

✓ Importing Libraries

```
import keras
from keras.datasets import cifar10
from keras.models import Sequential
from keras import datasets, layers, models
#from keras.utils import np_utils
from keras.utils import to_categorical
from keras import regularizers
from keras.layers import Dense, Dropout, BatchNormalization
import matplotlib.pyplot as plt
import numpy as np
```

✓ Splitting data into training and testing datasets

```
(train_images, train_labels), (test_images, test_labels) = datasets.cifar10.load_data
```



Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>
170498071/170498071 [=====] - 3s 0us/step

✓ Checking the number of rows (records) and columns (features)

```
print(train_images.shape)
print(train_labels.shape)
print(test_images.shape)
print(test_labels.shape)
```

```
(50000, 32, 32, 3)
(50000, 1)
(10000, 32, 32, 3)
(10000, 1)
```

✓ Checking the number of unique classes

```
print(np.unique(train_labels))
print(np.unique(test_labels))
```

```
[0 1 2 3 4 5 6 7 8 9]
```

```
[0 1 2 3 4 5 6 7 8 9]
```

✓ Creating a list of all the class labels

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

✓ Visualizing some of the images from the training dataset

```
plt.figure(figsize=[10,10])  
for i in range (25):      # for first 25 images  
    plt.subplot(5, 5, i+1)  
    plt.xticks([])  
    plt.yticks([])  
    plt.grid(False)  
    plt.imshow(train_images[i], cmap=plt.cm.binary)  
    plt.xlabel(class_names[train_labels[i][0]])  
  
plt.show()
```



✓ Converting the pixels data to float type



```
train_images = train_images.astype('float32')
test_images = test_images.astype('float32')
```



✓ Standardizing (255 is the total number of pixels an image can have)



```
train_images = train_images / 255
test_images = test_images / 255
```



✓ One hot encoding the target class (labels)

```
num_classes = 10
train_labels = to_categorical(train_labels, num_classes)
test_labels = to_categorical(test_labels, num_classes)
```

✓ Creating a sequential model and adding layers to it

```
model = Sequential()

model.add(layers.Conv2D(32, (3,3), padding='same', activation='relu', input_shape=
model.add(layers.BatchNormalization())
model.add(layers.Conv2D(32, (3,3), padding='same', activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D(pool_size=(2,2)))
```

```
model.add(layers.Dropout(0.3))

model.add(layers.Conv2D(64, (3,3), padding='same', activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.Conv2D(64, (3,3), padding='same', activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D(pool_size=(2,2)))
model.add(layers.Dropout(0.5))

model.add(layers.Conv2D(128, (3,3), padding='same', activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.Conv2D(128, (3,3), padding='same', activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D(pool_size=(2,2)))
model.add(layers.Dropout(0.5))

model.add(layers.Flatten())
model.add(layers.Dense(128, activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.Dropout(0.5))
model.add(layers.Dense(num_classes, activation='softmax'))      # num_classes = 10
```

✓ Checking the model summary

```
model.summary()

model.compile(optimizer='adam', loss=keras.losses.categorical_crossentropy, metrics=['accuracy'])

history = model.fit(train_images, train_labels, batch_size=64, epochs=100,
                    validation_data=(test_images, test_labels))
```

Model: "sequential"

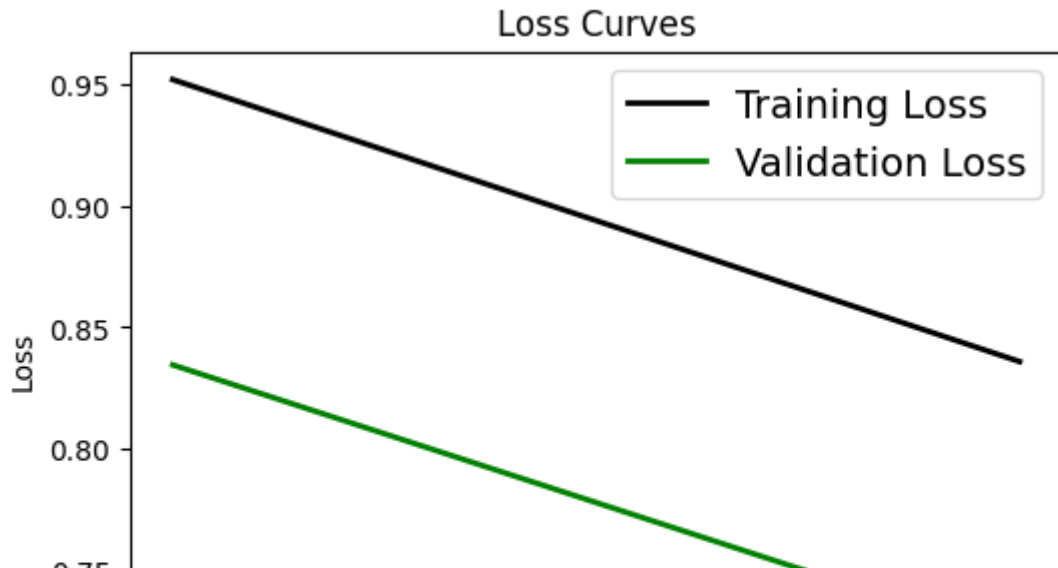
Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 32, 32, 32)	896
batch_normalization (Batch Normalization)	(None, 32, 32, 32)	128
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
batch_normalization_1 (Batch Normalization)	(None, 32, 32, 32)	128
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
dropout (Dropout)	(None, 16, 16, 32)	0

conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_2 (Batch Normalization)	(None, 16, 16, 64)	256
conv2d_3 (Conv2D)	(None, 16, 16, 64)	36928
batch_normalization_3 (Batch Normalization)	(None, 16, 16, 64)	256
max_pooling2d_1 (Max Pooling2D)	(None, 8, 8, 64)	0
dropout_1 (Dropout)	(None, 8, 8, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_4 (Batch Normalization)	(None, 8, 8, 128)	512
conv2d_5 (Conv2D)	(None, 8, 8, 128)	147584
batch_normalization_5 (Batch Normalization)	(None, 8, 8, 128)	512
max_pooling2d_2 (Max Pooling2D)	(None, 4, 4, 128)	0
dropout_2 (Dropout)	(None, 4, 4, 128)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 128)	262272
batch_normalization_6 (Batch Normalization)	(None, 128)	512
dropout_3 (Dropout)	(None, 128)	0

✓ Loss curve

```
plt.figure(figsize=[6,4])
plt.plot(history.history['loss'], 'black', linewidth=2.0)
plt.plot(history.history['val_loss'], 'green', linewidth=2.0)
plt.legend(['Training Loss', 'Validation Loss'], fontsize=14)
plt.xlabel('Epochs', fontsize=10)
plt.ylabel('Loss', fontsize=10)
plt.title('Loss Curves', fontsize=12)
```

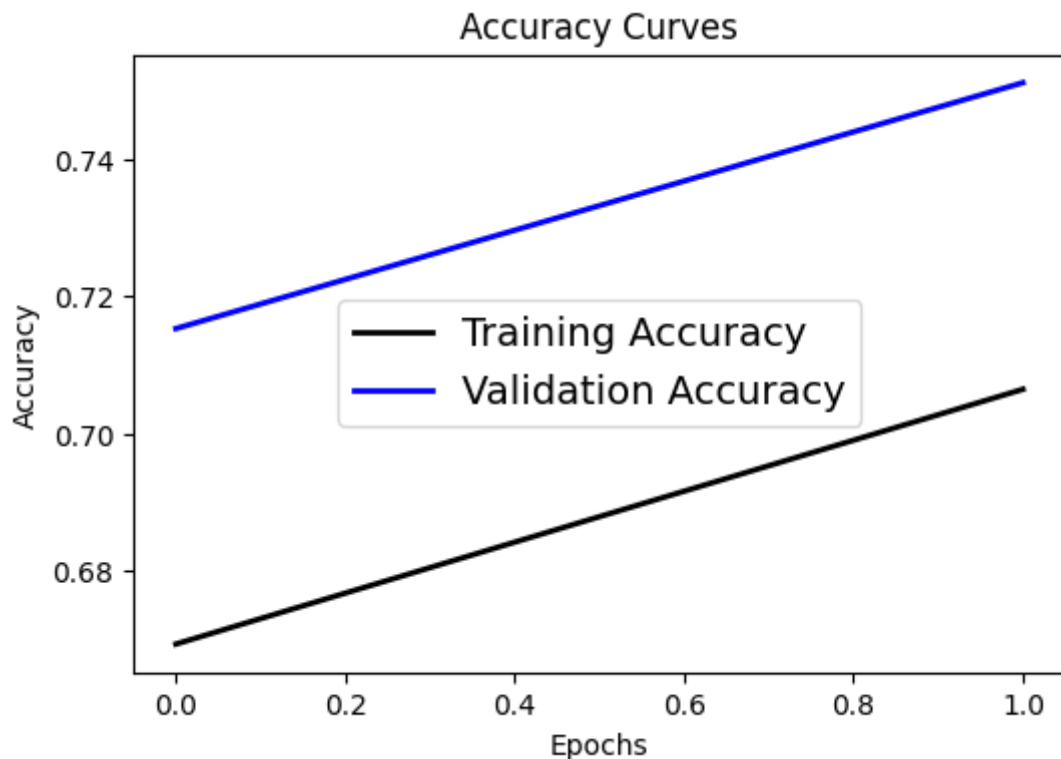
```
Text(0.5, 1.0, 'Loss Curves')
```



✓ Accuracy curve

```
plt.figure(figsize=[6,4])
plt.plot(history.history['accuracy'], 'black', linewidth=2.0)
plt.plot(history.history['val_accuracy'], 'blue', linewidth=2.0)
plt.legend(['Training Accuracy', 'Validation Accuracy'], fontsize=14)
plt.xlabel('Epochs', fontsize=10)
plt.ylabel('Accuracy', fontsize=10)
plt.title('Accuracy Curves', fontsize=12)
```

```
Text(0.5, 1.0, 'Accuracy Curves')
```



Making the Predictions

✓

```
pred = model.predict(test_images)
print(pred)

313/313 [=====] - 20s 64ms/step
[[1.9509140e-04 1.6188844e-04 1.0282345e-03 ... 1.1444237e-03
 3.1774105e-03 1.3830820e-04]
 [1.2504031e-03 1.5327419e-02 5.7257776e-06 ... 4.1446785e-07
 9.8314309e-01 2.6729645e-04]
 [4.6444847e-03 4.0397976e-02 1.0297043e-04 ... 7.0543523e-05
 9.5220649e-01 2.3188286e-03]
 ...
 [9.3175840e-06 4.2566026e-06 5.6574837e-04 ... 9.3918946e-03
 7.3802762e-06 1.9131574e-05]
 [2.8119084e-01 1.7026539e-01 3.9798256e-02 ... 1.6703511e-02
 1.2007578e-03 5.1971967e-03]
 [3.6756487e-07 5.8796502e-07 3.3132452e-05 ... 9.8400670e-01
 4.1580527e-08 3.7064035e-07]]
```

✓ Converting the predictions into label index

```
pred_classes = np.argmax(pred, axis=1)
print(pred_classes)
```

```
[3 8 8 ... 5 4 7]
```

✓ Plotting the Actual vs. Predicted results

```
fig, axes = plt.subplots(5, 5, figsize=(15,15))
axes = axes.ravel()

for i in np.arange(0, 25):
    axes[i].imshow(test_images[i])
    axes[i].set_title("True: %s \nPredict: %s" % (class_names[np.argmax(test_label
    axes[i].axis('off')
    plt.subplots_adjust(wspace=1)
```

True: cat
Predict: cat



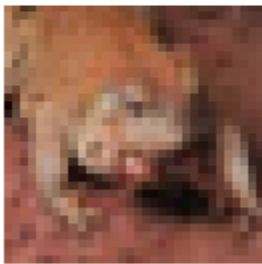
True: ship
Predict: ship



True: ship
Predict: ship



True: frog
Predict: frog



True: automobile
Predict: automobile



True: frog
Predict: deer



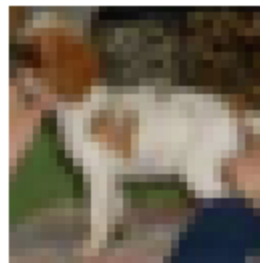
True: airplane
Predict: deer



True: truck
Predict: truck



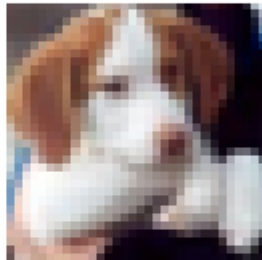
True: dog
Predict: dog



True: ship
Predict: ship



True: dog
Predict: dog



True: horse
Predict: horse



True: horse
Predict: horse



True: airplane
Predict: airplane



True: deer
Predict: deer



