Introducction

I have created a convolutional neural network (CNN) for image classification on the CIFAR-10 dataset. I used the Tensorflow and Kera libraries to build the model.

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The dataset is divided into four training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class.

Libraries

Importing packages

In [1]:

```
import numpy as np
import pandas as pd
import cv2
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, BatchNormalization, Fl
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import optimizers
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping
from tensorflow.keras.datasets import cifar10
#from vit_keras import vit, utils
#import tensorflow_addons as tfa
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns
import gc


import warnings
warnings.filterwarnings('ignore')
```

Loading the Dataset

In [2]:

```
x_train = np.load('x_train.npy')
```

In [3]:

```
x_test= np.load('x_test.npy')
```

In [4]:

```
y_test= np.load('y_test.npy')
```

In [5]:

```
y_train = np.load('y_train.npy')
```

In [6]:

```
x_train.shape
```

Out[6]:

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

In [7]:

```
x_test.shape
```

Out[7]:

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

In [8]:

```
y_train.shape
```

Out[8]:

```
(50000, 1)
```

In [9]:

```
y_test.shape
```

Out[9]:

```
(10000, 1)
```

Define the class each item of array represent integer value of labels.

In [10]:

```
classes =['Airplane', 'Automobile', 'Bird', 'Cat', 'Deer', 'Dog', 'Frog', 'Horse', 'Ship'
classes
```

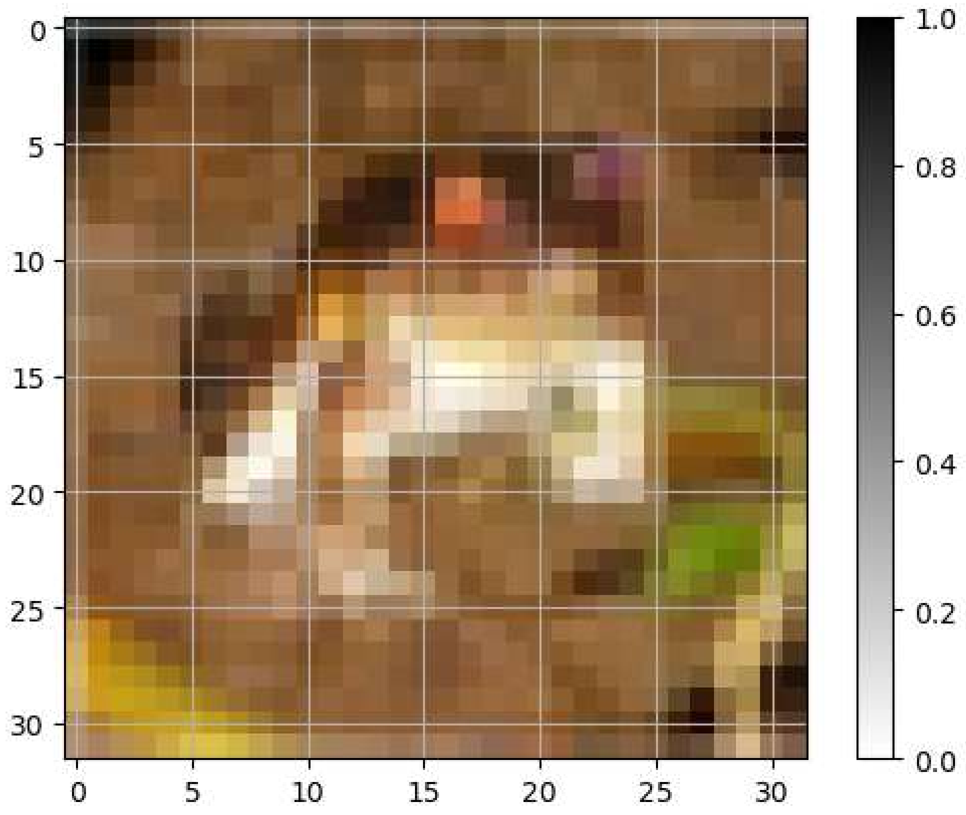
Out[10]:

```
['Airplane',
 'Automobile',
 'Bird',
 'Cat',
 'Deer',
 'Dog',
 'Frog',
 'Horse',
 'Ship',
 'Truck']
```

Evaluation of the data

In [11]:

```
index=0
plt.imshow(x_train[index], cmap=plt.cm.binary) # printing 10th image.
plt.colorbar() # shows the bar on the right side of the image
plt.grid(True)
plt.show()# Show images
print("Class ID=> %s and Class name : %s" % (y_train[index], classes[y_train[index][0]]))
```



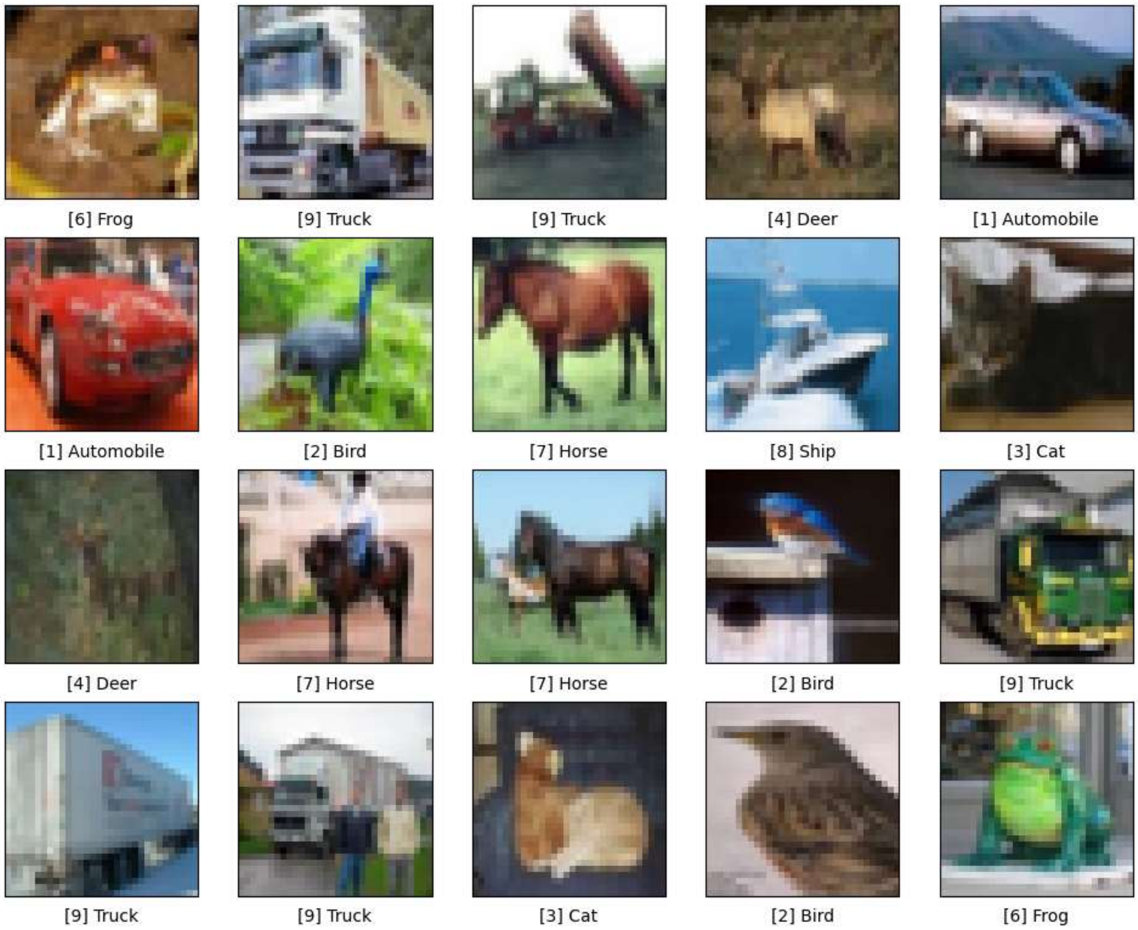

```
Class ID=> [6] and Class name : Frog
```

Show images

In [12]:

```
# Assigning name to each image
plt.figure(figsize=(12,12))
for i in range(20): # 20 images
  plt.subplot(5,5,i+1) # matrix of 5 X 5 array
  plt.xticks([])
  plt.yticks([])
  plt.grid(False)
  plt.imshow(x_train[i], cmap=plt.cm.binary)

  plt.xlabel("%s %s" % (y_train[i], classes[y_train[i][0]]))
plt.show()
```



Data Preparation

Scaling the image values

In [13]:

```
x_train = x_train/255 # So, we are scale the value between 0 to 1 before by deviding each
print(x_train.shape)

x_test = x_test/255 # So, we are scale the value between 0 to 1 before by deviding each v
print(x_test.shape)
```

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

One hot encoding of the labels.

In [39]:

```
# Before one hot encoding
print("ytrain Shape: %s and value: %s" % (y_train.shape, y_train))
print("ytest Shape: %s and value: %s" % (y_test.shape,y_test))

y_train=to_categorical(y_train)
y_test=to_categorical(y_test)

# After one hot encoding
print("y_train Shape: %s and value: %s" % (y_train.shape, y_train[0]))
print("y_test Shape: %s and value: %s" % (y_test.shape, y_test[1]))
```

```
ytrain Shape: (50000, 1) and value: [[6]
 [9]
 [9]
 ...
 [9]
 [1]
 [1]]
ytest Shape: (10000, 1) and value: [[3]
 [8]
 [8]
 ...
 [5]
 [1]
 [7]]
y_train Shape: (50000, 10) and value: [0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
y_test Shape: (10000, 10) and value: [0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
```

Modelling - Model on CNN

In [40]:

```
model=models.Sequential()

model.add(layers.Conv2D(64,(3,3),input_shape=(32,32,3),activation='relu'))
model.add(layers.Conv2D(64,(3,3),input_shape=(32,32,3),activation='relu'))
#Add the max pooling layer
model.add(layers.MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))

#Add Second convolutional block
model.add(layers.Conv2D(128,(3,3),activation='relu'))
model.add(layers.Conv2D(128,(3,3),activation='relu'))
# Add the max pooling layer
model.add(layers.MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))
model.add(layers.Conv2D(256,(3,3),activation='relu'))
model.add(layers.MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))

#Add Flatten layer. Flatten simply converts matrics to array
model.add(layers.Flatten(input_shape=(32,32)))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dense(80, activation='relu'))

#Add the output layer
model.add(layers.Dense(10, activation='softmax'))

# Ploting the Model
print(model)
```

```
<keras.engine.sequential.Sequential object at 0x00000157B655DC70>
```

Compile the model

In [20]:

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

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 64)        1792      
                                                                 
 conv2d_1 (Conv2D)           (None, 28, 28, 64)        36928     
                                                                 
 max_pooling2d (MaxPooling2D  (None, 14, 14, 64)       0         
 )                                                               
                                                                 
 dropout (Dropout)           (None, 14, 14, 64)        0         
                                                                 
 conv2d_2 (Conv2D)           (None, 12, 12, 128)       73856     
                                                                 
 conv2d_3 (Conv2D)           (None, 10, 10, 128)       147584    
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 5, 5, 128)        0         
 2D)                                                             
                                                                 
 dropout_1 (Dropout)         (None, 5, 5, 128)         0         
                                                                 
 conv2d_4 (Conv2D)           (None, 3, 3, 256)         295168    
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 1, 1, 256)        0         
 2D)                                                             
                                                                 
 dropout_2 (Dropout)         (None, 1, 1, 256)         0         
                                                                 
 flatten (Flatten)           (None, 256)               0         
                                                                 
 dense (Dense)               (None, 128)               32896     
                                                                 
 dense_1 (Dense)             (None, 100)               12900     
                                                                 
 dense_2 (Dense)             (None, 80)                8080      
                                                                 
 dense_3 (Dense)             (None, 10)                810       
                                                                 
=================================================================
Total params: 610,014
Trainable params: 610,014
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```

```

Train the model

In [21]:

```
x_train1=x_train.reshape(50000,32,32,3)
x_test1=x_test.reshape(10000,32,32,3)

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(50000, 32, 32, 3)
(10000, 32, 32, 3)
(50000, 10)
(10000, 10)
```

In [22]:

```
model.fit(x_train1,y_train,epochs=20,batch_size=50,verbose=True,validation_data=(x_test1,
```

```
Epoch 1/20
1000/1000 [==============================] - 572s 560ms/step - loss: 2.302
8 - accuracy: 0.0971 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 2/20
1000/1000 [==============================] - 505s 505ms/step - loss: 2.302
7 - accuracy: 0.0991 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 3/20
1000/1000 [==============================] - 559s 559ms/step - loss: 2.302
8 - accuracy: 0.0967 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 4/20
1000/1000 [==============================] - 545s 546ms/step - loss: 2.302
7 - accuracy: 0.0998 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 5/20
1000/1000 [==============================] - 563s 563ms/step - loss: 2.302
7 - accuracy: 0.0969 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 6/20
1000/1000 [==============================] - 609s 609ms/step - loss: 2.302
7 - accuracy: 0.0998 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 7/20
1000/1000 [==============================] - 573s 573ms/step - loss: 2.302
8 - accuracy: 0.0975 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 8/20
1000/1000 [==============================] - 523s 523ms/step - loss: 2.302
7 - accuracy: 0.0980 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 9/20
1000/1000 [==============================] - 527s 527ms/step - loss: 2.302
7 - accuracy: 0.0982 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 10/20
1000/1000 [==============================] - 544s 544ms/step - loss: 2.302
7 - accuracy: 0.0976 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 11/20
1000/1000 [==============================] - 533s 533ms/step - loss: 2.302
7 - accuracy: 0.0972 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 12/20
1000/1000 [==============================] - 532s 532ms/step - loss: 2.302
8 - accuracy: 0.0974 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 13/20
1000/1000 [==============================] - 494s 494ms/step - loss: 2.302
7 - accuracy: 0.0988 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 14/20
1000/1000 [==============================] - 494s 494ms/step - loss: 2.302
7 - accuracy: 0.0979 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 15/20
1000/1000 [==============================] - 470s 470ms/step - loss: 2.302
7 - accuracy: 0.0970 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 16/20
1000/1000 [==============================] - 482s 482ms/step - loss: 2.302
8 - accuracy: 0.0992 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 17/20
1000/1000 [==============================] - 478s 478ms/step - loss: 2.302
7 - accuracy: 0.0989 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 18/20
1000/1000 [==============================] - 483s 483ms/step - loss: 2.302
8 - accuracy: 0.0993 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 19/20
1000/1000 [==============================] - 473s 473ms/step - loss: 2.302
7 - accuracy: 0.0974 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 20/20
1000/1000 [==============================] - 489s 489ms/step - loss: 2.302
8 - accuracy: 0.0989 - val_loss: 2.3026 - val_accuracy: 0.1000
```

Out[22]:

```
&lt;keras.callbacks.History at 0x1578ed7c220&gt;
```

Evaluate the model accuracy

In [23]:

```
test_loss, test_acc = model.evaluate(x_test1, y_test)
print("accuracy:", test_acc)
```

```
313/313 [==============================] - 22s 67ms/step - loss: 2.3026 -
accuracy: 0.1000
accuracy: 0.10000000149011612
```

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