CS 5720 Neural Network Deep Learning
ICP-7

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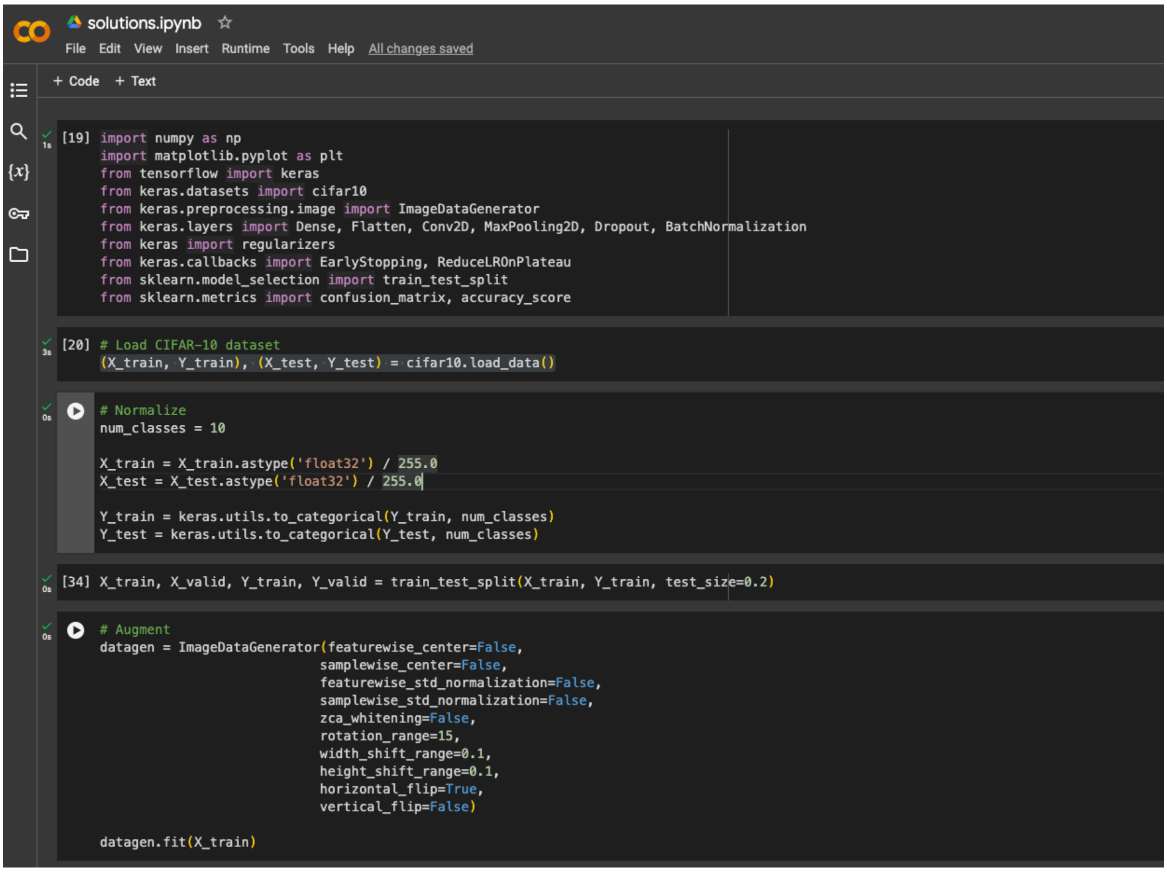
GitHub Repository:

https://github.com/mxb40210/700754021-NeuralNetworkDeepLearning

Assignment 7:

https://github.com/mxb40210/700754021-NeuralNetworkDeepLearning/tree/main/assignments/assignment7

Screenshots:



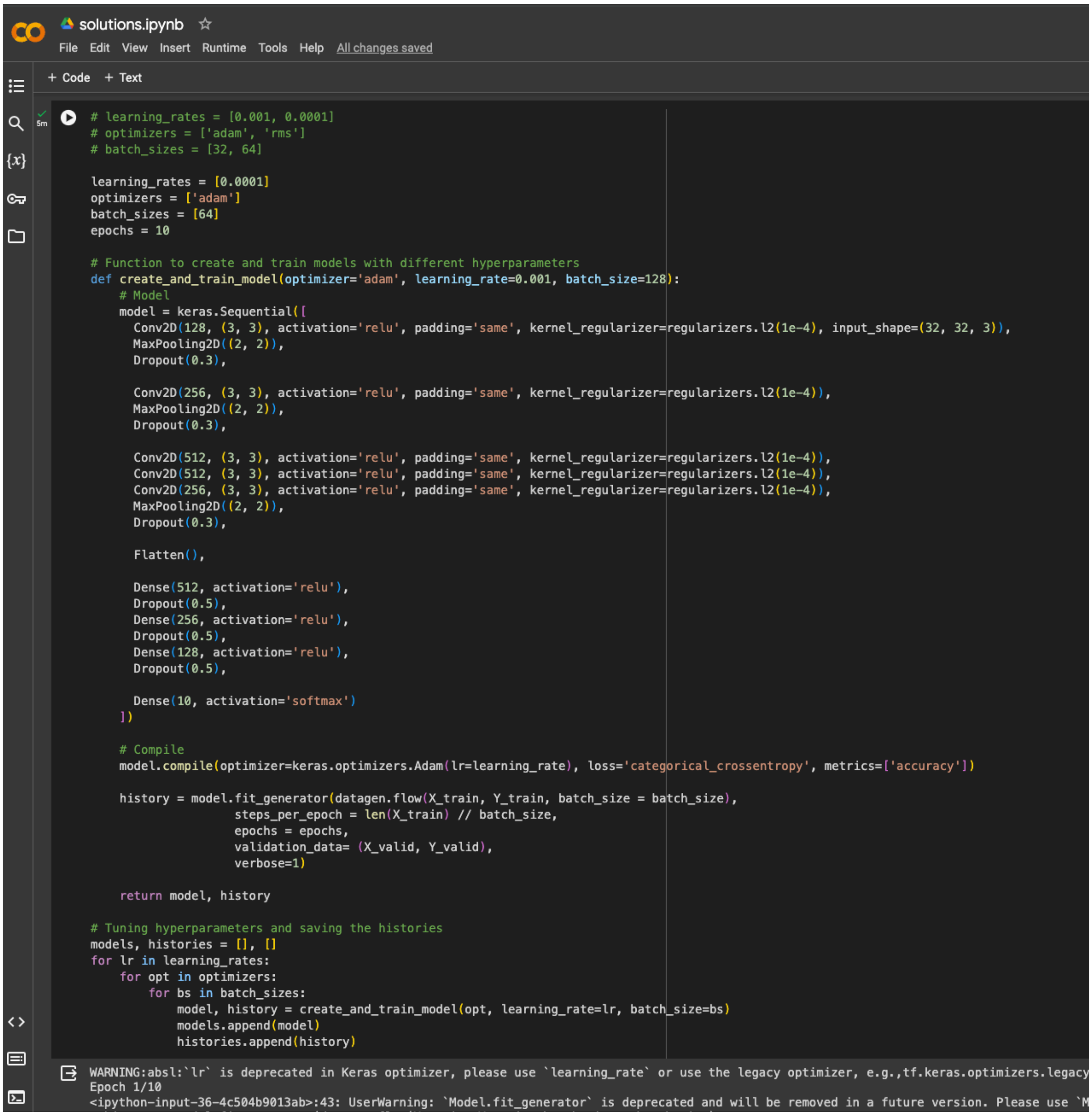
```
[19] import numpy as np
     import matplotlib.pyplot as plt
     from tensorflow import keras
     from keras.datasets import cifar10
     from keras.preprocessing.image import ImageDataGenerator
     from keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout, BatchNormalization
     from keras import regularizers
     from keras.callbacks import EarlyStopping, ReduceLROnPlateau
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import confusion_matrix, accuracy_score
```

```
[20] # Load CIFAR-10 dataset
     (X_train, Y_train), (X_test, Y_test) = cifar10.load_data()
```

```
# Normalize
num_classes = 10

X_train = X_train.astype('float32') / 255.0
X_test = X_test.astype('float32') / 255.0

Y_train = keras.utils.to_categorical(Y_train, num_classes)
Y_test = keras.utils.to_categorical(Y_test, num_classes)
```

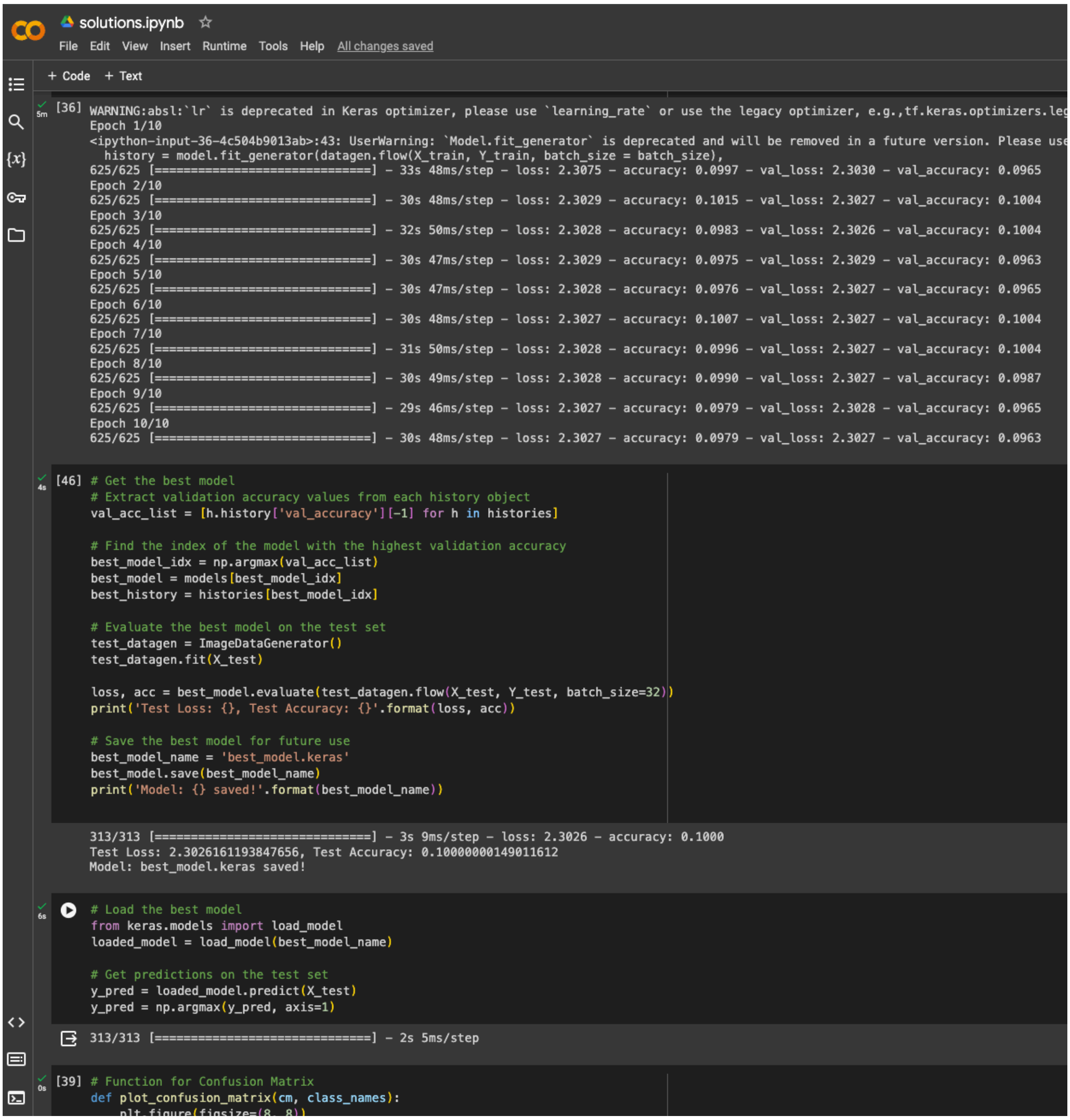
```
[34] X_train, X_valid, Y_train, Y_valid = train_test_split(X_train, Y_train, test_size=0.2)
```

```
# Augment
datagen = ImageDataGenerator(featurewise_center=False,
                             samplewise_center=False,
                             featurewise_std_normalization=False,
                             samplewise_std_normalization=False,
                             zca_whitening=False,
                             rotation_range=15,
                             width_shift_range=0.1,
                             height_shift_range=0.1,
                             horizontal_flip=True,
                             vertical_flip=False)

datagen.fit(X_train)
```



```python
# learning_rates = [0.001, 0.0001]
# optimizers = ['adam', 'rms']
# batch_sizes = [32, 64]

learning_rates = [0.0001]
optimizers = ['adam']
batch_sizes = [64]
epochs = 10

# Function to create and train models with different hyperparameters
def create_and_train_model(optimizer='adam', learning_rate=0.001, batch_size=128):
    # Model
    model = keras.Sequential([
      Conv2D(128, (3, 3), activation='relu', padding='same', kernel_regularizer=regularizers.l2(1e-4), input_shape=(32, 32, 3)),
      MaxPooling2D((2, 2)),
      Dropout(0.3),

      Conv2D(256, (3, 3), activation='relu', padding='same', kernel_regularizer=regularizers.l2(1e-4)),
      MaxPooling2D((2, 2)),
      Dropout(0.3),

      Conv2D(512, (3, 3), activation='relu', padding='same', kernel_regularizer=regularizers.l2(1e-4)),
      Conv2D(512, (3, 3), activation='relu', padding='same', kernel_regularizer=regularizers.l2(1e-4)),
      Conv2D(256, (3, 3), activation='relu', padding='same', kernel_regularizer=regularizers.l2(1e-4)),
      MaxPooling2D((2, 2)),
      Dropout(0.3),

      Flatten(),

      Dense(512, activation='relu'),
      Dropout(0.5),
      Dense(256, activation='relu'),
      Dropout(0.5),
      Dense(128, activation='relu'),
      Dropout(0.5),

      Dense(10, activation='softmax')
    ])

    # Compile
    model.compile(optimizer=keras.optimizers.Adam(lr=learning_rate), loss='categorical_crossentropy', metrics=['accuracy'])

    history = model.fit_generator(datagen.flow(X_train, Y_train, batch_size = batch_size),
                    steps_per_epoch = len(X_train) // batch_size,
                    epochs = epochs,
                    validation_data= (X_valid, Y_valid),
                    verbose=1)

    return model, history

# Tuning hyperparameters and saving the histories
models, histories = [], []
for lr in learning_rates:
    for opt in optimizers:
        for bs in batch_sizes:
            model, history = create_and_train_model(opt, learning_rate=lr, batch_size=bs)
            models.append(model)
            histories.append(history)
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.optimizers.legacy
Epoch 1/10
<ipython-input-36-4c504b9013ab>:43: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `M
```



```
[36] WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.optimizers.leg
     Epoch 1/10
     <ipython-input-36-4c504b9013ab>:43: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use
       history = model.fit_generator(datagen.flow(X_train, Y_train, batch_size = batch_size),
     625/625 [==============================] - 33s 48ms/step - loss: 2.3075 - accuracy: 0.0997 - val_loss: 2.3030 - val_accuracy: 0.0965
     Epoch 2/10
     625/625 [==============================] - 30s 48ms/step - loss: 2.3029 - accuracy: 0.1015 - val_loss: 2.3027 - val_accuracy: 0.1004
     Epoch 3/10
     625/625 [==============================] - 32s 50ms/step - loss: 2.3028 - accuracy: 0.0983 - val_loss: 2.3026 - val_accuracy: 0.1004
     Epoch 4/10
     625/625 [==============================] - 30s 47ms/step - loss: 2.3029 - accuracy: 0.0975 - val_loss: 2.3029 - val_accuracy: 0.0963
     Epoch 5/10
     625/625 [==============================] - 30s 47ms/step - loss: 2.3028 - accuracy: 0.0976 - val_loss: 2.3027 - val_accuracy: 0.0965
     Epoch 6/10
     625/625 [==============================] - 30s 48ms/step - loss: 2.3027 - accuracy: 0.1007 - val_loss: 2.3027 - val_accuracy: 0.1004
     Epoch 7/10
     625/625 [==============================] - 31s 50ms/step - loss: 2.3028 - accuracy: 0.0996 - val_loss: 2.3027 - val_accuracy: 0.1004
     Epoch 8/10
     625/625 [==============================] - 30s 49ms/step - loss: 2.3028 - accuracy: 0.0990 - val_loss: 2.3027 - val_accuracy: 0.0987
     Epoch 9/10
     625/625 [==============================] - 29s 46ms/step - loss: 2.3027 - accuracy: 0.0979 - val_loss: 2.3028 - val_accuracy: 0.0965
     Epoch 10/10
     625/625 [==============================] - 30s 48ms/step - loss: 2.3027 - accuracy: 0.0979 - val_loss: 2.3027 - val_accuracy: 0.0963
```

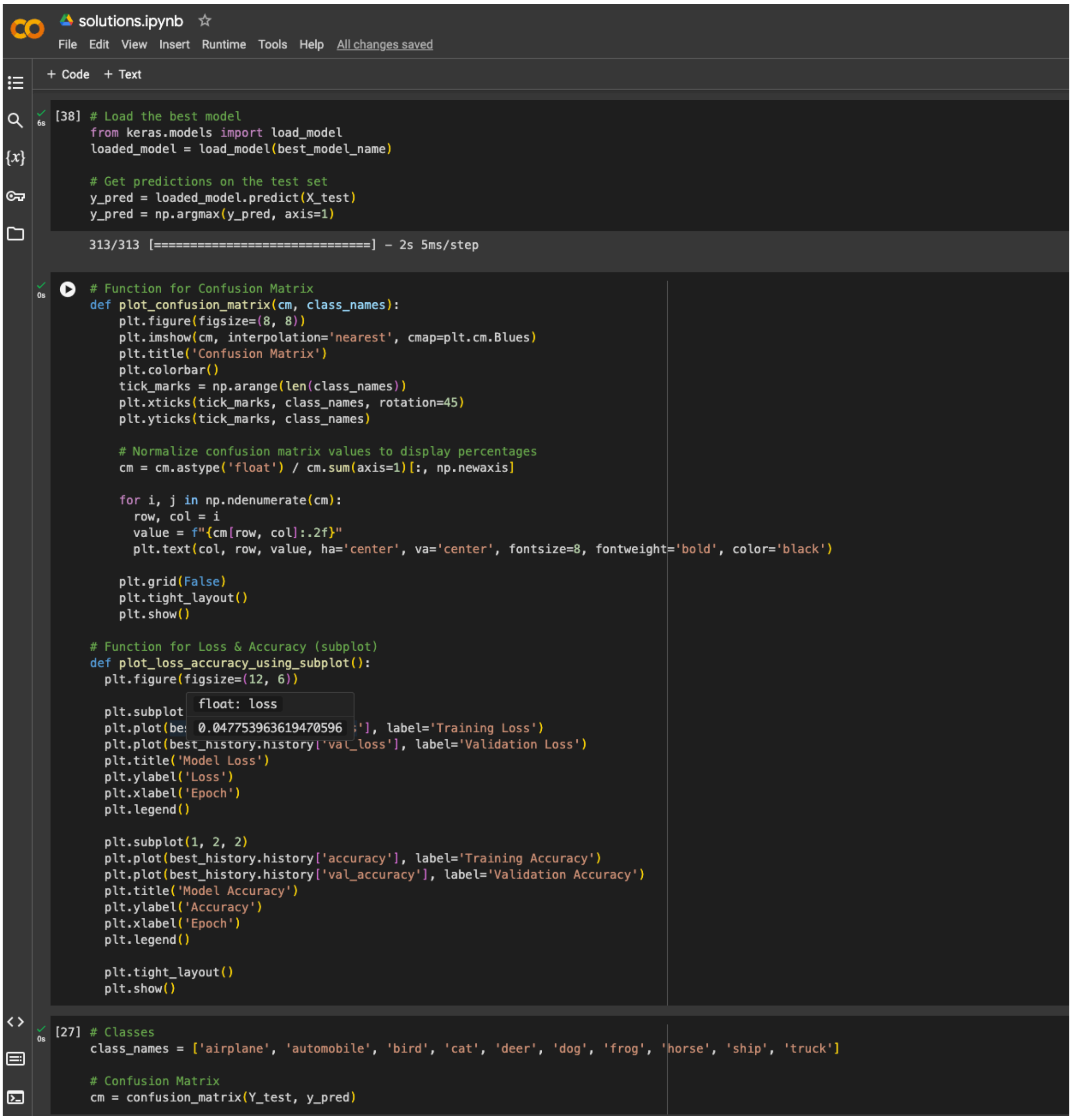
```
[46] # Get the best model
     # Extract validation accuracy values from each history object
     val_acc_list = [h.history['val_accuracy'][-1] for h in histories]

     # Find the index of the model with the highest validation accuracy
     best_model_idx = np.argmax(val_acc_list)
     best_model = models[best_model_idx]
     best_history = histories[best_model_idx]

     # Evaluate the best model on the test set
     test_datagen = ImageDataGenerator()
     test_datagen.fit(X_test)

     loss, acc = best_model.evaluate(test_datagen.flow(X_test, Y_test, batch_size=32))
     print('Test Loss: {}, Test Accuracy: {}'.format(loss, acc))

     # Save the best model for future use
     best_model_name = 'best_model.keras'
     best_model.save(best_model_name)
     print('Model: {} saved!'.format(best_model_name))
```

```
     313/313 [==============================] - 3s 9ms/step - loss: 2.3026 - accuracy: 0.1000
     Test Loss: 2.3026161193847656, Test Accuracy: 0.10000000149011612
     Model: best_model.keras saved!
```

```
     # Load the best model
     from keras.models import load_model
     loaded_model = load_model(best_model_name)

     # Get predictions on the test set
     y_pred = loaded_model.predict(X_test)
     y_pred = np.argmax(y_pred, axis=1)
```

```
     313/313 [==============================] - 2s 5ms/step
```

```
[39] # Function for Confusion Matrix
     def plot_confusion_matrix(cm, class_names):
         plt.figure(figsize=(8, 8))
```

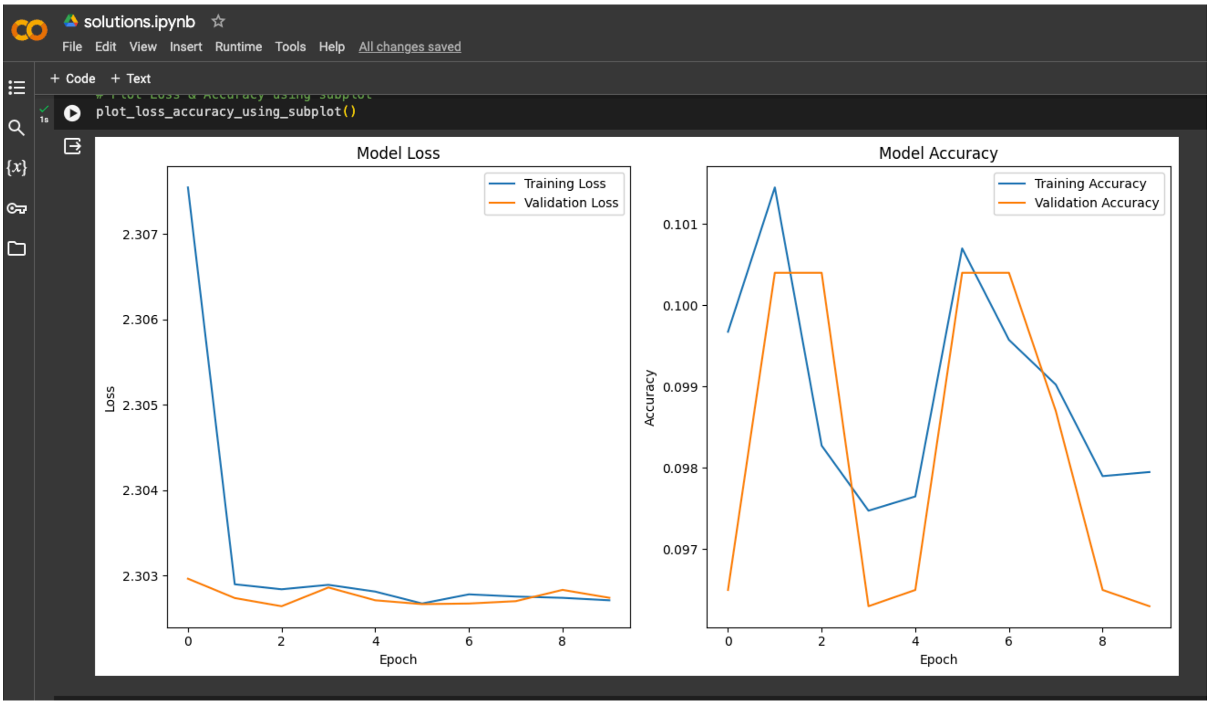


```
[38] # Load the best model
     from keras.models import load_model
     loaded_model = load_model(best_model_name)

     # Get predictions on the test set
     y_pred = loaded_model.predict(X_test)
     y_pred = np.argmax(y_pred, axis=1)
```

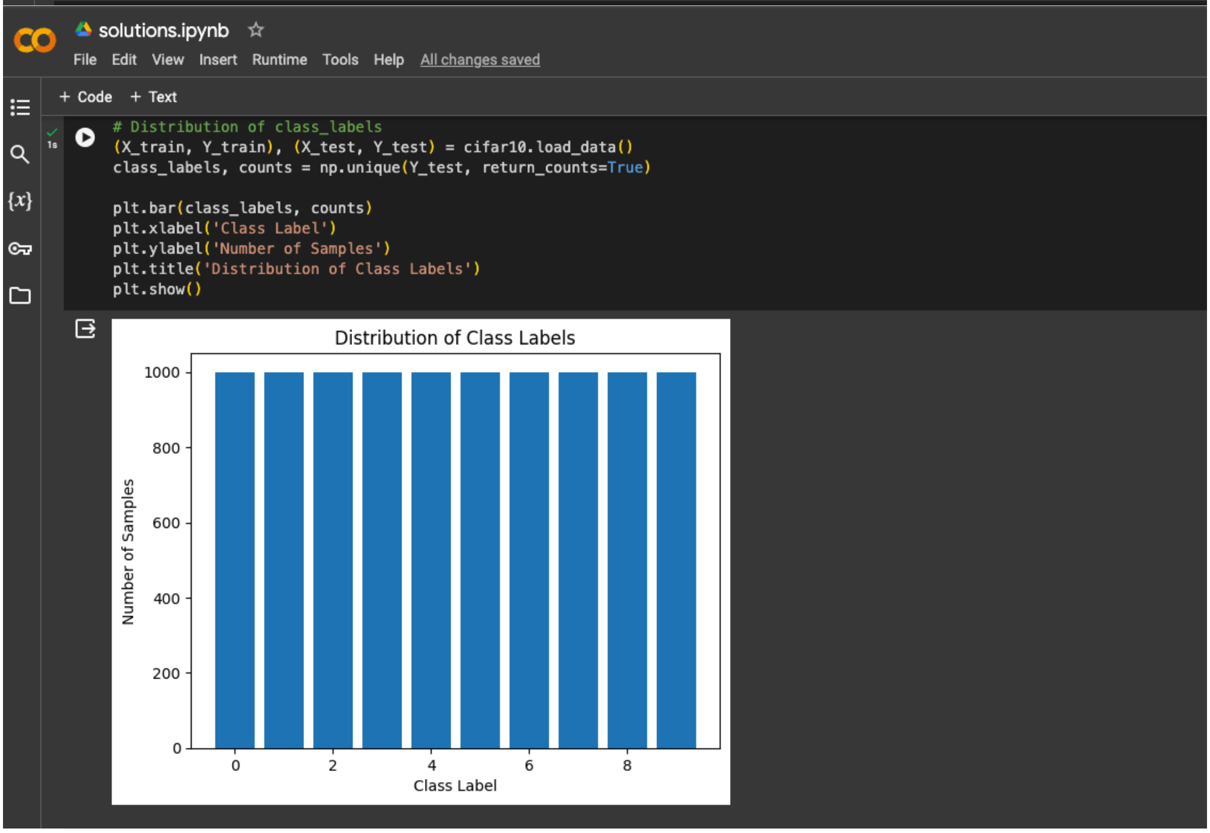
```
313/313 [==============================] - 2s 5ms/step
```

```
# Function for Confusion Matrix
def plot_confusion_matrix(cm, class_names):
    plt.figure(figsize=(8, 8))
    plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
    plt.title('Confusion Matrix')
    plt.colorbar()
    tick_marks = np.arange(len(class_names))
    plt.xticks(tick_marks, class_names, rotation=45)
    plt.yticks(tick_marks, class_names)

    # Normalize confusion matrix values to display percentages
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    for i, j in np.ndenumerate(cm):
      row, col = i
      value = f"{cm[row, col]:.2f}"
      plt.text(col, row, value, ha='center', va='center', fontsize=8, fontweight='bold', color='black')

    plt.grid(False)
    plt.tight_layout()
    plt.show()

# Function for Loss & Accuracy (subplot)
def plot_loss_accuracy_using_subplot():
  plt.figure(figsize=(12, 6))

  plt.subplot  float: loss
  plt.plot(bes 0.047753963619470596 s'], label='Training Loss')
  plt.plot(best_history.history['val_loss'], label='Validation Loss')
  plt.title('Model Loss')
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
  plt.legend()

  plt.subplot(1, 2, 2)
  plt.plot(best_history.history['accuracy'], label='Training Accuracy')
  plt.plot(best_history.history['val_accuracy'], label='Validation Accuracy')
  plt.title('Model Accuracy')
  plt.ylabel('Accuracy')
  plt.xlabel('Epoch')
  plt.legend()

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

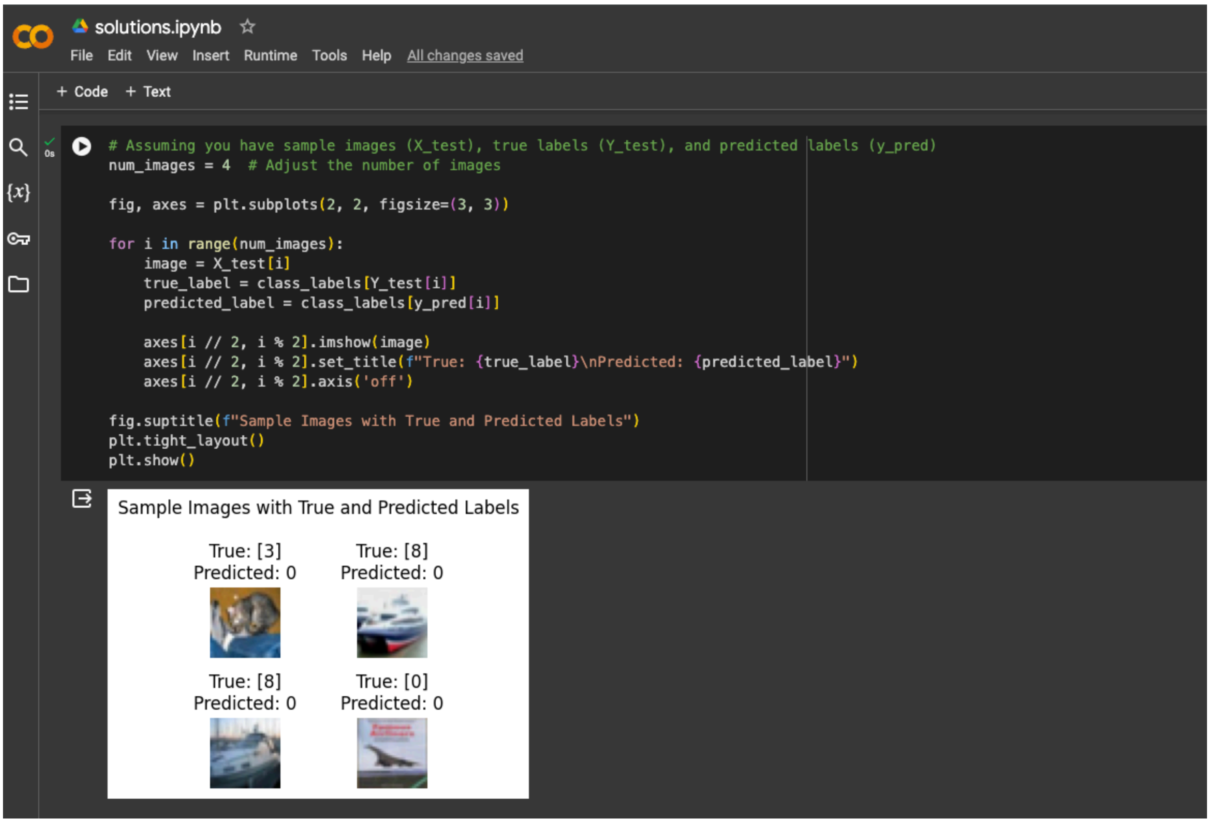
```
[27] # Classes
     class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']

     # Confusion Matrix
     cm = confusion_matrix(Y_test, y_pred)
```



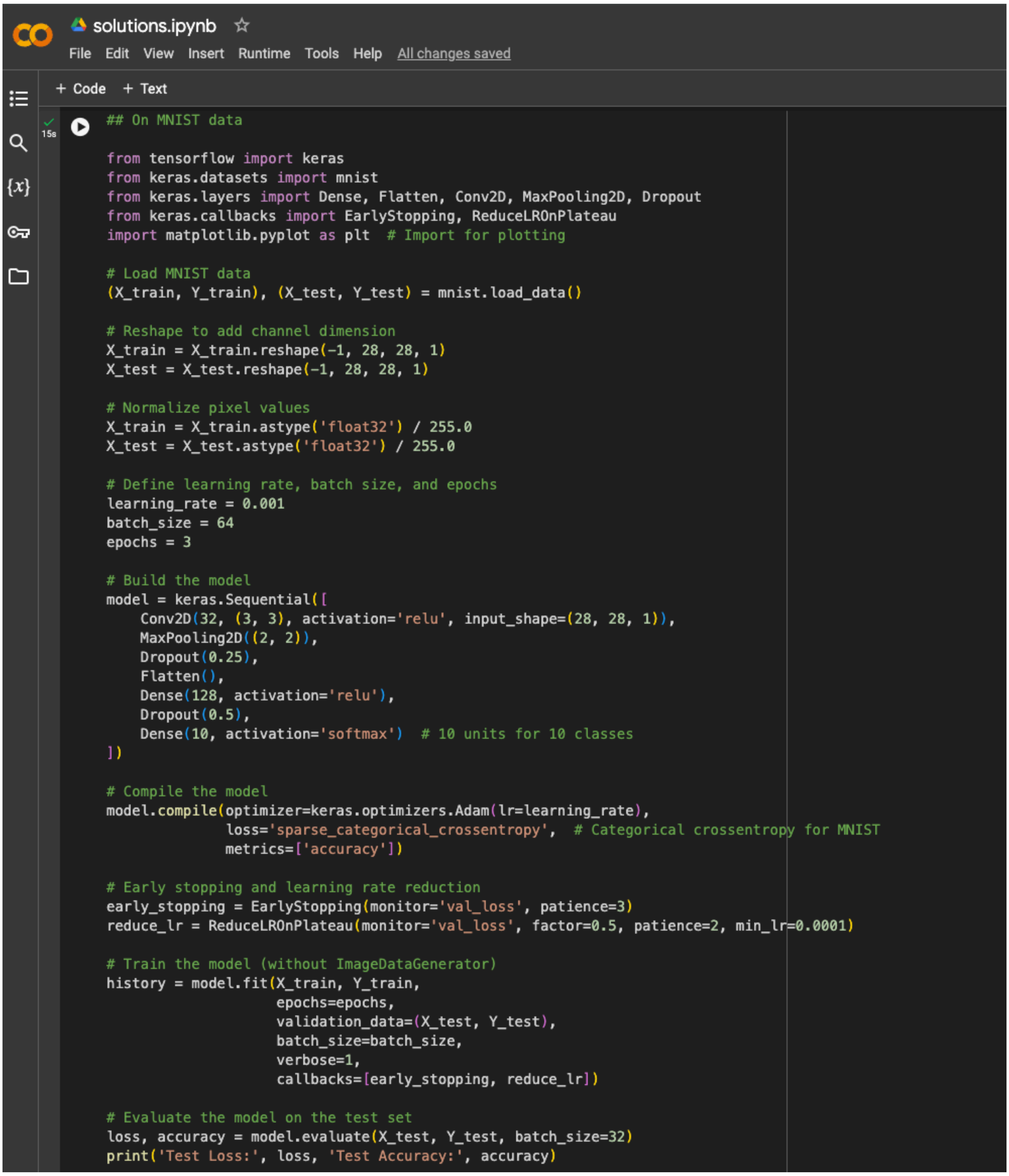
```
# Plot Loss & Accuracy using subplot
plot_loss_accuracy_using_subplot()
```


solutions.ipynb
File Edit View Insert Runtime Tools Help All changes saved
+ Code + Text
Distribution of Class Labels
Number of Samples
1000
800
600
400
200
0
0 2 4 6 8
Class Label

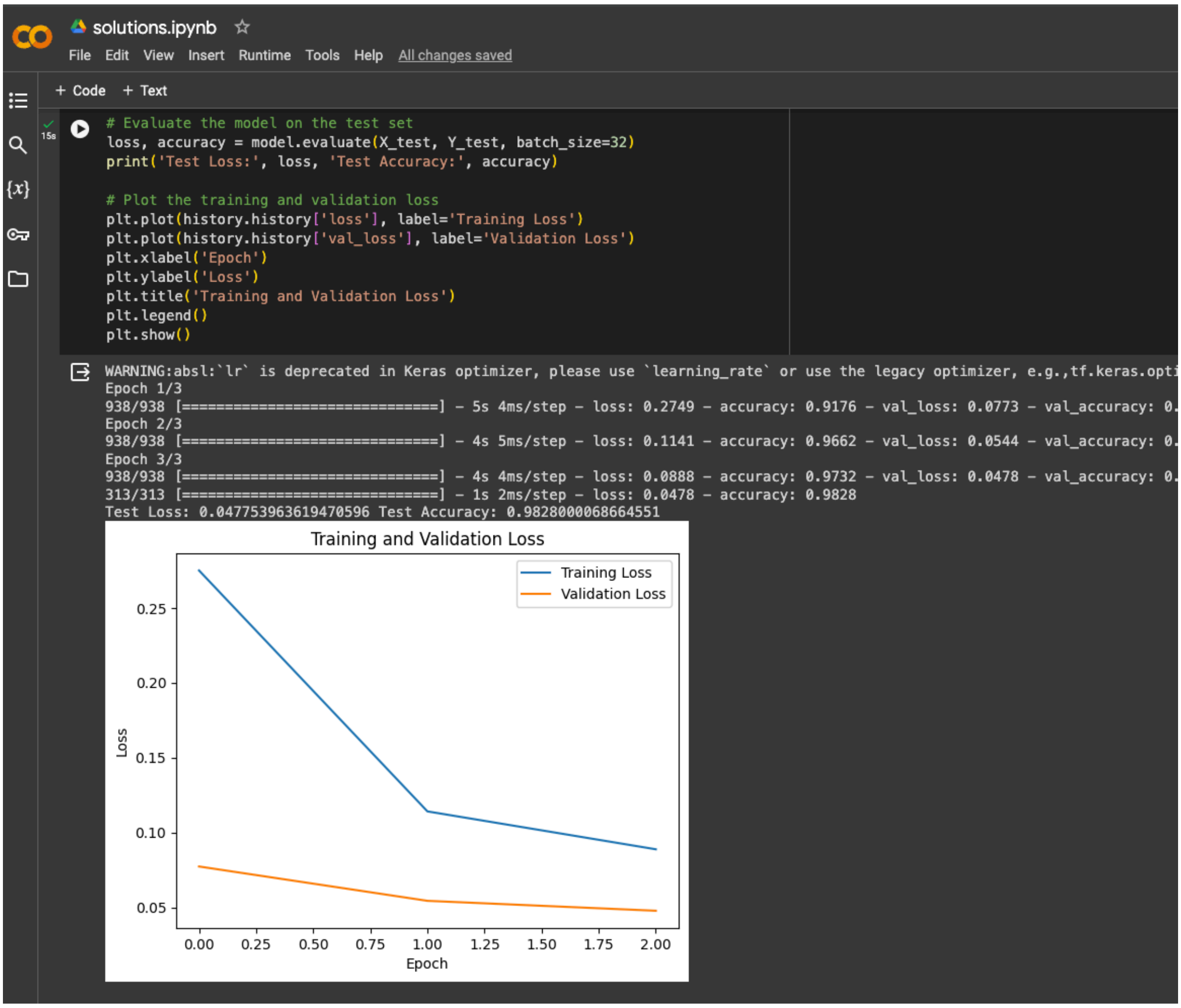
```
# Distribution of class_labels
(X_train, Y_train), (X_test, Y_test) = cifar10.load_data()
class_labels, counts = np.unique(Y_test, return_counts=True)

plt.bar(class_labels, counts)
plt.xlabel('Class Label')
plt.ylabel('Number of Samples')
plt.title('Distribution of Class Labels')
plt.show()
```



```python
# Assuming you have sample images (X_test), true labels (Y_test), and predicted labels (y_pred)
num_images = 4  # Adjust the number of images

fig, axes = plt.subplots(2, 2, figsize=(3, 3))

for i in range(num_images):
    image = X_test[i]
    true_label = class_labels[Y_test[i]]
    predicted_label = class_labels[y_pred[i]]

    axes[i // 2, i % 2].imshow(image)
    axes[i // 2, i % 2].set_title(f"True: {true_label}\nPredicted: {predicted_label}")
    axes[i // 2, i % 2].axis('off')

fig.suptitle(f"Sample Images with True and Predicted Labels")
plt.tight_layout()
plt.show()
```

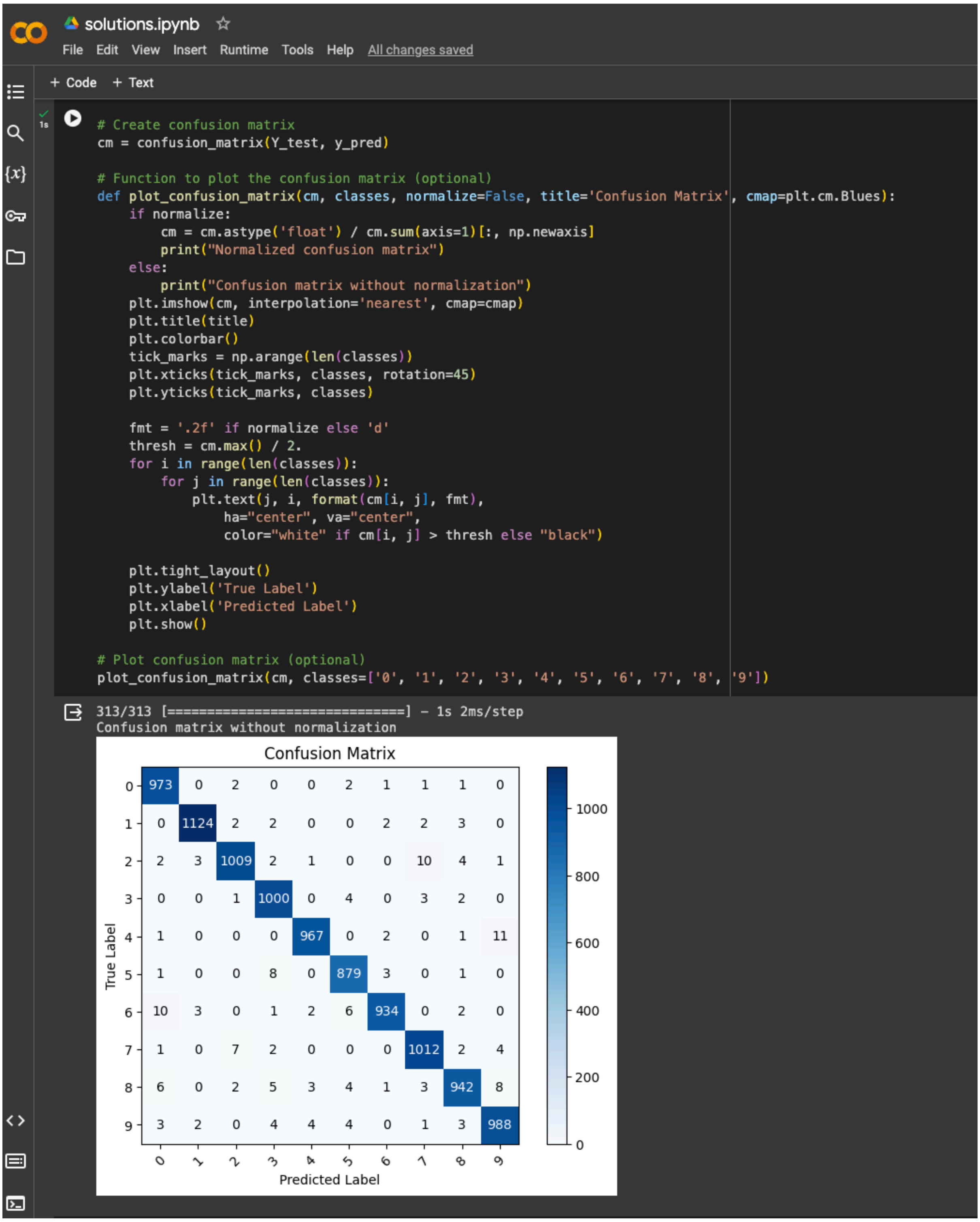


```
## On MNIST data

from tensorflow import keras
from keras.datasets import mnist
from keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout
from keras.callbacks import EarlyStopping, ReduceLROnPlateau
import matplotlib.pyplot as plt  # Import for plotting

# Load MNIST data
(X_train, Y_train), (X_test, Y_test) = mnist.load_data()

# Reshape to add channel dimension
X_train = X_train.reshape(-1, 28, 28, 1)
X_test = X_test.reshape(-1, 28, 28, 1)

# Normalize pixel values
X_train = X_train.astype('float32') / 255.0
X_test = X_test.astype('float32') / 255.0

# Define learning rate, batch size, and epochs
learning_rate = 0.001
batch_size = 64
epochs = 3

# Build the model
model = keras.Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D((2, 2)),
    Dropout(0.25),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')  # 10 units for 10 classes
])

# Compile the model
model.compile(optimizer=keras.optimizers.Adam(lr=learning_rate),
              loss='sparse_categorical_crossentropy',  # Categorical crossentropy for MNIST
              metrics=['accuracy'])

# Early stopping and learning rate reduction
early_stopping = EarlyStopping(monitor='val_loss', patience=3)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=2, min_lr=0.0001)

# Train the model (without ImageDataGenerator)
history = model.fit(X_train, Y_train,
                    epochs=epochs,
                    validation_data=(X_test, Y_test),
                    batch_size=batch_size,
                    verbose=1,
                    callbacks=[early_stopping, reduce_lr])

# Evaluate the model on the test set
loss, accuracy = model.evaluate(X_test, Y_test, batch_size=32)
print('Test Loss:', loss, 'Test Accuracy:', accuracy)
```



```
# Evaluate the model on the test set
loss, accuracy = model.evaluate(X_test, Y_test, batch_size=32)
print('Test Loss:', loss, 'Test Accuracy:', accuracy)

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

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.opti
Epoch 1/3
938/938 [==============================] - 5s 4ms/step - loss: 0.2749 - accuracy: 0.9176 - val_loss: 0.0773 - val_accuracy: 0.
Epoch 2/3
938/938 [==============================] - 4s 5ms/step - loss: 0.1141 - accuracy: 0.9662 - val_loss: 0.0544 - val_accuracy: 0.
Epoch 3/3
938/938 [==============================] - 4s 4ms/step - loss: 0.0888 - accuracy: 0.9732 - val_loss: 0.0478 - val_accuracy: 0.
313/313 [==============================] - 1s 2ms/step - loss: 0.0478 - accuracy: 0.9828
Test Loss: 0.047753963619470596 Test Accuracy: 0.9828000068664551
```

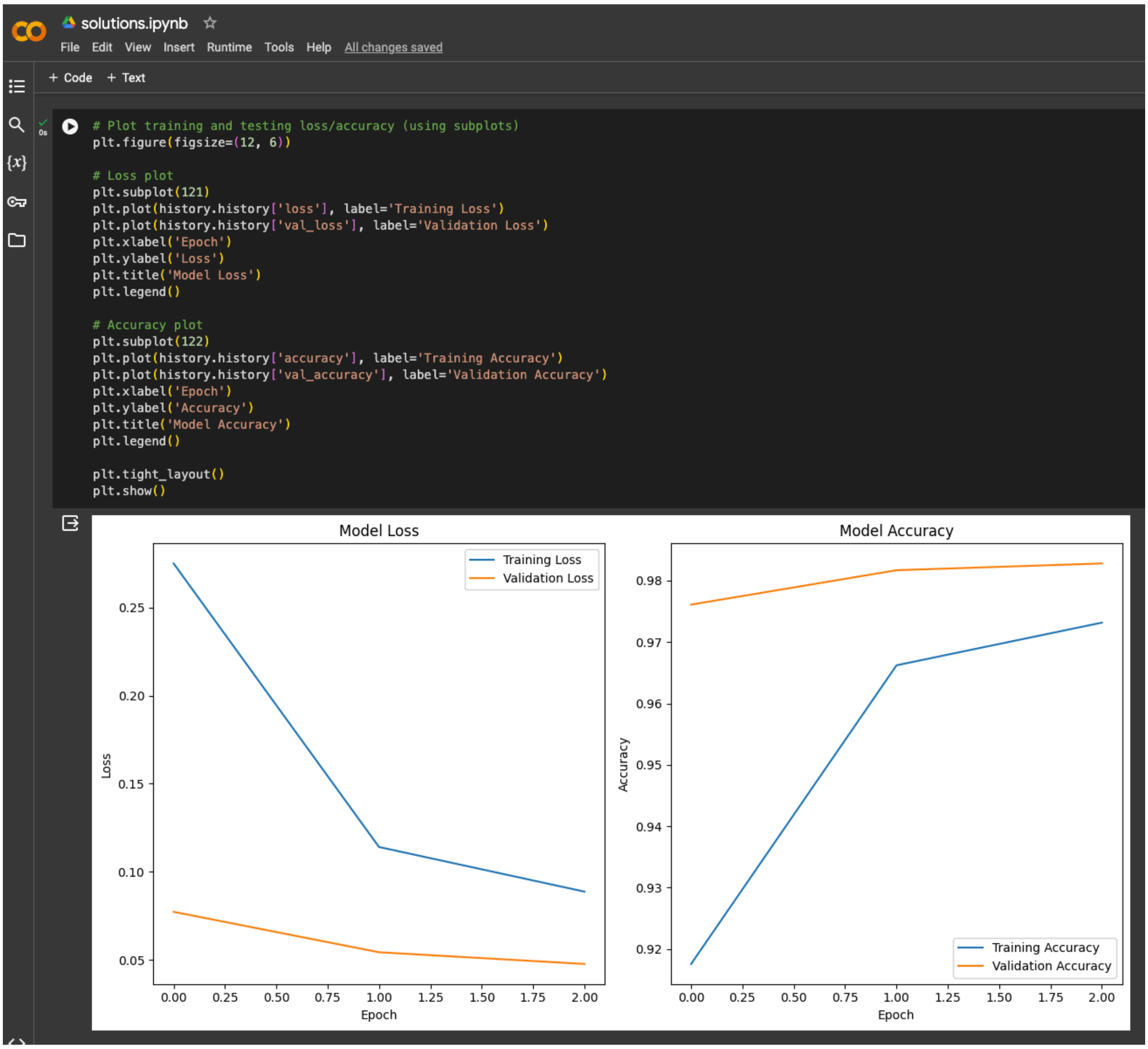


```python
# Create confusion matrix
cm = confusion_matrix(Y_test, y_pred)

# Function to plot the confusion matrix (optional)
def plot_confusion_matrix(cm, classes, normalize=False, title='Confusion Matrix', cmap=plt.cm.Blues):
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print("Confusion matrix without normalization")
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i in range(len(classes)):
        for j in range(len(classes)):
            plt.text(j, i, format(cm[i, j], fmt),
                ha="center", va="center",
                color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.show()

# Plot confusion matrix (optional)
plot_confusion_matrix(cm, classes=['0', '1', '2', '3', '4', '5', '6', '7', '8', '9'])
```

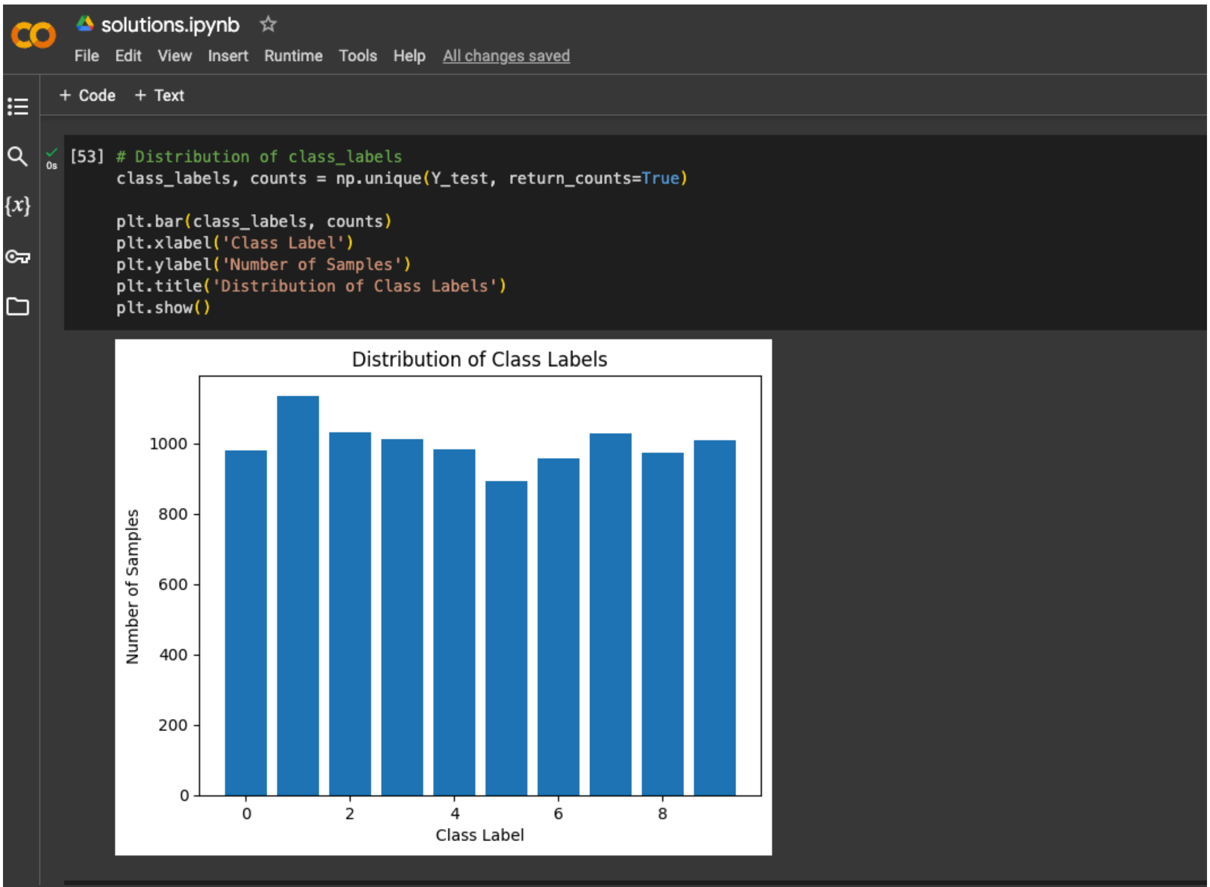
```
313/313 [==============================] - 1s 2ms/step
Confusion matrix without normalization
```

Confusion Matrix

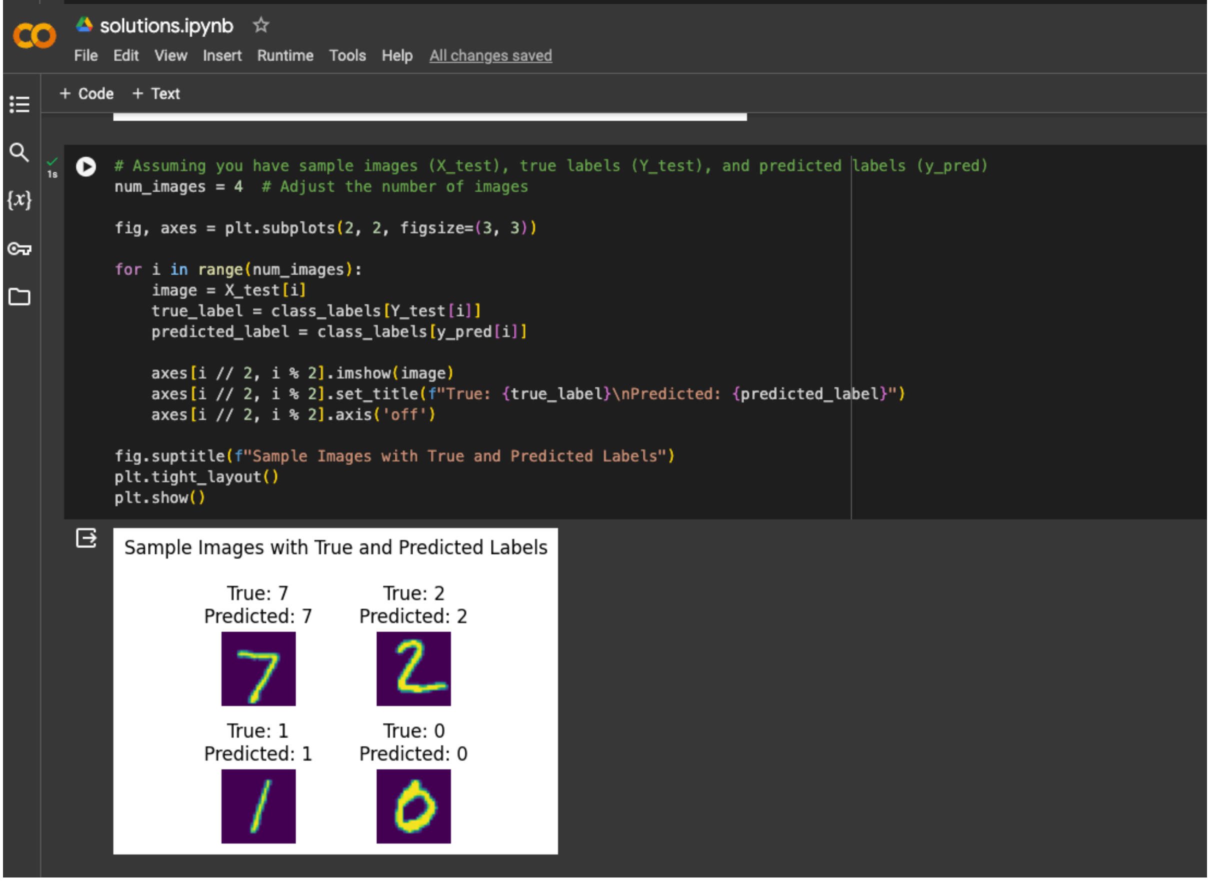
True Label \ Predicted Label	0	1	2	3	4	5	6	7	8	9
0	973	0	2	0	0	2	1	1	1	0
1	0	1124	2	2	0	0	2	2	3	0
2	2	3	1009	2	1	0	0	10	4	1
3	0	0	1	1000	0	4	0	3	2	0
4	1	0	0	0	967	0	2	0	1	11
5	1	0	0	8	0	879	3	0	1	0
6	10	3	0	1	2	6	934	0	2	0
7	1	0	7	2	0	0	0	1012	2	4
8	6	0	2	5	3	4	1	3	942	8
9	3	2	0	4	4	4	0	1	3	988



```
# Plot training and testing loss/accuracy (using subplots)
plt.figure(figsize=(12, 6))

# Loss plot
plt.subplot(121)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Model Loss')
plt.legend()

# Accuracy plot
plt.subplot(122)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Model Accuracy')
plt.legend()

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


solutions.ipynb
File Edit View Insert Runtime Tools Help All changes saved
+ Code + Text
[53]
Distribution of Class Labels
Number of Samples
0
200
400
600
800
1000
0
2
4
6
8
Class Label

```
# Distribution of class_labels
class_labels, counts = np.unique(Y_test, return_counts=True)

plt.bar(class_labels, counts)
plt.xlabel('Class Label')
plt.ylabel('Number of Samples')
plt.title('Distribution of Class Labels')
plt.show()
```



```
# Assuming you have sample images (X_test), true labels (Y_test), and predicted labels (y_pred)
num_images = 4  # Adjust the number of images

fig, axes = plt.subplots(2, 2, figsize=(3, 3))

for i in range(num_images):
    image = X_test[i]
    true_label = class_labels[Y_test[i]]
    predicted_label = class_labels[y_pred[i]]

    axes[i // 2, i % 2].imshow(image)
    axes[i // 2, i % 2].set_title(f"True: {true_label}\nPredicted: {predicted_label}")
    axes[i // 2, i % 2].axis('off')

fig.suptitle(f"Sample Images with True and Predicted Labels")
plt.tight_layout()
plt.show()
```