CIFAR

December 6, 2021

0.1 Define a class to handle all functions

[1]:
```python
class cifar():
    def __init__(self,filepath):
        """ This initialises the filepath to the directory where the files are␣
↪present """
        self.filepath=filepath
        self.batch1=None
        self.batch2=None
        self.map=dict()
        self.map_labels()
        self.n_labels=len(self.map)
        self.model=None

    def load_best_model(self):
      """ The function will load the model from the folder thus making it␣
↪easier to do predictions and testing
      """
      import pickle
      self.model=pickle.load(open('cnnModel81.sav','rb'))

    def test_prediction(self,array):
      """ The function takes as input an image, does the prediction
      and the prints the image along with the predicted label thus helping to␣
↪make testing easier

      If the model has to be changed to a custom model, do
      cf.model=<newmodel>
      to restore the best model do
      cf.load_best_model()
      """
      self.plot(array,cf.label_decode(np.argmax(self.model.predict(array.
↪reshape(1,32,32,3)))))


    def map_labels(self):
        """ The function reads the batches.meta file and converts the lists and␣
↪labels to a dictionary for
```

```
        easy access later """
        content=self.unpickle('batches.meta')
        content=content[b'label_names']
        for i,number in enumerate(content):
            self.map[i]=number.decode('utf-8')

    def label_decode(self,id):
        """ Returns the Label name of the ID which is being passed into the␣
↪function"""
        return self.map[id]

    def unpickle(self,filename):
        """ The function takes a filename and returns the dictionary of data␣
↪inside the file.
            The data is pickled and stored in the files and hence this function␣
↪helps to unpack
            the data.

            Usage : data=unpickle('batches.meta')
            Return : Dictionary of data
            Data inside the dictionary can be explored using data.keys and␣
↪other dictionary functions """

        filepath=self.filepath+filename
        import pickle
        with open(filepath,'rb') as foo:
            dict=pickle.load(foo,encoding='bytes')
        return dict

    def convert_to_rgb(self,array):
        """ The function takes a flattened array as input and converts it into␣
↪a RGB Image.
        It normalises the image by didving by 255 and then stacks it depth wise␣
↪to get an RGB Image. """

        import numpy as np
        r=array[0:1024].reshape(32,32)/255
        g=array[1024:2048].reshape(32,32)/255
        b=array[2048:].reshape(32,32)/255
        im=np.dstack((r,g,b))
        return im


    def read_batch_data(self,id):
        """ Function takes as input the number of the batch file to be read
```

```
            It then reads the data and corresponding label of the data from the␣
↪file
            and then converts it into RGB images.
            The function return the images and labels which can later be used␣
↪for training
            or validation.
            """
        import numpy as np
        filename='data_batch_'+str(id)
        data=self.unpickle(filename)
        y=data[b'labels']
        x=data[b'data']
        images=[]
        for image in x:
            images.append(self.convert_to_rgb(image))
        return np.array(images),np.array(y)


    def read_test_batch(self):
        """ The function already has a set of testing data file. Calling this␣
↪function would
        read the corresponding testing file and would then convert the data␣
↪into images and labels
        in the same way as in the read-batch-data function.
        The function then returns the images and its associated labels which␣
↪are later used as test data
        during the process
        """
        import numpy as np
        filename='test_batch'
        data=self.unpickle(filename)
        y=data[b'labels']
        x=data[b'data']
        images=[]
        for image in x:
            images.append(self.convert_to_rgb(image))
        return np.array(images),np.array(y)

    def OHE(self,list_of_values):
        """ Since the output columns are label encoded, invoking the OHE␣
↪function
        would convert the label encoded outputs to One Hot Encoded Outputs and␣
↪returns the same
        The function takes as input a list of the labels
        """
        import numpy as np
```

```
        result=np.zeros((len(list_of_values),self.n_labels))
        for i in range(len(list_of_values)):
            result[i][list_of_values[i]]=1
        return result

    def plot(self,array,label):
      """ A helper function to plot an image """
      import matplotlib.pyplot as plt
      print(label)
      plt.imshow(array)
```

[2]:
```
from google.colab import drive
drive.mount('/gdrive')
%cd /gdrive
```

```
Mounted at /gdrive
/gdrive
```

[3]:
```
cd '/gdrive/MyDrive/Colab Notebooks/Object Detection with CIFAR'
```

```
/gdrive/MyDrive/Colab Notebooks/Object Detection with CIFAR
```

[4]:
```
# Creating an object of the class

cf=cifar('cifar-10-batches-py/') # The location of data directory is given
```

0.2 Understanding the data

[5]:
```
# Understanding the way classes have been labelled
cf.map
```

[5]:
```
{0: 'airplane',
 1: 'automobile',
 2: 'bird',
 3: 'cat',
 4: 'deer',
 5: 'dog',
 6: 'frog',
 7: 'horse',
 8: 'ship',
 9: 'truck'}
```

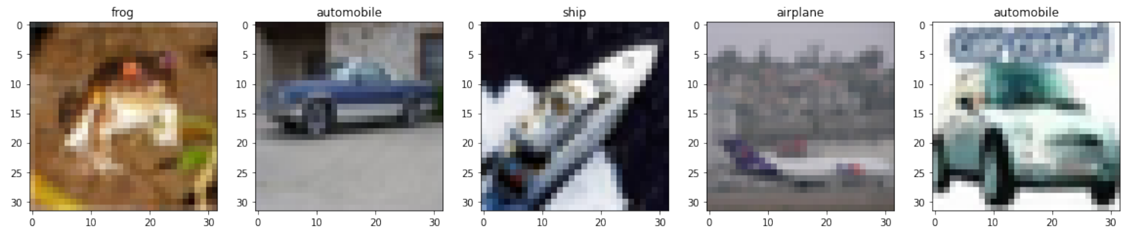
0.2.1 Read the batch data

[6]:
```
# Call the class function to read the file and to convert it into images and␣
↪labels
x_train1,y_train1=cf.read_batch_data(1)
x_train2,y_train2=cf.read_batch_data(2)
x_train3,y_train3=cf.read_batch_data(3)
x_train4,y_train4=cf.read_batch_data(4)
x_train5,y_train5=cf.read_batch_data(5)
```

0.3 Print images and verify from each batch

[7]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(20,5))

#Printing image from batch 1
plt.subplot(1,5,1)
plt.title(cf.label_decode(y_train1[0]))
plt.imshow(x_train1[0])

# Printing image from batch 2
plt.subplot(1,5,2)
plt.title(cf.label_decode(y_train2[0]))
plt.imshow(x_train2[0])

#Printing image from batch 3
plt.subplot(1,5,3)
plt.title(cf.label_decode(y_train3[0]))
plt.imshow(x_train3[0])

#Printing image from batch 4
plt.subplot(1,5,4)
plt.title(cf.label_decode(y_train4[0]))
plt.imshow(x_train4[0])

#Printing image from batch 5
plt.subplot(1,5,5)
plt.title(cf.label_decode(y_train5[0]))
plt.imshow(x_train5[0])
```

[7]:
```
<matplotlib.image.AxesImage at 0x7f58e00d2dd0>
```



0.4 Reading the test batch of images

[8]:
```
x_test,y_test=cf.read_test_batch()
```

0.5 Creating a training, Validation and testing data

[9]:
```
import numpy as np
x_train=np.vstack((x_train1,x_train2,x_train3,x_train4))
y_train=np.hstack((y_train1,y_train2,y_train3,y_train4))

x_val=x_train5
y_val=y_train5
```

0.6 One Hot Encoding the output

[10]:
```
y_test=cf.OHE(y_test)
y_val=cf.OHE(y_val)
y_train=cf.OHE(y_train)
```

0.7 Designing a neural network

[11]:
```
from keras import Sequential
from tensorflow.keras.layers import␣
 ↪Conv2D,MaxPooling2D,Flatten,Dense,BatchNormalization,Dropout
model=Sequential()

model.
 ↪add(Conv2D(filters=32,kernel_size=(3,3),padding='same',input_shape=(32,32,3),activation='re
model.add(Conv2D(filters=64,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.
 ↪add(Conv2D(filters=128,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.
 ↪add(Conv2D(filters=256,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
```

```
model.
 ↪add(Conv2D(filters=512,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.add(Flatten())
model.add(Dense(1024,activation='relu'))
model.add(Dense(256,activation='relu'))
model.add(Dense(128,activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(10,activation='softmax'))
```

[12]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 32, 32, 32)        896

 conv2d_1 (Conv2D)           (None, 32, 32, 64)        18496

 max_pooling2d (MaxPooling2D  (None, 16, 16, 64)       0
 )

 conv2d_2 (Conv2D)           (None, 16, 16, 128)       73856

 max_pooling2d_1 (MaxPooling  (None, 8, 8, 128)        0
 2D)

 conv2d_3 (Conv2D)           (None, 8, 8, 256)         295168

 max_pooling2d_2 (MaxPooling  (None, 4, 4, 256)        0
 2D)

 conv2d_4 (Conv2D)           (None, 4, 4, 512)         1180160

 max_pooling2d_3 (MaxPooling  (None, 2, 2, 512)        0
 2D)

 flatten (Flatten)           (None, 2048)              0

 dense (Dense)               (None, 1024)              2098176

 dense_1 (Dense)             (None, 256)               262400

 dense_2 (Dense)             (None, 128)               32896

 dense_3 (Dense)             (None, 32)                4128
```

```
 dense_4 (Dense)             (None, 10)               330

=================================================================
Total params: 3,966,506
Trainable params: 3,966,506
Non-trainable params: 0
_________________________________________________________________
```

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

[ ]:
```
model.
 ↪fit(x_train,y_train,batch_size=200,epochs=10,validation_data=(x_val,y_val),verbose=1)
```

```
Epoch 1/7
200/200 [==============================] - 492s 2s/step - loss: 1.8147 -
accuracy: 0.3170 - val_loss: 1.4675 - val_accuracy: 0.4535
Epoch 2/7
200/200 [==============================] - 490s 2s/step - loss: 1.2611 -
accuracy: 0.5423 - val_loss: 1.0709 - val_accuracy: 0.6178
Epoch 3/7
200/200 [==============================] - 490s 2s/step - loss: 0.9597 -
accuracy: 0.6579 - val_loss: 0.9379 - val_accuracy: 0.6743
Epoch 4/7
200/200 [==============================] - 491s 2s/step - loss: 0.7469 -
accuracy: 0.7364 - val_loss: 0.7780 - val_accuracy: 0.7293
Epoch 5/7
200/200 [==============================] - 490s 2s/step - loss: 0.5845 -
accuracy: 0.7957 - val_loss: 0.7078 - val_accuracy: 0.7593
Epoch 6/7
200/200 [==============================] - 490s 2s/step - loss: 0.4461 -
accuracy: 0.8442 - val_loss: 0.7203 - val_accuracy: 0.7664
Epoch 7/7
200/200 [==============================] - 490s 2s/step - loss: 0.3372 -
accuracy: 0.8811 - val_loss: 0.8189 - val_accuracy: 0.7527
```

[ ]: <keras.callbacks.History at 0x7f1110a9f3d0>

[ ]:
```
import pickle
pickle.dump(model, open('model.sav', 'wb'))
```

```
INFO:tensorflow:Assets written to:
ram://98cb39c6-fba9-4e34-aa0b-e679f08fd3b3/assets
```

The model has 75 % on data. However, on training for more than 20 epochs, it was seen that the training loss was decreasing, but the validation loss was increasing. Hence, inorder to avoid overfitting the number of epochs were reduced to 10. We

can try to reduce overfitting by adding Dropput as it will avoid a few percentage of neurons during the process

0.7.1 Creating another model , same as above but with Dropout layers

[13]:
```
from keras import Sequential
from tensorflow.keras.layers import␣
↪Conv2D,MaxPooling2D,Flatten,Dense,BatchNormalization,Dropout
model=Sequential()

model.
↪add(Conv2D(filters=32,kernel_size=(3,3),padding='same',input_shape=(32,32,3),activation='re
model.add(Conv2D(filters=64,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.4))
model.
↪add(Conv2D(filters=128,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.3))
model.
↪add(Conv2D(filters=256,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.
↪add(Conv2D(filters=512,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.2))
model.add(Flatten())
model.add(Dense(1024,activation='relu'))
model.add(Dense(256,activation='relu'))
model.add(Dense(128,activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(10,activation='softmax'))
```

[ ]:
```
model.summary()
```

```
Model: "sequential_1"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_5 (Conv2D)           (None, 32, 32, 32)        896

 conv2d_6 (Conv2D)           (None, 32, 32, 64)        18496

 max_pooling2d_4 (MaxPooling  (None, 16, 16, 64)       0
 2D)

 dropout (Dropout)           (None, 16, 16, 64)        0
```

```
 conv2d_7 (Conv2D)           (None, 16, 16, 128)       73856

 max_pooling2d_5 (MaxPooling  (None, 8, 8, 128)        0
 2D)

 dropout_1 (Dropout)         (None, 8, 8, 128)         0

 conv2d_8 (Conv2D)           (None, 8, 8, 256)         295168

 max_pooling2d_6 (MaxPooling  (None, 4, 4, 256)        0
 2D)

 conv2d_9 (Conv2D)           (None, 4, 4, 512)         1180160

 max_pooling2d_7 (MaxPooling  (None, 2, 2, 512)        0
 2D)

 dropout_2 (Dropout)         (None, 2, 2, 512)         0

 flatten_1 (Flatten)         (None, 2048)              0

 dense_5 (Dense)             (None, 1024)              2098176

 dense_6 (Dense)             (None, 256)               262400

 dense_7 (Dense)             (None, 128)               32896

 dense_8 (Dense)             (None, 32)                4128

 dense_9 (Dense)             (None, 10)                330

=================================================================
Total params: 3,966,506
Trainable params: 3,966,506
Non-trainable params: 0
_________________________________________________________________
```

[15]:

```
from sklearn.model_selection import KFold


kF=KFold(n_splits=5)
count=1
for train_index,test_index in kF.split(x_train):
  print('\n Fold '+str(count)+'\n')
  model=Sequential()
```

```
model.
↪add(Conv2D(filters=32,kernel_size=(3,3),padding='same',input_shape=(32,32,3),activation='re
model.
↪add(Conv2D(filters=64,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.4))
model.
↪add(Conv2D(filters=128,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.3))
model.
↪add(Conv2D(filters=256,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.
↪add(Conv2D(filters=512,kernel_size=(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(2,2))
model.add(Dropout(0.2))
model.add(Flatten())
model.add(Dense(1024,activation='relu'))
model.add(Dense(256,activation='relu'))
model.add(Dense(128,activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(10,activation='softmax'))
model.
↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
model.
↪fit(x_train[train_index],y_train[train_index],batch_size=50,epochs=10,validation_data=(x_va
model.evaluate(x_train[test_index],y_train[test_index])
count+=1
```

```
Fold 1

Epoch 1/10
640/640 [==============================] - 21s 31ms/step - loss: 1.8083 -
accuracy: 0.3106 - val_loss: 1.5221 - val_accuracy: 0.4261
Epoch 2/10
640/640 [==============================] - 18s 29ms/step - loss: 1.3673 -
accuracy: 0.4953 - val_loss: 1.2570 - val_accuracy: 0.5377
Epoch 3/10
640/640 [==============================] - 18s 29ms/step - loss: 1.1619 -
accuracy: 0.5803 - val_loss: 1.0276 - val_accuracy: 0.6369
Epoch 4/10
640/640 [==============================] - 19s 30ms/step - loss: 1.0297 -
accuracy: 0.6346 - val_loss: 0.9395 - val_accuracy: 0.6696
Epoch 5/10
640/640 [==============================] - 20s 31ms/step - loss: 0.9365 -
```

```
accuracy: 0.6712 - val_loss: 0.9277 - val_accuracy: 0.6761
Epoch 6/10
640/640 [==============================] - 18s 29ms/step - loss: 0.8573 -
accuracy: 0.6958 - val_loss: 0.8614 - val_accuracy: 0.6982
Epoch 7/10
640/640 [==============================] - 19s 30ms/step - loss: 0.8020 -
accuracy: 0.7183 - val_loss: 0.8166 - val_accuracy: 0.7176
Epoch 8/10
640/640 [==============================] - 18s 29ms/step - loss: 0.7303 -
accuracy: 0.7435 - val_loss: 0.7331 - val_accuracy: 0.7490
Epoch 9/10
640/640 [==============================] - 18s 29ms/step - loss: 0.6923 -
accuracy: 0.7565 - val_loss: 0.7427 - val_accuracy: 0.7483
Epoch 10/10
640/640 [==============================] - 19s 30ms/step - loss: 0.6448 -
accuracy: 0.7707 - val_loss: 0.7780 - val_accuracy: 0.7349
250/250 [==============================] - 2s 9ms/step - loss: 0.7727 -
accuracy: 0.7330

 Fold 2

Epoch 1/10
640/640 [==============================] - 20s 29ms/step - loss: 2.0049 -
accuracy: 0.2216 - val_loss: 1.6473 - val_accuracy: 0.3595
Epoch 2/10
640/640 [==============================] - 20s 30ms/step - loss: 1.4408 -
accuracy: 0.4564 - val_loss: 1.2674 - val_accuracy: 0.5365
Epoch 3/10
640/640 [==============================] - 18s 29ms/step - loss: 1.1981 -
accuracy: 0.5648 - val_loss: 1.1075 - val_accuracy: 0.5951
Epoch 4/10
640/640 [==============================] - 18s 29ms/step - loss: 1.0560 -
accuracy: 0.6207 - val_loss: 1.0738 - val_accuracy: 0.6123
Epoch 5/10
640/640 [==============================] - 18s 29ms/step - loss: 0.9486 -
accuracy: 0.6612 - val_loss: 0.8719 - val_accuracy: 0.6968
Epoch 6/10
640/640 [==============================] - 18s 29ms/step - loss: 0.8666 -
accuracy: 0.6930 - val_loss: 0.8112 - val_accuracy: 0.7110
Epoch 7/10
640/640 [==============================] - 20s 31ms/step - loss: 0.8045 -
accuracy: 0.7192 - val_loss: 0.7660 - val_accuracy: 0.7319
Epoch 8/10
640/640 [==============================] - 18s 29ms/step - loss: 0.7515 -
accuracy: 0.7347 - val_loss: 0.7579 - val_accuracy: 0.7343
Epoch 9/10
640/640 [==============================] - 18s 29ms/step - loss: 0.7030 -
accuracy: 0.7536 - val_loss: 0.7492 - val_accuracy: 0.7408
```

```
Epoch 10/10
640/640 [==============================] - 18s 29ms/step - loss: 0.6583 -
accuracy: 0.7695 - val_loss: 0.7308 - val_accuracy: 0.7459
250/250 [==============================] - 2s 9ms/step - loss: 0.7586 -
accuracy: 0.7369

 Fold 3

Epoch 1/10
640/640 [==============================] - 21s 31ms/step - loss: 1.8752 -
accuracy: 0.2766 - val_loss: 1.5644 - val_accuracy: 0.4190
Epoch 2/10
640/640 [==============================] - 18s 29ms/step - loss: 1.4286 -
accuracy: 0.4702 - val_loss: 1.2050 - val_accuracy: 0.5583
Epoch 3/10
640/640 [==============================] - 20s 30ms/step - loss: 1.1868 -
accuracy: 0.5660 - val_loss: 1.1102 - val_accuracy: 0.6002
Epoch 4/10
640/640 [==============================] - 19s 30ms/step - loss: 1.0411 -
accuracy: 0.6236 - val_loss: 0.9289 - val_accuracy: 0.6722
Epoch 5/10
640/640 [==============================] - 20s 31ms/step - loss: 0.9369 -
accuracy: 0.6703 - val_loss: 0.8697 - val_accuracy: 0.6965
Epoch 6/10
640/640 [==============================] - 18s 29ms/step - loss: 0.8526 -
accuracy: 0.7007 - val_loss: 0.7939 - val_accuracy: 0.7281
Epoch 7/10
640/640 [==============================] - 20s 31ms/step - loss: 0.7808 -
accuracy: 0.7266 - val_loss: 0.7994 - val_accuracy: 0.7204
Epoch 8/10
640/640 [==============================] - 19s 30ms/step - loss: 0.7264 -
accuracy: 0.7428 - val_loss: 0.7397 - val_accuracy: 0.7423
Epoch 9/10
640/640 [==============================] - 20s 31ms/step - loss: 0.6758 -
accuracy: 0.7638 - val_loss: 0.8109 - val_accuracy: 0.7237
Epoch 10/10
640/640 [==============================] - 19s 30ms/step - loss: 0.6492 -
accuracy: 0.7715 - val_loss: 0.7151 - val_accuracy: 0.7558
250/250 [==============================] - 2s 9ms/step - loss: 0.7315 -
accuracy: 0.7539

 Fold 4

Epoch 1/10
640/640 [==============================] - 21s 31ms/step - loss: 1.9871 -
accuracy: 0.2328 - val_loss: 1.6566 - val_accuracy: 0.3736
Epoch 2/10
640/640 [==============================] - 19s 29ms/step - loss: 1.4735 -
```

```
accuracy: 0.4534 - val_loss: 1.2967 - val_accuracy: 0.5184
Epoch 3/10
640/640 [==============================] - 19s 29ms/step - loss: 1.2328 -
accuracy: 0.5504 - val_loss: 1.1068 - val_accuracy: 0.6013
Epoch 4/10
640/640 [==============================] - 19s 29ms/step - loss: 1.0831 -
accuracy: 0.6079 - val_loss: 0.9826 - val_accuracy: 0.6475
Epoch 5/10
640/640 [==============================] - 20s 31ms/step - loss: 0.9817 -
accuracy: 0.6514 - val_loss: 0.9252 - val_accuracy: 0.6733
Epoch 6/10
640/640 [==============================] - 20s 31ms/step - loss: 0.9039 -
accuracy: 0.6814 - val_loss: 0.8734 - val_accuracy: 0.7027
Epoch 7/10
640/640 [==============================] - 19s 29ms/step - loss: 0.8406 -
accuracy: 0.7028 - val_loss: 0.8148 - val_accuracy: 0.7132
Epoch 8/10
640/640 [==============================] - 19s 29ms/step - loss: 0.7829 -
accuracy: 0.7239 - val_loss: 0.7924 - val_accuracy: 0.7226
Epoch 9/10
640/640 [==============================] - 19s 29ms/step - loss: 0.7393 -
accuracy: 0.7414 - val_loss: 0.8062 - val_accuracy: 0.7184
Epoch 10/10
640/640 [==============================] - 20s 31ms/step - loss: 0.7026 -
accuracy: 0.7534 - val_loss: 0.7641 - val_accuracy: 0.7410
250/250 [==============================] - 2s 9ms/step - loss: 0.7510 -
accuracy: 0.7408

 Fold 5

Epoch 1/10
640/640 [==============================] - 21s 31ms/step - loss: 1.8252 -
accuracy: 0.2916 - val_loss: 1.5150 - val_accuracy: 0.4298
Epoch 2/10
640/640 [==============================] - 20s 31ms/step - loss: 1.3850 -
accuracy: 0.4845 - val_loss: 1.2528 - val_accuracy: 0.5431
Epoch 3/10
640/640 [==============================] - 20s 31ms/step - loss: 1.1518 -
accuracy: 0.5847 - val_loss: 1.0575 - val_accuracy: 0.6206
Epoch 4/10
640/640 [==============================] - 20s 31ms/step - loss: 0.9891 -
accuracy: 0.6505 - val_loss: 0.9873 - val_accuracy: 0.6448
Epoch 5/10
640/640 [==============================] - 19s 29ms/step - loss: 0.8925 -
accuracy: 0.6878 - val_loss: 0.8346 - val_accuracy: 0.7101
Epoch 6/10
640/640 [==============================] - 20s 31ms/step - loss: 0.8096 -
accuracy: 0.7147 - val_loss: 0.8018 - val_accuracy: 0.7224
```

```
Epoch 7/10
640/640 [==============================] - 19s 29ms/step - loss: 0.7392 -
accuracy: 0.7424 - val_loss: 0.7922 - val_accuracy: 0.7324
Epoch 8/10
640/640 [==============================] - 20s 31ms/step - loss: 0.6942 -
accuracy: 0.7572 - val_loss: 0.7336 - val_accuracy: 0.7511
Epoch 9/10
640/640 [==============================] - 19s 29ms/step - loss: 0.6463 -
accuracy: 0.7746 - val_loss: 0.7259 - val_accuracy: 0.7471
Epoch 10/10
640/640 [==============================] - 20s 31ms/step - loss: 0.6076 -
accuracy: 0.7872 - val_loss: 0.7001 - val_accuracy: 0.7613
250/250 [==============================] - 2s 9ms/step - loss: 0.7222 -
accuracy: 0.7542
```

[ ]:
```
model.
 ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
model.
 ↪fit(x_train,y_train,batch_size=50,epochs=20,validation_data=(x_val,y_val),verbose=1)
```

```
Epoch 1/20
800/800 [==============================] - 311s 388ms/step - loss: 1.6707 -
accuracy: 0.3834 - val_loss: 1.3837 - val_accuracy: 0.4981
Epoch 2/20
800/800 [==============================] - 307s 384ms/step - loss: 1.2032 -
accuracy: 0.5706 - val_loss: 0.9606 - val_accuracy: 0.6538
Epoch 3/20
800/800 [==============================] - 307s 384ms/step - loss: 0.9874 -
accuracy: 0.6521 - val_loss: 0.9107 - val_accuracy: 0.6762
Epoch 4/20
800/800 [==============================] - 307s 384ms/step - loss: 0.8684 -
accuracy: 0.6958 - val_loss: 0.7493 - val_accuracy: 0.7364
Epoch 5/20
800/800 [==============================] - 307s 384ms/step - loss: 0.7812 -
accuracy: 0.7312 - val_loss: 0.7172 - val_accuracy: 0.7527
Epoch 6/20
800/800 [==============================] - 308s 385ms/step - loss: 0.7169 -
accuracy: 0.7503 - val_loss: 0.6876 - val_accuracy: 0.7644
Epoch 7/20
800/800 [==============================] - 307s 384ms/step - loss: 0.6649 -
accuracy: 0.7660 - val_loss: 0.6687 - val_accuracy: 0.7718
Epoch 8/20
800/800 [==============================] - 306s 383ms/step - loss: 0.6218 -
accuracy: 0.7835 - val_loss: 0.6621 - val_accuracy: 0.7752
Epoch 9/20
800/800 [==============================] - 307s 384ms/step - loss: 0.5826 -
accuracy: 0.7958 - val_loss: 0.6244 - val_accuracy: 0.7854
Epoch 10/20
```

```
800/800 [==============================] - 308s 385ms/step - loss: 0.5526 -
accuracy: 0.8047 - val_loss: 0.6435 - val_accuracy: 0.7867
Epoch 11/20
800/800 [==============================] - 306s 383ms/step - loss: 0.5223 -
accuracy: 0.8147 - val_loss: 0.6036 - val_accuracy: 0.8005
Epoch 12/20
800/800 [==============================] - 306s 383ms/step - loss: 0.5016 -
accuracy: 0.8253 - val_loss: 0.6389 - val_accuracy: 0.7905
Epoch 13/20
800/800 [==============================] - 306s 383ms/step - loss: 0.4789 -
accuracy: 0.8321 - val_loss: 0.6128 - val_accuracy: 0.8018
Epoch 14/20
800/800 [==============================] - 305s 382ms/step - loss: 0.4608 -
accuracy: 0.8380 - val_loss: 0.6164 - val_accuracy: 0.8045
Epoch 15/20
800/800 [==============================] - 305s 381ms/step - loss: 0.4466 -
accuracy: 0.8415 - val_loss: 0.6331 - val_accuracy: 0.8030
Epoch 16/20
800/800 [==============================] - 305s 381ms/step - loss: 0.4364 -
accuracy: 0.8439 - val_loss: 0.6110 - val_accuracy: 0.8066
Epoch 17/20
800/800 [==============================] - 307s 383ms/step - loss: 0.4148 -
accuracy: 0.8532 - val_loss: 0.6074 - val_accuracy: 0.8120
Epoch 18/20
800/800 [==============================] - 307s 383ms/step - loss: 0.4070 -
accuracy: 0.8563 - val_loss: 0.5929 - val_accuracy: 0.8144
Epoch 19/20
800/800 [==============================] - 305s 382ms/step - loss: 0.3916 -
accuracy: 0.8626 - val_loss: 0.6401 - val_accuracy: 0.7984
Epoch 20/20
800/800 [==============================] - 305s 382ms/step - loss: 0.3788 -
accuracy: 0.8664 - val_loss: 0.6184 - val_accuracy: 0.8113
```

[ ]: <keras.callbacks.History at 0x7f19ebdeb5d0>

[ ]:
```
model.evaluate(x_test,y_test)
```

```
313/313 [==============================] - 19s 61ms/step - loss: 0.6527 -
accuracy: 0.7988
```

[ ]: [0.6526737213134766, 0.798799991607666]

[ ]:
```
# Saving the model

import pickle
pickle.dump(model,open('cnnModel81.sav','wb'))
```

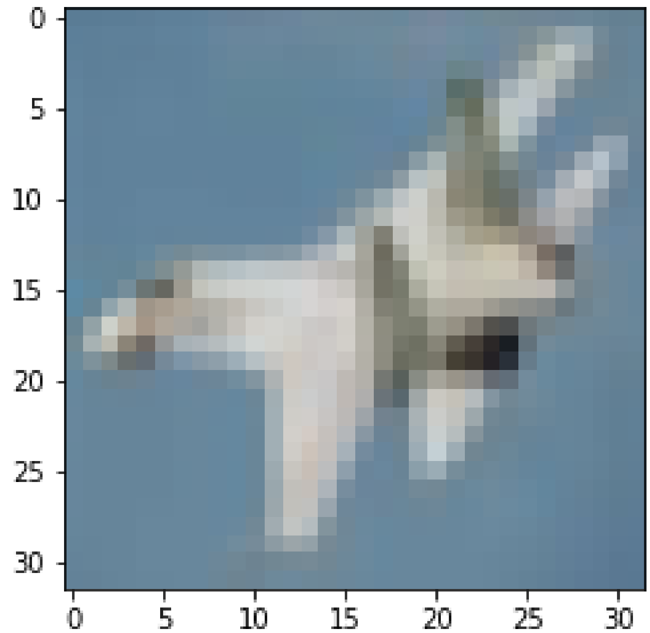
```
INFO:tensorflow:Assets written to:
```

ram://9f446629-a858-46c9-946d-b8857f1310db/assets

0.8 Testing the working of the model

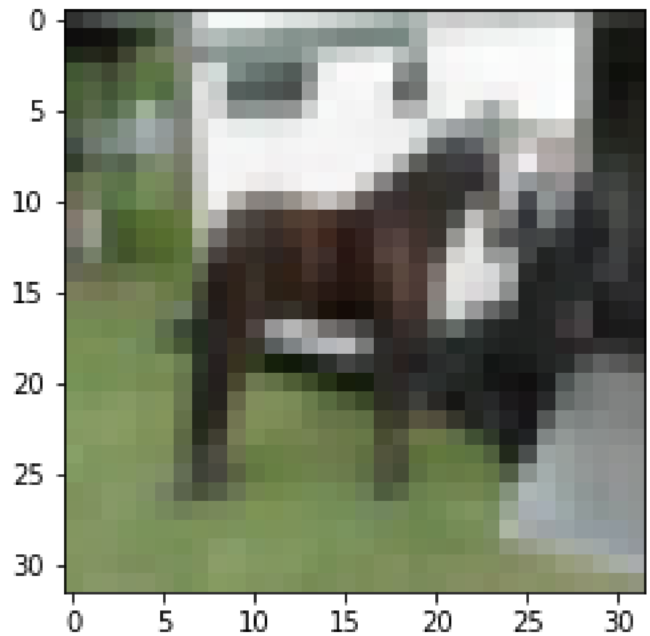
[ ]:
```
cf.test_prediction(x_test[10])
```

airplane



[ ]:
```
cf.test_prediction(x_test[20])
```

horse



0.9 We can see that the model is predicting properly

[ ]:

```

```