In [93]:
```
"""
Description: This program replicates the practice given at the following URL: https://github.com/josephlee94/intuitive-deep-learning
The program will implement a neural network in order to recognize images of the CIFAR-10 dataset.

Name: Andrea Marcelli
"""
# Importing SSL to solve the issue related to Security Certificate of the dataset CIFAR10
import ssl
ssl._create_default_https_context = ssl._create_unverified_context

from keras.datasets import cifar10
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

In [94]:
```
print('x_train shape:', x_train.shape)
```

```
x_train shape: (50000, 32, 32, 3)
```

In [95]:
```
print('y_train shape:', y_train.shape)
```

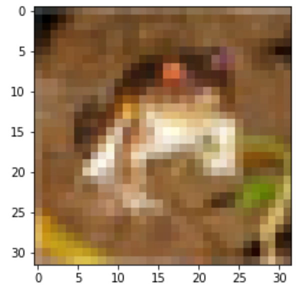
```
y_train shape: (50000, 1)
```

In [96]:
```
# Display pixels of an image
print(x_train[0])
```

```
[[[ 59  62  63]
  [ 43  46  45]
  [ 50  48  43]
  ...
  [158 132 108]
  [152 125 102]
  [148 124 103]]

 [[ 16  20  20]
  [  0   0   0]
  [ 18   8   0]
  ...
  [123  88  55]
  [119  83  50]
  [122  87  57]]

 [[ 25  24  21]
  [ 16   7   0]
  [ 49  27   8]
  ...
  [118  84  50]
  [120  84  50]
  [109  73  42]]

 ...

 [[208 170  96]
  [201 153  34]
  [198 161  26]
  ...
  [160 133  70]
  [ 56  31   7]
  [ 53  34  20]]

 [[180 139  96]
  [173 123  42]
  [186 144  30]
  ...
  [184 148  94]
  [ 97  62  34]
  [ 83  53  34]]

 [[177 144 116]
  [168 129  94]
  [179 142  87]
  ...
  [216 184 140]
  [151 118  84]
  [123  92  72]]]
```

In [97]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

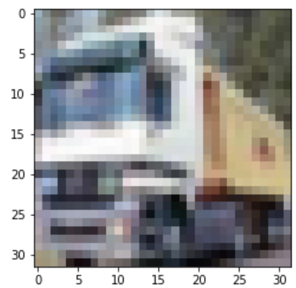
In [98]:
```
# Displaying an image
img = plt.imshow(x_train[0])
```




In [99]:
```
# Displaying the label of the image
print('The label is:', y_train[0])
```

```
The label is: [6]
```

In [100…
```
img = plt.imshow(x_train[1])
```




In [101…
```
print('The label is:', y_train[1])
```

```
The label is: [9]
```

In [102…
```
import keras
y_train_one_hot = keras.utils.to_categorical(y_train, 10)
y_test_one_hot = keras.utils.to_categorical(y_test, 10)
```

In [103…
```
print('The one hot label is:', y_train_one_hot[1])
```

```
The one hot label is: [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
```

In [104…
```
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train = x_train / 255
x_test = x_test / 255
```

In [105…
```
x_train[0]
```

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Out[105]:
```
array([[[0.23137255, 0.24313726, 0.24705882],
         [0.16862746, 0.18039216, 0.1764706 ],
         [0.19607843, 0.1882353 , 0.16862746],
         ...,
         [0.61960787, 0.5176471 , 0.42352942],
         [0.59607846, 0.49019608, 0.4       ],
         [0.5803922 , 0.4862745 , 0.40392157]],

        [[0.0627451 , 0.07843138, 0.07843138],
         [0.        , 0.        , 0.        ],
         [0.07058824, 0.03137255, 0.        ],
         ...,
         [0.48235294, 0.34509805, 0.21568628],
         [0.46666667, 0.3254902 , 0.19607843],
         [0.47843137, 0.34117648, 0.22352941]],

        [[0.09803922, 0.09411765, 0.08235294],
         [0.0627451 , 0.02745098, 0.        ],
         [0.19215687, 0.10588235, 0.03137255],
         ...,
         [0.4627451 , 0.32941177, 0.19607843],
         [0.47058824, 0.32941177, 0.19607843],
         [0.42745098, 0.28627452, 0.16470589]],

        ...,

        [[0.8156863 , 0.6666667 , 0.3764706 ],
         [0.7882353 , 0.6       , 0.13333334],
         [0.7764706 , 0.6313726 , 0.10196079],
         ...,
         [0.627451  , 0.52156866, 0.27450982],
         [0.21960784, 0.12156863, 0.02745098],
         [0.20784314, 0.13333334, 0.07843138]],

        [[0.7058824 , 0.54509807, 0.3764706 ],
         [0.6784314 , 0.48235294, 0.16470589],
         [0.7294118 , 0.5647059 , 0.11764706],
         ...,
         [0.72156864, 0.5803922 , 0.36862746],
         [0.38039216, 0.24313726, 0.13333334],
         [0.3254902 , 0.20784314, 0.13333334]],

        [[0.69411767, 0.5647059 , 0.45490196],
         [0.65882355, 0.5058824 , 0.36862746],
         [0.7019608 , 0.5568628 , 0.34117648],
         ...,
         [0.84705883, 0.72156864, 0.54901963],
         [0.5921569 , 0.4627451 , 0.32941177],
         [0.48235294, 0.36078432, 0.28235295]]], dtype=float32)
```

In [106…
```python
# Creating a model building and training the neural network (Using Conventional 2D tensor and MaxPooling layers)
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D
```

In [107…
```python
model = Sequential()
```

In [108…
```python
model.add(Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(32, 32, 3)))
```

In [109…
```python
model.add(Conv2D(32, (3, 3), activation='relu', padding='same'))
```

In [110…
```python
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

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

model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))
```

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```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_25 (Conv2D)          (None, 32, 32, 32)        896       
                                                                 
 conv2d_26 (Conv2D)          (None, 32, 32, 32)        9248      
                                                                 
 max_pooling2d_8 (MaxPooling  (None, 16, 16, 32)       0         
 2D)                                                             
                                                                 
 dropout_9 (Dropout)         (None, 16, 16, 32)        0         
                                                                 
 conv2d_27 (Conv2D)          (None, 16, 16, 64)        18496     
                                                                 
 conv2d_28 (Conv2D)          (None, 16, 16, 64)        36928     
                                                                 
 max_pooling2d_9 (MaxPooling  (None, 8, 8, 64)         0         
 2D)                                                             
                                                                 
 dropout_10 (Dropout)        (None, 8, 8, 64)          0         
                                                                 
 flatten_3 (Flatten)         (None, 4096)              0         
                                                                 
 dense_4 (Dense)             (None, 512)               2097664   
                                                                 
 dropout_11 (Dropout)        (None, 512)               0         
                                                                 
 dense_5 (Dense)             (None, 10)                5130      
                                                                 
=================================================================
Total params: 2,168,362
Trainable params: 2,168,362
Non-trainable params: 0
_________________________________________________________________
```

In [111…

```
# Configuring the algorithm, the loss function, and the metrics to track
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
# Training our neural network with a batch size of 32 and 20 epochs, splitting the dataset using validation split(20%).
hist = model.fit(x_train, y_train_one_hot, batch_size=32, epochs=20, validation_split=0.2)
```

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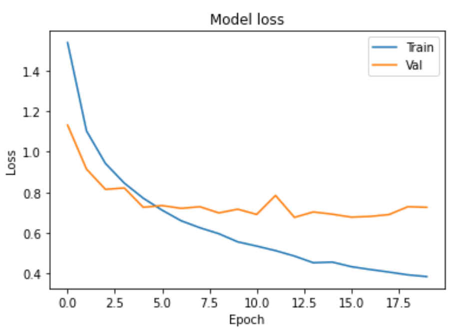
```
Epoch 1/20
1250/1250 [==============================] - 83s 66ms/step - loss: 1.5367 - accuracy: 0.4418 - val_loss: 1.1309 - val_accuracy: 0.6005
Epoch 2/20
1250/1250 [==============================] - 75s 60ms/step - loss: 1.1022 - accuracy: 0.6087 - val_loss: 0.9142 - val_accuracy: 0.6784
Epoch 3/20
1250/1250 [==============================] - 78s 63ms/step - loss: 0.9424 - accuracy: 0.6643 - val_loss: 0.8148 - val_accuracy: 0.7175
Epoch 4/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.8455 - accuracy: 0.7048 - val_loss: 0.8214 - val_accuracy: 0.7144
Epoch 5/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.7712 - accuracy: 0.7263 - val_loss: 0.7264 - val_accuracy: 0.7508
Epoch 6/20
1250/1250 [==============================] - 79s 63ms/step - loss: 0.7123 - accuracy: 0.7493 - val_loss: 0.7349 - val_accuracy: 0.7445
Epoch 7/20
1250/1250 [==============================] - 79s 63ms/step - loss: 0.6604 - accuracy: 0.7654 - val_loss: 0.7213 - val_accuracy: 0.7563
Epoch 8/20
1250/1250 [==============================] - 81s 64ms/step - loss: 0.6257 - accuracy: 0.7782 - val_loss: 0.7291 - val_accuracy: 0.7519
Epoch 9/20
1250/1250 [==============================] - 82s 65ms/step - loss: 0.5964 - accuracy: 0.7893 - val_loss: 0.6988 - val_accuracy: 0.7576
Epoch 10/20
1250/1250 [==============================] - 81s 64ms/step - loss: 0.5564 - accuracy: 0.8045 - val_loss: 0.7171 - val_accuracy: 0.7661
Epoch 11/20
1250/1250 [==============================] - 82s 65ms/step - loss: 0.5355 - accuracy: 0.8095 - val_loss: 0.6913 - val_accuracy: 0.7756
Epoch 12/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.5132 - accuracy: 0.8175 - val_loss: 0.7848 - val_accuracy: 0.7490
Epoch 13/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.4864 - accuracy: 0.8284 - val_loss: 0.6768 - val_accuracy: 0.7753
Epoch 14/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.4535 - accuracy: 0.8401 - val_loss: 0.7035 - val_accuracy: 0.7790
Epoch 15/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.4568 - accuracy: 0.8392 - val_loss: 0.6925 - val_accuracy: 0.7732
Epoch 16/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.4343 - accuracy: 0.8465 - val_loss: 0.6780 - val_accuracy: 0.7823
Epoch 17/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.4203 - accuracy: 0.8516 - val_loss: 0.6815 - val_accuracy: 0.7777
Epoch 18/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.4077 - accuracy: 0.8562 - val_loss: 0.6906 - val_accuracy: 0.7857
Epoch 19/20
1250/1250 [==============================] - 79s 63ms/step - loss: 0.3940 - accuracy: 0.8604 - val_loss: 0.7293 - val_accuracy: 0.7758
Epoch 20/20
1250/1250 [==============================] - 80s 64ms/step - loss: 0.3854 - accuracy: 0.8648 - val_loss: 0.7264 - val_accuracy: 0.7750
```

In [112…

```python
# Creating a plot to visualize the losses and validation loss of the model
plt.plot(hist.history['loss'])
plt.plot(hist.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()
```




In [113…

```python
# Creating a plot to visualize the accuracy and validation accuracy of the model
plt.plot(hist.history['accuracy'])
plt.plot(hist.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='lower right')
```

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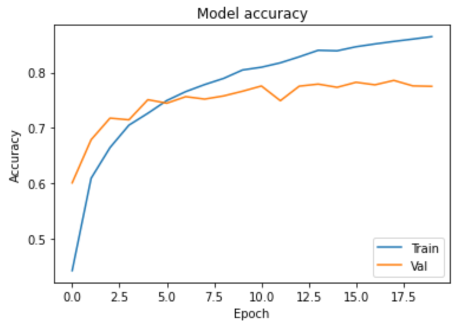



In [114…

```
model.evaluate(x_test, y_test_one_hot)[1]
```

```
313/313 [==============================] - 3s 11ms/step - loss: 0.7358 - accuracy: 0.7686
```

Out[114]:

```
0.7685999870300293
```

In [115…

```
# Saving the model
model.save('my_cifar10_model.h5')
```

In [116…

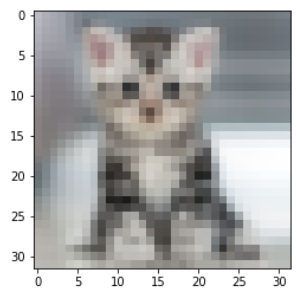
```
# Importing local image
my_image = plt.imread("cat.jpg")
```

In [117…

```
# Resizing the image
from skimage.transform import resize
my_image_resized = resize(my_image, (32,32,3))
```

In [118…

```
img = plt.imshow(my_image_resized)
```



In [119…

```
# Store into a variable the predictionof the resized image
import numpy as np
probabilities = model.predict(np.array([my_image_resized,]))
```

```
1/1 [==============================] - 0s 68ms/step
```

In [120…

```
# Display the probabilities rates
probabilities
```

Out[120]:

```
array([[9.0924734e-03, 3.0980249e-05, 3.0993947e-03, 1.9674745e-01,
        4.8504602e-02, 6.5319723e-01, 9.0583977e-05, 8.8800870e-02,
        2.8678469e-04, 1.4964798e-04]], dtype=float32)
```

In [122…

```
# Predicting the image identity
number_to_class = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
index = np.argsort(probabilities[0,:])
print("Most likely class:", number_to_class[index[9]], "-- Probability:", probabilities[0,index[9]])
print("Second most likely class:", number_to_class[index[8]], "-- Probability:", probabilities[0,index[8]])
print("Third most likely class:", number_to_class[index[7]], "-- Probability:", probabilities[0,index[7]])
print("Fourth most likely class:", number_to_class[index[6]], "-- Probability:", probabilities[0,index[6]])
print("Fifth most likely class:", number_to_class[index[5]], "-- Probability:", probabilities[0,index[5]])
```

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```
Most likely class: dog -- Probability: 0.6531972
Second most likely class: cat -- Probability: 0.19674745
Third most likely class: horse -- Probability: 0.08880087
Fourth most likely class: deer -- Probability: 0.048504602
Fifth most likely class: airplane -- Probability: 0.009092473
```