_best_only=True,
            monitor="val loss")
    ]
    # Re-compiling with a very low learning rate
    model.compile(loss="binary_crossentropy",
                  optimizer=keras.optimizers.RMSprop(learning rate=1e
                  metrics=["accuracy"])
    history_phase2 = model.fit(
        train_ds,
        epochs=30, # Fine-tune for 30 epochs
        validation_data=val_ds,
        callbacks=callbacks phase2,
        verbose=0)
    print("Phase 2 complete. Plotting results...")
    plot_history(history_phase2, f"Pretrained (Phase 2 Fine-Tune): {sr
    # 5. --- FINAL EVALUATION ---
    print("Evaluating best model on test set...")
    test_model = keras.models.load_model(checkpoint_filepath_phase2) ;
    test loss, test acc = test model.evaluate(test ds)
    print(f"Test accuracy for {subset_name}: {test_acc:.4f}")
    return test acc
# --- Running the Pretrained Experiments ---
# Step 4 (part 1): Train=1000, Val=500, Test=500
results["pretrained 1000"] = build and train pretrained(
```

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```
SUDSEL_1000_000_000 , LTain_0s_1, val_0s_1, Lest_0s_1)
# Step 4 (part 2): Train=2000, Val=500, Test=500
results["pretrained_2000"] = build_and_train_pretrained(
     "subset_2000_500_500", train_ds_2, val_ds_2, test_ds_2)
# Step 4 (part 3): Train=2000, Val=1000, Test=1000 (The "ideal")
results["pretrained_ideal"] = build_and_train_pretrained(
     "subset 2000 1000 1000", train ds 3, val ds 3, test ds 3)
--- Training Pretrained Model on subset 1000 500 500 ---
Downloading data from <a href="https://storage.googleapis.com/tensorflow/keras-red">https://storage.googleapis.com/tensorflow/keras-red</a>
58889256/58889256 -
                                                - 0s Ous/step
... Phase 1: Training classifier head ...
Phase 1 complete. Plotting results...
                            Pretrained (Phase 1): subset_1000_500_500
           Training and validation accuracy
                                                           Training and validation loss
 1.00
                                                                              Training loss
                                                                              Validation loss
                                                25
 0.98
 0.96
                                                20
 0.94
                                                15
 0.92
                                                10
 0.90
                                 Training acc
 0.88
                                 Validation acc
           10
                   20
                                 40
                                                         10
... Phase 2: Fine-tuning ...
Phase 2 complete. Plotting results...
                         Pretrained (Phase 2 Fine-Tune): subset 1000 500 500
            Training and validation accuracy
                                                           Training and validation loss
                                                4.0
                                                                              Training loss
                                                                              Validation loss
 0.985
                                                3.5
                                                3.0
 0.980
                                                2.5
 0.975
                                                2.0
 0.970
                                                1.5
                                 Training acc
 0.965
                                 Validation acc
                                                1.0
                 10
                       15
Evaluating best model on test set...
16/16 -
                                 2s 95ms/step - accuracy: 0.9635 - loss: 7.9
Test accuracy for subset 1000 500 500: 0.9660
--- Training Pretrained Model on subset_2000_500_500 ---
... Phase 1: Training classifier head ...
Phase 1 complete. Plotting results...
                            Pretrained (Phase 1): subset 2000 500 500
           Training and validation accuracy
                                                           Training and validation loss
```





Evaluating best model on test set...

32/32 — 3s 93ms/step - accuracy: 0.9870 - loss: 1.4!

Test accuracy for subset_2000_1000_1000: 0.9830

In Step 4, Transfer learning (pretrained VGG16 + fine-tuning) outperformed the model trained from scratch by a large margin for all sample sizes. Even with only 1,000 training images, the pretrained model reached ~96.6% test accuracy, whereas the scratch model reached ~75.8%. Also noticeably, Pretrained models improved significantly with more train data (96.6% \rightarrow 97.4% \rightarrow 98.3%), indicating diminishing returns but still measurable gains from additional labeled data when combined with transfer learning and fine-tuning.

```
print("\n\n--- FINAL RESULTS ---")
print(results)

--- FINAL RESULTS ---
{'scratch_1000': 0.7580000162124634, 'scratch_2000': 0.839999973773956.
```