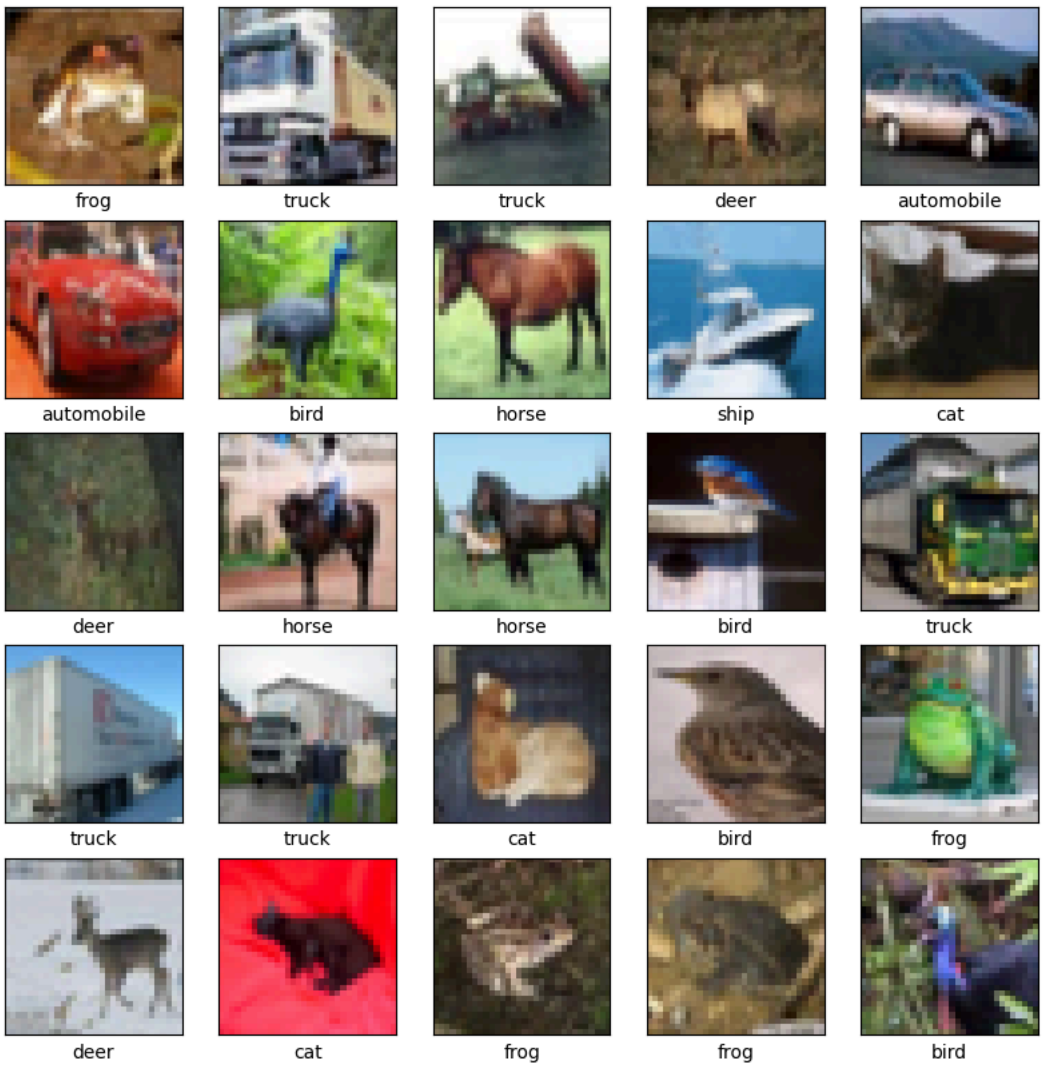
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt

print("TensorFlow Version:", tf.__version__)
```

```
TensorFlow Version: 2.19.0
```

```
# Load the CIFAR-10 dataset
(train_images, train_labels), (test_images, test_labels) = keras.datasets.cifar10.load_data()

# Normalize pixel values to be between 0 and 1
train_images, test_images = train_images / 255.0, test_images / 255.0

# Let's define the class names to see what our data looks like
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
               'dog', 'frog', 'horse', 'ship', 'truck']

# Visualize a few images from the training set
plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(train_images[i])
    # The CIFAR labels are arrays, so we need to access the first element
    plt.xlabel(class_names[train_labels[i][0]])
plt.show()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 8s 0us/step
```



```
# Create the convolutional base
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))

# Add Dense layers on top for classification
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10)) # Output layer has 10 neurons for 10 classes

# Print the model's architecture
model.summary()
```

```
/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not pass ar
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_1 (Conv2D)	(None, 13, 13, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_2 (Conv2D)	(None, 4, 4, 64)	36,928
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 64)	65,600
dense_1 (Dense)	(None, 10)	650

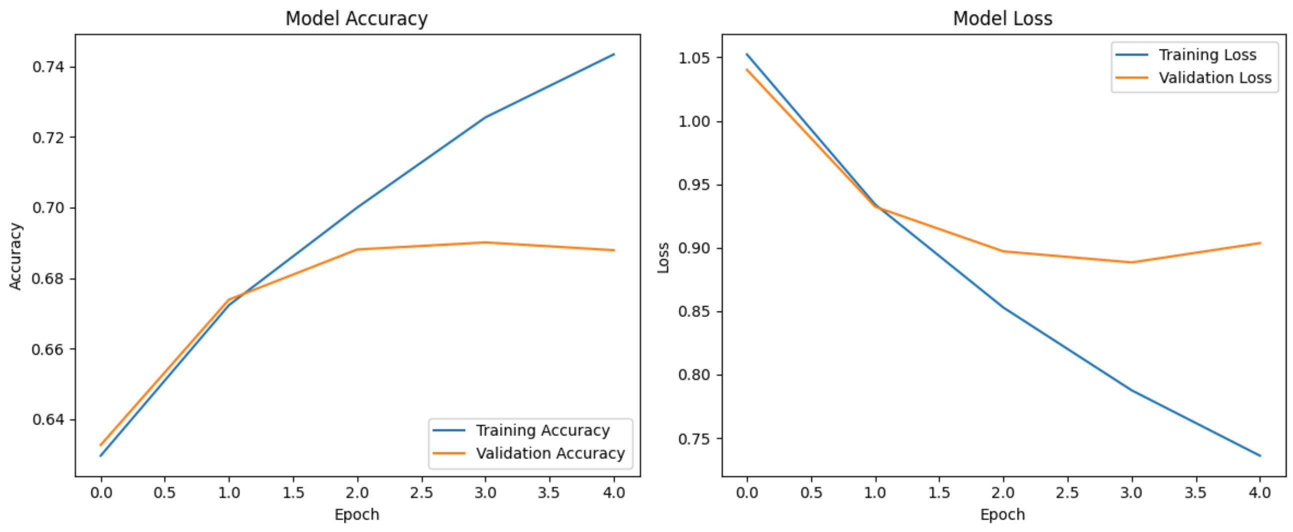
```
 Total params: 122,570 (478.79 KB)
 Trainable params: 122,570 (478.79 KB)
 Non-trainable params: 0 (0.00 B)
```

```
# Compile the model
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

# Train the model
# We store the training history to analyze it in the next step
history = model.fit(train_images, train_labels, epochs=5,
                    validation_data=(test_images, test_labels))
```

```
Epoch 1/5
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 71s 44ms/step - accuracy: 0.6221 - loss: 1.0787 - val_accuracy: 0.6327 - val_loss: 1.
Epoch 2/5
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 67s 43ms/step - accuracy: 0.6696 - loss: 0.9407 - val_accuracy: 0.6739 - val_loss: 0.
Epoch 3/5
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 66s 42ms/step - accuracy: 0.7003 - loss: 0.8512 - val_accuracy: 0.6881 - val_loss: 0.
Epoch 4/5
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 68s 44ms/step - accuracy: 0.7286 - loss: 0.7792 - val_accuracy: 0.6901 - val_loss: 0.
Epoch 5/5
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 69s 44ms/step - accuracy: 0.7494 - loss: 0.7203 - val_accuracy: 0.6879 - val_loss: 0.
```

```
# 1. Quantitative Estimation on the test set
test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
print(f"\nTest accuracy: {test_acc:.4f}")

# 2. Qualitative Estimation by plotting training history
plt.figure(figsize=(12, 5))

# Plot training & validation accuracy values
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='upper right')

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

```
313/313 - 5s - 15ms/step - accuracy: 0.6879 - loss: 0.9036

Test accuracy: 0.6879
```


Model Accuracy
Accuracy
Epoch
Training Accuracy
Validation Accuracy
Model Loss
Loss
Epoch
Training Loss
Validation Loss