PART 1

```
import tensorflow as tf
from pathlib import Path
from PIL import Image

base_dir  = Path.home() / "Desktop" / "data.set" / "indoorCVPR_09" / "Images"
train_txt = Path.home() / "Desktop" / "data.set" / "TrainImages.txt"
test_txt  = Path.home() / "Desktop" / "data.set" / "TestImages.txt"
```

```
with open(train_txt, "r") as f:
    train_paths = [base_dir / line.strip() for line in f]

with open(test_txt, "r") as f:
    test_paths  = [base_dir / line.strip() for line in f]

print(f"Toplam Train görüntü: {len(train_paths)}, Test görüntü:
{len(test_paths)}")
```

Output:
Toplam Train görüntü: 5360, Test görüntü: 1340

```
train_labels = [p.parent.name for p in train_paths]
test_labels  = [p.parent.name for p in test_paths]
```

```
class_names    = sorted(set(train_labels))
label_to_index = {name: idx for idx, name in enumerate(class_names)}

train_indices = [label_to_index[l] for l in train_labels]
test_indices  = [label_to_index[l] for l in test_labels]

print("Sınıf sayısı:", len(class_names))
```

Output:
Sınıf sayısı: 67

```
train_path_strs = [str(p) for p in train_paths]
test_path_strs  = [str(p) for p in test_paths]
```

```
def deep_filter(path_strs, labels):
    valid_p, valid_l = [], []
    for p, l in zip(path_strs, labels):
        try:
            with Image.open(p) as img:
                img.load()
            valid_p.append(p)
            valid_l.append(l)
        except Exception:
            # bozuk dosya, atla
            pass
    return valid_p, valid_l

train_path_strs, train_indices = deep_filter(train_path_strs, train_indices)
test_path_strs,  test_indices  = deep_filter(test_path_strs,  test_indices)

print(f"Filtre sonrası: Train={len(train_path_strs)},
Test={len(test_path_strs)}")
```

Output:

Filtre sonrası: Train=5360, Test=1340

```
IMG_SIZE   = (224, 224)
BATCH_SIZE = 32

def load_and_preprocess(path, label):
    img = tf.io.read_file(path)
    img = tf.image.decode_image(img, channels=3, expand_animations=False)
    img.set_shape([None, None, 3])
    img = tf.image.resize(img, IMG_SIZE)
    img = img / 255.0
    return img, label
```

```
train_ds = (
    tf.data.Dataset.from_tensor_slices((train_path_strs, train_indices))
      .map(load_and_preprocess, num_parallel_calls=tf.data.AUTOTUNE)
      .shuffle(1000)
      .batch(BATCH_SIZE)
      .prefetch(tf.data.AUTOTUNE)
      .ignore_errors()     # Hatalı örnekleri atla
)

test_ds = (
    tf.data.Dataset.from_tensor_slices((test_path_strs, test_indices))
      .map(load_and_preprocess, num_parallel_calls=tf.data.AUTOTUNE)
      .batch(BATCH_SIZE)
      .prefetch(tf.data.AUTOTUNE)
      .ignore_errors()    # Hatalı örnekleri atla
)
```

```
from sklearn.model_selection import train_test_split

train_paths_split, val_paths_split, train_idx_split, val_idx_split =
train_test_split(
    train_path_strs,
    train_indices,
    test_size=0.2,
    stratify=train_indices,
    random_state=42
)

val_ds = (
    tf.data.Dataset.from_tensor_slices((val_paths_split, val_idx_split))
      .map(load_and_preprocess, num_parallel_calls=tf.data.AUTOTUNE)
      .batch(BATCH_SIZE)
      .prefetch(tf.data.AUTOTUNE)
)
```

```
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, 3, activation='relu',
input_shape=(*IMG_SIZE,3)),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(64, 3, activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(len(class_names), activation='softmax'),
])

model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

model.summary()
```

Output:

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
flatten (Flatten)	(None, 186624)	0
dense (Dense)	(None, 128)	23,888,000
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 67)	8,643

```
Total params: 23,916,035 (91.23 MB)

Trainable params: 23,916,035 (91.23 MB)

Non-trainable params: 0 (0.00 B)
```

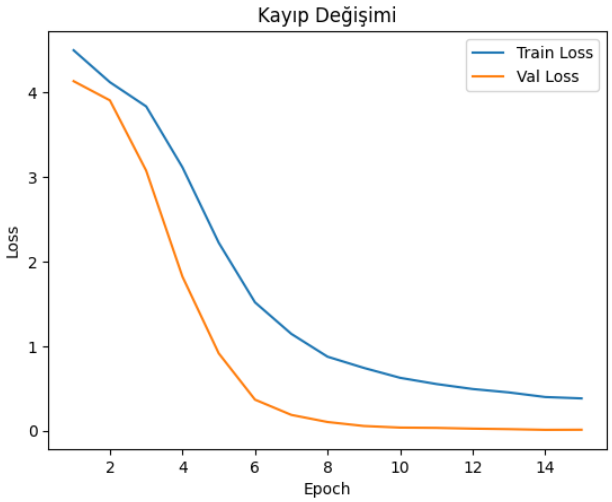
```python
from tensorflow.keras.callbacks import EarlyStopping
es = EarlyStopping(monitor='val_loss', patience=1, restore_best_weights=True)

history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=19,
    callbacks=[es]
)
```

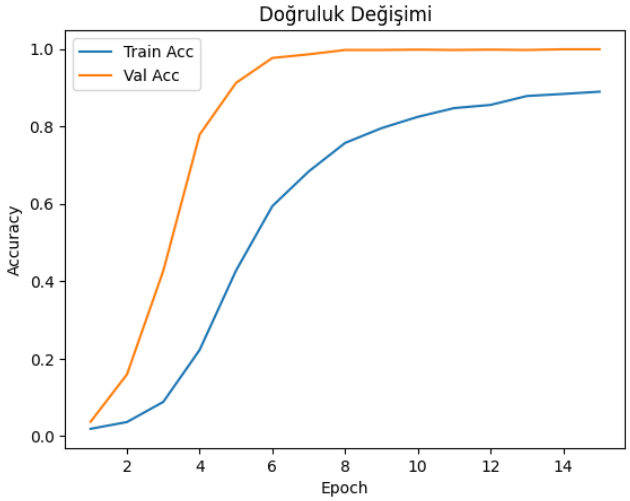
Output:

```
168/168 ━━━━━━━━━━━━━━━━━━━━ 34s 197ms/step - accuracy: 0.0166 - loss: 5.5112 - val_accuracy: 0.0373 - val_loss: 4.1356
Epoch 2/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 33s 193ms/step - accuracy: 0.0334 - loss: 4.1470 - val_accuracy: 0.1595 - val_loss: 3.9085
Epoch 3/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 33s 192ms/step - accuracy: 0.0734 - loss: 3.9216 - val_accuracy: 0.4272 - val_loss: 3.0766
Epoch 4/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 33s 194ms/step - accuracy: 0.1948 - loss: 3.2665 - val_accuracy: 0.7789 - val_loss: 1.8222
Epoch 5/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 37s 217ms/step - accuracy: 0.4058 - loss: 2.3488 - val_accuracy: 0.9123 - val_loss: 0.9143
Epoch 6/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 37s 220ms/step - accuracy: 0.5712 - loss: 1.5963 - val_accuracy: 0.9767 - val_loss: 0.3662
Epoch 7/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 38s 224ms/step - accuracy: 0.6604 - loss: 1.2298 - val_accuracy: 0.9860 - val_loss: 0.1859
Epoch 8/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 39s 230ms/step - accuracy: 0.7503 - loss: 0.8918 - val_accuracy: 0.9972 - val_loss: 0.1016
Epoch 9/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 39s 230ms/step - accuracy: 0.7864 - loss: 0.7689 - val_accuracy: 0.9972 - val_loss: 0.0544
Epoch 10/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 39s 231ms/step - accuracy: 0.8174 - loss: 0.6416 - val_accuracy: 0.9981 - val_loss: 0.0355
Epoch 11/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 39s 230ms/step - accuracy: 0.8382 - loss: 0.5753 - val_accuracy: 0.9972 - val_loss: 0.0321
Epoch 12/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 39s 229ms/step - accuracy: 0.8515 - loss: 0.5159 - val_accuracy: 0.9981 - val_loss: 0.0230
Epoch 13/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 38s 225ms/step - accuracy: 0.8813 - loss: 0.4542 - val_accuracy: 0.9972 - val_loss: 0.0172
Epoch 14/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 39s 227ms/step - accuracy: 0.8803 - loss: 0.4131 - val_accuracy: 0.9991 - val_loss: 0.0090
Epoch 15/19
168/168 ━━━━━━━━━━━━━━━━━━━━ 38s 224ms/step - accuracy: 0.8935 - loss: 0.3862 - val_accuracy: 0.9991 - val_loss: 0.0102
```

```python
import matplotlib.pyplot as plt

epochs = range(1, len(history.history['loss']) + 1)

plt.figure()
plt.plot(epochs, history.history['loss'],     label='Train Loss')
plt.plot(epochs, history.history['val_loss'],label='Val Loss')
plt.title('Kayıp Değişimi')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()

plt.figure()
plt.plot(epochs, history.history['accuracy'],     label='Train Acc')
plt.plot(epochs, history.history['val_accuracy'],label='Val Acc')
plt.title('Doğruluk Değişimi')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

Output:





```
# Orijinal dataset
orig_train = train_ds.unbatch()
orig_val   = val_ds.unbatch()

input_shape = (*IMG_SIZE, 3)    # IMG_SIZE = (224,224)
num_classes = len(class_names)

histories = {}

for lr in [1e-2, 1e-3, 1e-4]:
    for bs in [32, 64]:
        train_ds_bs = (
            orig_train
            .shuffle(1000)
            .batch(bs)
            .prefetch(tf.data.AUTOTUNE)
            .apply(tf.data.experimental.ignore_errors())
        )
        val_ds_bs = (
            orig_val
            .batch(bs)
            .prefetch(tf.data.AUTOTUNE)
        )

        model = tf.keras.Sequential([
            tf.keras.layers.Conv2D(32, 3, activation='relu',
input_shape=input_shape),
            tf.keras.layers.MaxPooling2D(),
            tf.keras.layers.Conv2D(64, 3, activation='relu'),
            tf.keras.layers.MaxPooling2D(),
            tf.keras.layers.Flatten(),
            tf.keras.layers.Dense(128, activation='relu'),
            tf.keras.layers.Dropout(0.5),
            tf.keras.layers.Dense(num_classes, activation='softmax'),
        ])

        model.compile(
            optimizer=tf.keras.optimizers.Adam(learning_rate=lr),
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy']
        )

        es = EarlyStopping(monitor='val_loss', patience=1,
restore_best_weights=True)
        hist = model.fit(
            train_ds_bs,
            validation_data=val_ds_bs,
            epochs=100,
            callbacks=[es],
```

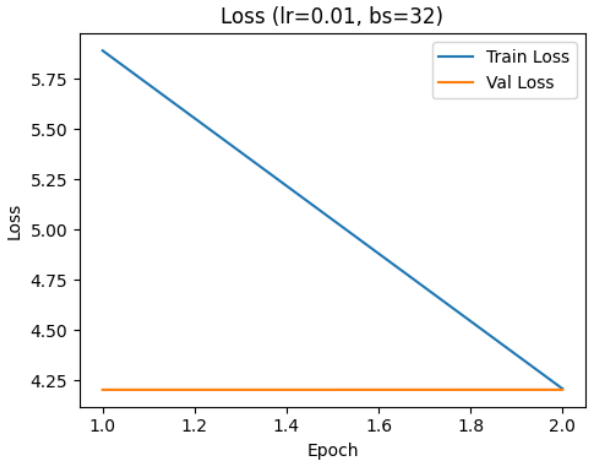
```
            verbose=2
        )

        histories[(lr, bs)] = hist.history
```

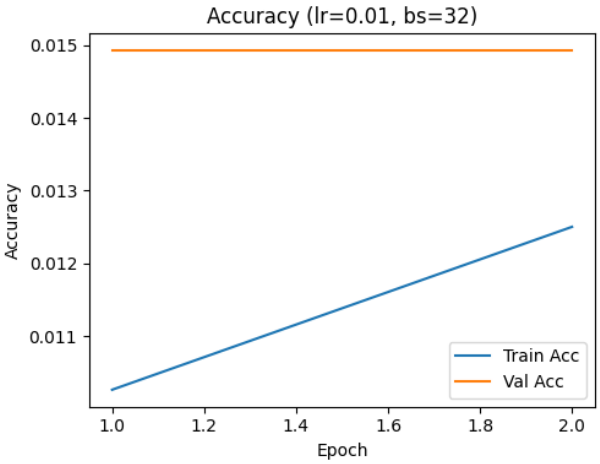
Output:

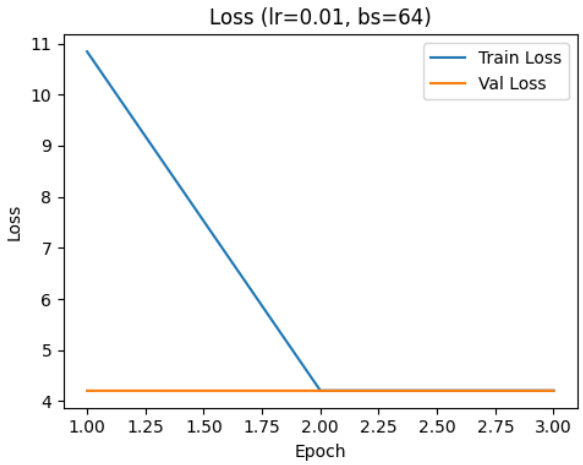
```
WARNING:tensorflow:From C:\Users\Can\AppData\Local\Temp\ipykernel_22472\951501377.py:23: ignore_errors (from tensorflow.python.data.experimental.ops.error_ops) is deprecated and will b
Instructions for updating:
Use `tf.data.Dataset.ignore_errors` instead.
Epoch 1/100
168/168 - 39s - 229ms/step - accuracy: 0.0103 - loss: 5.8912 - val_accuracy: 0.0149 - val_loss: 4.2050
Epoch 2/100
168/168 - 37s - 223ms/step - accuracy: 0.0125 - loss: 4.2102 - val_accuracy: 0.0149 - val_loss: 4.2050
Epoch 1/100
84/84 - 33s - 388ms/step - accuracy: 0.0140 - loss: 10.8408 - val_accuracy: 0.0149 - val_loss: 4.2050
Epoch 2/100
84/84 - 32s - 379ms/step - accuracy: 0.0108 - loss: 4.2081 - val_accuracy: 0.0149 - val_loss: 4.2048
Epoch 3/100
84/84 - 32s - 379ms/step - accuracy: 0.0099 - loss: 4.2083 - val_accuracy: 0.0149 - val_loss: 4.2049
Epoch 1/100
168/168 - 39s - 230ms/step - accuracy: 0.0177 - loss: 4.5195 - val_accuracy: 0.0392 - val_loss: 4.1954
Epoch 2/100
168/168 - 38s - 228ms/step - accuracy: 0.0278 - loss: 4.1579 - val_accuracy: 0.0700 - val_loss: 4.0364
Epoch 3/100
168/168 - 38s - 228ms/step - accuracy: 0.0648 - loss: 3.9736 - val_accuracy: 0.2015 - val_loss: 3.5790
Epoch 4/100
168/168 - 38s - 228ms/step - accuracy: 0.1187 - loss: 3.6152 - val_accuracy: 0.4188 - val_loss: 2.7757
Epoch 5/100
168/168 - 38s - 227ms/step - accuracy: 0.2000 - loss: 3.1142 - val_accuracy: 0.6595 - val_loss: 1.9294
Epoch 6/100
168/168 - 39s - 231ms/step - accuracy: 0.2907 - loss: 2.6235 - val_accuracy: 0.8032 - val_loss: 1.3877
...
Epoch 1/100
84/84 - 33s - 396ms/step - accuracy: 0.0121 - loss: 4.2190 - val_accuracy: 0.0159 - val_loss: 4.2046
Epoch 2/100
84/84 - 33s - 387ms/step - accuracy: 0.0132 - loss: 4.2049 - val_accuracy: 0.0149 - val_loss: 4.2047
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
```

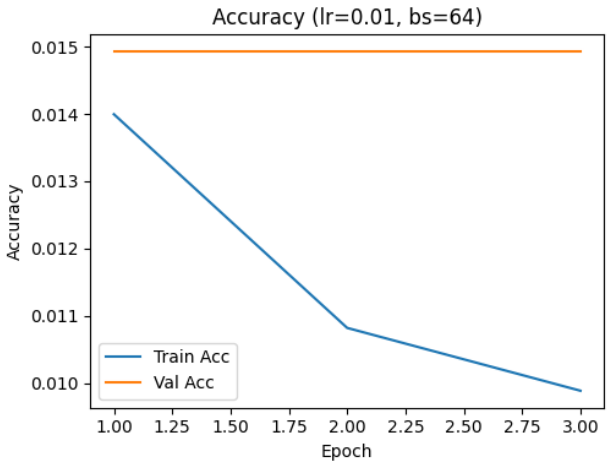
```python
for (lr, bs), h in histories.items():
    epochs = range(1, len(h['loss']) + 1)
    plt.figure(figsize=(10, 4))

    # Loss eğrisi
    plt.subplot(1, 2, 1)
    plt.plot(epochs, h['loss'],    label='Train Loss')
    plt.plot(epochs, h['val_loss'],label='Val Loss')
    plt.title(f'Loss (lr={lr}, bs={bs})')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy eğrisi
    plt.subplot(1, 2, 2)
    plt.plot(epochs, h['accuracy'],    label='Train Acc')
    plt.plot(epochs, h['val_accuracy'],label='Val Acc')
    plt.title(f'Accuracy (lr={lr}, bs={bs})')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

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

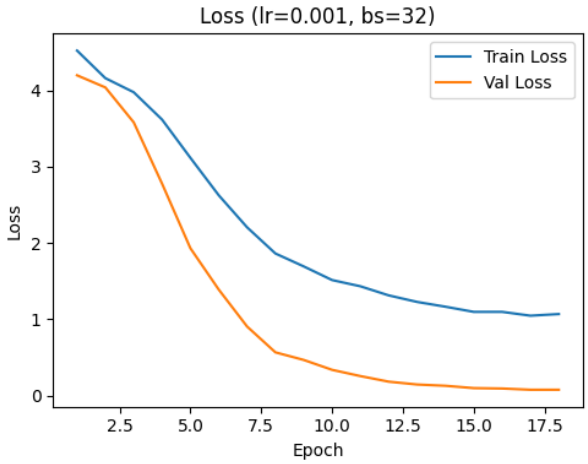
Output:

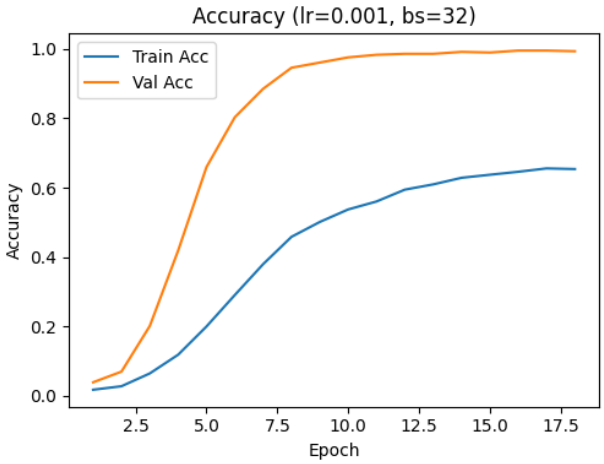

Loss (lr=0.01, bs=32)
Train Loss
Val Loss
Loss
Epoch

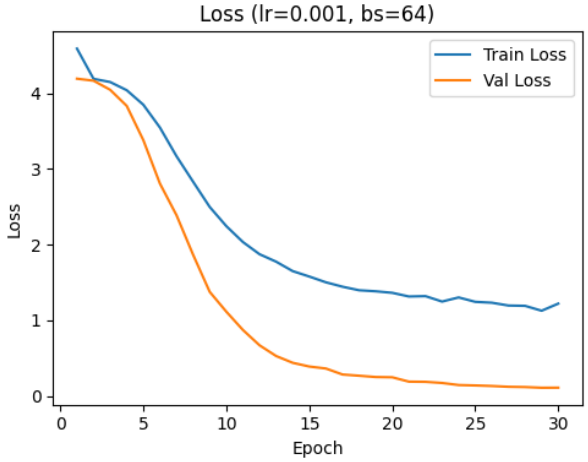

Accuracy (lr=0.01, bs=32)
Train Acc
Val Acc
Accuracy
Epoch

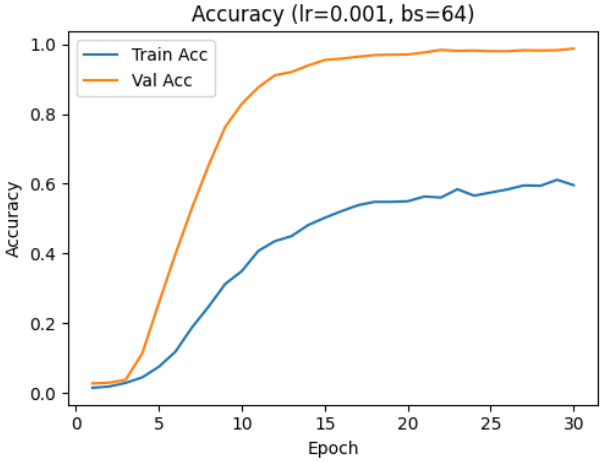

Loss (lr=0.01, bs=64)
Train Loss
Val Loss
Loss
Epoch

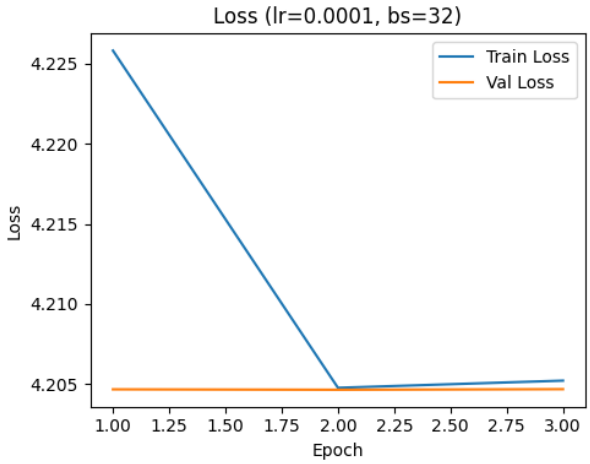

Accuracy (lr=0.01, bs=64)
Train Acc
Val Acc
Accuracy
Epoch

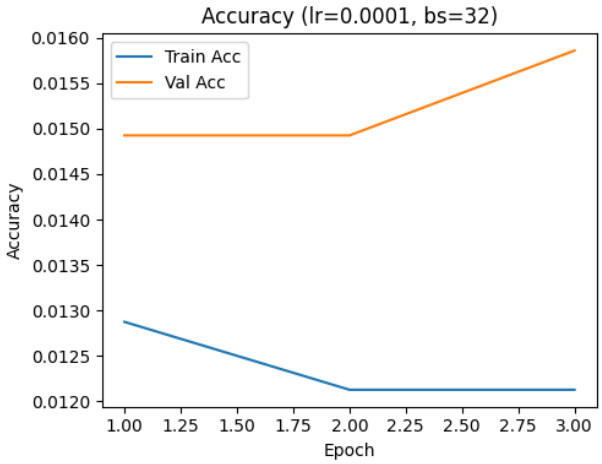

Loss (lr=0.001, bs=32)
Train Loss
Val Loss
Loss
Epoch

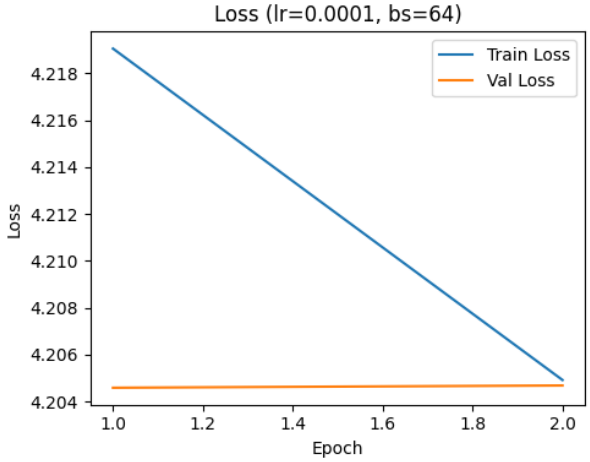

Accuracy (lr=0.001, bs=32)
Train Acc
Val Acc
Accuracy
Epoch

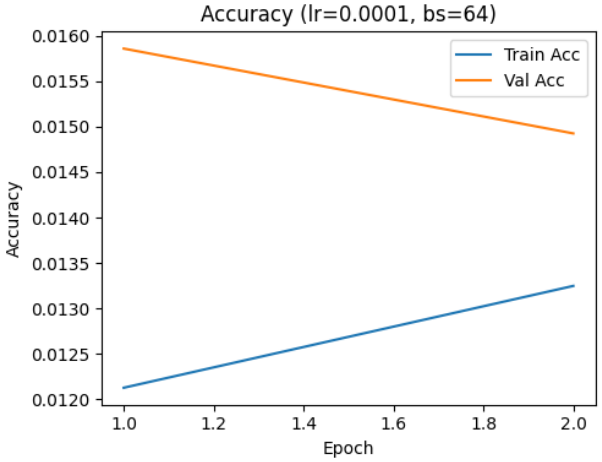

Loss (lr=0.001, bs=64)
Train Loss
Val Loss
Loss
Epoch


Accuracy (lr=0.001, bs=64)
Train Acc
Val Acc
Accuracy
Epoch


Loss (lr=0.0001, bs=32)
Train Loss
Val Loss
Loss
Epoch
4.225
4.220
4.215
4.210
4.205
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00


Accuracy (lr=0.0001, bs=32)
Train Acc
Val Acc
Accuracy
Epoch
0.0160
0.0155
0.0150
0.0145
0.0140
0.0135
0.0130
0.0125
0.0120
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00


Loss (lr=0.0001, bs=64)
Train Loss
Val Loss
Loss
Epoch
4.218
4.216
4.214
4.212
4.210
4.208
4.206
4.204
1.0
1.2
1.4
1.6
1.8
2.0


Accuracy (lr=0.0001, bs=64)
Train Acc
Val Acc
Accuracy
Epoch
0.0160
0.0155
0.0150
0.0145
0.0140
0.0135
0.0130
0.0125
0.0120
1.0
1.2
1.4
1.6
1.8
2.0

```python
import pandas as pd

records = []
for (lr, bs), h in histories.items():
    records.append({
        'learning_rate': lr,
        'batch_size':    bs,
        'max_val_acc':   max(h['val_accuracy']),
        'min_val_loss':  min(h['val_loss'])
    })
df_results = pd.DataFrame(records).sort_values(
    by='max_val_acc', ascending=False
).reset_index(drop=True)

df_results
```

Output:

	learning_rate	batch_size	max_val_acc	min_val_loss
0	0.0010	32	0.995336	0.074799
1	0.0010	64	0.987873	0.110327
2	0.0001	32	0.015858	4.204634
3	0.0001	64	0.015858	4.204595
4	0.0100	32	0.014925	4.204967
5	0.0100	64	0.014925	4.204752

```
best      = df_results.iloc[0]
lr_best   = best.learning_rate
bs_best   = int(best.batch_size)
```

```
import numpy as np
# Best combinationn
best      = df_results.iloc[0]
lr_best   = best.learning_rate
bs_best   = int(best.batch_size)

# Train + val data set prep
full_train = orig_train.shuffle(1000) \
                       .batch(bs_best) \
                       .prefetch(tf.data.AUTOTUNE)
val_ds_bs  = orig_val.batch(bs_best) \
                     .prefetch(tf.data.AUTOTUNE)

model_final = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, 3, activation='relu', input_shape=input_shape),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(64, 3, activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(num_classes, activation='softmax'),
])
model_final.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=lr_best),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

es = EarlyStopping(monitor='val_loss', patience=1, restore_best_weights=True)
model_final.fit(
    full_train,
    validation_data=val_ds_bs,
    epochs=50,
    callbacks=[es],
    verbose=2
)

orig_test   = test_ds.unbatch()
test_ds_bs  = orig_test.batch(bs_best) \
                       .prefetch(tf.data.AUTOTUNE)

for x_batch, y_batch in test_ds_bs.take(1):
    q_loss, q_acc = model_final.evaluate(x_batch, y_batch, verbose=2)
```

```
    print(f"[Quick test] Loss: {q_loss:.4f}, Acc: {q_acc:.4f}")
    break

x_list, y_list = [], []
for x_batch, y_batch in test_ds_bs:
    x_list.append(x_batch.numpy())
    y_list.append(y_batch.numpy())

x_test = np.concatenate(x_list, axis=0)
y_test = np.concatenate(y_list, axis=0)

test_loss, test_acc = model_final.evaluate(x_test, y_test, verbose=2)
print(f"[Full test] Loss: {test_loss:.4f}, Acc: {test_acc:.4f}")
```

Output:

```
168/168 - 39s - 232ms/step - accuracy: 0.0164 - loss: 4.3620 - val_accuracy: 0.0243 - val_loss: 4.1875
Epoch 2/50
168/168 - 38s - 228ms/step - accuracy: 0.0233 - loss: 4.1813 - val_accuracy: 0.0364 - val_loss: 4.1289
Epoch 3/50
168/168 - 38s - 228ms/step - accuracy: 0.0291 - loss: 4.1279 - val_accuracy: 0.0644 - val_loss: 4.0542
Epoch 4/50
168/168 - 38s - 226ms/step - accuracy: 0.0485 - loss: 4.0188 - val_accuracy: 0.1082 - val_loss: 3.7360
Epoch 5/50
168/168 - 38s - 228ms/step - accuracy: 0.0720 - loss: 3.8107 - val_accuracy: 0.2369 - val_loss: 3.3199
Epoch 6/50
168/168 - 38s - 228ms/step - accuracy: 0.1155 - loss: 3.5317 - val_accuracy: 0.3396 - val_loss: 2.8298
Epoch 7/50
168/168 - 38s - 228ms/step - accuracy: 0.1635 - loss: 3.2035 - val_accuracy: 0.5317 - val_loss: 2.2870
Epoch 8/50
168/168 - 38s - 228ms/step - accuracy: 0.2010 - loss: 2.9361 - val_accuracy: 0.6213 - val_loss: 1.8609
Epoch 9/50
168/168 - 38s - 226ms/step - accuracy: 0.2476 - loss: 2.6889 - val_accuracy: 0.7080 - val_loss: 1.5716
Epoch 10/50
168/168 - 38s - 227ms/step - accuracy: 0.2874 - loss: 2.4667 - val_accuracy: 0.7640 - val_loss: 1.2905
Epoch 11/50
168/168 - 38s - 227ms/step - accuracy: 0.3144 - loss: 2.3099 - val_accuracy: 0.8116 - val_loss: 1.1102
Epoch 12/50
168/168 - 38s - 227ms/step - accuracy: 0.3299 - loss: 2.2352 - val_accuracy: 0.8451 - val_loss: 0.8902
Epoch 13/50
168/168 - 38s - 227ms/step - accuracy: 0.3600 - loss: 2.0915 - val_accuracy: 0.8535 - val_loss: 0.7493
...
1/1 - 0s - 83ms/step - accuracy: 0.0938 - loss: 4.8116
[Quick test] Loss: 4.8116, Acc: 0.0938
42/42 - 2s - 56ms/step - accuracy: 0.0828 - loss: 4.7315
[Full test] Loss: 4.7315, Acc: 0.0828
```

```python
orig_test   = test_ds.unbatch()
test_ds_bs  = orig_test.batch(bs_best) \
                       .prefetch(tf.data.AUTOTUNE)

for x_batch, y_batch in test_ds_bs.take(1):
    q_loss, q_acc = model_final.evaluate(x_batch, y_batch, verbose=2)
    print(f"[Quick test] Loss: {q_loss:.4f}, Acc: {q_acc:.4f}")
    break

x_list, y_list = [], []
for x_batch, y_batch in test_ds_bs:
    x_list.append(x_batch.numpy())
    y_list.append(y_batch.numpy())

x_test = np.concatenate(x_list, axis=0)
y_test = np.concatenate(y_list, axis=0)

test_loss, test_acc = model_final.evaluate(x_test, y_test, verbose=2)
print(f"[Full test] Loss: {test_loss:.4f}, Acc: {test_acc:.4f}")
```

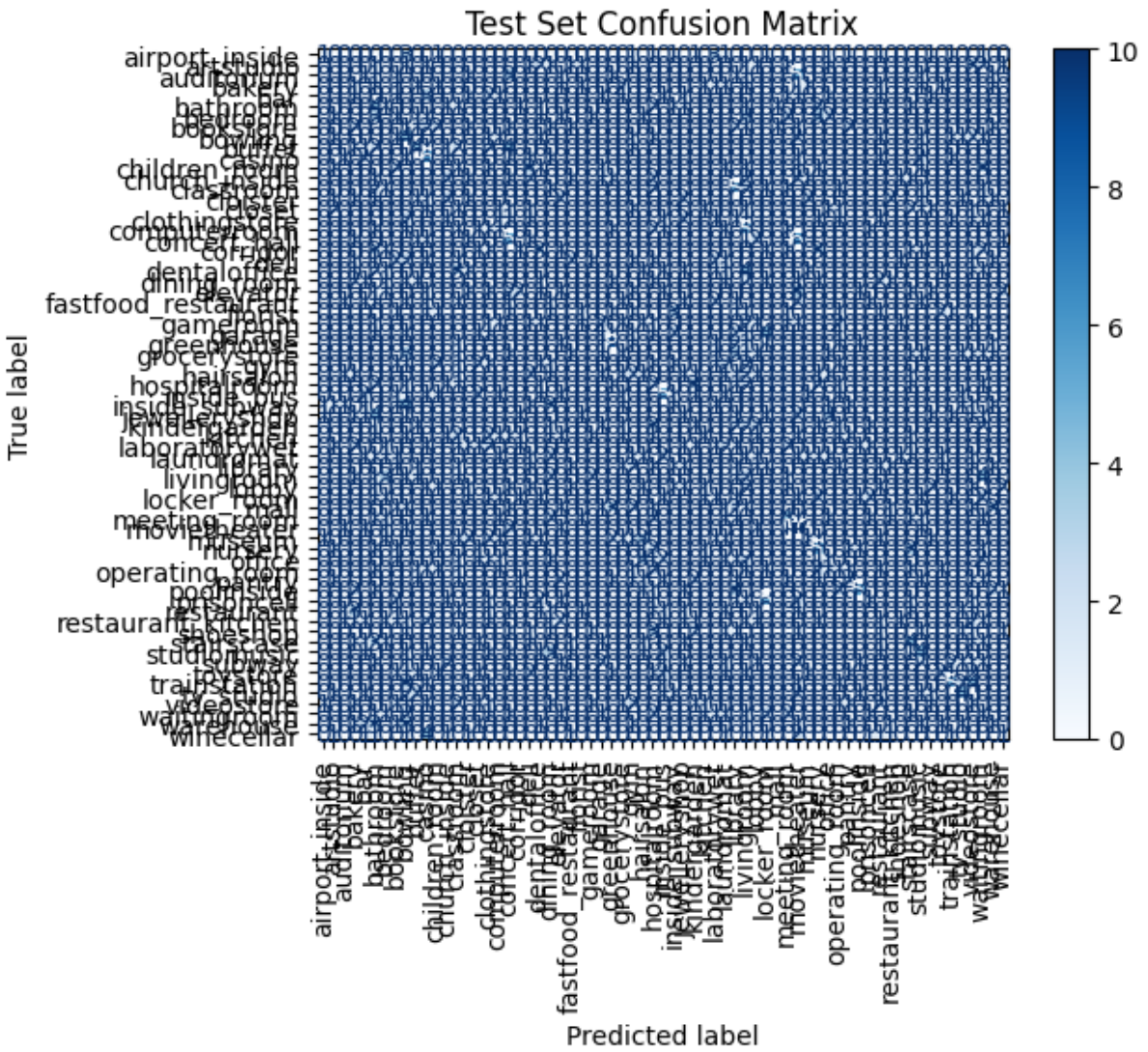
Output:

```
1/1 - 0s - 95ms/step - accuracy: 0.0938 - loss: 4.8116
[Quick test] Loss: 4.8116, Acc: 0.0938
42/42 - 2s - 57ms/step - accuracy: 0.0828 - loss: 4.7315
[Full test] Loss: 4.7315, Acc: 0.0828
```

```python
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import ConfusionMatrixDisplay

y_true = np.concatenate([y.numpy() for x, y in test_ds_bs], axis=0)
y_pred = np.concatenate([
    np.argmax(model_final.predict(x), axis=1) for x, y in test_ds_bs
], axis=0)

# Confusion matrix
cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
disp.plot(cmap='Blues', xticks_rotation='vertical')
plt.title("Test Set Confusion Matrix")
plt.show()

# Classification report
print(classification_report(y_true, y_pred, target_names=class_names))
```

Output:

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 140ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 82ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 84ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 83ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 77ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 72ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 74ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 83ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 78ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 75ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 77ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 77ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 74ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 74ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 77ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
...
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 75ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 70ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 99ms/step
```


Test Set Confusion Matrix
True label
Predicted label
airport_inside
fastfood_restaurant
restaurant_kitchen
operating_room
locker_room
laboratorywet
10
8
6
4
2
0

	precision	recall	f1-score	support
airport_inside	0.20	0.05	0.08	20
artstudio	0.00	0.00	0.00	20
auditorium	0.00	0.00	0.00	18
bakery	0.04	0.05	0.05	19
bar	0.00	0.00	0.00	18
bathroom	0.08	0.22	0.11	18
bedroom	0.00	0.00	0.00	21
bookstore	0.00	0.00	0.00	20
bowling	0.08	0.20	0.11	20
buffet	0.22	0.20	0.21	20
casino	0.17	0.32	0.22	19
children_room	0.00	0.00	0.00	18
church_inside	0.14	0.11	0.12	19
classroom	0.00	0.00	0.00	18
cloister	0.07	0.05	0.06	20
closet	0.00	0.00	0.00	18
clothingstore	0.00	0.00	0.00	18
computerroom	0.07	0.06	0.06	18
concert_hall	0.16	0.25	0.19	20
corridor	0.10	0.05	0.06	21
deli	0.00	0.00	0.00	19
dentaloffice	0.00	0.00	0.00	21
dining_room	0.00	0.00	0.00	18
...				
accuracy			0.08	1340
macro avg	0.08	0.08	0.08	1340
weighted avg	0.08	0.08	0.08	1340

```python
for x_batch, y_batch in test_ds.take(1):
    print("x_batch shape:", x_batch.shape)
    print("y_batch shape:", y_batch.shape)
    print("Unique labels in this batch:", np.unique(y_batch.numpy()))
    break

labels = [int(y.numpy()) for x, y in test_ds.unbatch()]
labels = np.array(labels)
unique, counts = np.unique(labels, return_counts=True)
print("\nClass distribution in test set:")
for cls, cnt in zip(unique, counts):
    print(f"  {class_names[cls]:<15}: {cnt}")

fig, axes = plt.subplots(3, 3, figsize=(6, 6))
for ax, (img, lbl) in zip(axes.flatten(), test_ds.unbatch().take(9)):
    ax.imshow(img.numpy())
    ax.set_title(class_names[int(lbl.numpy())])
    ax.axis('off')

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

Output:

```
 x_batch shape: (32, 224, 224, 3)
 y_batch shape: (32,)
 Unique labels in this batch: [ 4  9 14 17 18 21 27 29 30 32 33 35 36 37 39 40 42 44 45 49 50 52 55 63
  65]

 Class distribution in test set:
   airport_inside : 20
   artstudio      : 20
   auditorium     : 18
   bakery         : 19
   bar            : 18
   bathroom       : 18
   bedroom        : 21
   bookstore      : 20
   bowling        : 20
   buffet         : 20
   casino         : 19
   children_room  : 18
   church_inside  : 19
   classroom      : 18
   cloister       : 20
   closet         : 18
   clothingstore  : 18
   computerroom   : 18
   concert_hall   : 20
 ...
   videostore     : 22
   waitingroom    : 21
   warehouse      : 21
   winecellar     : 21
```

kitchen

operating_room

restaurant_kitchen

videostore

poolinside

videostore

poolinside

mall

kindergarden

PART 2

```
from tensorflow.keras import layers

data_augmentation = tf.keras.Sequential([
    layers.RandomFlip('horizontal'),
    layers.RandomRotation(0.1),
    layers.RandomZoom(0.2),
    layers.RandomContrast(0.2),
], name='data_augmentation')
```

```
AUTOTUNE = tf.data.AUTOTUNE

orig_train = train_ds.unbatch()

train_ds_tl = (
    orig_train
    .shuffle(1000)
    .batch(bs_best)
    .map(lambda x, y: (data_augmentation(x), y),
         num_parallel_calls=AUTOTUNE)
    .prefetch(AUTOTUNE)
)

orig_val = val_ds.unbatch()
val_ds_tl = (
    orig_val
    .batch(bs_best)
    .prefetch(AUTOTUNE)
)
```

```python
from tensorflow.keras import layers, models, callbacks
from tensorflow.keras.applications import VGG16, vgg16

base_model = VGG16(
    input_shape=(*IMG_SIZE, 3),
    include_top=False,
    weights='imagenet',
    pooling='avg'
)
base_model.trainable = False

inputs = layers.Input(shape=(*IMG_SIZE, 3), dtype=tf.float32)
x = vgg16.preprocess_input(inputs * 255.0)
x = base_model(x, training=False)
x = layers.Dense(256, activation='relu')(x)
x = layers.Dropout(0.3)(x)
outputs = layers.Dense(num_classes, activation='softmax')(x)

model_tl = models.Model(inputs, outputs, name='VGG16_head')

# Compile & summary
model_tl.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
model_tl.summary()

# Head-only eğitimi
es_head = callbacks.EarlyStopping(monitor='val_loss', patience=1,
restore_best_weights=True)
history_head = model_tl.fit(
    train_ds_tl,
    validation_data=val_ds_tl,
    epochs=10,
    callbacks=[es_head],
    verbose=2
)
```

Output:

Model: "VGG16_head"

Layer (type)	Output Shape	Param #	Connected to
input_layer_10 (InputLayer)	(None, 224, 224, 3)	0	-
multiply (Multiply)	(None, 224, 224, 3)	0	input_layer_10[0…
get_item (GetItem)	(None, 224, 224)	0	multiply[0][0]
get_item_1 (GetItem)	(None, 224, 224)	0	multiply[0][0]
get_item_2 (GetItem)	(None, 224, 224)	0	multiply[0][0]
stack (Stack)	(None, 224, 224, 3)	0	get_item[0][0], get_item_1[0][0], get_item_2[0][0]
add (Add)	(None, 224, 224, 3)	0	stack[0][0]
vgg16 (Functional)	(None, 512)	14,714,688	add[0][0]
dense_16 (Dense)	(None, 256)	131,328	vgg16[0][0]
dropout_8 (Dropout)	(None, 256)	0	dense_16[0][0]
dense_17 (Dense)	(None, 67)	17,219	dropout_8[0][0]

```
Total params: 14,863,235 (56.70 MB)

Trainable params: 148,547 (580.26 KB)

Non-trainable params: 14,714,688 (56.13 MB)
```

```
168/168 - 732s - 4s/step - accuracy: 0.0927 - loss: 4.3246 - val_accuracy: 0.3032 - val_loss: 2.8420
Epoch 2/10
168/168 - 629s - 4s/step - accuracy: 0.2237 - loss: 3.1177 - val_accuracy: 0.4711 - val_loss: 1.9486
Epoch 3/10
168/168 - 629s - 4s/step - accuracy: 0.3411 - loss: 2.5439 - val_accuracy: 0.5485 - val_loss: 1.6511
Epoch 4/10
168/168 - 620s - 4s/step - accuracy: 0.3999 - loss: 2.2526 - val_accuracy: 0.6157 - val_loss: 1.3828
Epoch 5/10
168/168 - 618s - 4s/step - accuracy: 0.4314 - loss: 2.0985 - val_accuracy: 0.6642 - val_loss: 1.2001
Epoch 6/10
168/168 - 618s - 4s/step - accuracy: 0.4676 - loss: 1.9602 - val_accuracy: 0.6726 - val_loss: 1.1009
Epoch 7/10
168/168 - 621s - 4s/step - accuracy: 0.4891 - loss: 1.8256 - val_accuracy: 0.6884 - val_loss: 1.0748
Epoch 8/10
168/168 - 617s - 4s/step - accuracy: 0.5132 - loss: 1.7241 - val_accuracy: 0.6959 - val_loss: 1.0362
Epoch 9/10
168/168 - 618s - 4s/step - accuracy: 0.5329 - loss: 1.6638 - val_accuracy: 0.7090 - val_loss: 0.9615
Epoch 10/10
168/168 - 619s - 4s/step - accuracy: 0.5436 - loss: 1.5983 - val_accuracy: 0.7211 - val_loss: 0.9389
```

```python
from tensorflow.keras import callbacks

# Base modelin tümünü aç sonra baştan birkaç bloğu freeze et
base_model.trainable = True
for layer in base_model.layers:
    layer.trainable = layer.name.startswith("block5_")

model_tl.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-5),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

# Fine-tune
es_ft = callbacks.EarlyStopping(
    monitor='val_loss', patience=2, restore_best_weights=True
)
history_finetune = model_tl.fit(
    train_ds_tl,
    validation_data=val_ds_tl,
    epochs=10,
    callbacks=[es_ft],
    verbose=2
)
```

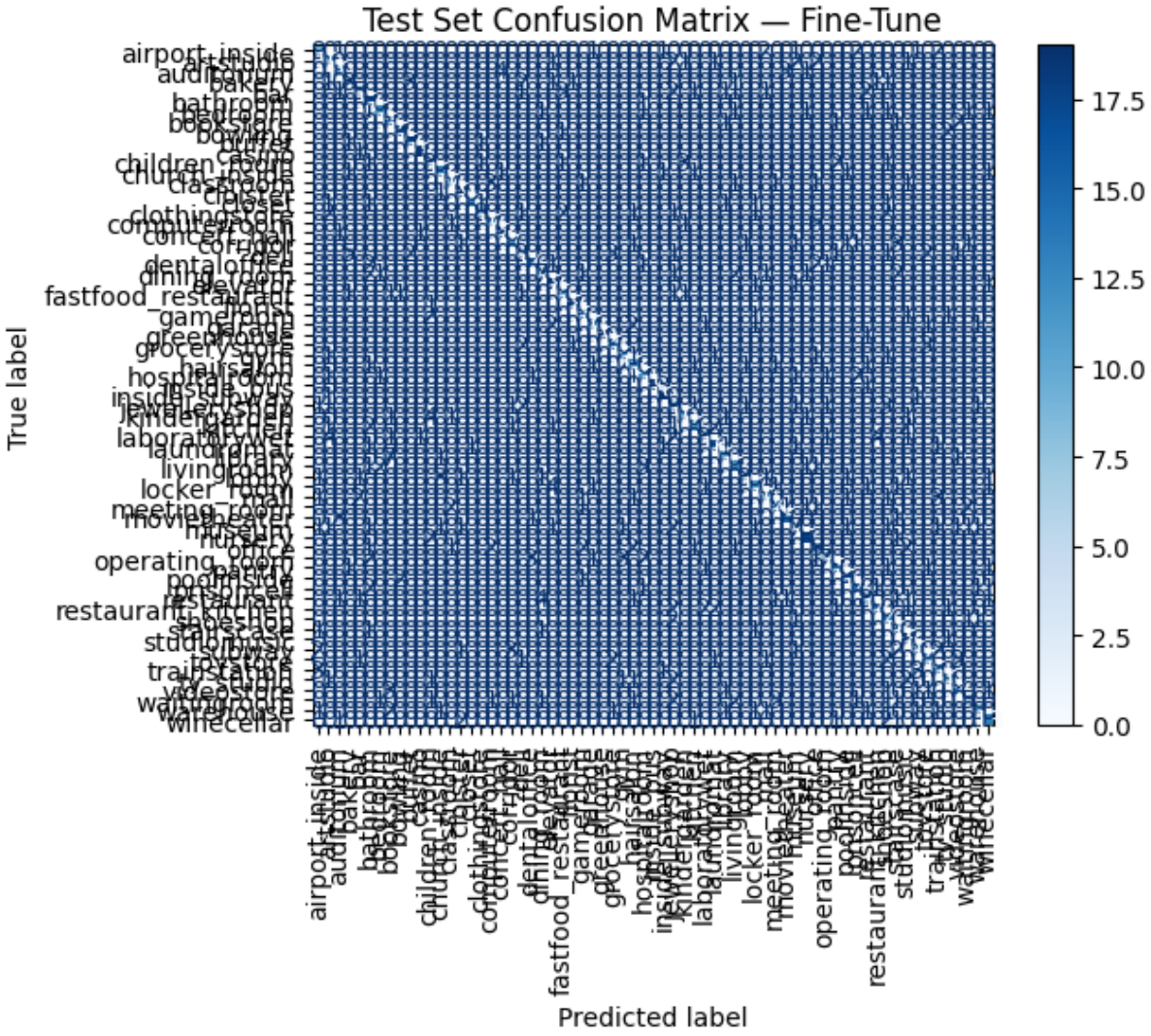
Output:

```
Epoch 1/10
168/168 - 725s - 4s/step - accuracy: 0.4130 - loss: 2.2329 - val_accuracy: 0.6744 - val_loss: 1.0976
Epoch 2/10
168/168 - 711s - 4s/step - accuracy: 0.5350 - loss: 1.6432 - val_accuracy: 0.7201 - val_loss: 0.9582
Epoch 3/10
168/168 - 721s - 4s/step - accuracy: 0.5645 - loss: 1.5127 - val_accuracy: 0.7519 - val_loss: 0.8562
Epoch 4/10
168/168 - 692s - 4s/step - accuracy: 0.5930 - loss: 1.4119 - val_accuracy: 0.7659 - val_loss: 0.8019
Epoch 5/10
168/168 - 28007s - 167s/step - accuracy: 0.5997 - loss: 1.3588 - val_accuracy: 0.7780 - val_loss: 0.7441
Epoch 6/10
168/168 - 762s - 5s/step - accuracy: 0.6246 - loss: 1.3002 - val_accuracy: 0.7920 - val_loss: 0.7066
Epoch 7/10
168/168 - 717s - 4s/step - accuracy: 0.6300 - loss: 1.2505 - val_accuracy: 0.8032 - val_loss: 0.6748
Epoch 8/10
168/168 - 710s - 4s/step - accuracy: 0.6462 - loss: 1.1777 - val_accuracy: 0.8116 - val_loss: 0.6161
Epoch 9/10
168/168 - 707s - 4s/step - accuracy: 0.6662 - loss: 1.1305 - val_accuracy: 0.8134 - val_loss: 0.6159
Epoch 10/10
168/168 - 710s - 4s/step - accuracy: 0.6637 - loss: 1.0922 - val_accuracy: 0.8274 - val_loss: 0.5687
```

```python
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,
classification_report

# Test setini unbatch batch ile hazırla
orig_test  = test_ds.unbatch()
test_ds_tl = orig_test.batch(bs_best).prefetch(tf.data.AUTOTUNE)

xb, yb = next(iter(test_ds_tl))
q_loss, q_acc = model_tl.evaluate(xb, yb, verbose=2)
print(f"[Quick TL eval] Loss: {q_loss:.4f}, Acc: {q_acc:.4f}")

x_list, y_list = [], []
for xb, yb in test_ds_tl:
    x_list.append(xb.numpy())
    y_list.append(yb.numpy())
x_test = np.concatenate(x_list, axis=0)
y_test = np.concatenate(y_list, axis=0)

test_loss, test_acc = model_tl.evaluate(x_test, y_test, verbose=2)
print(f"[Full TL eval] Loss: {test_loss:.4f}, Acc: {test_acc:.4f}")

# Confusion Matrix
y_pred = np.argmax(model_tl.predict(x_test), axis=1)
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(cm, display_labels=class_names)
disp.plot(cmap='Blues', xticks_rotation='vertical')
plt.title("Test Set Confusion Matrix – Fine-Tune")
plt.show()

# Classification Report
print(classification_report(y_test, y_pred, target_names=class_names))
```

Output:

```
1/1 - 3s - 3s/step - accuracy: 0.5312 - loss: 1.6342
[Quick TL eval] Loss: 1.6342, Acc: 0.5312
42/42 - 116s - 3s/step - accuracy: 0.6187 - loss: 1.4531
[Full TL eval] Loss: 1.4531, Acc: 0.6187
42/42 ━━━━━━━━━━━━━━━━━━━━ 130s 3s/step
```



	precision	recall	f1-score	support
airport_inside	0.45	0.45	0.45	20
artstudio	0.40	0.50	0.44	20
auditorium	0.56	0.56	0.56	18
bakery	0.47	0.42	0.44	19
bar	0.45	0.28	0.34	18
bathroom	0.47	0.94	0.63	18
bedroom	0.71	0.57	0.63	21
bookstore	0.50	0.75	0.60	20
bowling	0.85	0.85	0.85	20
buffet	0.77	0.85	0.81	20
casino	0.90	0.95	0.92	19
children_room	0.42	0.44	0.43	18
church_inside	0.65	0.68	0.67	19
classroom	0.67	0.56	0.61	18
cloister	0.76	0.95	0.84	20
closet	0.92	0.67	0.77	18
clothingstore	0.73	0.44	0.55	18
computerroom	0.62	0.56	0.59	18
concert_hall	0.78	0.90	0.84	20
corridor	0.61	0.52	0.56	21
deli	0.23	0.16	0.19	19
dentaloffice	0.74	0.67	0.70	21
dining_room	0.44	0.39	0.41	18
...				
accuracy			0.62	1340
macro avg	0.63	0.62	0.61	1340
weighted avg	0.63	0.62	0.61	1340

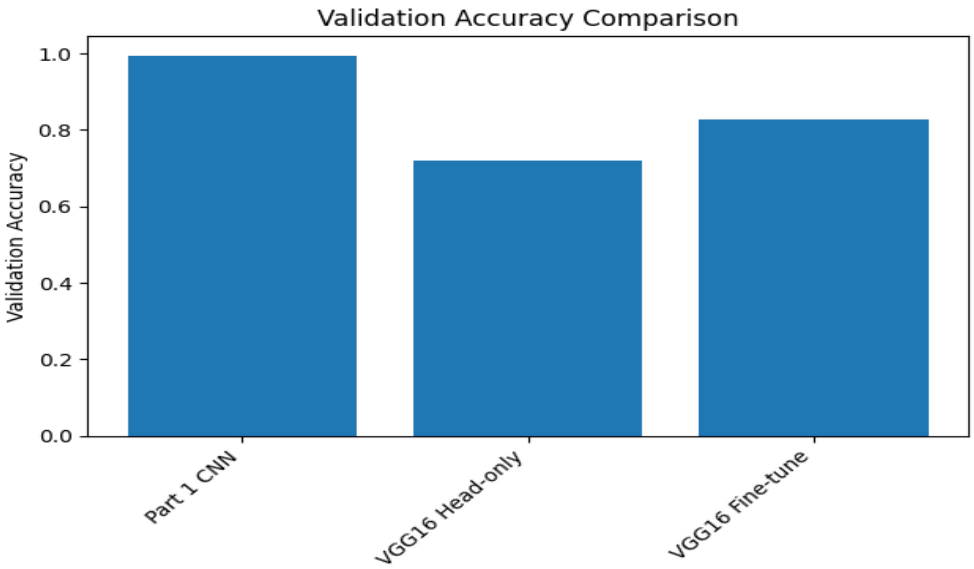
```
from IPython.display import display, FileLink

records = []
for (lr, bs), h in histories.items():
    records.append({
        'learning_rate': lr,
        'batch_size':    bs,
        'max_val_acc':   max(h['val_accuracy']),
        'min_val_loss':  min(h['val_loss'])
    })
df_results = pd.DataFrame(records).sort_values(
    by='max_val_acc', ascending=False
).reset_index(drop=True)

part1_val_acc  = df_results.loc[0, 'max_val_acc']
part1_val_loss = df_results.loc[0, 'min_val_loss']
head_val_acc   = max(history_head.history['val_accuracy'])
head_val_loss  = min(history_head.history['val_loss'])
ft_val_acc     = max(history_finetune.history['val_accuracy'])
ft_val_loss    = min(history_finetune.history['val_loss'])

df_cmp = pd.DataFrame([
    {'Method': 'Part 1 CNN',       'Val Accuracy': part1_val_acc, 'Val Loss':
part1_val_loss},
    {'Method': 'VGG16 Head-only',  'Val Accuracy': head_val_acc,  'Val Loss':
head_val_loss},
    {'Method': 'VGG16 Fine-tune',  'Val Accuracy': ft_val_acc,    'Val Loss':
ft_val_loss},
])

display(df_cmp)
df_cmp.to_csv('validation_comparison.csv', index=False)
display(FileLink('validation_comparison.csv'))
```

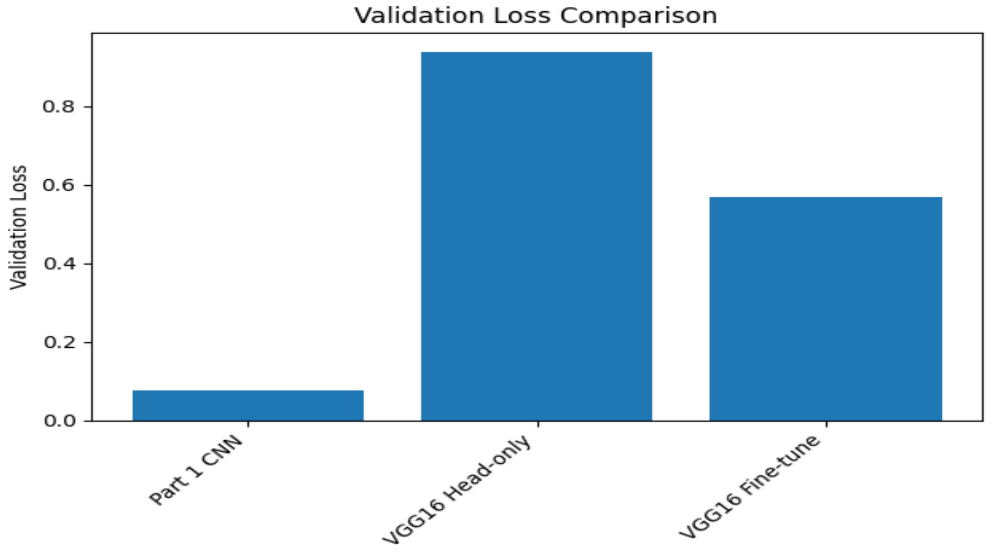
Output:

	Method	Val Accuracy	Val Loss
0	Part 1 CNN	0.995336	0.074799
1	VGG16 Head-only	0.721082	0.938893
2	VGG16 Fine-tune	0.827425	0.568702

```
plt.figure()
plt.bar(df_cmp['Method'], df_cmp['Val Accuracy'])
plt.ylabel('Validation Accuracy')
plt.xticks(rotation=45, ha='right')
plt.title('Validation Accuracy Comparison')
plt.tight_layout()
plt.show()

plt.figure()
plt.bar(df_cmp['Method'], df_cmp['Val Loss'])
plt.ylabel('Validation Loss')
plt.xticks(rotation=45, ha='right')
plt.title('Validation Loss Comparison')
plt.tight_layout()
plt.show()
```

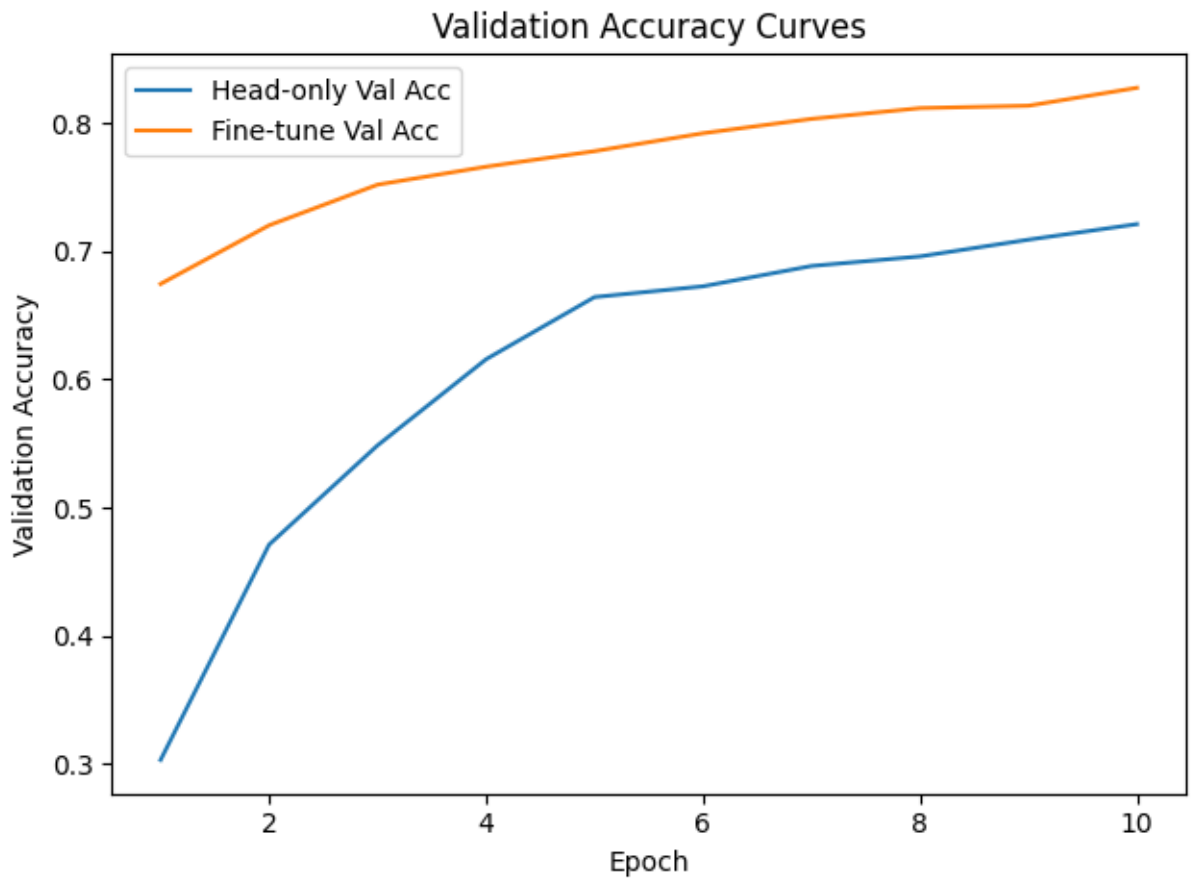
Output:

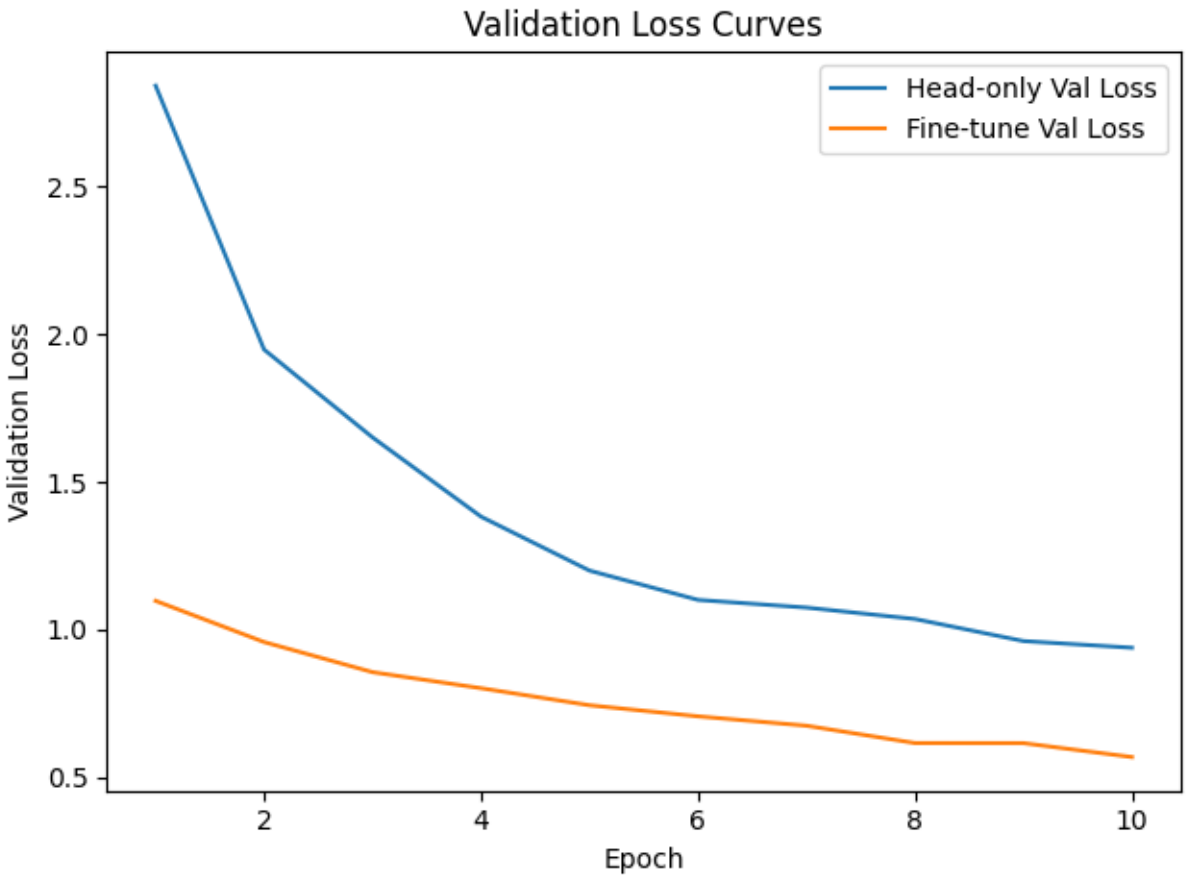




```
epochs_head = range(1, len(history_head.history['val_accuracy']) + 1)
epochs_ft   = range(1, len(history_finetune.history['val_accuracy']) + 1)

plt.figure()
plt.plot(epochs_head, history_head.history['val_accuracy'], label='Head-only
Val Acc')
plt.plot(epochs_ft,   history_finetune.history['val_accuracy'], label='Fine-
tune Val Acc')
plt.xlabel('Epoch'); plt.ylabel('Validation Accuracy')
plt.legend(); plt.title('Validation Accuracy Curves')
plt.tight_layout(); plt.show()

plt.figure()
plt.plot(epochs_head, history_head.history['val_loss'], label='Head-only Val
Loss')
plt.plot(epochs_ft,   history_finetune.history['val_loss'], label='Fine-tune
Val Loss')
plt.xlabel('Epoch'); plt.ylabel('Validation Loss')
plt.legend(); plt.title('Validation Loss Curves')
plt.tight_layout(); plt.show()
```

Output:




Validation Loss Curves
Head-only Val Loss
Fine-tune Val Loss
Validation Loss
2.5
2.0
1.5
1.0
0.5
2
4
6
8
10
Epoch