```
!git clone https://github.com/mybothy/bangkit-machine-learning.git
```

```
Cloning into 'bangkit-machine-learning'...
remote: Enumerating objects: 3006, done.
remote: Counting objects: 100% (3006/3006), done.
remote: Compressing objects: 100% (3005/3005), done.
remote: Total 3006 (delta 0), reused 3006 (delta 0), pack-reused 0 (from 0)
Receiving objects: 100% (3006/3006), 38.68 MiB | 11.61 MiB/s, done.
Updating files: 100% (3000/3000), done.
```

```
%cd bangkit-machine-learning/data
```

```
/content/bangkit-machine-learning/data
```

```
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import pathlib
import os
from sklearn.model_selection import train_test_split

print('\u2022 Using TensorFlow Version:', tf.__version__)
print("\u2022 Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
print('\u2022 GPU Device Found.' if tf.config.list_physical_devices('GPU') else '\u2022 GPU Device Not Found. Running on CPU')
```

```
• Using TensorFlow Version: 2.17.1
• Num GPUs Available:  1
• GPU Device Found.
```

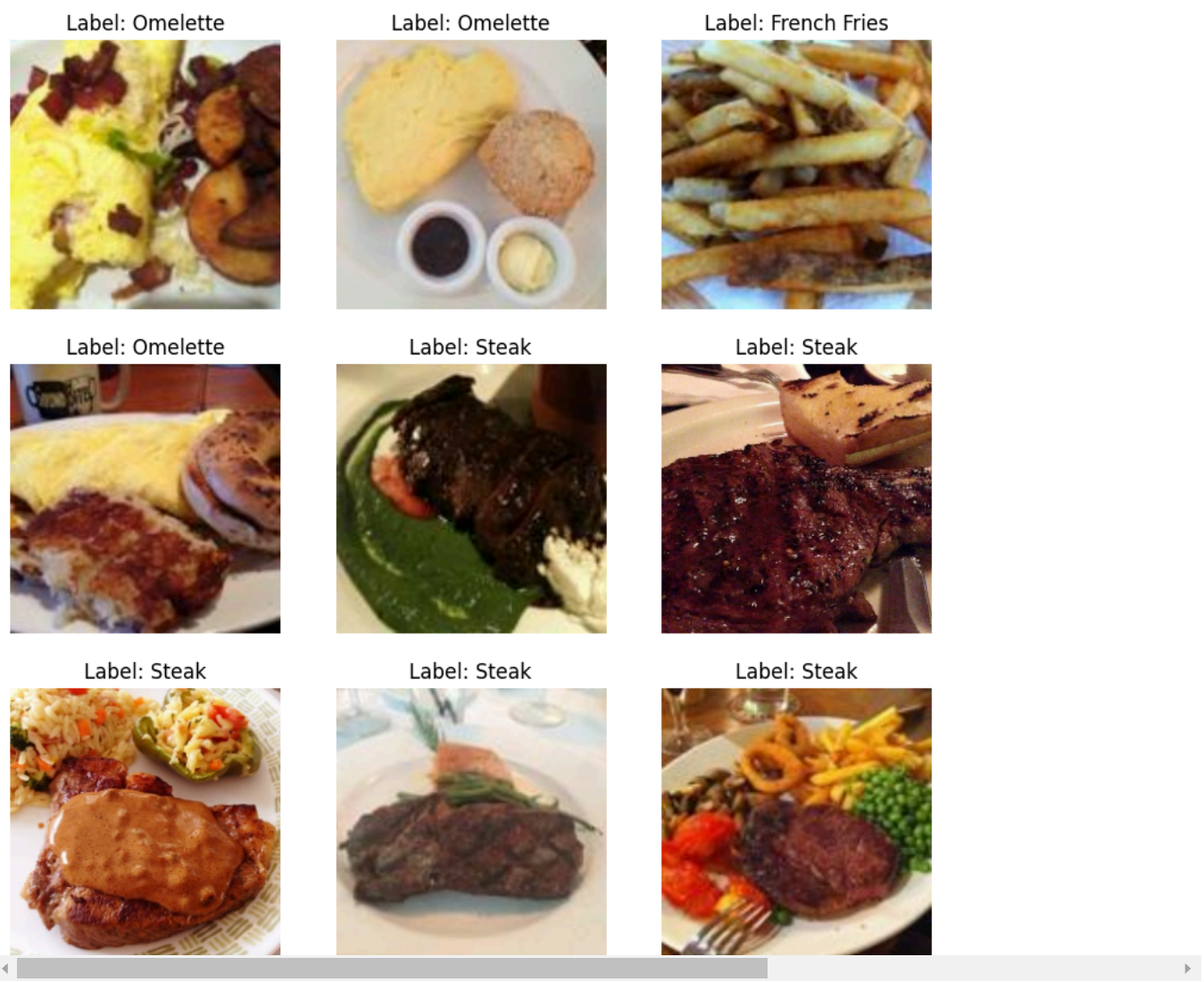
```
DATA_DIR = f'./'
print(f"There are {len(os.listdir(DATA_DIR))} categories of food.")
```

```
There are 3 categories of food.
```

```
def train_val_test_ds():
    # Load the entire dataset
    full_ds = tf.keras.utils.image_dataset_from_directory(
        directory=DATA_DIR,
        image_size=(224, 224),
        batch_size=32,
        shuffle=True,
        labels='inferred',
        label_mode='int',
        seed=42
    )

    # Get the total size of the dataset
    total_size = int(tf.data.experimental.cardinality(full_ds))

    # Define the sizes for the splits
    train_size = int(total_size * 0.70)
    val_size = int(total_size * 0.20)
    test_size = total_size - train_size - val_size

    # Split the dataset
    test_ds = full_ds.take(test_size)
    val_ds = full_ds.skip(test_size).take(val_size)
    train_ds = full_ds.skip(test_size + val_size)

    return train_ds, val_ds, test_ds

# Load the datasets
train_ds, val_ds, test_ds = train_val_test_ds()

train_ds_size = tf.data.experimental.cardinality(train_ds)
val_ds_size = tf.data.experimental.cardinality(val_ds)
test_ds_size = tf.data.experimental.cardinality(test_ds)

print(f"Train Dataset size: {train_ds_size}")
print(f"Validation Dataset size: {val_ds_size}")
print(f"Test Dataset size: {test_ds_size}")
```

```
Found 3000 files belonging to 3 classes.
Train Dataset size: 65
Validation Dataset size: 18
Test Dataset size: 11
```

```
label_names = {
    0: "French Fries",
    1: "Omelette",
    2: "Steak"
}

# Visualize images with label names
for images, labels in val_ds.take(1):
    plt.figure(figsize=(10, 10))
    for i in range(9):
        plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        label_name = label_names[labels[i].numpy()]  # Get the label name
        plt.title(f"Label: {label_name}")
        plt.axis("off")
    plt.show()
```




```
#Loading the EfficientNetB0 model for transfer learning
base_model = tf.keras.applications.EfficientNetB0(
    input_shape=(224, 224, 3),
    include_top=False,
    weights='imagenet'
)

base_model.trainable = False

base_model.summary()
```

```
Downloading data from https://storage.googleapis.com/keras-applications/efficientnetb0_notop.h5
16705208/16705208 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Model: "efficientnetb0"
```

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 224, 224, 3)	0	-
rescaling (Rescaling)	(None, 224, 224, 3)	0	input_layer[0][0]
normalization (Normalization)	(None, 224, 224, 3)	7	rescaling[0][0]
rescaling_1 (Rescaling)	(None, 224, 224, 3)	0	normalization[0][0]
stem_conv_pad (ZeroPadding2D)	(None, 225, 225, 3)	0	rescaling_1[0][0]
stem_conv (Conv2D)	(None, 112, 112, 32)	864	stem_conv_pad[0][0]
stem_bn (BatchNormalization)	(None, 112, 112, 32)	128	stem_conv[0][0]
stem_activation (Activation)	(None, 112, 112, 32)	0	stem_bn[0][0]
block1a_dwconv (DepthwiseConv2D)	(None, 112, 112, 32)	288	stem_activation[0][0]
block1a_bn (BatchNormalization)	(None, 112, 112, 32)	128	block1a_dwconv[0][0]
block1a_activation (Activation)	(None, 112, 112, 32)	0	block1a_bn[0][0]
block1a_se_squeeze (GlobalAveragePooling2D)	(None, 32)	0	block1a_activation[0]…
block1a_se_reshape (Reshape)	(None, 1, 1, 32)	0	block1a_se_squeeze[0]…
block1a_se_reduce (Conv2D)	(None, 1, 1, 8)	264	block1a_se_reshape[0]…
block1a_se_expand (Conv2D)	(None, 1, 1, 32)	288	block1a_se_reduce[0][…
block1a_se_excite (Multiply)	(None, 112, 112, 32)	0	block1a_activation[0]… block1a_se_expand[0][…
block1a_project_conv (Conv2D)	(None, 112, 112, 16)	512	block1a_se_excite[0][…
block1a_project_bn (BatchNormalization)	(None, 112, 112, 16)	64	block1a_project_conv[…
block2a_expand_conv (Conv2D)	(None, 112, 112, 96)	1,536	block1a_project_bn[0]…

```
# fine tuning and add more layers

# Add custom classification head with more layers
inputs = tf.keras.Input(shape=(224, 224, 3))
x = base_model(inputs, training=False)

# Global Average Pooling Layer
x = tf.keras.layers.GlobalAveragePooling2D()(x)

# Add Dense Layers with Batch Normalization and Activation
x = tf.keras.layers.Dense(256)(x)
x = tf.keras.layers.BatchNormalization()(x)
x = tf.keras.layers.Activation('relu')(x)
x = tf.keras.layers.Dropout(0.4)(x)  # Increased dropout for regularization

x = tf.keras.layers.Dense(128)(x)
x = tf.keras.layers.BatchNormalization()(x)
x = tf.keras.layers.Activation('relu')(x)
x = tf.keras.layers.Dropout(0.3)(x)

# Final Classification Layer
outputs = tf.keras.layers.Dense(3, activation='softmax')(x)

# Create the Model
model = tf.keras.Model(inputs, outputs)

# Model summary
model.summary()
```

```
Model: "functional"
```

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 224, 224, 3)	0
efficientnetb0 (Functional)	(None, 7, 7, 1280)	4,049,571
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dense (Dense)	(None, 256)	327,936
batch_normalization (BatchNormalization)	(None, 256)	1,024
activation (Activation)	(None, 256)	0
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32,896
batch_normalization_1 (BatchNormalization)	(None, 128)	512
activation_1 (Activation)	(None, 128)	0
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 3)	387

```
Total params: 4,412,326 (16.83 MB)
Trainable params: 361,987 (1.38 MB)
Non-trainable params: 4,050,339 (15.45 MB)
```

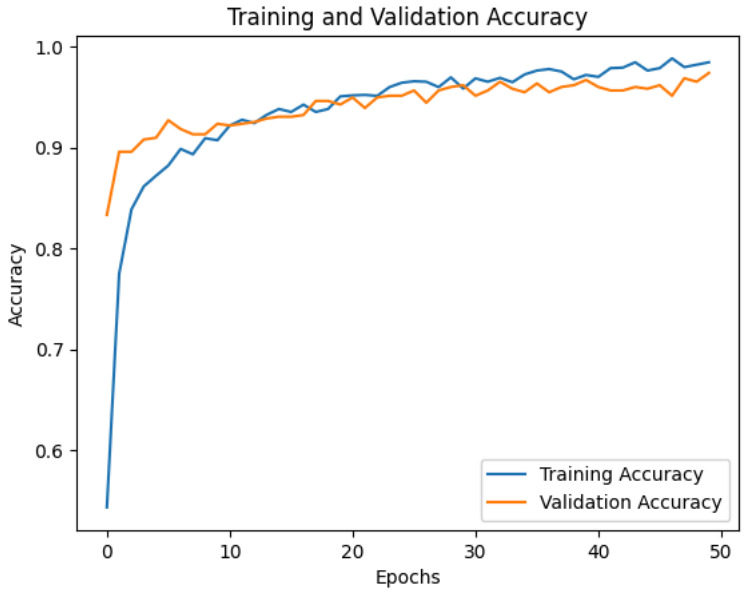
```
# Compile the Model
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),  # Lower learning rate for fine-tuning
              loss='sparse_categorical_crossentropy',  # Adjust for your task
              metrics=['accuracy'])
```

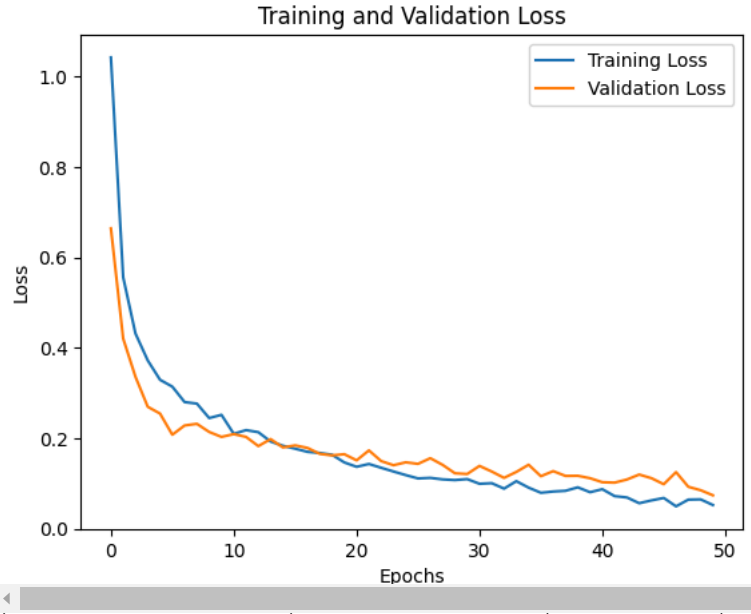
```
# Fit the model
history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=50  # Adjust based on your needs
    # batch_size=32  # Only needed if datasets are not batched
)
```

```
Epoch 1/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 50s 368ms/step - accuracy: 0.4388 - loss: 1.2893 - val_accuracy: 0.8333 - val_loss: 0.6639
Epoch 2/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 5s 61ms/step - accuracy: 0.7450 - loss: 0.6133 - val_accuracy: 0.8958 - val_loss: 0.4201
Epoch 3/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 5s 52ms/step - accuracy: 0.8332 - loss: 0.4488 - val_accuracy: 0.8958 - val_loss: 0.3358
Epoch 4/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 51ms/step - accuracy: 0.8497 - loss: 0.3942 - val_accuracy: 0.9080 - val_loss: 0.2695
Epoch 5/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 6s 77ms/step - accuracy: 0.8609 - loss: 0.3468 - val_accuracy: 0.9097 - val_loss: 0.2545
Epoch 6/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 57ms/step - accuracy: 0.8725 - loss: 0.3356 - val_accuracy: 0.9271 - val_loss: 0.2078
Epoch 7/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 51ms/step - accuracy: 0.8943 - loss: 0.2942 - val_accuracy: 0.9184 - val_loss: 0.2282
Epoch 8/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 5s 67ms/step - accuracy: 0.8856 - loss: 0.2850 - val_accuracy: 0.9132 - val_loss: 0.2318
Epoch 9/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 5s 61ms/step - accuracy: 0.9026 - loss: 0.2433 - val_accuracy: 0.9132 - val_loss: 0.2139
Epoch 10/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 51ms/step - accuracy: 0.9018 - loss: 0.2859 - val_accuracy: 0.9236 - val_loss: 0.2029
Epoch 11/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 6s 72ms/step - accuracy: 0.9300 - loss: 0.1981 - val_accuracy: 0.9219 - val_loss: 0.2091
Epoch 12/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 57ms/step - accuracy: 0.9333 - loss: 0.2120 - val_accuracy: 0.9236 - val_loss: 0.2029
Epoch 13/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 51ms/step - accuracy: 0.9184 - loss: 0.2167 - val_accuracy: 0.9253 - val_loss: 0.1826
Epoch 14/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 5s 63ms/step - accuracy: 0.9266 - loss: 0.2007 - val_accuracy: 0.9288 - val_loss: 0.1981
Epoch 15/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 51ms/step - accuracy: 0.9270 - loss: 0.2061 - val_accuracy: 0.9306 - val_loss: 0.1796
Epoch 16/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 58ms/step - accuracy: 0.9271 - loss: 0.1958 - val_accuracy: 0.9306 - val_loss: 0.1842
Epoch 17/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 7s 97ms/step - accuracy: 0.9363 - loss: 0.1826 - val_accuracy: 0.9323 - val_loss: 0.1786
Epoch 18/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 57ms/step - accuracy: 0.9255 - loss: 0.1863 - val_accuracy: 0.9462 - val_loss: 0.1655
Epoch 19/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 59ms/step - accuracy: 0.9373 - loss: 0.1658 - val_accuracy: 0.9462 - val_loss: 0.1621
Epoch 20/50
```

```
65/65 ━━━━━━━━━━━━━━━━━━━━ 5s 53ms/step - accuracy: 0.9399 - loss: 0.1792 - val_accuracy: 0.9427 - val_loss: 0.1647
Epoch 21/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 51ms/step - accuracy: 0.9457 - loss: 0.1479 - val_accuracy: 0.9497 - val_loss: 0.1511
Epoch 22/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 59ms/step - accuracy: 0.9462 - loss: 0.1678 - val_accuracy: 0.9392 - val_loss: 0.1731
Epoch 23/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 5s 57ms/step - accuracy: 0.9449 - loss: 0.1510 - val_accuracy: 0.9497 - val_loss: 0.1495
Epoch 24/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 50ms/step - accuracy: 0.9530 - loss: 0.1443 - val_accuracy: 0.9514 - val_loss: 0.1404
Epoch 25/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 6s 82ms/step - accuracy: 0.9574 - loss: 0.1351 - val_accuracy: 0.9514 - val_loss: 0.1468
Epoch 26/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 51ms/step - accuracy: 0.9637 - loss: 0.1304 - val_accuracy: 0.9566 - val_loss: 0.1434
Epoch 27/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 4s 51ms/step - accuracy: 0.9487 - loss: 0.1395 - val_accuracy: 0.9444 - val_loss: 0.1559
Epoch 28/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 5s 71ms/step - accuracy: 0.9616 - loss: 0.1110 - val_accuracy: 0.9566 - val_loss: 0.1411
Epoch 29/50
| (GlobalAveragePooling2D) |
```

```
import matplotlib.pyplot as plt

# Plot accuracy
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy')
plt.show()

# Plot loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss')
plt.show()
```

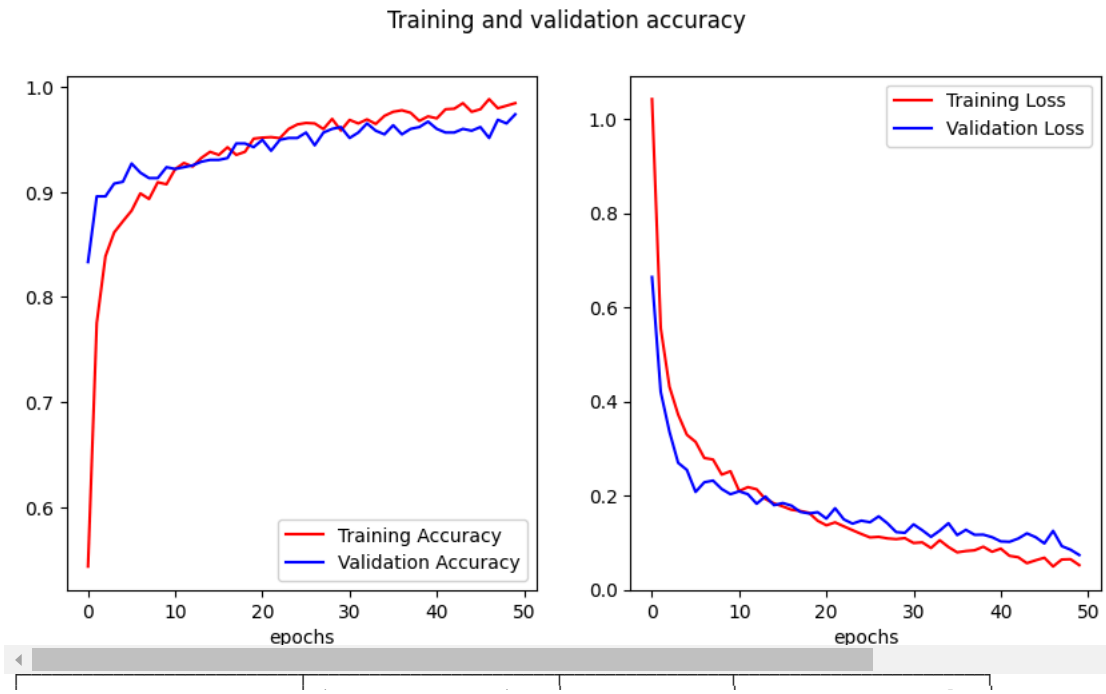





```
test_loss, test_accuracy = model.evaluate(test_ds)
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")
```

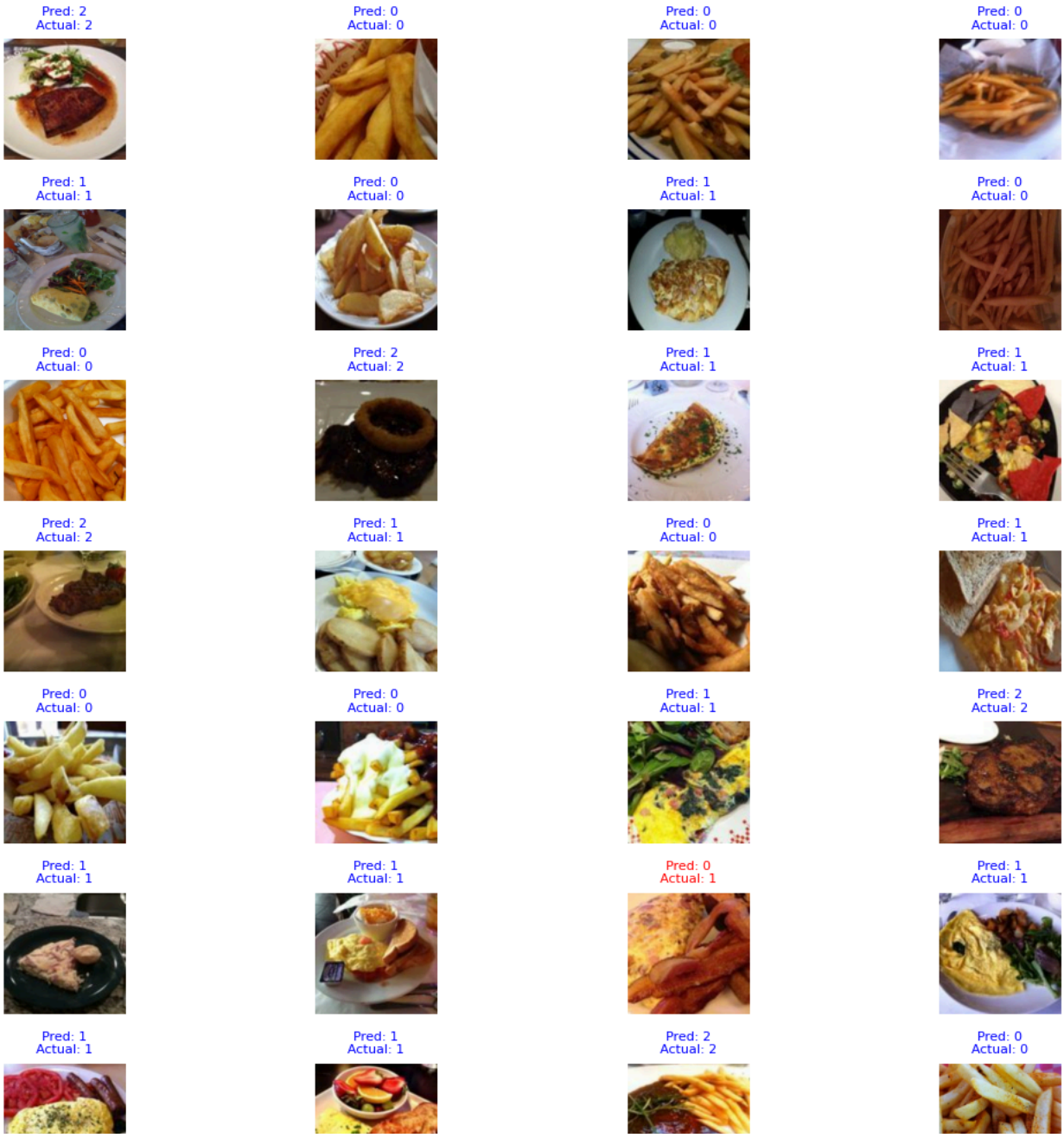
```
11/11 ━━━━━━━━━━━━━━━━━━━━ 1s 43ms/step - accuracy: 0.9503 - loss: 0.1434
Test Loss: 0.1448
Test Accuracy: 0.9489
```

```
# Get training and validation accuracies
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

fig, ax = plt.subplots(1, 2, figsize=(10, 5))
fig.suptitle('Training and validation accuracy')

for i, (data, label) in enumerate(zip([(acc, val_acc), (loss, val_loss)], ["Accuracy", "Loss"])):
    ax[i].plot(epochs, data[0], 'r', label="Training " + label)
    ax[i].plot(epochs, data[1], 'b', label="Validation " + label)
    ax[i].legend()
    ax[i].set_xlabel('epochs')

plt.show()
```




```
for images, labels in test_ds.take(1):
    # Make predictions on the batch
    predictions = model.predict(images)
    predicted_classes = np.argmax(predictions, axis=1)

    # Calculate rows and columns for the grid
    num_images = len(images)
    cols = 4  # Set a fixed number of columns
    rows = (num_images + cols - 1) // cols  # Compute the number of rows required

    # Display the images along with predictions and actual labels
    plt.figure(figsize=(12, 12))  # Adjust figure size as needed

    for i in range(num_images):
        plt.subplot(rows, cols, i + 1)  # Adjust grid based on batch size
        plt.imshow(images[i].numpy().astype("uint8"))  # Convert image tensor to uint8 for visualization
        plt.axis('off')  # Remove axis lines for clarity

        # Display predicted and actual labels as the title
        plt.title(f"Pred: {predicted_classes[i]}\nActual: {labels[i].numpy()}",
                  fontsize=8, color='blue' if predicted_classes[i] == labels[i].numpy() else 'red')

    plt.tight_layout()  # Adjust layout to avoid overlap
    plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 6s 6s/step
```




```
# Save the model in HDF5 format
model.save('my_model.h5')  # 'my_model.h5' is the filename where the model will be saved
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is c
```

```
import keras

keras.saving.save_model(model, 'my_model.keras')
```

```
import tensorflow as tf
import ipywidgets as widgets
from io import BytesIO
import numpy as np
from IPython.display import display

# Create the widget for file upload
uploader = widgets.FileUpload(accept="image/*", multiple=True)
display(uploader)
out = widgets.Output()
display(out)

# Preprocessing function to scale the image for EfficientNetB0
def preprocess_image(image):
    """ Function to preprocess the image for EfficientNetB0 input. """
```

```
        image = tf.keras.applications.efficientnet.preprocess_input(image)
        return image

    def file_predict(filename, file, out):
        """ A function for creating the prediction and printing the output."""
        # Load and preprocess the image
        image = tf.keras.utils.load_img(file, target_size=(224, 224))  # EfficientNetB0 expects (224, 224)
        image = tf.keras.utils.img_to_array(image)
        image = preprocess_image(image)  # EfficientNetB0 requires specific preprocessing
        image = np.expand_dims(image, axis=0)

        # Predict the class using the model
        prediction = model.predict(image, verbose=0)

        # Assuming the output layer has 3 classes (e.g., human, horse, other), apply softmax
        predicted_class = np.argmax(prediction)  # For multi-class classification

        with out:
            # Map prediction to class names
            class_names = ["French Fries", "Omelette", "Steak"]  # Modify based on your label names
            print(f"{filename} is predicted to be: {class_names[predicted_class]}")

    def on_upload_change(change):
        """ A function for getting files from the widget and running the prediction."""
        # Get the newly uploaded file(s)
        for name, data in change.new.items():  # Iterate through dictionary
            file_jpgdata = BytesIO(data['content'])  # Access 'content' from the dictionary
            file_predict(name, file_jpgdata, out)

    # Run the interactive widget
    # Note: it may take a bit after you select the image to upload and process before you see the output.
    uploader.observe(on_upload_change, names='value')
```


```
    import tensorflow as tf
    import ipywidgets as widgets
    from io import BytesIO
    import numpy as np
    from IPython.display import display

    # Create the widget for file upload
    uploader = widgets.FileUpload(accept="image/*", multiple=True)
    display(uploader)
    out = widgets.Output()
    display(out)

    # Preprocessing function to scale the image for EfficientNetB0
    def preprocess_image(image):
        """ Function to preprocess the image for EfficientNetB0 input. """
        image = tf.keras.applications.efficientnet.preprocess_input(image)
        return image

    def file_predict(filename, file, out):
        """ A function for creating the prediction and printing the output."""
        # Load and preprocess the image
        image = tf.keras.utils.load_img(file, target_size=(224, 224))  # EfficientNetB0 expects (224, 224)
        image = tf.keras.utils.img_to_array(image)
        image = preprocess_image(image)  # EfficientNetB0 requires specific preprocessing
        image = np.expand_dims(image, axis=0)

        # Predict the class using the model
        prediction = model.predict(image, verbose=0)

        # Assuming the output layer has 3 classes (e.g., human, horse, other), apply softmax
        predicted_class = np.argmax(prediction)  # For multi-class classification

        # Map prediction to class names and nutritional data
        class_names = ["French Fries", "Omelette", "Steak"]  # Modify based on your label names
        nutrition_data = {
            "French Fries": {
                "Calories": "312 kcal",
                "Carbohydrates": "41g",
                "Protein": "3.4g",
                "Fat": "15g",
                "Fiber": "3g"
            },
            "Omelette": {
                "Calories": "154 kcal",
                "Carbohydrates": "0.6g",
```

```
            "Protein": "11g",
            "Fat": "11g",
            "Cholesterol": "372mg"
        },
        "Steak": {
            "Calories": "271 kcal",
            "Carbohydrates": "0g",
            "Protein": "25g",
            "Fat": "18g",
            "Iron": "2.6mg"
        }
    }

    predicted_label = class_names[predicted_class]
    nutrition = nutrition_data[predicted_label]

    with out:
        # Print prediction and nutritional data
        print(f"{filename} is predicted to be: {predicted_label}")
        print("Nutritional Information:")
        for key, value in nutrition.items():
            print(f"  {key}: {value}")
        print("\n")

def on_upload_change(change):
    """ A function for getting files from the widget and running the prediction."""
    # Get the newly uploaded file(s)
    for name, data in change.new.items():  # Iterate through dictionary
        file_jpgdata = BytesIO(data['content'])  # Access 'content' from the dictionary
        file_predict(name, file_jpgdata, out)

# Run the interactive widget
# Note: it may take a bit after you select the image to upload and process before you see the output.
uploader.observe(on_upload_change, names='value')
```

```
Upload (1)
```

```
kentnag goreng.jpg is predicted to be: French Fries
Nutritional Information:
  Calories: 312 kcal
  Carbohydrates: 41g
  Protein: 3.4g
  Fat: 15g
  Fiber: 3g
```

```
| top_conv (Conv2D)         | (None, 7, 7, 1280)     |        409,600 | block7a_project_bn[0]… |
```

```
import tensorflow as tf
from keras.models import load_model

model = load_model("my_model.h5")

converter = tf.lite.TFLiteConverter.from_keras_model(model)

# converter.optimizations = [tf.lite.Optimize.DEFAULT]

lite_model = converter.convert()

with open("lite_my_model.tflite","wb") as f:
    f.write(lite_model)
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty unti
Saved artifact at '/tmp/tmparxcblqk'. The following endpoints are available:

* Endpoint 'serve'
  args_0 (POSITIONAL_ONLY): TensorSpec(shape=(None, 224, 224, 3), dtype=tf.float32, name='input_layer_1')
Output Type:
  TensorSpec(shape=(None, 3), dtype=tf.float32, name=None)
Captures:
  139030439533504: TensorSpec(shape=(1, 1, 1, 3), dtype=tf.float32, name=None)
  139030439534560: TensorSpec(shape=(1, 1, 1, 3), dtype=tf.float32, name=None)
  139030439540544: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439536320: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439536496: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439539840: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439560640: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439537904: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439562400: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439560816: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439563280: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439562224: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439567680: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439565568: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439569264: TensorSpec(shape=(), dtype=tf.resource, name=None)
```

```
  139030439568032: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439571024: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439569968: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439572432: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439559232: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439568560: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439574896: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439563632: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439569792: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439567152: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439574016: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439572080: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439660352: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439662464: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439658416: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439660176: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439665632: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439663520: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439667216: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439665984: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439668976: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439667920: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439670384: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439658064: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439666512: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439673024: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439763408: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439764112: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439759184: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439761472: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439766576: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439766224: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439767984: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030439764288: TensorSpec(shape=(), dtype=tf.resource, name=None)
```

```
# Load the model
model = load_model("my_model.h5")

# Compile the model with the same settings as during training
model.compile(
    optimizer="adam",  # Replace with your actual optimizer
    loss="sparse_categorical_crossentropy",  # Replace with your actual loss function
    metrics=["accuracy"]  # Replace with your actual metrics
)
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until y
```

```
# Convert the model to TensorFlow Lite format
converter = tf.lite.TFLiteConverter.from_keras_model(model)

converter.optimizations = [tf.lite.Optimize.DEFAULT]

lite_model = converter.convert()

# Save the TFLite model
with open("lite_my_model_compile.tflite", "wb") as f:
    f.write(lite_model)
```

```
Saved artifact at '/tmp/tmphd5ciysj'. The following endpoints are available:

 * Endpoint 'serve'
   args_0 (POSITIONAL_ONLY): TensorSpec(shape=(None, 224, 224, 3), dtype=tf.float32, name='input_layer_1')
 Output Type:
   TensorSpec(shape=(None, 3), dtype=tf.float32, name=None)
 Captures:
   139030137809808: TensorSpec(shape=(1, 1, 1, 3), dtype=tf.float32, name=None)
   139030137810864: TensorSpec(shape=(1, 1, 1, 3), dtype=tf.float32, name=None)
   139030137811392: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137539744: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137536928: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137538512: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137539040: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137544672: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137544320: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137546080: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137542384: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137543088: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137549072: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137546960: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137550656: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137549424: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137552416: TensorSpec(shape=(), dtype=tf.resource, name=None)
   139030137543440: TensorSpec(shape=(), dtype=tf.resource, name=None)
```

```
  139030137551008: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137542912: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137552592: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137545376: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137293456: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137291872: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137295744: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137293280: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137298560: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137298208: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137299968: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137296096: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137296976: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137302960: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137300848: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137304544: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137303312: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137306304: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137299616: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137304896: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137296800: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137301200: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137299264: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137342256: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137341200: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137344544: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137342080: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137347184: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137346832: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137348592: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137344896: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137345600: TensorSpec(shape=(), dtype=tf.resource, name=None)
  139030137351584: TensorSpec(shape=(), dtype=tf.resource, name=None)
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
!ls "/content/drive/My Drive/tes"
```

```
french_fries  omelette  steak
```

```
import tensorflow as tf
from keras.models import load_model

# Load a pre-trained model
model = load_model("my_model.h5")

# Compile the model (optional if already compiled)
model.compile(optimizer="adam", loss="sparse_categorical_crossentropy", metrics=["accuracy"])

# Prepare the test dataset
test_ds = tf.keras.utils.image_dataset_from_directory(
    directory="/content/drive/My Drive/tes",
    image_size=(224, 224),
    batch_size=32,
    shuffle=False,
    label_mode="int"
)

# Evaluate the model
test_loss, test_accuracy = model.evaluate(test_ds)

# Display the results
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until y
Found 17 files belonging to 3 classes.
1/1 ━━━━━━━━━━━━━━━━━━━━ 17s 17s/step - accuracy: 1.0000 - loss: 0.1101
Test Loss: 0.1101
Test Accuracy: 1.0000
```

```
# Get class names (if available from directory)
class_names = test_ds.class_names
print("Class names:", class_names)

# Loop through the test dataset to predict and display images
```

```
for images, labels in test_ds.take(1):  # Take 1 batch from the test dataset
    predictions = model.predict(images)  # Predict on the batch
    predicted_classes = np.argmax(predictions, axis=1)  # Get the class with the highest probability

    # Create a 4x4 grid for plotting images
    fig, axes = plt.subplots(4, 4, figsize=(12, 12))  # Create a 4x4 grid of subplots
    axes = axes.ravel()  # Flatten the axes array for easy iteration

    # Plot images in the 4x4 grid
    for i in range(16):  # 16 images in total (4x4 grid)
        axes[i].imshow(images[i].numpy().astype("uint8"))  # Show the image
        axes[i].set_title(f"Pred: {class_names[predicted_classes[i]]}\nTrue: {class_names[labels[i]]}"
        axes[i].axis('off')  # Remove axis for a cleaner look

    # Show the plot
    plt.tight_layout()
```

```
Class names: ['french_fries', 'omelette', 'steak']
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step
```