Classifying CIFAR-10 dataset with the help of Convolutional Neural Networks (CNN):

Import required libraries

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

%matplotlib inline
```

Import CIFAR-10 dataset

In [2]:
```
from tensorflow.keras.datasets import cifar10
```

In [3]:
```
(X_train, y_train), (X_test, y_test) = cifar10.load_data()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170500096/170498071 [==============================] - 32s 0us/step
```

Checking shape of training and testing data

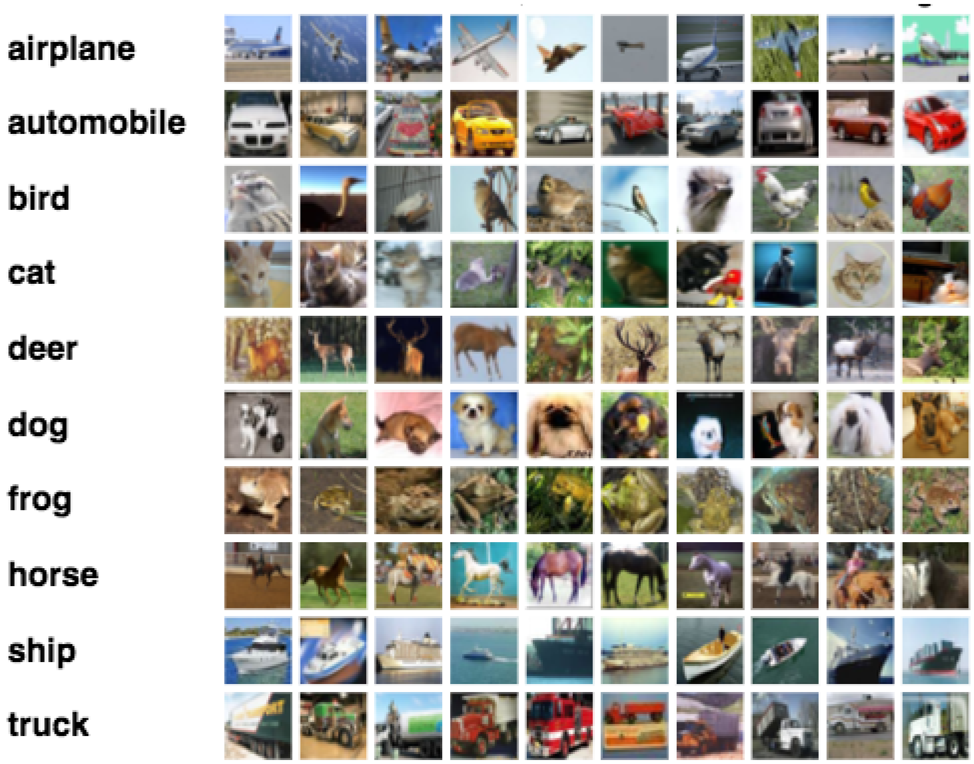
In [4]:
```
print('Shape of Dataset: ')
print(X_train.shape,'\t',X_test.shape,'\t',y_train.shape,'\t',y_test.shape)
```

```
Shape of Dataset: 
(50000, 32, 32, 3)       (10000, 32, 32, 3)      (50000, 1)      (10000, 1)
```

Display some sample images of the dataset

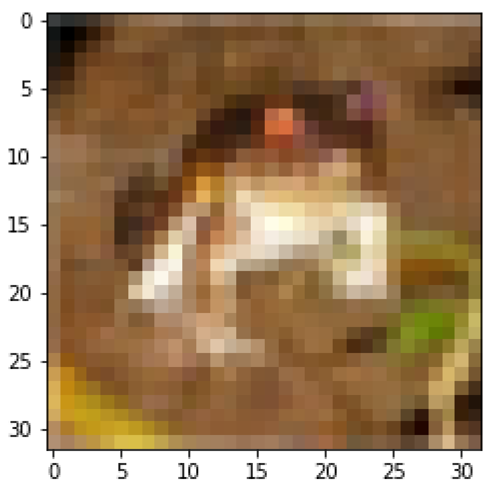
In [25]:
```
from PIL import Image
Image.open('cifar-10.png')
```

Out[25]:



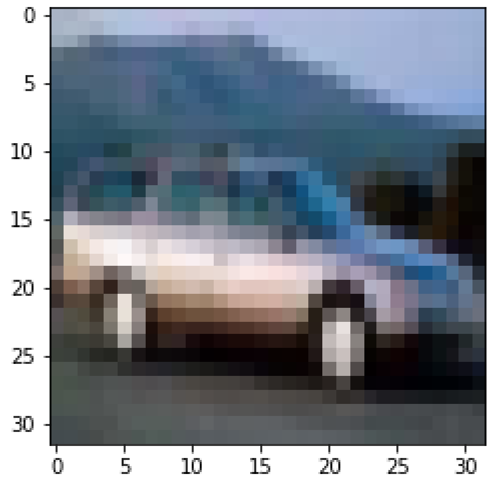
In [8]:
```
plt.imshow(X_train[0])
```

Out[8]: <matplotlib.image.AxesImage at 0x24d4d2bb148>



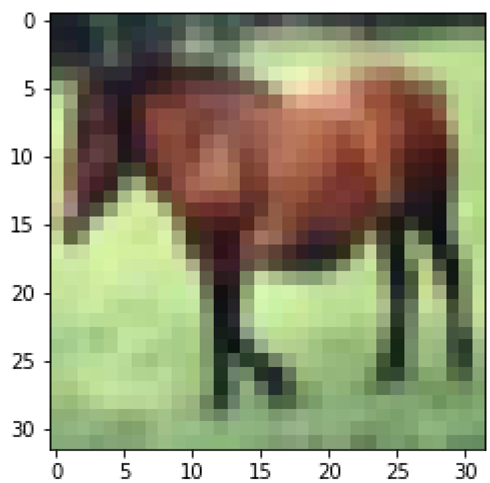
In [9]:
```
plt.imshow(X_train[4])
```

Out[9]: <matplotlib.image.AxesImage at 0x24d4d36d248>



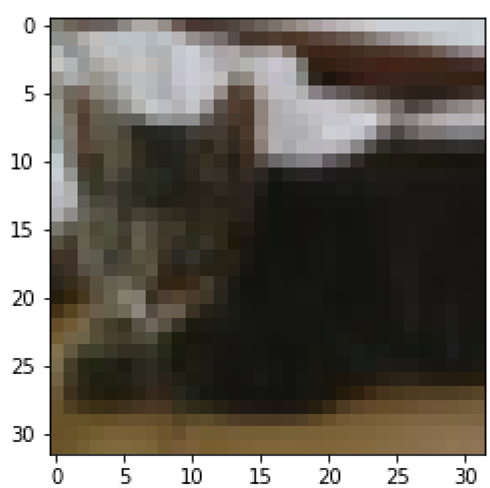
In [10]:
```
plt.imshow(X_train[7])
```

Out[10]: <matplotlib.image.AxesImage at 0x24d4d3d5048>



In [12]:
```
plt.imshow(X_train[9])
```

Out[12]: <matplotlib.image.AxesImage at 0x24d4d49b5c8>



Checking max and min size and scaling the dataset

In [13]:
```
X_train.max()
```

Out[13]: 255

In [14]:
```
X_train.min()
```

Out[14]: 0

In [15]:
```
X_train = X_train/255
X_test = X_test/255
```

In [19]:
```
y_train[0:11]
```

Out[19]:
```
array([[6],
       [9],
       [9],
       [4],
       [1],
       [1],
       [2],
       [7],
       [8],
       [3],
       [4]], dtype=uint8)
```

Convert y to categorical values: One hot encoding

In [20]:
```
from tensorflow.keras.utils import to_categorical
```

In [21]:
```
y_cat_train = to_categorical(y_train, 10)
y_cat_test = to_categorical(y_test, 10)
```

In [22]:
```
y_cat_train[0:11]
```

Out[22]:
```
array([[0., 0., 0., 0., 0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 1., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 1., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 1., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.]], dtype=float32)
```

Import libraries for building the CNN

In [26]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import MaxPool2D, Conv2D, Flatten, Dense
```

Build the model

In [29]:
```
model = Sequential()

#Add Convolution Layer
model.add(Conv2D(filters=32, kernel_size=(4,4), input_shape = (32,32,3), activation='re
#Add Pooling Layer
model.add(MaxPool2D(pool_size=(2,2)))
```

```
#Pixels/Total no of values inside a single MNIST image = 28*28 = 784
#Pixels/Total no of values inside a single CIFAR-10 image = 32*32*3 = 3072
#Since there is a lot more information present, it is better to add more Conv layers to

#Add Convolution Layer
model.add(Conv2D(filters=32, kernel_size=(4,4), input_shape = (32,32,3), activation='re
#Add Pooling Layer
model.add(MaxPool2D(pool_size=(2,2)))

model.add(Flatten())

model.add(Dense(256,activation='relu'))

model.add(Dense(10,activation='softmax'))

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

View model summary

In [30]:

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_4 (Conv2D)            (None, 29, 29, 32)        1568      
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 14, 14, 32)        0         
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 11, 11, 32)        16416     
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 5, 5, 32)          0         
_________________________________________________________________
flatten_2 (Flatten)          (None, 800)               0         
_________________________________________________________________
dense_4 (Dense)              (None, 256)               205056    
_________________________________________________________________
dense_5 (Dense)              (None, 10)                2570      
=================================================================
Total params: 225,610
Trainable params: 225,610
Non-trainable params: 0
_________________________________________________________________
```

Adding Early Stopping

In [31]:

```
from tensorflow.keras.callbacks import EarlyStopping
```

In [32]:

```
early_stop = EarlyStopping(monitor='val_loss', patience=2)
```

Train the model

In [33]:

```
model.fit(X_train, y_cat_train, epochs=20, callbacks = [early_stop], validation_data=(X
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/20
50000/50000 [==============================] - 82s 2ms/sample - loss: 1.5065 - accuracy:
0.4553 - val_loss: 1.2682 - val_accuracy: 0.5467
Epoch 2/20
50000/50000 [==============================] - 61s 1ms/sample - loss: 1.1653 - accuracy:
0.5867 - val_loss: 1.0939 - val_accuracy: 0.6142
```

```
Epoch 3/20
50000/50000 [==============================] - 60s 1ms/sample - loss: 1.0066 - accuracy:
0.6474 - val_loss: 1.0839 - val_accuracy: 0.6196
Epoch 4/20
50000/50000 [==============================] - 59s 1ms/sample - loss: 0.8986 - accuracy:
0.6865 - val_loss: 1.0611 - val_accuracy: 0.6235
Epoch 5/20
50000/50000 [==============================] - 57s 1ms/sample - loss: 0.8018 - accuracy:
0.7186 - val_loss: 0.9956 - val_accuracy: 0.6623
Epoch 6/20
50000/50000 [==============================] - 57s 1ms/sample - loss: 0.7275 - accuracy:
0.7445 - val_loss: 0.9774 - val_accuracy: 0.6732
Epoch 7/20
50000/50000 [==============================] - 64s 1ms/sample - loss: 0.6469 - accuracy:
0.7720 - val_loss: 0.9624 - val_accuracy: 0.6800
Epoch 8/20
50000/50000 [==============================] - 67s 1ms/sample - loss: 0.5795 - accuracy:
0.7960 - val_loss: 1.0283 - val_accuracy: 0.6739
Epoch 9/20
50000/50000 [==============================] - 65s 1ms/sample - loss: 0.5209 - accuracy:
0.8150 - val_loss: 1.0656 - val_accuracy: 0.6741
```

Out[33]: <tensorflow.python.keras.callbacks.History at 0x24d4358c888>

Check model performance

In [37]:
```
metrics = pd.DataFrame(model.history.history)
```

In [38]:
```
metrics.columns
```

Out[38]: Index(['loss', 'accuracy', 'val_loss', 'val_accuracy'], dtype='object')

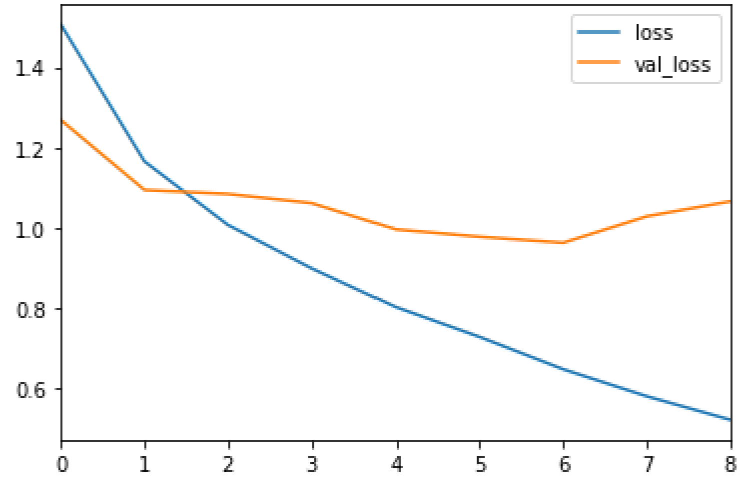
In [39]:
```
metrics.head()
```

Out[39]:

	loss	accuracy	val_loss	val_accuracy
0	1.506543	0.45526	1.268239	0.5467
1	1.165329	0.58668	1.093938	0.6142
2	1.006639	0.64738	1.083885	0.6196
3	0.898590	0.68648	1.061140	0.6235
4	0.801830	0.71856	0.995604	0.6623

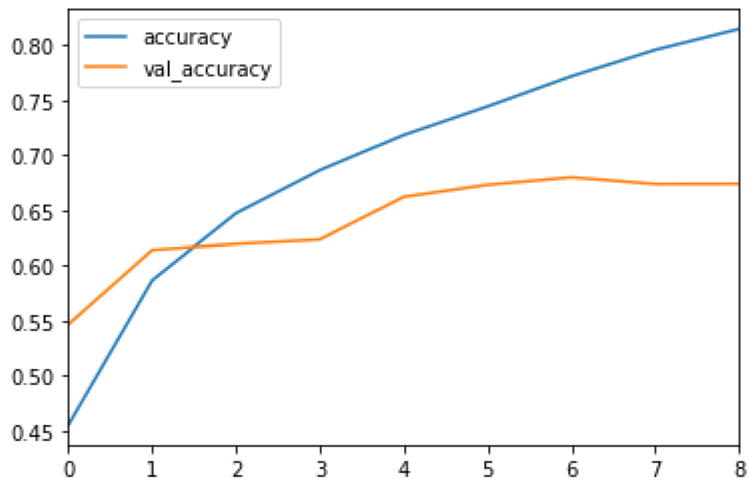
In [40]:
```
metrics[['loss','val_loss']].plot()
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x24d001a2648>



In [43]:
```
metrics[['accuracy','val_accuracy']].plot()
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x24d00222208>



In [44]:
```
#We stopped the training based on the loss and not on the accuracy
```

Compare the same result using evaluate

In [45]:
```
model.evaluate(X_test,y_cat_test,verbose=0)
```

Out[45]: [1.0655978028297424, 0.6741]

Do model prediction

In [50]:
```
predictions = model.predict_classes(X_test)
```

Evaluation metrics and Reporting

In [51]:
```
from sklearn.metrics import classification_report, confusion_matrix
```

In [53]:
```
print(classification_report(y_test,predictions))
print('\n')
print(confusion_matrix(y_test,predictions))
```

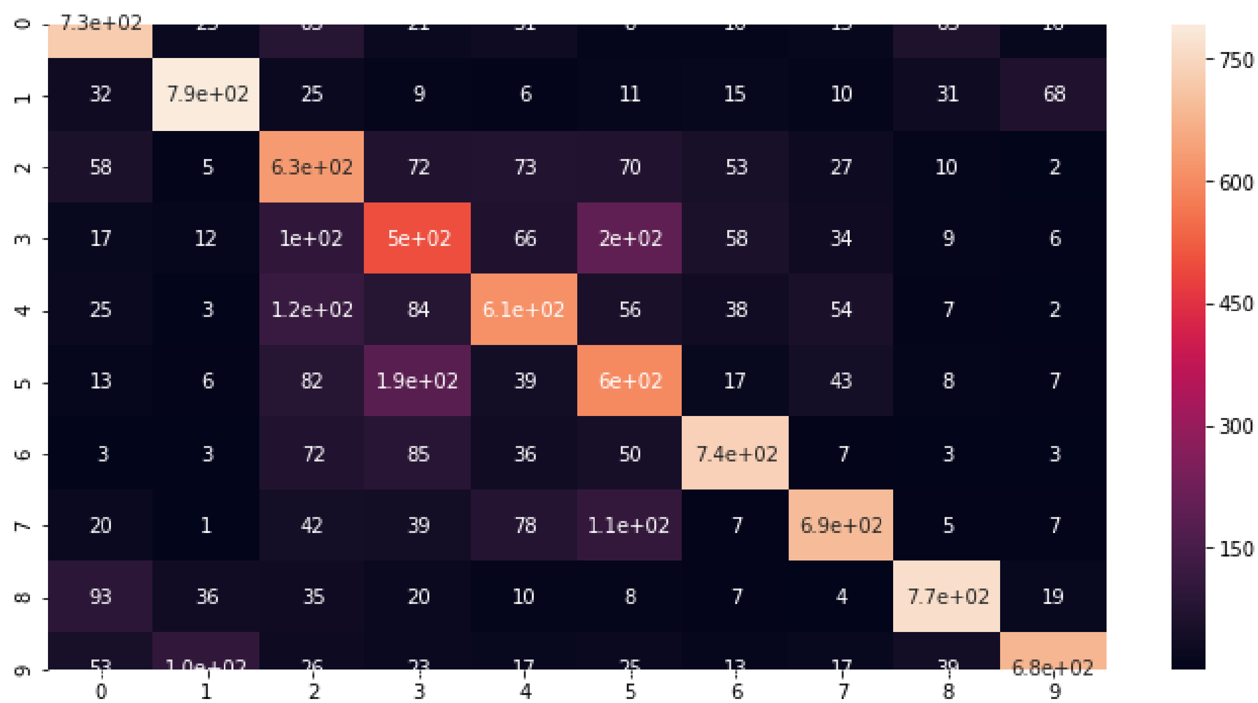
```
              precision    recall  f1-score   support
```

```
           0       0.70      0.73      0.71      1000
           1       0.80      0.79      0.80      1000
           2       0.52      0.63      0.57      1000
           3       0.48      0.50      0.49      1000
           4       0.63      0.61      0.62      1000
           5       0.53      0.60      0.56      1000
           6       0.77      0.74      0.75      1000
           7       0.77      0.69      0.73      1000
           8       0.81      0.77      0.79      1000
           9       0.84      0.68      0.75      1000

    accuracy                           0.67     10000
   macro avg       0.69      0.67      0.68     10000
weighted avg       0.69      0.67      0.68     10000



[[726  25  83  21  31   8  10  15  65  16]
 [ 32 793  25   9   6  11  15  10  31  68]
 [ 58   5 630  72  73  70  53  27  10   2]
 [ 17  12 101 500  66 197  58  34   9   6]
 [ 25   3 120  84 611  56  38  54   7   2]
 [ 13   6  82 186  39 599  17  43   8   7]
 [  3   3  72  85  36  50 738   7   3   3]
 [ 20   1  42  39  78 107   7 694   5   7]
 [ 93  36  35  20  10   8   7   4 768  19]
 [ 53 105  26  23  17  25  13  17  39 682]]
```

Visualize confusion matrix

In [55]:
```
plt.figure(figsize=(12,6))
sns.heatmap(confusion_matrix(y_test,predictions),annot=True)
```

Out[55]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24d01d76708>
```

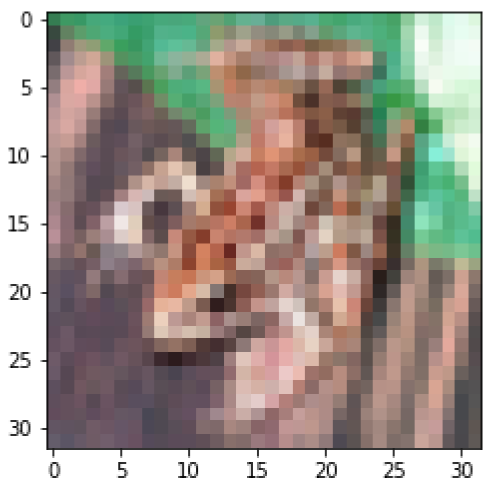


Predicting single image

In [56]:
```
new_img = X_test[95]
```

```
plt.imshow(new_img)
```

Out[56]: <matplotlib.image.AxesImage at 0x24d43415288>



In [58]:
```
y_test[95]
```

Out[58]: array([6], dtype=uint8)

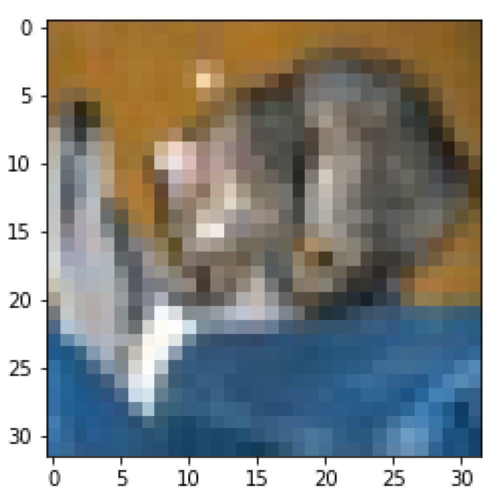
In [60]:
```
model.predict_classes(new_img.reshape(1,32,32,3))
```

Out[60]: array([6], dtype=int64)

So from above, it shows that our model predicted the frog correctly

In [61]:
```
new_img2 = X_test[0]
plt.imshow(new_img2)
```

Out[61]: <matplotlib.image.AxesImage at 0x24d026dbc88>



In [62]:
```
y_test[0]
```

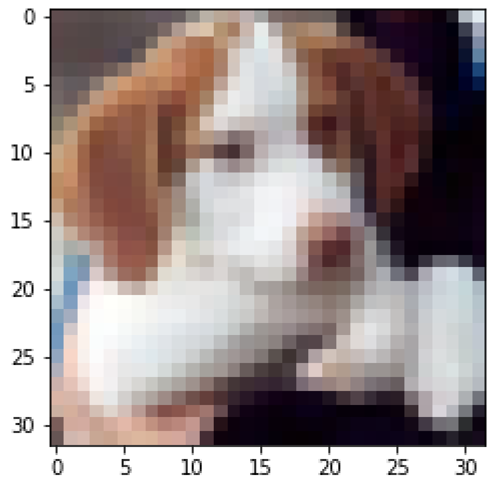
Out[62]: array([3], dtype=uint8)

In [63]:
```
model.predict_classes(new_img2.reshape(1,32,32,3))
```

Out[63]: array([3], dtype=int64)

In [65]:
```
new_img3 = X_test[16]
plt.imshow(new_img3)
```

Out[65]: <matplotlib.image.AxesImage at 0x24d024170c8>



In [66]:
```
y_test[16]
```

Out[66]: array([5], dtype=uint8)

In [67]:
```
model.predict_classes(new_img3.reshape(1,32,32,3))
```

Out[67]: array([5], dtype=int64)

In [ ]: