Ajmal_Assignment2

November 3, 2025

Ajmal_Assignment2

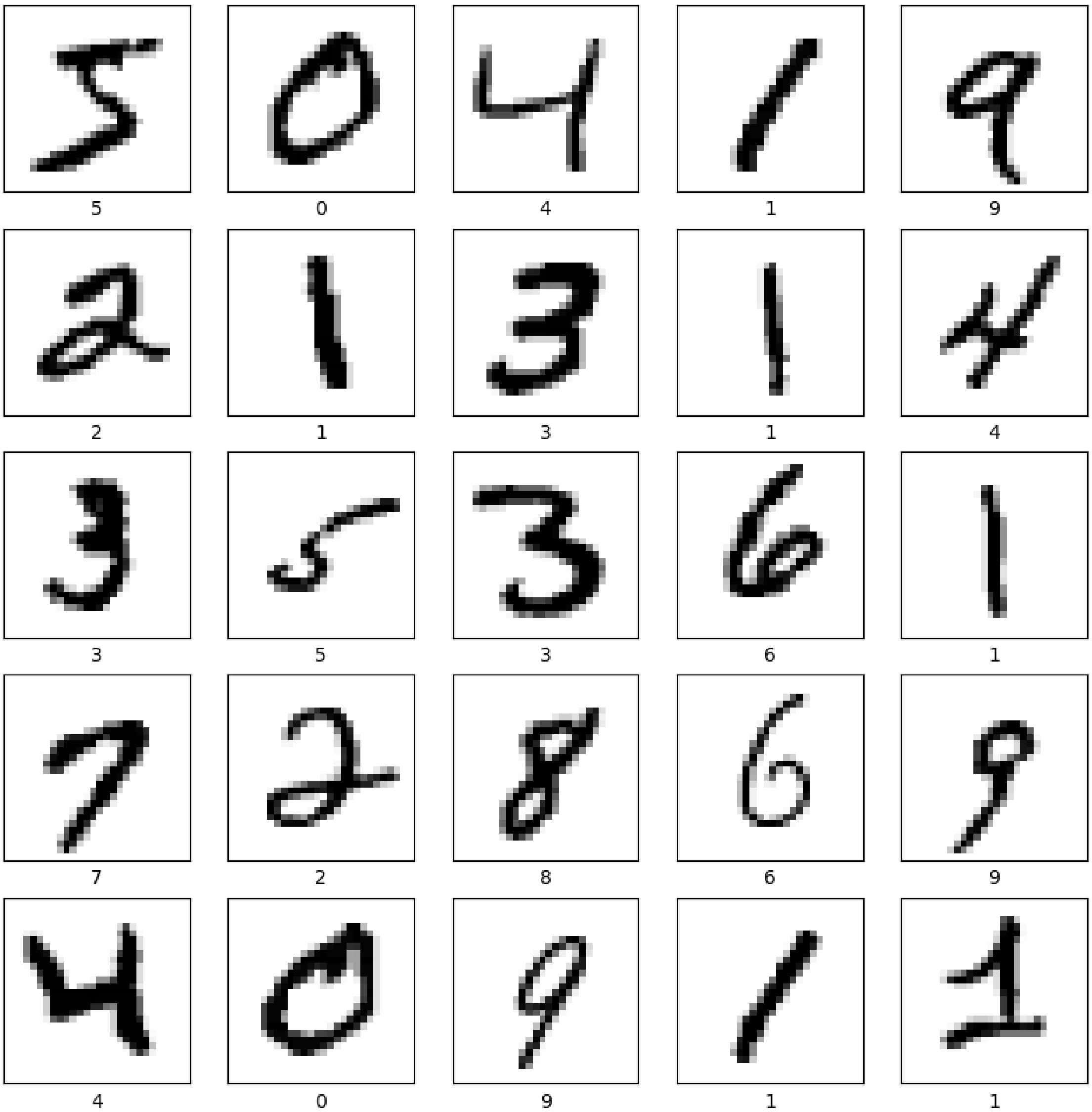
[9]:
```
import keras
import tensorflow as tf
from tensorflow.keras.layers import MaxPooling2D
from keras.datasets import mnist, cifar10
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Activation
from keras.layers import Conv2D
from keras.layers import BatchNormalization
import matplotlib.pyplot as plt
from keras.utils import to_categorical
from keras.layers import Dense
from keras import optimizers
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from keras import backend as K
```

[35]:
```
# Create train and test dataset
(X_train, y_train), (X_test, y_test) = mnist.load_data()

# Kears allows us to add the number of channels either to the beggining of␣
↪shape or the end of it
img_rows, img_cols = 28, 28

if K.image_data_format() == 'channels_first':
    X_train = X_train.reshape(X_train.shape[0], 1, img_rows, img_cols)
    X_test = X_test.reshape(X_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    X_train = X_train.reshape(X_train.shape[0], img_rows, img_cols, 1)
    X_test = X_test.reshape(X_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)

# Encode outputs
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
num_classes = y_test.shape[1]
```

1.a. start with creating a visualization of your input data

[3]:
```
#1.a. Create the visualization here
# Let's look into the dataset by visualizing some data opints

(X_train, y_train), (X_test, y_test) = mnist.load_data()

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(X_train[i], cmap=plt.cm.binary)
    plt.xlabel(y_train[i])
plt.show()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/mnist.npz
11490434/11490434              0s
0us/step
```



[36]:

```
# You need to apply some preprocessing on X and y

# normalize inputs from 0-255 to 0-1
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train = X_train / 255.0
X_test = X_test / 255.0

# Encode outputs
# This code has been moved to the data loading cell (U2TWWBPaPHOD)
# y_train = to_categorical(y_train)
# y_test = to_categorical(y_test)
```

```
# num_classes = y_test.shape[1]
```

1.b. Create a CNN model with 4 convolution layers in which two of them have 32 and two of them have 64 filters. The fully connected layer has one hidden layer (512 nodes). Draw the Learning curve. What is your understanding from learning curve? Batch size=128 and epochs=20

[31]:
```
#1.b.
# Create model here
from keras import backend as K
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Activation
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import BatchNormalization # Import BatchNormalization

img_rows, img_cols = 28, 28

if K.image_data_format() == 'channels_first':
    input_shape = (1, img_rows, img_cols)
else:
    input_shape = (img_rows, img_cols, 1)

model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=input_shape, activation='relu',␣
 ↪padding='same', data_format='channels_last'))
model.add(BatchNormalization())
model.add(MaxPooling2D(data_format='channels_last'))
model.add(Conv2D(32, (3, 3), activation='relu', padding='same',␣
 ↪data_format='channels_last'))
model.add(BatchNormalization())
model.add(MaxPooling2D(data_format='channels_last'))
model.add(Conv2D(64, (3, 3), activation='relu', padding='same',␣
 ↪data_format='channels_last'))
model.add(BatchNormalization())
model.add(MaxPooling2D(data_format='channels_last')) # Added MaxPooling2D here
model.add(Conv2D(64, (3, 3), activation='relu', padding='same',␣
 ↪data_format='channels_last'))
model.add(BatchNormalization())
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(BatchNormalization())
model.add(Dense(num_classes, activation='softmax'))
```

```
/usr/local/lib/python3.12/dist-
packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
```

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

0.1 Conclusion

Summarize your findings from the experiments with different models and techniques (data augmentation, dropout, pre-trained models) on both MNIST and CIFAR-10 datasets. Discuss the learning curves, accuracy, and any observations about overfitting or underfitting.

[37]:
```
model.compile(loss='categorical_crossentropy', optimizer='adam', 
 ↪metrics=['accuracy'])
hist = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=20,
 ↪batch_size=128)
```

```
Epoch 1/20
469/469              16s 17ms/step -
accuracy: 0.9312 - loss: 0.2222 - val_accuracy: 0.9378 - val_loss: 0.1960
Epoch 2/20
469/469              3s 7ms/step -
accuracy: 0.9883 - loss: 0.0358 - val_accuracy: 0.9781 - val_loss: 0.0678
Epoch 3/20
469/469              3s 6ms/step -
accuracy: 0.9914 - loss: 0.0265 - val_accuracy: 0.9843 - val_loss: 0.0487
Epoch 4/20
469/469              5s 6ms/step -
accuracy: 0.9937 - loss: 0.0190 - val_accuracy: 0.9890 - val_loss: 0.0351
Epoch 5/20
469/469              3s 6ms/step -
accuracy: 0.9956 - loss: 0.0143 - val_accuracy: 0.9829 - val_loss: 0.0513
Epoch 6/20
469/469              3s 6ms/step -
accuracy: 0.9953 - loss: 0.0131 - val_accuracy: 0.9893 - val_loss: 0.0350
Epoch 7/20
469/469              3s 6ms/step -
accuracy: 0.9958 - loss: 0.0135 - val_accuracy: 0.9868 - val_loss: 0.0420
Epoch 8/20
469/469              3s 6ms/step -
accuracy: 0.9962 - loss: 0.0113 - val_accuracy: 0.9829 - val_loss: 0.0642
Epoch 9/20
469/469              3s 6ms/step -
accuracy: 0.9965 - loss: 0.0103 - val_accuracy: 0.9905 - val_loss: 0.0304
Epoch 10/20
469/469              3s 6ms/step -
accuracy: 0.9973 - loss: 0.0084 - val_accuracy: 0.9930 - val_loss: 0.0263
Epoch 11/20
469/469              3s 5ms/step -
accuracy: 0.9970 - loss: 0.0096 - val_accuracy: 0.9893 - val_loss: 0.0365
Epoch 12/20
469/469              3s 6ms/step -
```

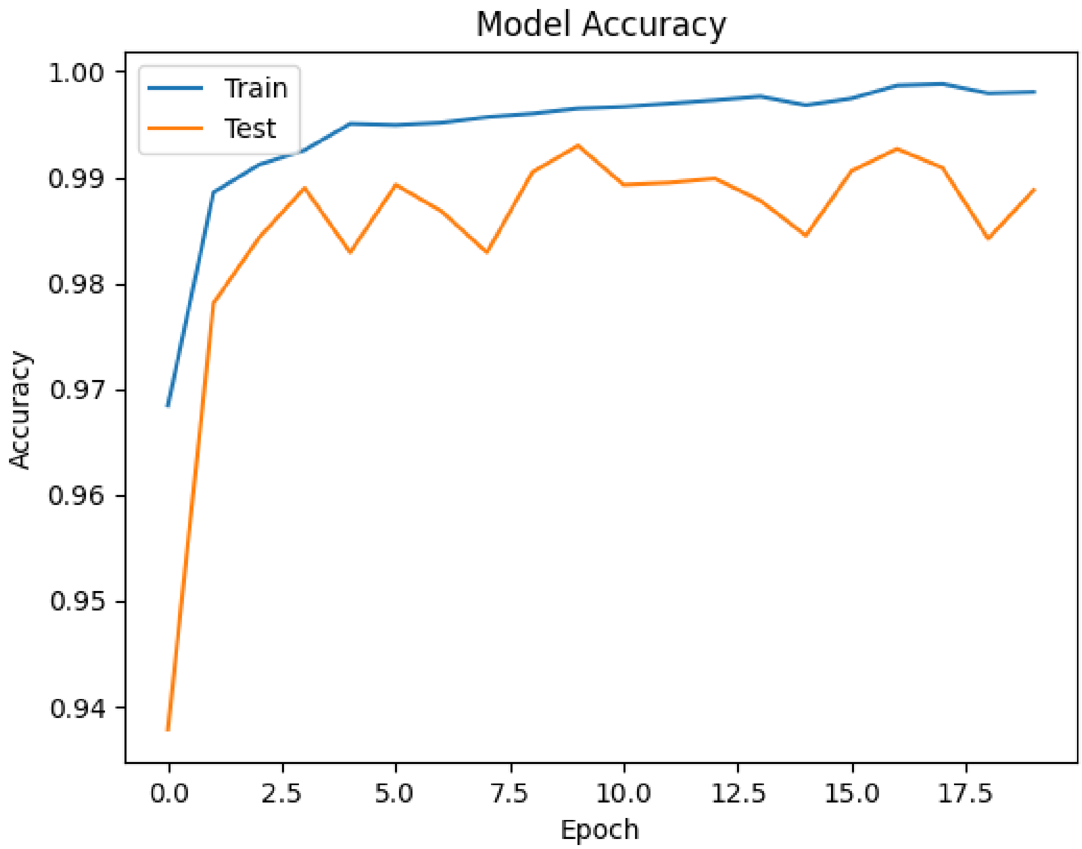
```
accuracy: 0.9972 - loss: 0.0082 - val_accuracy: 0.9895 - val_loss: 0.0434
Epoch 13/20
469/469              3s 6ms/step -
accuracy: 0.9975 - loss: 0.0066 - val_accuracy: 0.9899 - val_loss: 0.0408
Epoch 14/20
469/469              3s 6ms/step -
accuracy: 0.9984 - loss: 0.0055 - val_accuracy: 0.9878 - val_loss: 0.0463
Epoch 15/20
469/469              5s 6ms/step -
accuracy: 0.9971 - loss: 0.0080 - val_accuracy: 0.9845 - val_loss: 0.0590
Epoch 16/20
469/469              3s 6ms/step -
accuracy: 0.9976 - loss: 0.0076 - val_accuracy: 0.9906 - val_loss: 0.0355
Epoch 17/20
469/469              3s 6ms/step -
accuracy: 0.9985 - loss: 0.0049 - val_accuracy: 0.9927 - val_loss: 0.0318
Epoch 18/20
469/469              3s 6ms/step -
accuracy: 0.9991 - loss: 0.0031 - val_accuracy: 0.9909 - val_loss: 0.0416
Epoch 19/20
469/469              3s 6ms/step -
accuracy: 0.9981 - loss: 0.0071 - val_accuracy: 0.9842 - val_loss: 0.0661
Epoch 20/20
469/469              6s 8ms/step -
accuracy: 0.9986 - loss: 0.0048 - val_accuracy: 0.9888 - val_loss: 0.0439
```

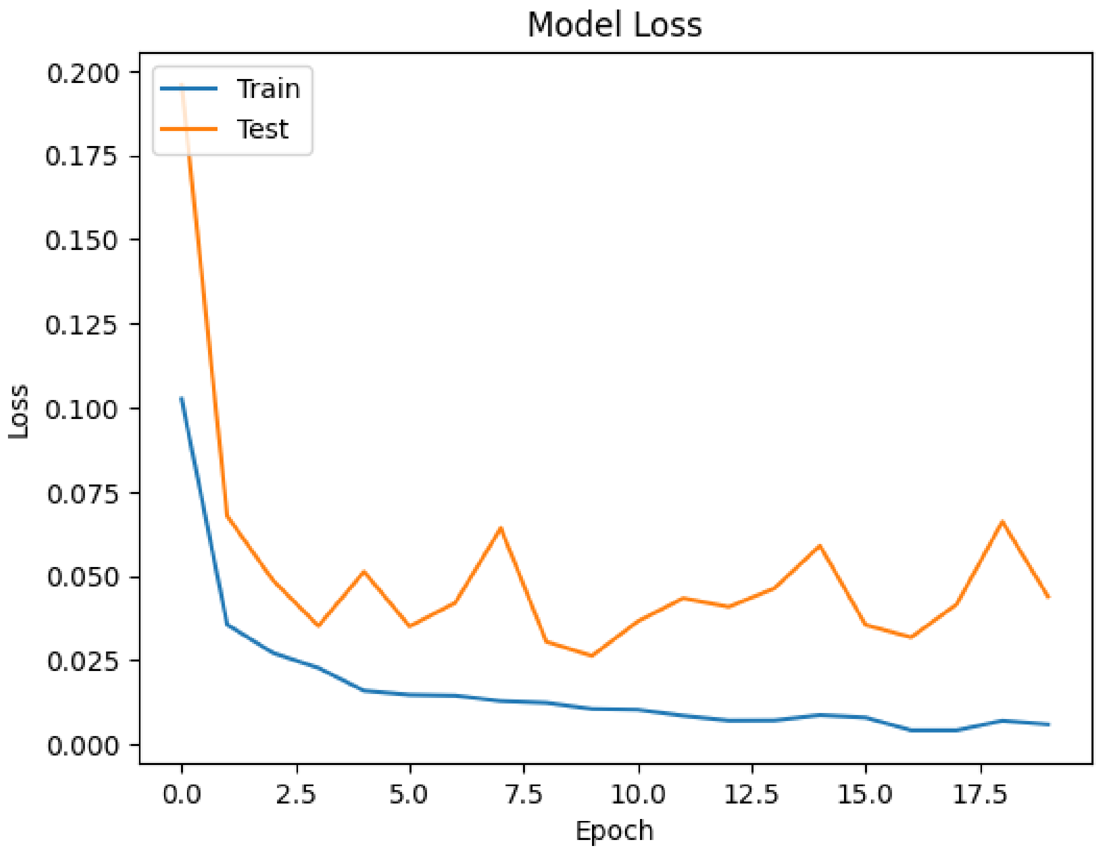
[38]:
```
# Measure test accuracy
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

```
Accuracy: 98.88%
```

[39]:
```
# Draw Learning curve
def learning_curve(hist):
  #Create a function to draw learning curves
  # This will help you to just call this function in future for drawing the␣
↪learning curves
  plt.plot(hist.history['accuracy'])
  plt.plot(hist.history['val_accuracy'])
  plt.title('Model Accuracy')
  plt.ylabel('Accuracy')
  plt.xlabel('Epoch')
  plt.legend(['Train', 'Test'], loc='upper left')
  plt.show()

  plt.plot(hist.history['loss'])
  plt.plot(hist.history['val_loss'])
  plt.title('Model Loss')
```

```
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
  plt.legend(['Train', 'Test'], loc='upper left')
  plt.show()


learning_curve(hist)
```





[ ]:
```
## What is your understanding from the learning curve?
# They look fine. There is a little bit of overfitting but nothing to be␣
↪worried about
```

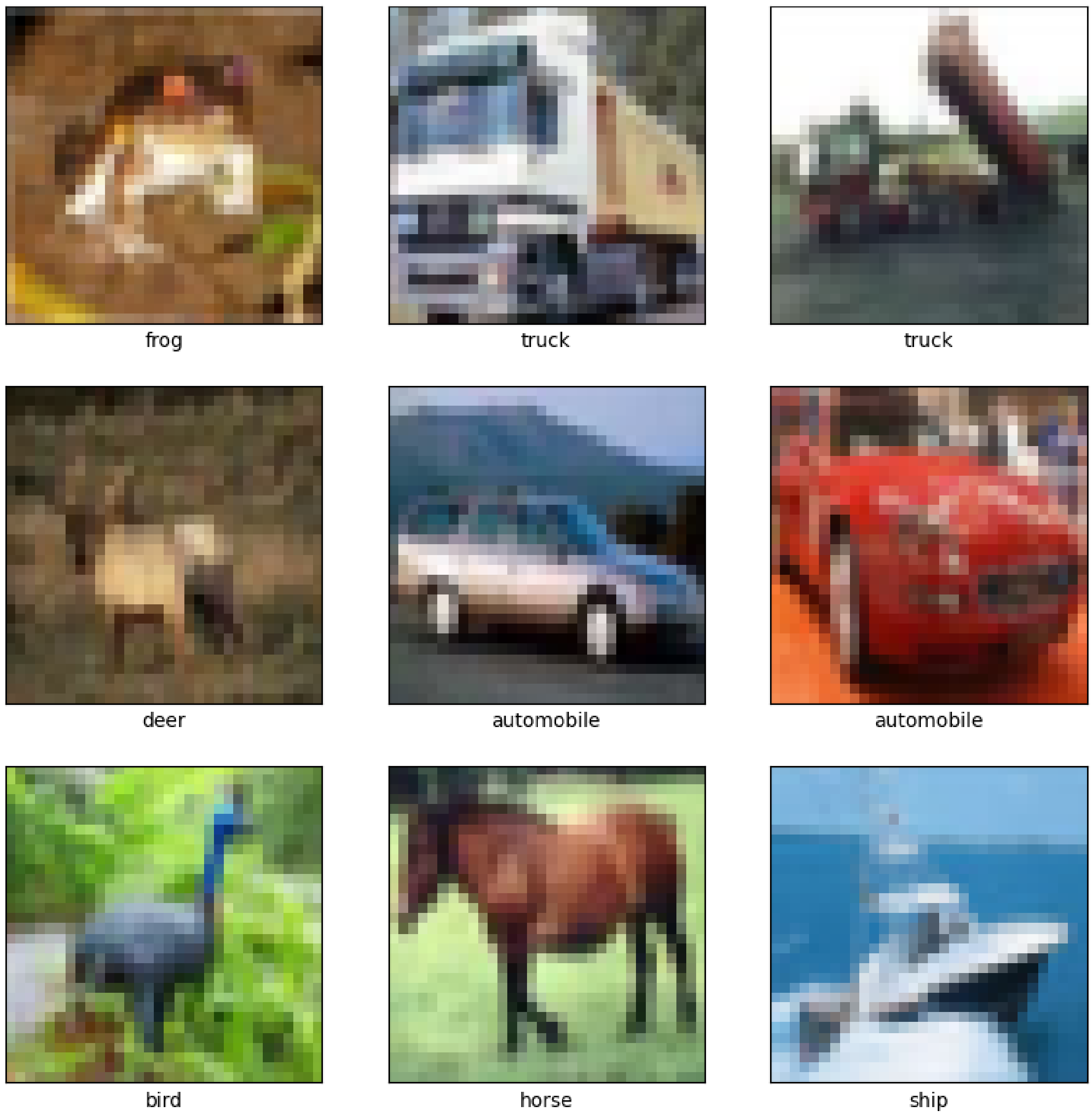
Part 2- CIFAR10

[40]:
```
(X_train, y_train), (X_test, y_test) = cifar10.load_data()
labels=␣
↪["airplane","automobile","bird","cat","deer","dog","frog","horse","ship","truck"]
print(X_train.shape)
print(X_test.shape)
```

```
(50000, 32, 32, 3)
(10000, 32, 32, 3)
```

[41]:
```
# 2.a. Let's look into the dataset by visualizing some data opints
plt.figure(figsize=(10,10))
for i in range(9):
    plt.subplot(3,3,i+1)
    plt.xticks([])
    plt.yticks([])
```

```
    plt.grid(False)
    plt.imshow(X_train[i])
    plt.xlabel(labels[y_train[i][0]])
plt.show()
```



2.b. Apply the pre-processing algorithms that we discussed last week. The augmented images are supposed to be seared by 20%, zoomed by 20% and horizontally flipped. Now, design a CNN model with 4 convolution layers in which two of them have 32 and two of them have 64 filters. The fully connected layer has two hidden layers (512 and 256 nodes respectively). Draw the Learning curve. What is your understanding from learning curve?

```
[42]: # 2.b
# Encoding output
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
num_classes = y_test.shape[1]

# create data generator
datagen = ImageDataGenerator(shear_range=0.2, zoom_range=0.2,␣
 ↪horizontal_flip=True)
# prepare iterator
it_train = datagen.flow(X_train, y_train, batch_size=128)


# Create model here
model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=X_train.shape[1:], activation='relu',␣
 ↪padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(32, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(BatchNormalization())
model.add(Dense(256, activation='relu'))
model.add(BatchNormalization())
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy']) #Compile model
hist = model.fit(it_train, steps_per_epoch=len(it_train), epochs=20,␣
 ↪validation_data=(X_test, y_test))# start training
```

```
/usr/local/lib/python3.12/dist-
packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/usr/local/lib/python3.12/dist-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121:
UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in
```

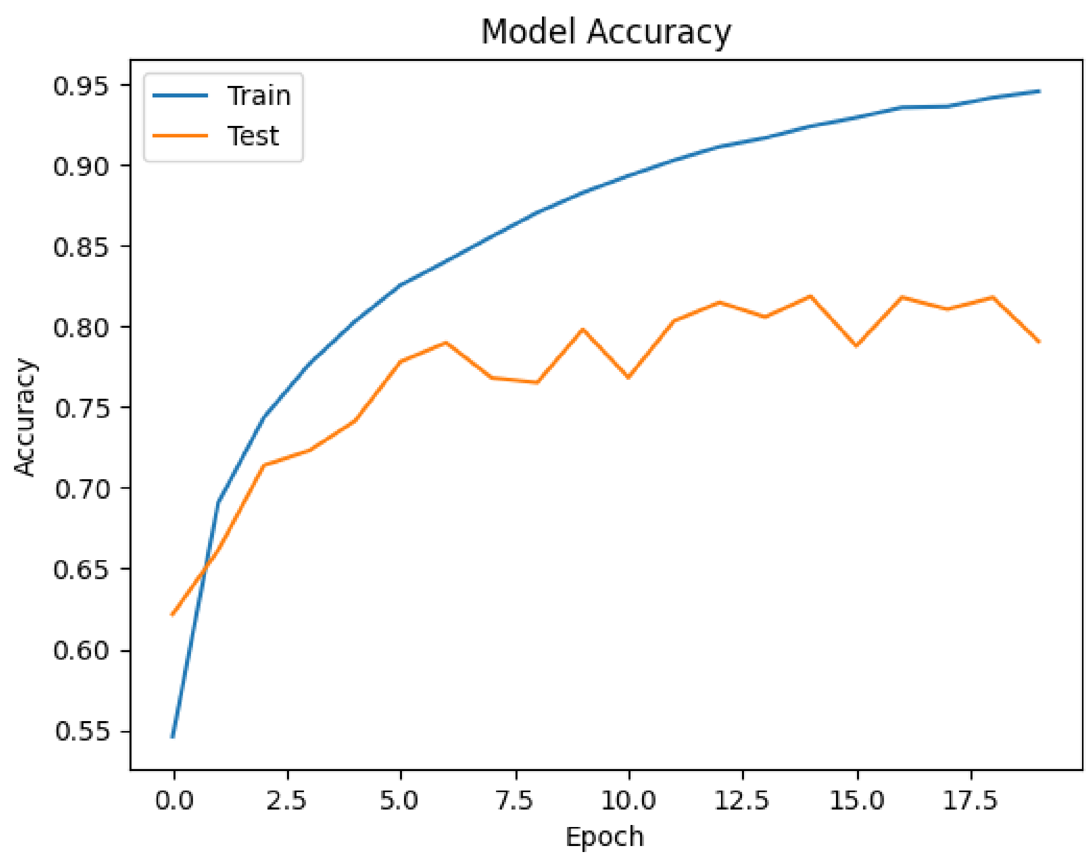
```
its constructor. `**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will be
ignored.
  self._warn_if_super_not_called()
```

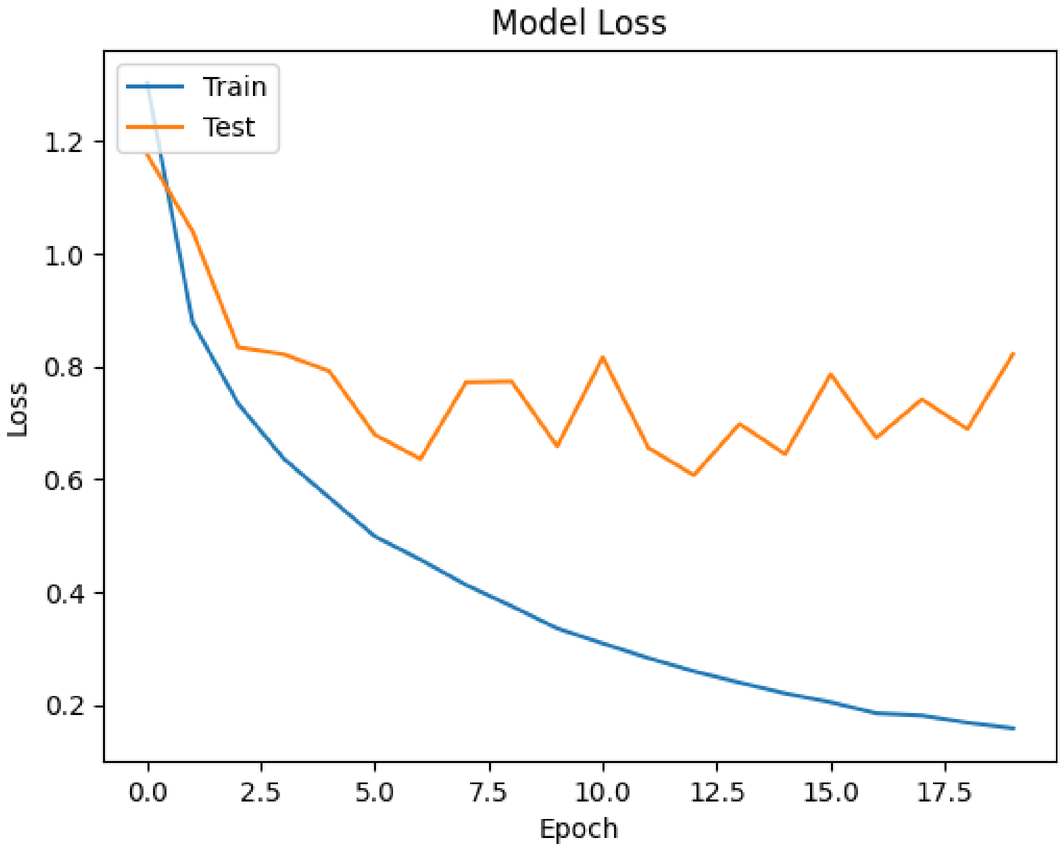
```
Epoch 1/20
391/391            42s 86ms/step -
accuracy: 0.4628 - loss: 1.5865 - val_accuracy: 0.6218 - val_loss: 1.1758
Epoch 2/20
391/391            28s 71ms/step -
accuracy: 0.6818 - loss: 0.9039 - val_accuracy: 0.6614 - val_loss: 1.0393
Epoch 3/20
391/391            28s 71ms/step -
accuracy: 0.7380 - loss: 0.7468 - val_accuracy: 0.7139 - val_loss: 0.8339
Epoch 4/20
391/391            29s 75ms/step -
accuracy: 0.7772 - loss: 0.6352 - val_accuracy: 0.7231 - val_loss: 0.8213
Epoch 5/20
391/391            28s 71ms/step -
accuracy: 0.8025 - loss: 0.5655 - val_accuracy: 0.7414 - val_loss: 0.7912
Epoch 6/20
391/391            27s 70ms/step -
accuracy: 0.8304 - loss: 0.4806 - val_accuracy: 0.7781 - val_loss: 0.6784
Epoch 7/20
391/391            28s 71ms/step -
accuracy: 0.8436 - loss: 0.4442 - val_accuracy: 0.7899 - val_loss: 0.6357
Epoch 8/20
391/391            28s 72ms/step -
accuracy: 0.8589 - loss: 0.4034 - val_accuracy: 0.7681 - val_loss: 0.7716
Epoch 9/20
391/391            28s 71ms/step -
accuracy: 0.8755 - loss: 0.3607 - val_accuracy: 0.7652 - val_loss: 0.7730
Epoch 10/20
391/391            27s 70ms/step -
accuracy: 0.8891 - loss: 0.3180 - val_accuracy: 0.7981 - val_loss: 0.6581
Epoch 11/20
391/391            28s 72ms/step -
accuracy: 0.8997 - loss: 0.2943 - val_accuracy: 0.7683 - val_loss: 0.8157
Epoch 12/20
391/391            28s 71ms/step -
accuracy: 0.9055 - loss: 0.2761 - val_accuracy: 0.8033 - val_loss: 0.6553
Epoch 13/20
391/391            28s 70ms/step -
accuracy: 0.9163 - loss: 0.2464 - val_accuracy: 0.8148 - val_loss: 0.6068
Epoch 14/20
391/391            41s 71ms/step -
accuracy: 0.9221 - loss: 0.2304 - val_accuracy: 0.8058 - val_loss: 0.6977
Epoch 15/20
```

```
391/391              28s 71ms/step -
accuracy: 0.9257 - loss: 0.2145 - val_accuracy: 0.8185 - val_loss: 0.6442
Epoch 16/20
391/391              27s 70ms/step -
accuracy: 0.9307 - loss: 0.1980 - val_accuracy: 0.7878 - val_loss: 0.7858
Epoch 17/20
391/391              28s 70ms/step -
accuracy: 0.9397 - loss: 0.1743 - val_accuracy: 0.8179 - val_loss: 0.6729
Epoch 18/20
391/391              28s 71ms/step -
accuracy: 0.9390 - loss: 0.1756 - val_accuracy: 0.8106 - val_loss: 0.7414
Epoch 19/20
391/391              28s 71ms/step -
accuracy: 0.9453 - loss: 0.1591 - val_accuracy: 0.8178 - val_loss: 0.6886
Epoch 20/20
391/391              27s 70ms/step -
accuracy: 0.9474 - loss: 0.1509 - val_accuracy: 0.7908 - val_loss: 0.8217
```

[43]:

```
# Draw learning curve here
learning_curve(hist)
```





[53]:
```
# What is the issue and possible solution for this learning curve?
# Based on the learning curve you observed after training the model on␣
↪augmented CIFAR-10 data without dropout, the likely issue is overfitting.␣
↪This is typically seen when the training accuracy continues to improve, but␣
↪the validation accuracy plateaus or even decreases, and the validation loss␣
↪starts to increase.
# A common solution to address overfitting in neural networks is to use Dropout.
↪ Dropout randomly sets a fraction of the input units to 0 at each training␣
↪step, which helps prevent the network from relying too heavily on specific␣
↪neurons and encourages it to learn more robust features.
```

[44]:
```
#2.c. Solution to resolve overfitting
# One solution is adding drop out
# Implement your solution here and train model

model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=X_train.shape[1:], activation='relu',␣
↪padding='same'))
model.add(BatchNormalization())
```

```python
model.add(Conv2D(32, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2, 2)))
model.add(Dropout(0.25)) # Added Dropout

model.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2, 2)))
model.add(Dropout(0.25)) # Added Dropout

model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5)) # Added Dropout
model.add(Dense(256, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5)) # Added Dropout
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam',␣
↪metrics=['accuracy']) #Compile model
hist = model.fit(it_train, steps_per_epoch=len(it_train), epochs=20,␣
↪validation_data=(X_test, y_test))# start training
```

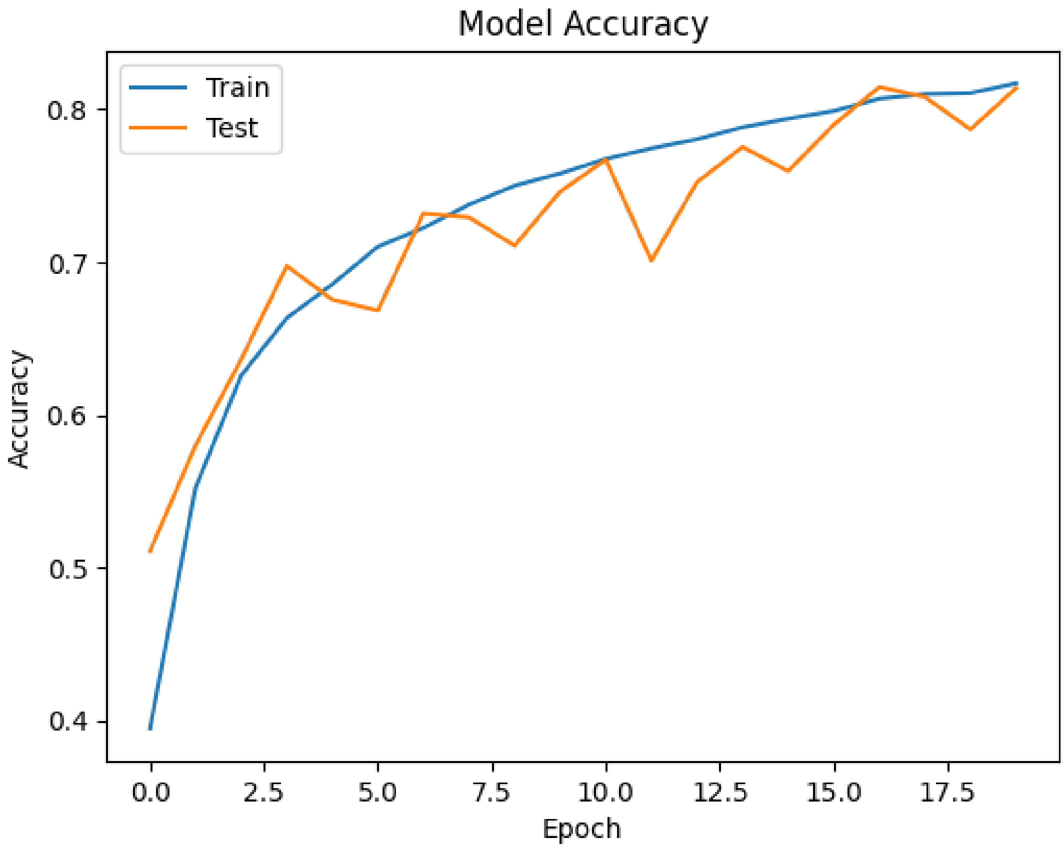
```
/usr/local/lib/python3.12/dist-
packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

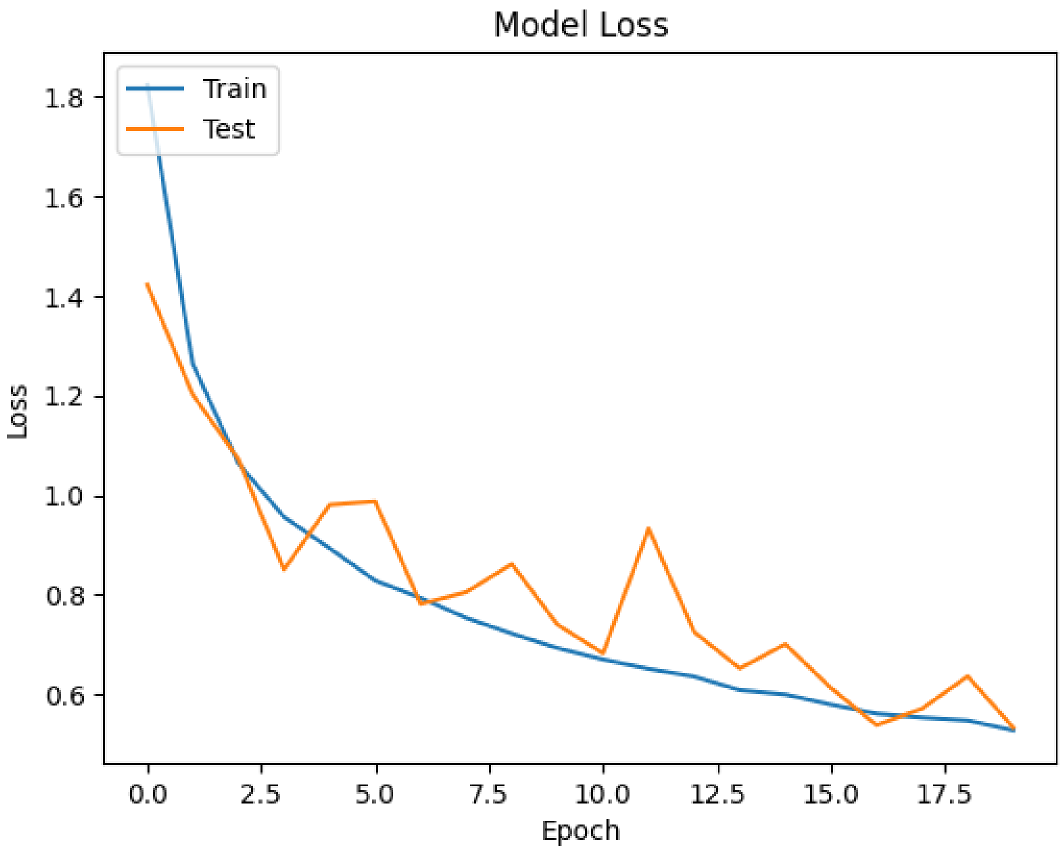
```
Epoch 1/20
391/391            47s 93ms/step -
accuracy: 0.3167 - loss: 2.2101 - val_accuracy: 0.5107 - val_loss: 1.4222
Epoch 2/20
391/391            27s 69ms/step -
accuracy: 0.5284 - loss: 1.3302 - val_accuracy: 0.5800 - val_loss: 1.2015
Epoch 3/20
391/391            28s 72ms/step -
accuracy: 0.6151 - loss: 1.0928 - val_accuracy: 0.6363 - val_loss: 1.0725
Epoch 4/20
391/391            27s 70ms/step -
accuracy: 0.6584 - loss: 0.9734 - val_accuracy: 0.6975 - val_loss: 0.8505
Epoch 5/20
391/391            28s 71ms/step -
accuracy: 0.6784 - loss: 0.9135 - val_accuracy: 0.6754 - val_loss: 0.9806
```

```
Epoch 6/20
391/391            28s 72ms/step -
accuracy: 0.7068 - loss: 0.8405 - val_accuracy: 0.6683 - val_loss: 0.9875
Epoch 7/20
391/391            27s 70ms/step -
accuracy: 0.7200 - loss: 0.7946 - val_accuracy: 0.7319 - val_loss: 0.7819
Epoch 8/20
391/391            27s 70ms/step -
accuracy: 0.7364 - loss: 0.7572 - val_accuracy: 0.7293 - val_loss: 0.8057
Epoch 9/20
391/391            28s 71ms/step -
accuracy: 0.7487 - loss: 0.7277 - val_accuracy: 0.7108 - val_loss: 0.8619
Epoch 10/20
391/391            28s 71ms/step -
accuracy: 0.7556 - loss: 0.6985 - val_accuracy: 0.7462 - val_loss: 0.7403
Epoch 11/20
391/391            27s 69ms/step -
accuracy: 0.7680 - loss: 0.6681 - val_accuracy: 0.7670 - val_loss: 0.6828
Epoch 12/20
391/391            27s 70ms/step -
accuracy: 0.7731 - loss: 0.6548 - val_accuracy: 0.7010 - val_loss: 0.9331
Epoch 13/20
391/391            28s 72ms/step -
accuracy: 0.7819 - loss: 0.6286 - val_accuracy: 0.7523 - val_loss: 0.7255
Epoch 14/20
391/391            27s 70ms/step -
accuracy: 0.7893 - loss: 0.6036 - val_accuracy: 0.7754 - val_loss: 0.6526
Epoch 15/20
391/391            27s 69ms/step -
accuracy: 0.7963 - loss: 0.5965 - val_accuracy: 0.7596 - val_loss: 0.7011
Epoch 16/20
391/391            28s 71ms/step -
accuracy: 0.7982 - loss: 0.5820 - val_accuracy: 0.7899 - val_loss: 0.6133
Epoch 17/20
391/391            27s 70ms/step -
accuracy: 0.8073 - loss: 0.5599 - val_accuracy: 0.8147 - val_loss: 0.5387
Epoch 18/20
391/391            27s 70ms/step -
accuracy: 0.8112 - loss: 0.5482 - val_accuracy: 0.8082 - val_loss: 0.5717
Epoch 19/20
391/391            27s 69ms/step -
accuracy: 0.8110 - loss: 0.5490 - val_accuracy: 0.7869 - val_loss: 0.6367
Epoch 20/20
391/391            28s 71ms/step -
accuracy: 0.8183 - loss: 0.5235 - val_accuracy: 0.8140 - val_loss: 0.5338
```

[45]:

```
# Draw learning curve
learning_curve(hist)
```





[46]:
```
# 2.d- This part is up to you to choose proper pre-trained model
# I chose VGG16 and RESNet50
# Implementing VGG16
from keras.applications.vgg16 import VGG16
from keras.preprocessing import image
from keras.applications.vgg16 import preprocess_input
from keras.models import Model
import numpy as np

vgg_model = VGG16(weights='imagenet', include_top=False, input_shape=(32, 32,␣
↪3))

# Add a new top layer
x = vgg_model.output
x = Flatten()(x)
x = Dense(512, activation='relu')(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(num_classes, activation='softmax')(x)
```

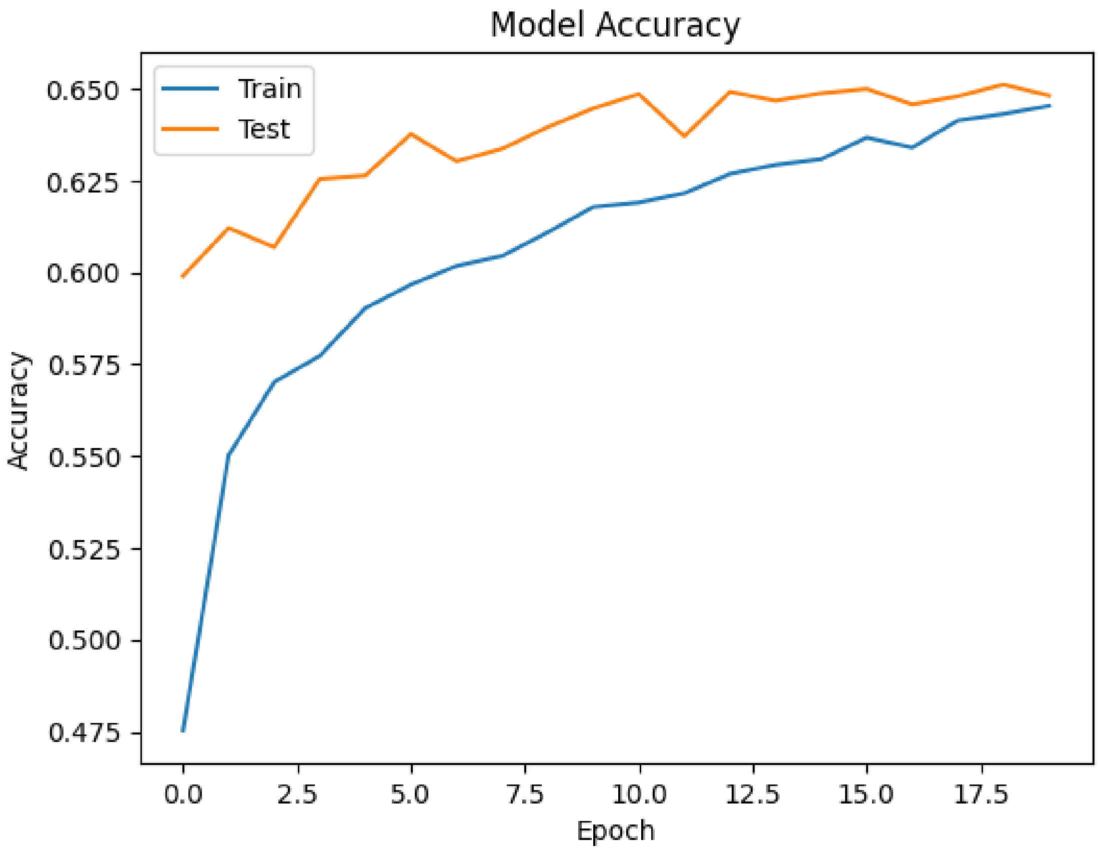
```python
model = Model(inputs=vgg_model.input, outputs=x)

# Freeze the layers of the pre-trained model
for layer in vgg_model.layers:
    layer.trainable = False

model.compile(loss='categorical_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])   #Compile VGG16 model
hist = model.fit(it_train, steps_per_epoch=len(it_train), epochs=20,␣
 ↪validation_data=(X_test, y_test))
```

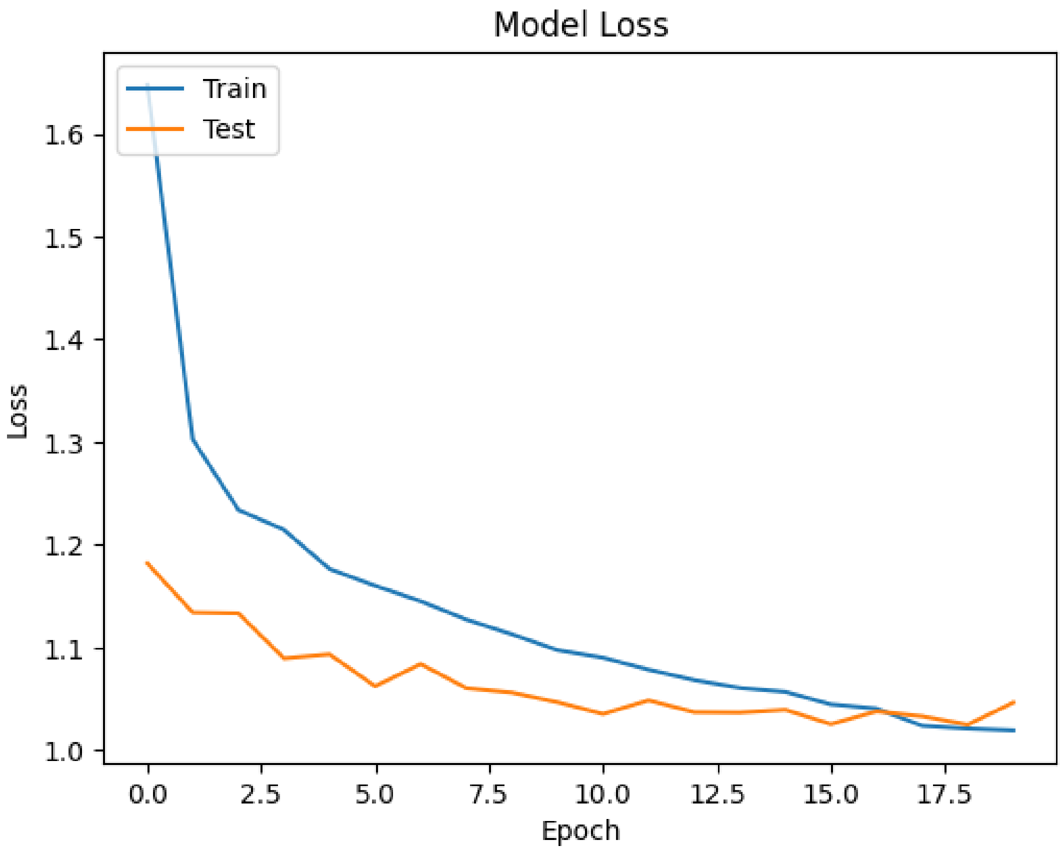
```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58889256/58889256            0s
0us/step
Epoch 1/20
391/391              42s 93ms/step -
accuracy: 0.4166 - loss: 1.9411 - val_accuracy: 0.5991 - val_loss: 1.1821
Epoch 2/20
391/391              30s 77ms/step -
accuracy: 0.5432 - loss: 1.3226 - val_accuracy: 0.6121 - val_loss: 1.1341
Epoch 3/20
391/391              30s 77ms/step -
accuracy: 0.5698 - loss: 1.2374 - val_accuracy: 0.6069 - val_loss: 1.1334
Epoch 4/20
391/391              30s 77ms/step -
accuracy: 0.5781 - loss: 1.2122 - val_accuracy: 0.6255 - val_loss: 1.0896
Epoch 5/20
391/391              30s 77ms/step -
accuracy: 0.5892 - loss: 1.1829 - val_accuracy: 0.6264 - val_loss: 1.0935
Epoch 6/20
391/391              30s 77ms/step -
accuracy: 0.5996 - loss: 1.1523 - val_accuracy: 0.6377 - val_loss: 1.0624
Epoch 7/20
391/391              30s 78ms/step -
accuracy: 0.6034 - loss: 1.1371 - val_accuracy: 0.6303 - val_loss: 1.0839
Epoch 8/20
391/391              41s 78ms/step -
accuracy: 0.6077 - loss: 1.1169 - val_accuracy: 0.6337 - val_loss: 1.0606
Epoch 9/20
391/391              31s 78ms/step -
accuracy: 0.6125 - loss: 1.1060 - val_accuracy: 0.6396 - val_loss: 1.0562
Epoch 10/20
391/391              31s 78ms/step -
accuracy: 0.6219 - loss: 1.0901 - val_accuracy: 0.6447 - val_loss: 1.0468
Epoch 11/20
391/391              31s 79ms/step -
```

```
accuracy: 0.6229 - loss: 1.0880 - val_accuracy: 0.6486 - val_loss: 1.0354
Epoch 12/20
391/391              30s 77ms/step -
accuracy: 0.6232 - loss: 1.0722 - val_accuracy: 0.6371 - val_loss: 1.0486
Epoch 13/20
391/391              31s 79ms/step -
accuracy: 0.6316 - loss: 1.0560 - val_accuracy: 0.6492 - val_loss: 1.0372
Epoch 14/20
391/391              31s 78ms/step -
accuracy: 0.6348 - loss: 1.0474 - val_accuracy: 0.6468 - val_loss: 1.0368
Epoch 15/20
391/391              30s 77ms/step -
accuracy: 0.6314 - loss: 1.0542 - val_accuracy: 0.6488 - val_loss: 1.0395
Epoch 16/20
391/391              30s 78ms/step -
accuracy: 0.6421 - loss: 1.0328 - val_accuracy: 0.6500 - val_loss: 1.0255
Epoch 17/20
391/391              30s 77ms/step -
accuracy: 0.6361 - loss: 1.0333 - val_accuracy: 0.6458 - val_loss: 1.0380
Epoch 18/20
391/391              31s 78ms/step -
accuracy: 0.6463 - loss: 1.0099 - val_accuracy: 0.6480 - val_loss: 1.0332
Epoch 19/20
391/391              30s 77ms/step -
accuracy: 0.6437 - loss: 1.0203 - val_accuracy: 0.6512 - val_loss: 1.0250
Epoch 20/20
391/391              31s 79ms/step -
accuracy: 0.6487 - loss: 1.0071 - val_accuracy: 0.6482 - val_loss: 1.0464
```

[47]:

```
learning_curve(hist)
```


Model Accuracy
Train
Test
0.650
0.625
0.600
0.575
0.550
0.525
0.500
0.475
Accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epoch



[52]:
```
model.evaluate(X_test, y_test, batch_size=256, verbose=1)
```

```
40/40               1s 19ms/step -
accuracy: 0.6399 - loss: 1.0375
```

[52]: [1.0357760190963745, 0.6456999778747559]

[ ]:
```

```

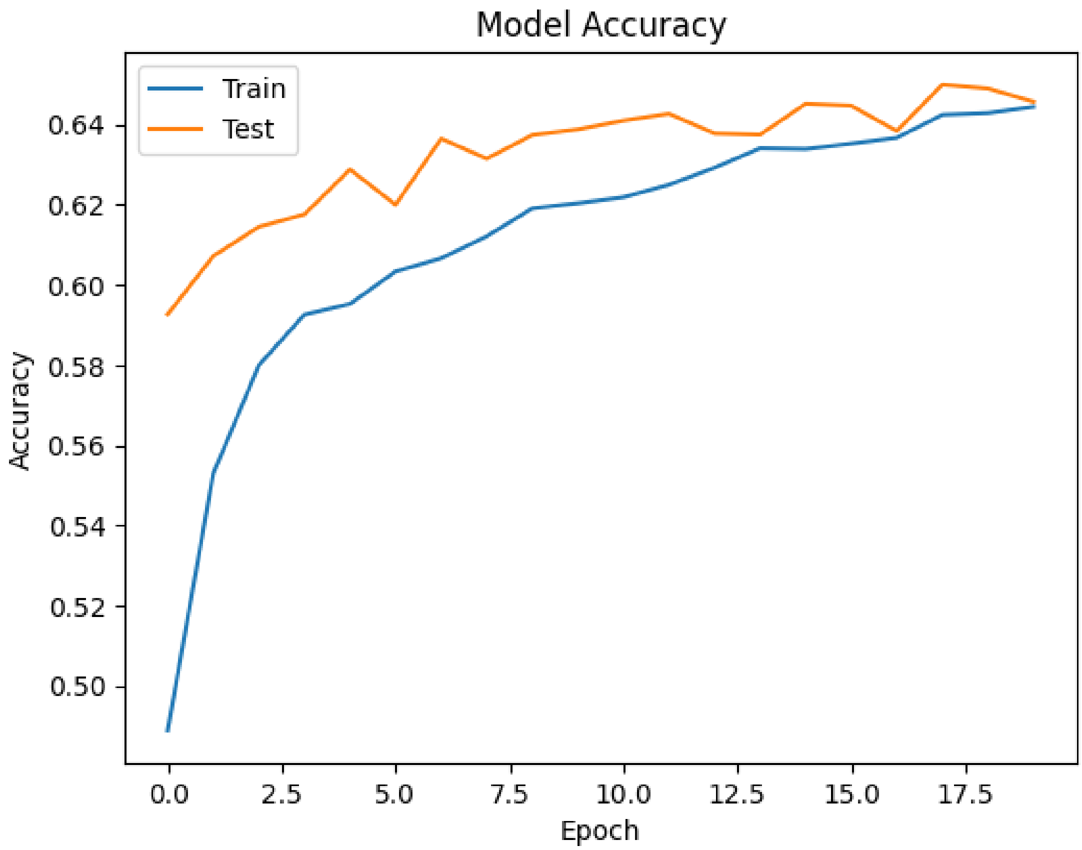
[49]:
```
# This is my second pre-trained model
from tensorflow.keras.applications.resnet50 import ResNet50
from keras.layers import GlobalAveragePooling2D

base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(32,␣
 ↪32, 3))

# Add a new top layer
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation='relu')(x)
```

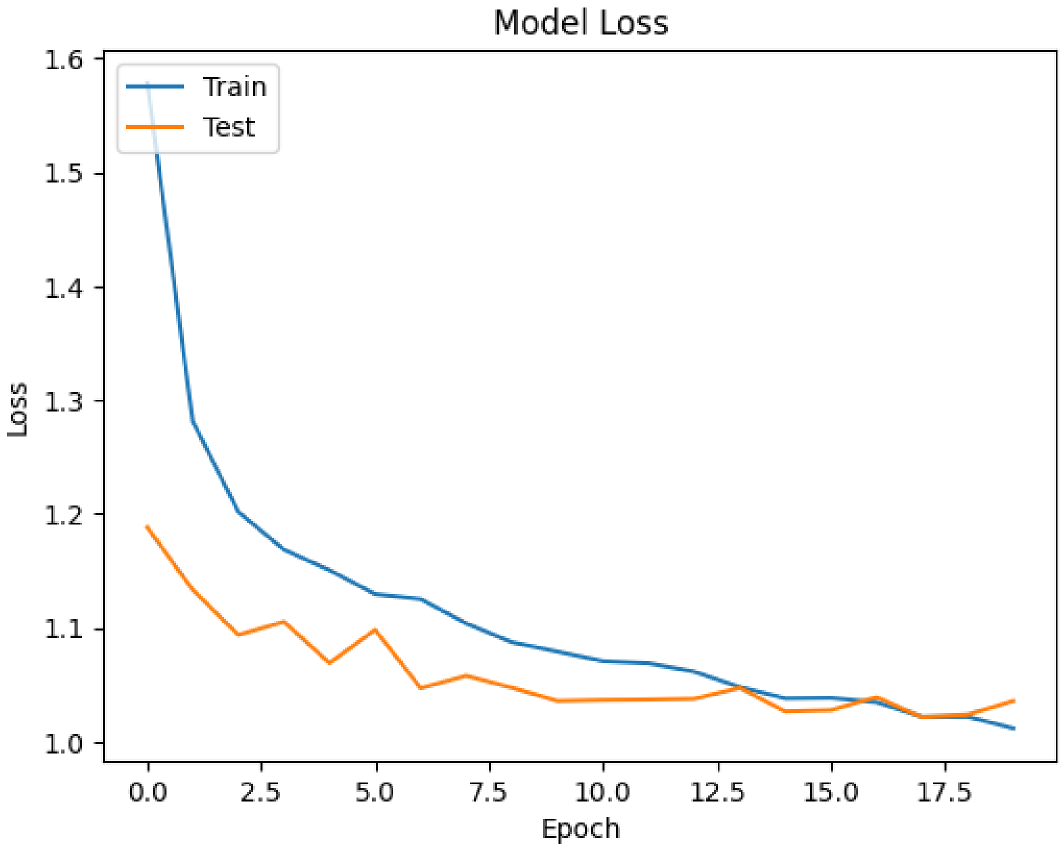
```
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(num_classes, activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=x)

# Freeze the layers of the pre-trained model
for layer in base_model.layers:
    layer.trainable = False


# Let's train the model using RMSprop
model.compile(loss='categorical_crossentropy', optimizer='RMSprop',␣
 ↪metrics=['accuracy'])
hist= model.fit(it_train, steps_per_epoch=len(it_train), epochs=20,␣
 ↪validation_data=(X_test, y_test))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736            0s
0us/step
Epoch 1/20
391/391             53s 106ms/step -
accuracy: 0.4409 - loss: 1.8291 - val_accuracy: 0.5927 - val_loss: 1.1882
Epoch 2/20
391/391             30s 76ms/step -
accuracy: 0.5481 - loss: 1.3011 - val_accuracy: 0.6072 - val_loss: 1.1334
Epoch 3/20
391/391             29s 74ms/step -
accuracy: 0.5798 - loss: 1.2052 - val_accuracy: 0.6145 - val_loss: 1.0939
Epoch 4/20
391/391             30s 76ms/step -
accuracy: 0.5938 - loss: 1.1735 - val_accuracy: 0.6176 - val_loss: 1.1054
Epoch 5/20
391/391             29s 74ms/step -
accuracy: 0.5943 - loss: 1.1557 - val_accuracy: 0.6288 - val_loss: 1.0692
Epoch 6/20
391/391             29s 74ms/step -
accuracy: 0.6029 - loss: 1.1323 - val_accuracy: 0.6200 - val_loss: 1.0983
Epoch 7/20
391/391             29s 74ms/step -
accuracy: 0.6108 - loss: 1.1223 - val_accuracy: 0.6365 - val_loss: 1.0472
Epoch 8/20
391/391             29s 73ms/step -
accuracy: 0.6193 - loss: 1.0870 - val_accuracy: 0.6315 - val_loss: 1.0580
Epoch 9/20
391/391             30s 76ms/step -
accuracy: 0.6221 - loss: 1.0792 - val_accuracy: 0.6374 - val_loss: 1.0475
```

```
Epoch 10/20
391/391            29s 74ms/step -
accuracy: 0.6249 - loss: 1.0721 - val_accuracy: 0.6388 - val_loss: 1.0359
Epoch 11/20
391/391            30s 76ms/step -
accuracy: 0.6235 - loss: 1.0646 - val_accuracy: 0.6410 - val_loss: 1.0367
Epoch 12/20
391/391            29s 73ms/step -
accuracy: 0.6285 - loss: 1.0616 - val_accuracy: 0.6427 - val_loss: 1.0370
Epoch 13/20
391/391            29s 75ms/step -
accuracy: 0.6296 - loss: 1.0583 - val_accuracy: 0.6378 - val_loss: 1.0377
Epoch 14/20
391/391            29s 73ms/step -
accuracy: 0.6337 - loss: 1.0455 - val_accuracy: 0.6375 - val_loss: 1.0473
Epoch 15/20
391/391            29s 74ms/step -
accuracy: 0.6362 - loss: 1.0325 - val_accuracy: 0.6452 - val_loss: 1.0266
Epoch 16/20
391/391            29s 75ms/step -
accuracy: 0.6381 - loss: 1.0295 - val_accuracy: 0.6447 - val_loss: 1.0279
Epoch 17/20
391/391            29s 74ms/step -
accuracy: 0.6410 - loss: 1.0257 - val_accuracy: 0.6384 - val_loss: 1.0392
Epoch 18/20
391/391            30s 76ms/step -
accuracy: 0.6450 - loss: 1.0147 - val_accuracy: 0.6500 - val_loss: 1.0218
Epoch 19/20
391/391            29s 74ms/step -
accuracy: 0.6452 - loss: 1.0119 - val_accuracy: 0.6490 - val_loss: 1.0240
Epoch 20/20
391/391            41s 76ms/step -
accuracy: 0.6468 - loss: 1.0084 - val_accuracy: 0.6457 - val_loss: 1.0358
```

[51]:
```
learning_curve(hist)
```


Model Accuracy
Train
Test
0.64
0.62
0.60
0.58
0.56
0.54
0.52
0.50
Accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epoch


Model Loss
Train
Test
Loss
Epoch
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

```
[ ]:
```