Import Libraries

In this step, we import all the necessary libraries for loading, preprocessing, visualizing the dataset, building and training the CNN model, and evaluating its performance.

- `os` and `random` are used for file operations and controlling randomness.
- `numpy` handles numerical operations on arrays and image data.
- `matplotlib.pyplot` is used for visualizing images and dataset distribution.
- `tensorflow` and `keras` provide the deep learning framework.
- `ImageDataGenerator` loads images from directories and applies data augmentation.
- `load_img` loads an image from a file path as a PIL image, useful for visualization or preprocessing.
- `img_to_array` converts a PIL image into a NumPy array for neural network input.
- The CNN is built using `Sequential`, `Conv2D`, `MaxPooling2D`, `Dense`, `Dropout`, `BatchNormalization`, and `GlobalAveragePooling2D`.
- `Adam` is the optimizer for training the model.
- `classification_report` and `confusion_matrix` from `sklearn` are used for model evaluation.
- `EfficientNetB0` is imported for transfer learning experiments.

```
import os
import random
import numpy as np
import matplotlib.pyplot as plt
from tensorflow import keras
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator,load_img, img_to_array
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout, InputLayer, BatchNormalization, GlobalAverageI
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import classification_report, confusion_matrix
from tensorflow.keras.applications import EfficientNetB0
import seaborn as sns
```

Load and Preprocess Data

Dataset Overview

Dataset Path: `Human face emotions dataset URL`
Classes: List of human facial emotion categories.

In this step, we explore the dataset by identifying the emotion classes, counting the number of images in each class, and visualizing the data distribution.

Emotion Classes

```
Classes: ['Fear', 'Suprise', 'Angry', 'Sad', 'Happy']

Number of Images per Class
    •  Fear: 9,732 images
    •  Suprise: 8,227 images
    •  Angry: 10,148 images
    •  Sad: 12,553 images
    •  Happy: 18,439 images
```

```
data_dir = "/kaggle/input/human-face-emotions/Data"
classes = os.listdir(data_dir)
print(f"Classes: {classes}\n")

counts = {}

for cls in classes:
    folder_path = os.path.join(data_dir,cls)
    counts[cls]= len(os.listdir(folder_path))

for cls in classes:
    print(f"{cls}: {counts[cls]} images.")
```

```
Classes: ['Fear', 'Suprise', 'Angry', 'Sad', 'Happy']

Fear: 9732 images.
Suprise: 8227 images.
Angry: 10148 images.
Sad: 12553 images.
Happy: 18439 images.
```

Visualizing Sample Images from Each Class

To better understand the dataset, we visualize **5 random images from each emotion class**.
This helps us see variations in facial expressions and verify the quality of the dataset.

What this code does:

- Iterates through each emotion class directory
- Selects **5 random images** using `random.sample()`
- Loads each image with `load_img()` and resizes it to `(128, 128)`
- Displays all images in a grid where:
  - Each **row** represents one class
  - Each **column** shows one random sample
- Removes axis labels for cleaner visualization
- Uses `plt.tight_layout()` to prevent overlap

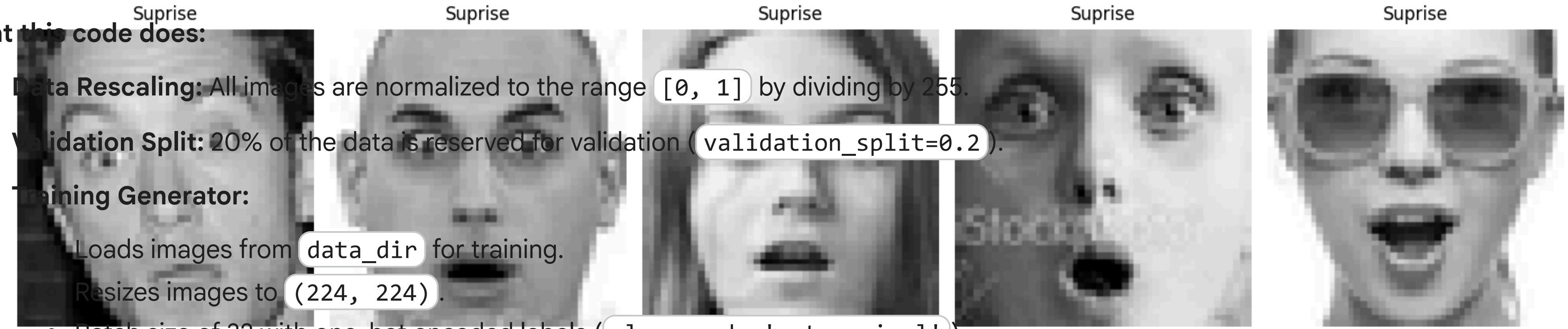
```
plt.figure(figsize=(15, 20))
index = 1
for cls in classes:
    class_path = os.path.join(data_dir, cls)
    images = os.listdir(class_path)
    samples = random.sample(images, 5)

    for img_name in samples:
        img_path = os.path.join(class_path, img_name)
        img = load_img(img_path, target_size=(128,128))
        plt.subplot(len(classes), 5, index)
        plt.imshow(img)
        plt.axis("off")
        plt.title(cls)
        index +=1

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

Fear Fear Fear Fear Fear

Train / Validation Split with ImageDataGenerator

In this step, we split our dataset into training and validation sets using Keras' `ImageDataGenerator`. This also includes data augmentation for the training set to improve model generalization.

Suprise Suprise Suprise Suprise Suprise

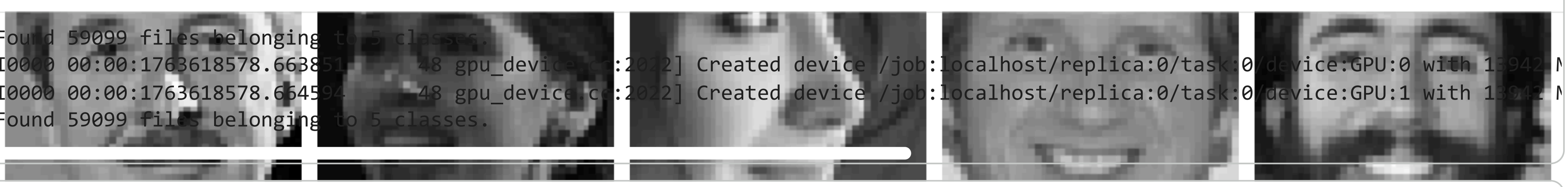


What this code does:

- **Data Rescaling:** All images are normalized to the range `[0, 1]` by dividing by 255.
- **Validation Split:** 20% of the data is reserved for validation (`validation_split=0.2`).
- **Training Generator:**
  - Loads images from `data_dir` for training.
  - Resizes images to `(224, 224)`.
  - Batch size of 32 with one-hot encoded labels (`class_mode='categorical'`).
  - Only uses the training subset of the data.
  - Applies data augmentation including rotation, width/height shift, zoom, shear, and horizontal flip.
- **Validation Generator:**
  - Same as training, but only uses the validation subset.
  - No data augmentation, only rescaling.

Angry Angry Angry Angry Angry

```
train_generator = tf.keras.utils.image_dataset_from_directory(
    directory=data_dir,
    labels='inferred',
    label_mode='categorical',
    batch_size=64,
    image_size=(224, 224)
)

validation_generator = tf.keras.utils.image_dataset_from_directory(
    directory=data_dir,
    labels='inferred',
    label_mode='categorical',
    batch_size=64,
    image_size=(224, 224)
)

data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip("horizontal"),
    tf.keras.layers.RandomRotation(0.1),
    tf.keras.layers.RandomZoom(0.1),
    tf.keras.layers.RandomBrightness(0.2),
])
```



```
Found 59099 files belonging to 5 classes.
I0000 00:00:1763618578.663851      48 gpu_device.cc:2022] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 13942 M
I0000 00:00:1763618578.664594      48 gpu_device.cc:2022] Created device /job:localhost/replica:0/task:0/device:GPU:1 with 13942 M
Found 59099 files belonging to 5 classes.
```

```
AUTOTUNE = tf.data.AUTOTUNE

train_generator = train_generator.map(lambda x, y: (data_augmentation(x, training=True), y),
                        num_parallel_calls=AUTOTUNE)

train_generator = train_generator.prefetch(buffer_size=AUTOTUNE)
validation_generator = validation_generator.prefetch(buffer_size=AUTOTUNE)
```

Transfer Learning Model Implementation

In this step, we build a model using **transfer learning** with the pre-trained `EfficientNetB0` as the base.

What this code does:

- **Load Pre-trained Base Model:**
  - `EfficientNetB0` pretrained on `ImageNet` is used.
  - `include_top=False` removes the default classification head.
  - Input shape is set to `(224, 224, 3)` to match our dataset.
- **Freeze Base Model:**
  - `base_model.trainable = False` ensures the pre-trained weights are not updated during initial training.
- **Add Custom Classification Head:**
  - `GlobalAveragePooling2D()` reduces spatial dimensions of feature maps.
  - `Dropout(0.35)` adds regularization to prevent overfitting.
  - `Dense(256, activation="relu")` adds a fully connected layer.
  - Another `Dropout(0.35)` for regularization.
  - `Dense(len(classes), activation="softmax")` outputs probabilities for each emotion class.
- **Build the Model:**
  - `keras.Model(inputs=base_model.inputs, outputs=outputs)` combines the base model and custom head into a single model ready for training.

```
base_model = EfficientNetB0(
    weights="imagenet",
    include_top=False,
    input_shape=(224,224,3)
)

base_model.trainable = False

x = GlobalAveragePooling2D()(base_model.output)
x = Dropout(0.35)(x)
x = Dense(256, activation="relu")(x)
x = Dropout(0.35)(x)
outputs = Dense(len(classes), activation="softmax")(x)

model = keras.Model(
    inputs=base_model.inputs,
    outputs=outputs
)
```

```
Downloading data from https://storage.googleapis.com/keras-applications/efficientnetb0_notop.h5
16705208/16705208 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

```
model.summary()
```

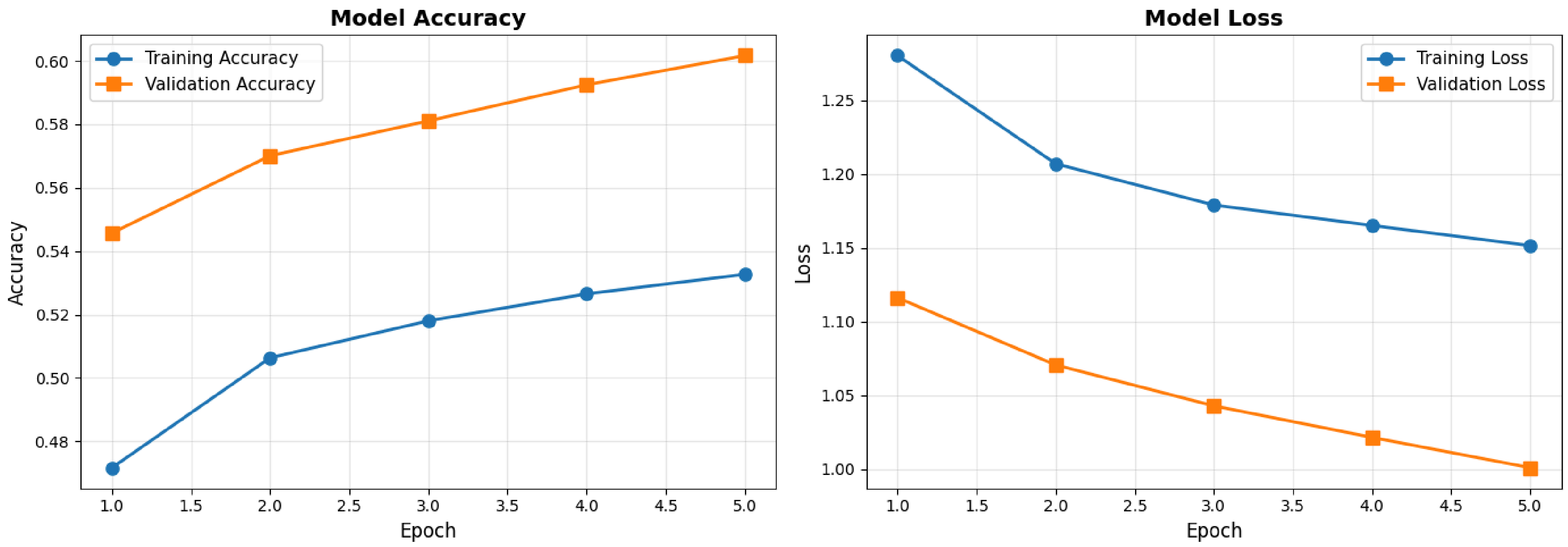
Show hidden output

```
base_model.trainable = False

model.compile(optimizer=Adam(learning_rate=1e-3),
              loss="categorical_crossentropy", metrics=["accuracy"])

warm_up_history = model.fit(train_generator, epochs=5, validation_data=validation_generator)
```

```
Epoch 1/5
/usr/local/lib/python3.11/dist-packages/keras/src/models/functional.py:237: UserWarning: The structure of `inputs` doesn't match t
Expected: ['keras_tensor_5']
Received: inputs=Tensor(shape=(None, 224, 224, 3))
  warnings.warn(msg)
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1763618608.261665     119 service.cc:148] XLA service 0x7d601c007100 initialized for platform CUDA (this does not guar
I0000 00:00:1763618608.262659     119 service.cc:156]   StreamExecutor device (0): Tesla T4, Compute Capability 7.5
I0000 00:00:1763618608.262679     119 service.cc:156]   StreamExecutor device (1): Tesla T4, Compute Capability 7.5
I0000 00:00:1763618610.884506     119 cuda_dnn.cc:529] Loaded cuDNN version 90300
  2/924 ━━━━━━━━━━━━━━━━━━━━ 1:25 93ms/step - accuracy: 0.2227 - loss: 1.7320  I0000 00:00:1763618622.033910     119 device_compi
924/924 ━━━━━━━━━━━━━━━━━━━━ 432s 441ms/step - accuracy: 0.4432 - loss: 1.3409 - val_accuracy: 0.5457 - val_loss: 1.1162
Epoch 2/5
924/924 ━━━━━━━━━━━━━━━━━━━━ 333s 359ms/step - accuracy: 0.5049 - loss: 1.2152 - val_accuracy: 0.5701 - val_loss: 1.0707
Epoch 3/5
924/924 ━━━━━━━━━━━━━━━━━━━━ 338s 365ms/step - accuracy: 0.5192 - loss: 1.1809 - val_accuracy: 0.5811 - val_loss: 1.0430
Epoch 4/5
924/924 ━━━━━━━━━━━━━━━━━━━━ 333s 360ms/step - accuracy: 0.5255 - loss: 1.1658 - val_accuracy: 0.5925 - val_loss: 1.0217
Epoch 5/5
924/924 ━━━━━━━━━━━━━━━━━━━━ 336s 363ms/step - accuracy: 0.5329 - loss: 1.1520 - val_accuracy: 0.6017 - val_loss: 1.0011
```

```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))
```

```
epochs_run = len(warm_up_history.history['accuracy'])
ax1.plot(range(1, epochs_run + 1), warm_up_history.history['accuracy'],
         'o-', linewidth=2, markersize=8, label='Training Accuracy')
ax1.plot(range(1, epochs_run + 1), warm_up_history.history['val_accuracy'],
         's-', linewidth=2, markersize=8, label='Validation Accuracy')
ax1.set_title('Model Accuracy', fontsize=14, fontweight='bold')
ax1.set_xlabel('Epoch', fontsize=12)
ax1.set_ylabel('Accuracy', fontsize=12)
ax1.legend(fontsize=11)
ax1.grid(True, alpha=0.3)

# Loss grafiği
ax2.plot(range(1, epochs_run + 1), warm_up_history.history['loss'],
         'o-', linewidth=2, markersize=8, label='Training Loss')
ax2.plot(range(1, epochs_run + 1), warm_up_history.history['val_loss'],
         's-', linewidth=2, markersize=8, label='Validation Loss')
ax2.set_title('Model Loss', fontsize=14, fontweight='bold')
ax2.set_xlabel('Epoch', fontsize=12)
ax2.set_ylabel('Loss', fontsize=12)
ax2.legend(fontsize=11)
ax2.grid(True, alpha=0.3)

plt.tight_layout()
```



Fine-Tuning the Transfer Learning Model

In this step, we **unfreeze part of the pre-trained base model** to fine-tune it on our dataset.

What this code does:

- **Unfreeze the base model:**

```
base_model.trainable = True
```

```
base_model.trainable = True
print(f" Base Model Layers Num: {len(base_model.layers)}")

#for layer in base_model.layers[:int(len(base_model.layers)*0.8)]:
#    layer.trainable = False

#for layer in base_model.layers[int(len(base_model.layers)*0.8):]:
#    layer.trainable = True

for layer in base_model.layers[:int(len(base_model.layers)*0.8)]:
    layer.trainable = False
```

```
 Base Model Layers Num: 238
```

Compile the Fine-Tuned Model

In this step, we **compile the model before training**. Compilation specifies the optimizer, loss function, and evaluation metrics.

What this code does:

- **Optimizer:**

```
optimizer=Adam(learning_rate=1e-5)
```

```
model.compile(
    optimizer=Adam(learning_rate=1e-5),
    loss="categorical_crossentropy",
    metrics=["accuracy"]
)
```

Finetune Training Callbacks: EarlyStopping, ReduceLROnPlateau & Learning Rate Scheduler

To improve training efficiency, prevent overfitting, and achieve better convergence, we use three Keras callbacks:

1. EarlyStopping

- Monitors the validation loss (`val_loss`).
- Stops training if the validation loss does not improve for **3 consecutive epochs** (`patience=3`).
- Automatically restores the model weights from the epoch with the **best validation loss** (`restore_best_weights=True`).
- Provides verbose output to track when training stops.

2. ReduceLROnPlateau

- Monitors the validation loss (`val_loss`).
- Reduces the learning rate by a factor of 0.5 if the validation loss does not improve for **2 consecutive epochs** (`patience=2`).
- Ensures the learning rate does not go below `min_lr=1e-5`.
- Helps the model converge by **lowering the learning rate when progress plateaus**.
- Provides verbose output to show when the learning rate is reduced.

3. Cosine Annealing Learning Rate Scheduler

- Dynamically adjusts the learning rate during training following a **cosine curve**.
- Starts with a higher learning rate (`initial_lr=1e-4`) and gradually decays to a minimum (`alpha=1e-6`).
- Smoothly reduces learning rate over the total number of training steps, helping **stable convergence**.
- Particularly effective in fine-tuning pre-trained models.

Benefits:

- Faster convergence
- Prevents overfitting
- Helps reach **better validation performance**
- Combines plateau detection and smooth LR decay for optimal training

```
early_stop = keras.callbacks.EarlyStopping(
    monitor="val_loss",
    patience=5,
    restore_best_weights=True,
    verbose=1
)

reduce_lr = keras.callbacks.ReduceLROnPlateau(
    monitor="val_loss",
    factor=0.5,
    patience=3,
    verbose=1,
    min_lr=1e-6
)

checkpoint_cb = keras.callbacks.ModelCheckpoint(
    "best_model.keras",
    monitor="val_accuracy",
    save_best_only=True,
    verbose=1
)

tensorboard_cb = keras.callbacks.TensorBoard(
    log_dir="./logs",
    histogram_freq=1,
```

```
    update_freq="batch"
)

#%load_ext tensorboard
#%tensorboard --logdir ./logs

callbacks_list = [early_stop, reduce_lr, checkpoint_cb, tensorboard_cb]
```

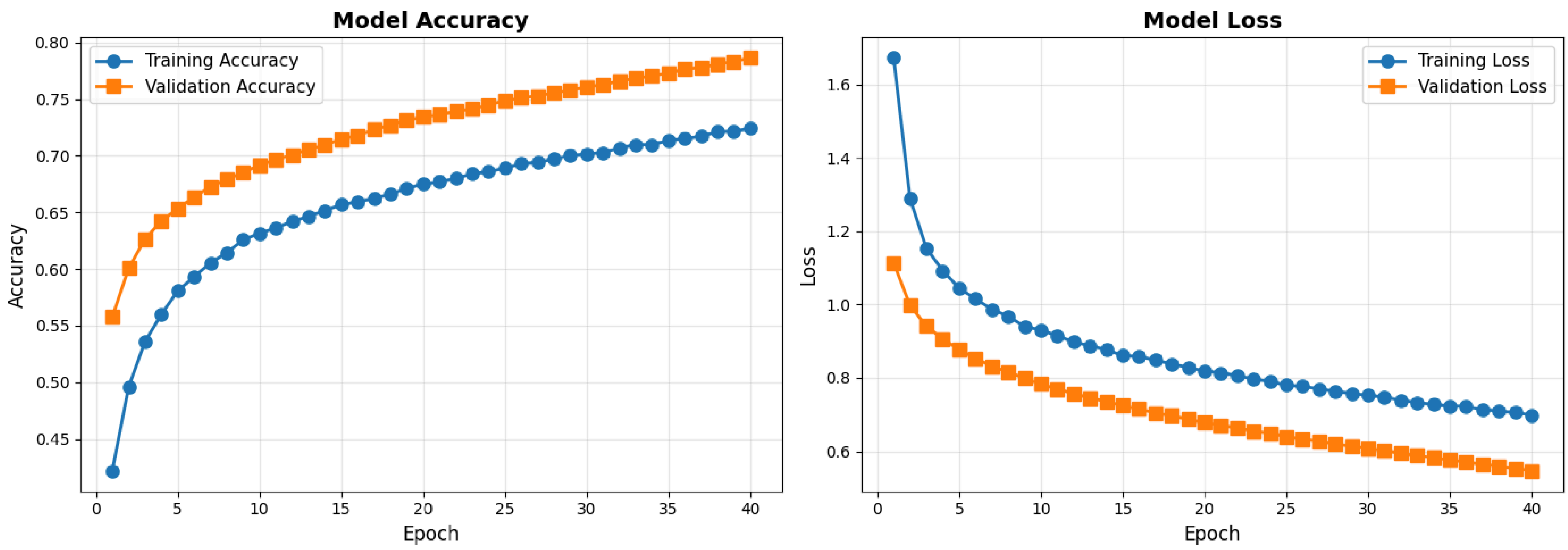
Start Finetune Training

```
history_finetune = model.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=40,
    callbacks=callbacks_list
)
```

```
Epoch 1/40
E0000 00:00:1763620391.605155     119 gpu_timer.cc:82] Delay kernel timed out: measured time has sub-optimal accuracy. There may
E0000 00:00:1763620391.747027     119 gpu_timer.cc:82] Delay kernel timed out: measured time has sub-optimal accuracy. There may
E0000 00:00:1763620392.161554     119 gpu_timer.cc:82] Delay kernel timed out: measured time has sub-optimal accuracy. There may
E0000 00:00:1763620392.305322     119 gpu_timer.cc:82] Delay kernel timed out: measured time has sub-optimal accuracy. There may
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 304ms/step - accuracy: 0.3905 - loss: 1.9077E0000 00:00:1763620686.297224     118 gpu_timer.cc:8
E0000 00:00:1763620686.436487     118 gpu_timer.cc:82] Delay kernel timed out: measured time has sub-optimal accuracy. There may
924/924 ━━━━━━━━━━━━━━━━━━━━ 0s 318ms/step - accuracy: 0.3905 - loss: 1.9074/usr/local/lib/python3.11/dist-packages/keras/src/mc
Expected: ['keras_tensor_5']
Received: inputs=Tensor(shape=(None, 224, 224, 3))
  warnings.warn(msg)

Epoch 1: val_accuracy improved from -inf to 0.55769, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 395s 393ms/step - accuracy: 0.3906 - loss: 1.9072 - val_accuracy: 0.5577 - val_loss: 1.1135 - learn
Epoch 2/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 303ms/step - accuracy: 0.4803 - loss: 1.3435
Epoch 2: val_accuracy improved from 0.55769 to 0.60074, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 342s 369ms/step - accuracy: 0.4803 - loss: 1.3434 - val_accuracy: 0.6007 - val_loss: 0.9969 - learn
Epoch 3/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 303ms/step - accuracy: 0.5268 - loss: 1.1760
Epoch 3: val_accuracy improved from 0.60074 to 0.62651, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 340s 367ms/step - accuracy: 0.5268 - loss: 1.1759 - val_accuracy: 0.6265 - val_loss: 0.9411 - learn
Epoch 4/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 303ms/step - accuracy: 0.5560 - loss: 1.1047
Epoch 4: val_accuracy improved from 0.62651 to 0.64245, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 343s 371ms/step - accuracy: 0.5560 - loss: 1.1047 - val_accuracy: 0.6424 - val_loss: 0.9061 - learn
Epoch 5/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 303ms/step - accuracy: 0.5779 - loss: 1.0497
Epoch 5: val_accuracy improved from 0.64245 to 0.65321, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 343s 371ms/step - accuracy: 0.5779 - loss: 1.0497 - val_accuracy: 0.6532 - val_loss: 0.8773 - learn
Epoch 6/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 307ms/step - accuracy: 0.5898 - loss: 1.0213
Epoch 6: val_accuracy improved from 0.65321 to 0.66367, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 345s 372ms/step - accuracy: 0.5898 - loss: 1.0213 - val_accuracy: 0.6637 - val_loss: 0.8532 - learn
Epoch 7/40
924/924 ━━━━━━━━━━━━━━━━━━━━ 0s 304ms/step - accuracy: 0.6021 - loss: 0.9891
Epoch 7: val_accuracy improved from 0.66367 to 0.67257, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 342s 370ms/step - accuracy: 0.6021 - loss: 0.9891 - val_accuracy: 0.6726 - val_loss: 0.8317 - learn
Epoch 8/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 304ms/step - accuracy: 0.6126 - loss: 0.9726
Epoch 8: val_accuracy improved from 0.67257 to 0.67917, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 342s 369ms/step - accuracy: 0.6126 - loss: 0.9725 - val_accuracy: 0.6792 - val_loss: 0.8157 - learn
Epoch 9/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 305ms/step - accuracy: 0.6227 - loss: 0.9453
Epoch 9: val_accuracy improved from 0.67917 to 0.68509, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 343s 370ms/step - accuracy: 0.6227 - loss: 0.9453 - val_accuracy: 0.6851 - val_loss: 0.7989 - learn
Epoch 10/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 303ms/step - accuracy: 0.6305 - loss: 0.9314
Epoch 10: val_accuracy improved from 0.68509 to 0.69177, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 341s 368ms/step - accuracy: 0.6305 - loss: 0.9314 - val_accuracy: 0.6918 - val_loss: 0.7828 - learn
Epoch 11/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 305ms/step - accuracy: 0.6328 - loss: 0.9186
Epoch 11: val_accuracy improved from 0.69177 to 0.69626, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 342s 369ms/step - accuracy: 0.6328 - loss: 0.9186 - val_accuracy: 0.6963 - val_loss: 0.7693 - learn
Epoch 12/40
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 307ms/step - accuracy: 0.6411 - loss: 0.9009
Epoch 12: val_accuracy improved from 0.69626 to 0.70071, saving model to best_model.keras
```

```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))

epochs_run = len(history_finetune.history['accuracy'])
ax1.plot(range(1, epochs_run + 1), history_finetune.history['accuracy'],
         'o-', linewidth=2, markersize=8, label='Training Accuracy')
ax1.plot(range(1, epochs_run + 1), history_finetune.history['val_accuracy'],
         's-', linewidth=2, markersize=8, label='Validation Accuracy')
```

```
ax1.set_title('Model Accuracy', fontsize=14, fontweight='bold')
ax1.set_xlabel('Epoch', fontsize=12)
ax1.set_ylabel('Accuracy', fontsize=12)
ax1.legend(fontsize=11)
ax1.grid(True, alpha=0.3)

# Loss grafiği
ax2.plot(range(1, epochs_run + 1), history_finetune.history['loss'],
         'o-', linewidth=2, markersize=8, label='Training Loss')
ax2.plot(range(1, epochs_run + 1), history_finetune.history['val_loss'],
         's-', linewidth=2, markersize=8, label='Validation Loss')
ax2.set_title('Model Loss', fontsize=14, fontweight='bold')
ax2.set_xlabel('Epoch', fontsize=12)
ax2.set_ylabel('Loss', fontsize=12)
ax2.legend(fontsize=11)
ax2.grid(True, alpha=0.3)

plt.tight_layout()
```

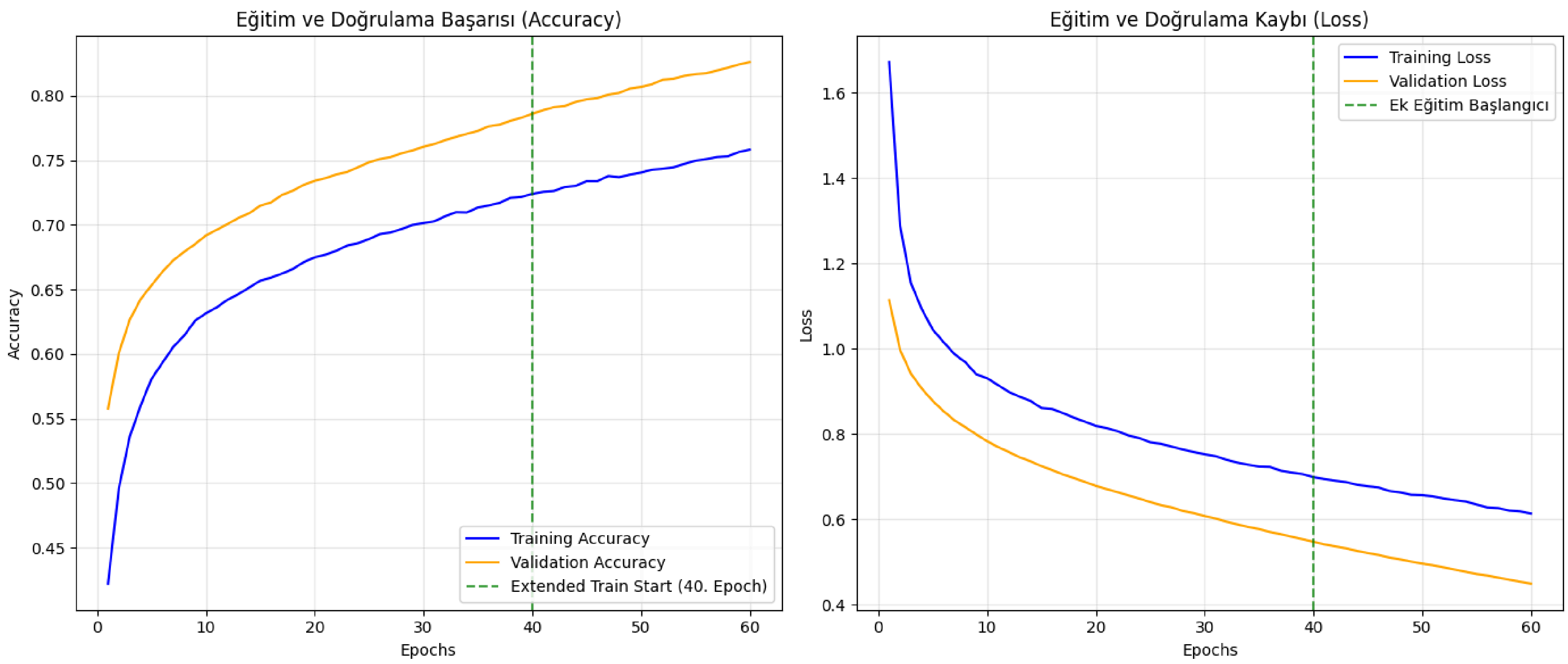


Extended Training for %80+ [Optional]

```
print("--- Final Step: Epoch 41-60 Start ---")

history_extended = model.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=60,
    initial_epoch=40,
    callbacks=callbacks_list
)
```

```
Epoch 53/60
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 311ms/step - accuracy: 0.7440 - loss: 0.6478
Epoch 53: val_accuracy improved from 0.81252 to 0.81328, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 349s 377ms/step - accuracy: 0.7440 - loss: 0.6478 - val_accuracy: 0.8133 - val_loss: 0.4818 - learn
Epoch 54/60
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 304ms/step - accuracy: 0.7449 - loss: 0.6442
Epoch 54: val_accuracy improved from 0.81328 to 0.81551, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 343s 370ms/step - accuracy: 0.7449 - loss: 0.6442 - val_accuracy: 0.8155 - val_loss: 0.4766 - learn
Epoch 55/60
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 312ms/step - accuracy: 0.7467 - loss: 0.6398
Epoch 55: val_accuracy improved from 0.81551 to 0.81683, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 352s 380ms/step - accuracy: 0.7467 - loss: 0.6398 - val_accuracy: 0.8168 - val_loss: 0.4715 - learn
Epoch 56/60
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 302ms/step - accuracy: 0.7503 - loss: 0.6318
Epoch 56: val_accuracy improved from 0.81683 to 0.81753, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 341s 368ms/step - accuracy: 0.7503 - loss: 0.6318 - val_accuracy: 0.8175 - val_loss: 0.4679 - learn
Epoch 57/60
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 312ms/step - accuracy: 0.7557 - loss: 0.6249
Epoch 57: val_accuracy improved from 0.81753 to 0.81969, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 349s 377ms/step - accuracy: 0.7557 - loss: 0.6249 - val_accuracy: 0.8197 - val_loss: 0.4630 - learn
Epoch 58/60
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 304ms/step - accuracy: 0.7531 - loss: 0.6208
Epoch 58: val_accuracy improved from 0.81969 to 0.82184, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 342s 369ms/step - accuracy: 0.7531 - loss: 0.6208 - val_accuracy: 0.8218 - val_loss: 0.4582 - learn
Epoch 59/60
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 315ms/step - accuracy: 0.7531 - loss: 0.6233
Epoch 59: val_accuracy improved from 0.82184 to 0.82429, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 352s 380ms/step - accuracy: 0.7531 - loss: 0.6233 - val_accuracy: 0.8243 - val_loss: 0.4534 - learn
Epoch 60/60
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 302ms/step - accuracy: 0.7561 - loss: 0.6152
Epoch 60: val_accuracy improved from 0.82429 to 0.82621, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 341s 367ms/step - accuracy: 0.7561 - loss: 0.6152 - val_accuracy: 0.8262 - val_loss: 0.4490 - learn
Restoring model weights from the end of the best epoch: 60.
```

```python
# Merge History
acc_1 = history_finetune.history['accuracy']
val_acc_1 = history_finetune.history['val_accuracy']
loss_1 = history_finetune.history['loss']
val_loss_1 = history_finetune.history['val_loss']

acc_2 = history_extended.history['accuracy']
val_acc_2 = history_extended.history['val_accuracy']
loss_2 = history_extended.history['loss']
val_loss_2 = history_extended.history['val_loss']

acc = acc_1 + acc_2
val_acc = val_acc_1 + val_acc_2
loss = loss_1 + loss_2
val_loss = val_loss_1 + val_loss_2

split_point = len(acc_1)

epochs_range = range(1, len(acc) + 1)

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy', color='blue')
plt.plot(epochs_range, val_acc, label='Validation Accuracy', color='orange')

plt.axvline(x=split_point, color='green', linestyle='--', alpha=0.7, label=f'Extended Train Start ({split_point}. Epoch)')

plt.legend(loc='lower right')
plt.title('Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.grid(True, alpha=0.3)

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss', color='blue')
plt.plot(epochs_range, val_loss, label='Validation Loss', color='orange')

plt.axvline(x=split_point, color='green', linestyle='--', alpha=0.7, label=f'Extended Train Start')

plt.legend(loc='upper right')
plt.title('Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid(True, alpha=0.3)

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



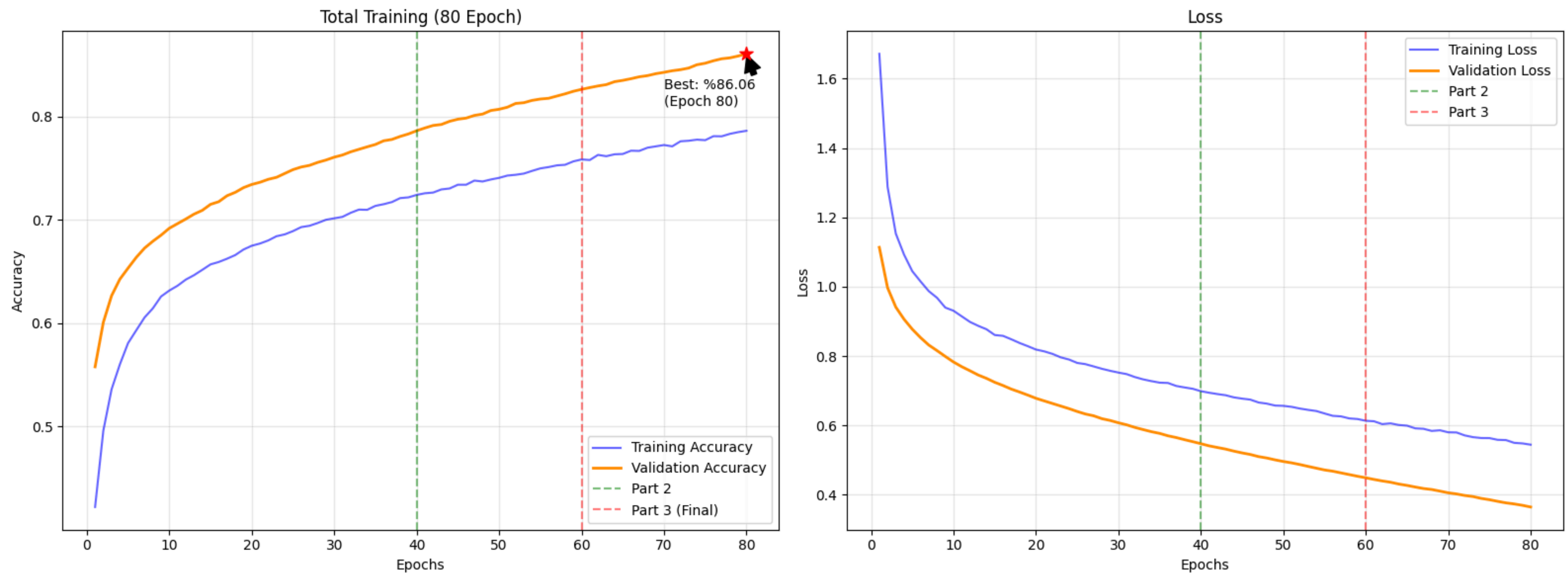
This is no longer an educational process, it's officially a show of force! 🤯

```
print("--- Record Attempt Continues: Epoch 61-80 ---")

model.save("backup_epoch_60_legendary.keras")

history_extended2 = model.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=80,
    initial_epoch=60,
    callbacks=callbacks_list
)
```

```
Epoch 67/80
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 308ms/step - accuracy: 0.7636 - loss: 0.5939
Epoch 67: val_accuracy improved from 0.83649 to 0.83834, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 346s 373ms/step - accuracy: 0.7636 - loss: 0.5939 - val_accuracy: 0.8383 - val_loss: 0.4180 - learn
Epoch 68/80
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 304ms/step - accuracy: 0.7696 - loss: 0.5873
Epoch 68: val_accuracy improved from 0.83834 to 0.83947, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 342s 369ms/step - accuracy: 0.7696 - loss: 0.5873 - val_accuracy: 0.8395 - val_loss: 0.4151 - learn
Epoch 69/80
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 308ms/step - accuracy: 0.7709 - loss: 0.5881
Epoch 69: val_accuracy improved from 0.83947 to 0.84133, saving model to best_model.keras
```

```
Epoch 76/80
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 307ms/step - accuracy: 0.7803 - loss: 0.5602
Epoch 76: val_accuracy improved from 0.85147 to 0.85387, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 346s 374ms/step - accuracy: 0.7803 - loss: 0.5602 - val_accuracy: 0.8539 - val_loss: 0.3810 - learn
Epoch 77/80
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 313ms/step - accuracy: 0.7815 - loss: 0.5577
Epoch 77: val_accuracy improved from 0.85387 to 0.85578, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 352s 380ms/step - accuracy: 0.7815 - loss: 0.5577 - val_accuracy: 0.8558 - val_loss: 0.3766 - learn
Epoch 78/80
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 308ms/step - accuracy: 0.7838 - loss: 0.5504
Epoch 78: val_accuracy improved from 0.85578 to 0.85668, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 346s 374ms/step - accuracy: 0.7838 - loss: 0.5504 - val_accuracy: 0.8567 - val_loss: 0.3735 - learn
Epoch 79/80
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 314ms/step - accuracy: 0.7822 - loss: 0.5510
Epoch 79: val_accuracy improved from 0.85668 to 0.85846, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 351s 379ms/step - accuracy: 0.7822 - loss: 0.5510 - val_accuracy: 0.8585 - val_loss: 0.3695 - learn
Epoch 80/80
923/924 ━━━━━━━━━━━━━━━━━━━━ 0s 308ms/step - accuracy: 0.7872 - loss: 0.5446
Epoch 80: val_accuracy improved from 0.85846 to 0.86057, saving model to best_model.keras
924/924 ━━━━━━━━━━━━━━━━━━━━ 348s 376ms/step - accuracy: 0.7872 - loss: 0.5446 - val_accuracy: 0.8606 - val_loss: 0.3646 - learn
Restoring model weights from the end of the best epoch: 80
```

```python
# 1. Step (First 40 Epoch)
h1 = history_finetune.history
# 2. Step (41-60 Epoch)
h2 = history_extended.history
# 3. Step (61-80 Epoch )
h3 = history_extended2.history

acc = h1['accuracy'] + h2['accuracy'] + h3['accuracy']
val_acc = h1['val_accuracy'] + h2['val_accuracy'] + h3['val_accuracy']
loss = h1['loss'] + h2['loss'] + h3['loss']
val_loss = h1['val_loss'] + h2['val_loss'] + h3['val_loss']

epochs_range = range(1, len(acc) + 1)

stage_1_end = len(h1['accuracy'])
stage_2_end = len(h1['accuracy']) + len(h2['accuracy'])

best_val_acc = max(val_acc)
best_epoch = val_acc.index(best_val_acc) + 1


plt.figure(figsize=(16, 6))

plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy', color='blue', alpha=0.6)
plt.plot(epochs_range, val_acc, label='Validation Accuracy', color='darkorange', linewidth=2)

plt.axvline(x=stage_1_end, color='green', linestyle='--', alpha=0.5, label='Part 2')
plt.axvline(x=stage_2_end, color='red', linestyle='--', alpha=0.5, label='Part 3 (Final)')

plt.scatter(best_epoch, best_val_acc, s=100, c='red', marker='*', zorder=5)
plt.annotate(f'Best: %{best_val_acc*100:.2f}\n(Epoch {best_epoch})',
             (best_epoch, best_val_acc),
             xytext=(best_epoch-10, best_val_acc-0.05),
             arrowprops=dict(facecolor='black', shrink=0.05))

plt.legend(loc='lower right')
plt.title(f'Total Training ({len(acc)} Epoch)')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.grid(True, alpha=0.3)

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss', color='blue', alpha=0.6)
plt.plot(epochs_range, val_loss, label='Validation Loss', color='darkorange', linewidth=2)

plt.axvline(x=stage_1_end, color='green', linestyle='--', alpha=0.5, label='Part 2')
plt.axvline(x=stage_2_end, color='red', linestyle='--', alpha=0.5, label='Part 3')

plt.legend(loc='upper right')
plt.title('Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid(True, alpha=0.3)

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



Evaluate Model on Validation Set

```
val_loss, val_accuracy = model.evaluate(validation_generator)
print(f"Validation Loss: {val_loss:.4f}")
print(f"Validation Accuracy: {val_accuracy:.4f}")
```

```
924/924 ━━━━━━━━━━━━━━━━━━━━ 60s 65ms/step - accuracy: 0.8615 - loss: 0.3646
Validation Loss: 0.3646
Validation Accuracy: 0.8606
```

Confusion Matrix & Classification Report

- Inspect which classes are being confused and the precision/recall/F1-score.

```
val_ds_eval = tf.keras.utils.image_dataset_from_directory(
    directory=data_dir,
    labels='inferred',
    label_mode='categorical',
    batch_size=64,
    image_size=(224, 224),
    shuffle=False
)

class_names = val_ds_eval.class_names
print(f"Classes: {class_names}")

print("Predict Start...")
y_pred_probs = model.predict(val_ds_eval)
y_pred_classes = np.argmax(y_pred_probs, axis=1)

print("Get True labes...")
y_true = np.concatenate([y for x, y in val_ds_eval], axis=0)
y_true_classes = np.argmax(y_true, axis=1)

print("\n--- Classification Report ---")
print(classification_report(y_true_classes, y_pred_classes, target_names=class_names))

cm = confusion_matrix(y_true_classes, y_pred_classes)
plt.figure(figsize=(10, 8))

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names,
            yticklabels=class_names)

plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```

```
Found 59099 files belonging to 5 classes.
Classes: ['Angry', 'Fear', 'Happy', 'Sad', 'Suprise']
Predict Start...
924/924 ━━━━━━━━━━━━━━━━━━━━ 78s 85ms/step
Get True labes...

--- Classification Report ---
              precision    recall  f1-score   support

       Angry       0.84      0.78      0.81     10148
        Fear       0.81      0.64      0.72      9732
       Happy       0.96      0.98      0.97     18439
         Sad       0.75      0.88      0.81     12553
     Suprise       0.90      0.93      0.91      8227

    accuracy                           0.86     59099
   macro avg       0.85      0.84      0.84     59099
weighted avg       0.86      0.86      0.86     59099
```